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Juxtaposing Gender Differentials in Credit Assessment of Farmers in Nigeria: A Hybridized Credit-Scoring Approach

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Abstract

Using data from 360 smallholder farmers in Southeast Nigeria, the study creates the architecture for a new farmer's hybrid credit rating system used in classifying farmers who applied for microfinance loans based on their creditworthiness. We discovered new evidence that the hybridized credit scoring algorithm demonstrated unprecedented concordance in assessing the financial viability of farmers along gender lines. The discriminant analysis, in particular, closely aligned with the credit score model, with 34.4% and 46.7% of male and female farmers grouped as creditworthy, reflecting the model's estimates of 33.3% and 45.5%, indicating gaps of 12.3% and 12.2%, respectively, to the advantage of the female farmers. Our findings further suggest that annual income, marital status, and farm size strongly influence the separation between creditworthy and non-creditworthy farmers. While age, loan term, and a history of defaults had a negative impact on discrimination, in light of the findings, we recommend a collaboration between authorities, financial institutions, and extension workers in offering tailored trainings to both male and female farmers, assisting them in meeting up-to-date credit prerequisites, adopting modified farming techniques, and improving their general preparedness to be accepted for loans in this changing credit evaluation landscape so as to bridge the disparity and promote financial inclusion for farmers irrespective of gender affiliations.

Keywords

Agricultural finance, credits scoring, discriminant analysis, smallholder farmers, microfinance lending, gender.

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Introduction

With nearly 206,000,000 inhabitants, Nigeria is Africa's most populous nation and the seventh-most populated nation globally (World Bank, 2021). For the Nigerian population, agribusiness offers the best opportunity for jobs, revenues, and food supplies. The cultivation of crops, raising animals, woodlands, and fisheries make up the bulk of the agricultural sector (Adewale et al., 2022). Availability of credit to agribusiness is particularly warranted when farmers have limited capital, inadequately structured rural financial systems, and access to suitable farmstead technologies whose appropriation is restricted by a lack of farm assets (Ukoha et al., 2020). According to the International Monetary Fund (2005), microfinance institutions (MFIs) exist to provide lending services to the underprivileged and extremely disadvantaged, especially in agrarian areas, as a more comprehensive evaluation of access adequacy includes evaluating the regulatory environment for MFIs.

In Nigeria, where agriculture is a significant sector, microfinance banks often extend credit to farmers and agricultural enterprises. It is critical to ascertain if lenders use prejudicial approaches to lending when evaluating the loan creditworthiness of smallholder farmers in light of the reported inequalities in access to bank-related products between farmers of both genders. A fundamental concern confronting the financial services sector is determining bad loan applicants, given that ongoing credit delivery to uncreditworthy consumers may generate grave issues in the years to come through escalating bank capital losses, reduced bank earnings, and insolvency (CBN, 2014).

According to the Economic Commission for Latin America and the Caribbean (2019), policymakers have recognized financial autonomy for women in agriculture as a crucial development objective. Hitherto, in the conventional loan market, there has been a gender gap in financial access, regardless of the reality that women possess greater creditworthiness and less risky preferences (Morsy, El-Shal, and Woldemichael 2019). This is because of a number of factors, such as job prospects, legal restrictions, social customs, and restricted access to agricultural credit (Chen et al., 2020; Paglia et al., 2014; Eckel et al., 2015; Moro et al., 2017).

In Nigeria, there are some occasions where clients know loan employees through personal contacts or through acquaintances, which may influence their evaluation capacities. There is a chance that female borrowers who applied for credit will face more obstacles than their male counterparts when trying to secure funding (De Andrés, Gimeno, and De Cabo, 2021). Possible causes of this include prejudice rooted in preferences that paint female borrowers as less competent and effective; issues relating to data that depend on the choice of whether to grant credit based on the average qualities of the group (statistical prejudice); or the prevalence of implicit biases (embedded bias). Female farmers would undoubtedly have more difficult financing access in any of these scenarios, which would have a severe negative impact on the Nigerian agricultural sector. Any possible malfunction in the financing medium for farmers, as well as any impediment or prejudice impeding the loan assessment process, might have a detrimental impact on the agricultural development of any nation.

To successfully appraise and predict small-holder farmer creditworthiness, it is vital to respect its complexities. Creditworthiness assessments are crucial in order to reduce defaults in financial institutions as well as determine whether to award credit and the amount that should be charged for that credit (Ofonyelu et al., 2013). Inadequate evaluation of borrowers' qualities makes it difficult for the financial institution to properly safeguard itself in the event of default outcomes since it determines the risks and default probability of prospective borrowers, which is a criterion that must be followed before credit is issued.

There are numerous publications on credit scores or credit evaluation for businesses (including MFBs), with the majority of them already commercialized. Among the foremost pertinent articles on worker credit scores, one puts forward an institutional reliability assessment technique using fuzzy rough sets. This suggested rule-driven technique was implemented to forecast farmers' financial standing and utilized with real bank data from 2044 agriculturalists across China for use in farm loan decision-making (Bai et al., 2019). Several studies have examined the determinants of creditworthiness and the potential gender differences in these factors. For instance, Agarwal et al. (2010) explored the impact of income, employment status, and educational attainment on creditworthiness. They found that gender differences in these factors significantly influenced creditworthiness outcomes, with women often facing disadvantageous conditions. Wilson et al. (2007) explored the role of gender norms and expectations in loan decisions. They found that traditional gender roles and stereotypes affected loan officers' perceptions of creditworthiness, leading to potential disparities. A large historical loan sample of the same credit type is classified into two types: positive loans and poor loans. The combination of clients' qualities distinguishing "acceptable" from undesirable credits generates a rating (or likelihood) that can be used as an assessment of the likelihood of default rating for every incoming loan whenever creditors determine whether or not to provide the loans or not (Limsombunchai et al., 2005).

Several studies have found that women have more constraints in agricultural production than men, resulting in decreased accessibility to and more competitive rates for loans, supplies, and technologies (Guétat-Bernard, 2014; Asadullah and Kambhampati, 2021; Beuchelt, 2016).

Financial services for smallholder farmers in developing countries are crucially provided by banks; however, gender disparities persist in accessing credit and financial services, affecting women disproportionately (Malhotra and Schuler, 2002; Kabeer, 2005; Kabeer, 2012). Sana and Shailja (2019) investigated the gender gaps in entrepreneurial activities and capitalization of small and medium enterprises. They were of the opinion that gaps in entrepreneurial activities could be a result of differences in financial, economic, and socio-cultural variables influencing the entrepreneur’s business environment.

Notwithstanding these noteworthy research inputs, there is still a substantial study vacuum, as we couldn’t find a study that analyzed and compared the gender-related differences in credit assessments for smallholder farmers by banks. The current study aims to fill this gap by juxtaposing the gender gaps in credit assessments among Southeast Nigerian smallholder farmers who applied for microfinance bank credit using a new hybridized credit scoring model specifically designed for smallholder farmers. In doing so, it seeks to further contribute to existing literature by classifying male and female farmers into creditworthy and non-creditworthy smallholder farmers using the CSMSF and discriminant analysis. Another important contribution of this study is that it empirically analyzed the gender gaps in credit assessments of male and female smallholder farmers.

Gender gaps in loan evaluations of Nigerian farmers by microfinance institutions hold important ramifications for the country's agricultural progress and SDG achievement. Adeosun and Owolabi (2021), Enakhe, and Tamuno (2021) affirmed that Nigeria is beleaguered by destitution, an insufficient food supply, and disparities in gender. These challenges are interconnected and can be alleviated by providing farmers with equal opportunities for agricultural financing. Gender prejudices in loan evaluations limit women's ability to use farm resources, thereby reducing crop yields and prolonging impoverishment. Nigeria's advancement in achieving the SDGs, particularly Goals 1 (no poverty) and 2 (zero hunger), is highly reliant on agricultural growth (Henry, 2022; Egberi, 2023). Hence, addressing disparities in gender assessment by financial institutions, particularly microfinance banks in Nigeria, could empower female farmers, raise revenues, and improve agricultural output, thereby connecting to Goals 5 (gender equality) and 10 (reducing inequalities) and supporting sustainable development.

This study focuses on gender differences in credit risk assessment among microfinance bank beneficiaries in Nigeria. In this regard, we juxtaposed a gender analysis in credit assessments of smallholder farmers by microfinance banks in south-east Nigeria using a hybridized farm credit scoring algorithm that incorporates the credit scoring model for smallholder farmers (CSMSF) and the discriminant analysis to shed light on the creditworthiness of male and female farmers, empirically ascertain the gender gaps in credit evaluation and assessment of male and female smallholder farmers, and also ascertain the efficacy of the hybridized credit scoring model specifically designed for smallholder farmers, thereby providing vital information for microfinance banks, agricultural policy makers, and stakeholder farmers. These results would help address gender-based credit gaps in farmer credit assessment so as to improve the level of final inclusion in the Nigerian agricultural sector.

Materials and methods

Study area

The geopolitical zone of south-east Nigeria was used as the research area. The south-east zone is made up of five states: Anambra, Abia, Enugu, Imo, and Ebonyi. With 169 microfinance banks in total, the south-east zone has the second-highest concentration of them in the nation, accounting for 19.4% of the total of these: 8 in Ebonyi, 23 in Enugu, 25 in Abia, 38 in Imo, and 75 in Anambra (Ukoha et al., 2020). This study adopted a multistage sample procedure. Firstly, Imo and Enugu States were purposefully chosen because they had a high percentage of female smallholder farmers and numerous microfinance institutions. Secondly, ten microfinance banks from each state (Imo and Enugu) were purposively selected due to their lending activities to smallholder farmers. From Enugu State: Lapo MFB, Umuchinemere MFB, Ifeanyichukwu MFB, Kenechukwu MFB, Nsukka MFB, Oha MFB, Aris MFB, Coal Camp MFB, Good Shepard MFB, and Isu-ozu MFB; from Imo State: All Workers MFB, Lapo MFB, Oche MFB, Osina MFB, Merit MFB, Ogbe-Ahiara MFB, Chikum MFB, Vantage MFB, Amaifeke MFB, and Orsu MFB. Thirdly, 18 loan applicants, consisting of nine male and nine female applicants, were randomly selected from a list of 30 loan applicants provided by each of the banks listed above, making a total of 360 respondents, comprising 180 male and 180 female applicants (180 farmers from Enugu State and 180 farmers from Imo State). There were three major reasons for our choice of the study location. First, the zealous economic activity; second, because the majority of the population are Igbos, who are largely recognized for their agricultural practices, independence, and commercial abilities, there is a substantial level of societal uniformity in the area; and lastly, there is a scarcity of empirical applications of credit scoring and credit risk assessments by microfinance banks in south-eastern Nigeria.

Methods of data analysis

Two stages of analysis were performed on the data. Firstly, a credit scoring model for smallholder farmers (CSMSF) was developed. This CSMSF is basically done by attaching weights to key variables used in accessing the eligibility of loan applicants by most banks so as to derive credit scores, which were further classified into four categories based on risk classes. The key variables that were used in this research were selected from a pre-survey of MFBs in Southeast Nigeria from the Development Finance Office of the CBN, Imo State. This study specifically assessed the eligibility of loan applicants who applied for and are yet to receive credit.

For the purpose of this research, the classification of farmers into creditworthy and non-creditworthy applicants acted as a pre-classifier, which was used in the second stage (discriminant function analysis). The second stage was done by making use of the preclassifiers from the first stage in the discriminant analysis (DA). The discriminant analysis was used in creditworthiness analysis (Onyenuchaya and Ukoha, 2007) (Table 1).

FACTORS	SCORE	MINIMUM SCORE	MAXIMUM SCORE
ACCOUNT OFFICER			
Yes	20		20
No	10	10	
FARM OWNERSHIP			
Owns a farm	20		20
Rents a farm	10	10	
EDUCATIONAL LEVEL			
Tertiary	40		40
Secondary	30		
Primary	20		
Vocational	10		
No formal education	0	0	
PROXIMITY TO MFB			
Yes	20		20
No	10	10	
MARITAL STATUS			
Married	30		30
Single/divorced/widowed	10	10	
OFF FARM INCOME			
Yes	10		10
No	0	0	
AGE			
20-30	40		40
31-40	30		
41-50	20		
51-60	10	10	
HOUSEHOLD SIZE			
1-3	30		30
4-5	20		
> 6	10	10	
FARMING EXPERIENCE (YEARS)			
13 and above	50		50
10-12	40		
7-9	30		
4-6	20		
1-3	10		
0	0	0	
LOAN TENURE			
3 months	30		30
6 months	20		
9 months	10		
1 year	0	0	
FARM INCOME (ANNUAL) (NAIRA '000)			
Above 90	50		50
71-90	40		
51-70	30		
31-50	20		
X.30	10	10	
DEFAULT HISTORY (MONTHS)			
90 days default	0	0	
60 days default	10		
30 days default	20		
None	30		30
LOAN FROM OTHER BANKS			
Yes	0	0	
No	10		30
RELATIONSHIP (YEARS)			
Above 8	50		50
07.VIII	40		
05.VI	30		
03.IV	20		
01.II	10		
0	0	0	
FARM SIZE (HECTARES)			
4 and above	50		50
03.IV	40		
02.III	30		
01.II	20		
Less than one ha	10	10	
ACCOUNT HOLDER			
YES	10		10
NO	0	0	
OVERALL TOTAL		**80**	**510**

Source: Data from a field survey, 2022

Table 1: Credit Scoring Model for Smallholder Farmers (CSMSF).

The socio-demographic factors were used to measure the credit risk levels of loan applicants. The CSMSF factors each have a number of qualities and corresponding scores, which were developed using 16 different variables, while the credit scores ranged from 80 to 510. This was further transformed into a credit score on a scale of 1–100.

Mathematically, 25% of a scale of 80 to 510 is 107.5 + 80 = 187.5.

50% = 215+80 = 295

75% = 322.5+80 = 402.5

100% = 430+80 = 510

Therefore, if a farmer's credit scores fall between 80 and 187.5 (on a scale of 80 to 510), he automatically falls between 1 and 25 (on a scale of 1 to 100); similarly, if he/she falls between 187.6 and 295, he/she automatically falls between 26 and 50; if he/she falls between 295.1 and 402.5, he/she automatically falls between 51 and 75; and if he/she scores between 402.6 and 510, he automatically scores between 76 and 100 on a scale of 1 to 100 (Table 2).

For this framework, 51% is the qualifying score. Applicants with scores of 51% and above were categorized as creditworthy farmers, while applicants with less than 51% were not qualified for a loan and were categorized as non-creditworthy farmers.

The discriminant analytical model classified the farmers by the same set of variables used in the CSMSF, which were used as independent variables, into two mutually exclusive categories. Applicants with a total credit score above 50% were categorized as creditworthy farmers, while applicants with a score of 50% or less were categorized as not creditworthy farmers. In the discriminant analysis, the following variables are used: age, gender, educational level, farmer's locative situation, proximity to the bank, marital status, off-farm income, farming experience, credit history, monthly income, loans from other banks, relationship with the bank, farm size, loan tenure, household size, and account holder. According to Onyenucheya and Ukoha (2007), the model is expressed as follows:

$$D_i = b_o + b_1 z_{1i} + b_2 z_{2i} \dots + b_n z_{ni} + e_i \qquad (1)$$

z_i is derived from the formula, $x_{ij} - x$

Where;

z_i = the discriminant score of the ith Farmer

D_i = the total discriminant score

x_{ij} = the ith distinct-value of the jth regressor.

b_{ij} = the jth variables discriminant coefficient

x = standard deviation of the independent variable.

e_i = error term

Let z_i, the discriminant score for each individual, be a function of the regressors. Therefore,

$$z_i = b_o + b_1 x_1 + b_2 x_2 \dots + b_n x_n \qquad (2)$$

The classification process is as outlined below;

When

$z_i = z_{crt}$ classify the applicant (i) as creditworthy,

$z_i < z_{crt}$ classify the individual (i) as non-creditworthy

Classification boundary is the locus of the point where;

$$b_o + b_1 x_1 + b_2 x_2 \dots + b_n x_n = z_{crt} \qquad (3)$$

Variables	**Explanations/Unit**
Dependent variable	
z_i	The discriminant score of the ith Farmer
Independent variables	
Age (x_1)	Years
Accessibility to Account Officer (x_2)	A dummy = (1) should the account officer interact with the farmer more than four times a year; (0) otherwise
Educational Level (x_3)	Number of years spent in school.
Farm ownership (x_4)	A dummy variable equals to (1) if the farmer Owns a farm and (0) otherwise
Proximity To Bank (x_5)	The distance in kilometers between farmers location and the MFBs
Marital Status (x_6)	Dummy = (1) if the farmer Married; (0) Otherwise
Annual Off-Farm Income (x_7)	Non-farming activities in Naira received by the farmer annually
Farming Experience (x_8)	Years.
default History (x_9)	Duration of the farmers' previous defaults in months.
Annual Farm Income (x_{10})	Naira
Loans From Other Banks(x_{11})	Dummy = (1) should the applicant have a credit running in another bank; (0) if he has not.
Relationship with Bank (x_{12})	Number of years a farmer has operated MFB account. Measured in years
Farm Size (x_{13})	Hectares
Loan Tenure (x_{14})	Tenure of the loan years.
Household Size (x_{15})	Number of people using the same catering setup with the applicant.
Account Holder (x_{16})	Dummy = (1) should the applicant have an account with the bank; (0) Otherwise.

CREDIT SCORE (Scale of 80 to 510)	**CREDIT SCORE (Scale of 1 to 100)**	**QUALITY**	**RISK CLASS**
402.6- 510	76-100	Excellent	A
295.1-402.5	51-75	Good	B
187.6-295	26-50	Average	C
80-187.5	1-25	Below Average	D

Source: Data from a field survey, 2022

Table 2: Credit risk class derived from the credit scores.

The credit scoring model and the discriminant function analysis is applied for male and female farmer loan applicants separately.

Results and discussion

Creditworthiness along gender lines as determined by the credit scoring methodology

Table 3 presents the distribution of the credit-worthiness of smallholder farmers by gender as derived from the credit scoring model.

As indicated in Table 3, most of the male loan applicants (66.7%) were not creditworthy, while only 33.3% of them were creditworthy in the study area. The same scenario was observed among the female loan applicants, where most (54.4%) of them were not creditworthy while a few (45.5%) were, indicating a gap of 12.2% in credit assessment along gender lines. For the entire group of respondents, 60.6% of applicants were not creditworthy, while 39.4% were creditworthy. The result, however, indicates that there were more creditworthy female loan applicants than males in the study area. This suggests that female loan applicants were more qualified and prepared to obtain loans than their male counterparts. This is on account of being more creditworthy. This result contrasts with existing literature. According to Zainuddin and Yasin (2020), traditional financial institutions, as well as government-funded initiatives, frequently focus on male customers. This could be due to their perceived creditworthiness. Our findings point to a notable departure from popular opinion and a considerable gender gap in creditworthiness in favour of female smallholder farmers.

Comparison of the creditworthiness of smallholder farmers by gender

Table 4 presents the z-test result of the significance difference in the creditworthiness (using credit score) of smallholder farmers along gender lines.

As shown in Table 4, we observed a significant difference in the average credit scores of the male and female loan applicants in the study area (Z = -3.704) at the 1% level of significance, while the mean credit scores of the male and female respondents in the study area were 63.857 and 71.892 respectively, suggesting that female loan applicants were more creditworthy than their male counterparts. The results above shows that the assessment of farmers credit applications was precisely and accurately evaluated. It shows statistical proof either in favour of or against the economic theory that the creditworthiness of male and female smallholder farmers differs meaningfully. The difference which is seen from the results above in from the average credit scores in this instance is not likely to be the product of chance, according to the significant Z-test result (-3.704 at the 1% level of significance).

Credit risk class as derived from the credit scores of smallholder farmers by gender

The distribution of the credit risk class derived from the credit scores of smallholder farmers by gender is presented in Table 5. The credit risk class shows the classification of the probability of default on a debt by a borrower and guides the decision-making process for granting loans.

Creditworthiness of farmers	Male		Female		Pooled	
	Freq.	%	Freq.	%	Freq.	%
Creditworthy farmers	60	33.3	82	45.5	142	39.4
None Creditworthy farmers	120	66.7	98	54.4	218	60.6
Total	180	100.0	180	100.0	360	100.0

Source: Data from a field survey, 2022

Table 3: Distribution of the creditworthiness of smallholder farmers by gender.

Sample	Mean	N	Standard Deviation	Standard Error	Df	Z-test
Creditworthy Male farmers	63.857	60	14.644	1.891		-3.704***
Creditworthy Female farmers	71.892	82	19.002	2.098		
Difference	-8.035		18.296	2.169	140	

Source: Data from a field survey, 2022

Table 4: Test of significance difference in the creditworthiness (using credit score) of smallholder farmers by gender.

Credit Score	Quality	Risk Class	Male		Female		Pooled	
			Freq.	%	Freq.	%	Freq.	%
76-100	Excellent	A	2	1.1	2	1.1	4	1.1
51-75	Good	B	58	32.2	80	44.4	138	38.3
26-50	Average	C	116	64.4	98	54.4	214	59.4
0-25	Below Ave-rage	D	4	2.2	-	-	4	1.1
Total			180	100.0	180	100.0	360	100.0

Source: Data from a field survey, 2022

Table 5: Credit risk class as derived from the credit scores.

The majority of male loan applicants as well as female loan applicants are classified as risk class C, indicating average borrower quality. Only a small percentage (1.1%) of applicants are exceptionally qualified for loans. This makes it difficult for most farmers to obtain loans, especially those rated as average or below average in creditworthiness. Overall, only a fraction of applicants (33.3% of males, 45.5% of females, and 39.4% of all farmers) are considered good-risk borrowers, making it riskier to grant loans to the majority. This has implications for debt financing in the farming sector in the study area.

Discriminant analysis of the determinants of the creditworthiness of smallholder farmers by gender

Having classified the creditworthiness of the loan applicants using the credit score model, we further employ the discriminant analysis technique to classify the loan applicants based on creditworthiness. This serves to complement the reliability of the results of the creditworthiness of the farmers done using the CSMSF approach.

Diagnostic tests

Box's test of equality of covariance matrices

The outcome of Box's test of equality of covariance matrices, used in examining the homogeneity both within and between the two sets of dependent variables, is shown in Table 6.

Parameters	Male	Female	Pooled
Box's M	207.617	259.605	334.655
F-value	1.359	1.729	2.074
Sig.	1.000	1.000	1.000

Source: Data from a field survey, 2022

Table 6: Box's test of equality of covariance matrices.

As shown in Table 6, Box’s M statistic was 207.617 and the F-value of 1.359 was not statistically significant, an indication that the covariance matrix is homogenous and the individuals in the group contribute equally to the discriminant model (Field, 2009; Hair et al., 2019). For the female smallholder farmers, the Box’s M statistic was 259.605 and the F-value of 1.729 was not statistically significant, an indication that the covariance matrix is also homogenous. According to the finding, the data sets utilized for the discriminant analysis did not deviate from normality, making it possible to classify the creditworthiness of farmers based on gender with confidence.

Eigen values of the canonical discriminant functions

The summary of the canonical discriminant functions indicating the eigenvalue and the canonical correlation is presented in Table 7.

Parameters	Male	Female	Pooled
Eigenvalue	1.915[a]	1.898[a]	1.244[a]
% of total variance	100.0	100.0	100.0
Cumulative %	100.0	100.0	100.0
Canonical Correlation	0.891	0.809	0.745

Note: [a] Canonical discriminant function is significant at $P < 0.05$.

Source: Data from a field survey, 2022

Table 7: Eigen values of the canonical discriminant functions.

From the Table 7 above, the eigen values shows evidence of the effectiveness of discriminant functions (Thomas, 1992; Bartkowiak and Zimroz, 2013; Benyamin et al., 2019). For the male smallholder farmers, higher engin values (1.915) suggests better information about the effectiveness of the dependent variable. The canonical correlation value (0.891) indicates a strong relationship between creditworthiness and the discriminant score for males. For females, the eigenvalue (1.898) explains a significant share of the variance, and the canonical correlation value (0.809) shows a sturdy relationship. For the pooled group of farmers, the eigenvalue (1.244) explains a significant variance, and the canonical correlation value (0.745) indicates a strong relationship. These results suggest a reliable classification of farmers based on creditworthiness and unprejudiced interpretations.

Wilk's Lambda Ratio of unexplained total variance of discriminant scores

Table 8 shows the ratio not explicated by the entire variance of Wilk's Lambda statistics discriminant scores. Wilk's lambda quantifies how successfully each function classifies groups.

Parameters	Male	Female	Pooled
Wilks' Lambda	0.452	0.345	0.446
Chi-square	109.820	180.897	281.689
Df	16	16	17
Sig.	0.000	0.000	0.000

Source: Data from a field survey, 2022

Table 8: Wilk's Lambda ratio for the total unexplained variation in discriminant scores.

A variable's potential for discriminating between groups is measured using the Wilks' lambda. Lower values suggest higher effectiveness in discriminating among groups (Pednekar and Tung, 2017). For male smallholder farmers, Wilks' Lambda was 0.452, indicating 45.2% of variance unexplained by differences among the groups. The chi-square test was significant at the 1% threshold, suggesting better than chance discrimination. For female farmers, Wilks' Lambda was 0.345, showing greater discriminatory ability, implying that 34.5% of the overall variation in the discriminant scores is unexplained by differences among the groups. The pooled model had a Wilks' Lambda of 0.446, also indicating good discrimination. The chi-square test was significant, suggesting an effective separation of creditworthy and non-creditworthy farmers. Table 8 indicates the female model as the best, followed by pooled and male models.

The Canonical discriminant function of coefficients

Table 9 provides the canonical discriminatory function coefficients for the male, female, and pooled respondents.

Variables	Male	Female	Pooled
Age of respondent	-1.029	-1.036	-2.034
Marital status	0.145	0.283	1.233
Household size	1.011	1.049	1.036
Farming experience	1.066	2.083	0.969
Annual income	2.034	2.780	1.992
Off farm income	1.020	0.000	0.459
Membership of cooperative society	-0.462	-0.132	-0.279
Location situation	-0.018	0.423	0.283
Farm size	1.134	1.162	1.139
Educational qualification	0.973	1.310	0.966
Proximity to Bank	0.486	0.586	0.334
Access to account officer	0.923	0.859	0.489
Loan duration (Months)	-1.098	-1.114	-2.113
Banking relationship	0.407	0.787	0.617
Default duration (months)	-0.806	-1.047	-1.083
Loans in other banks	-0.101	-0.599	-0.213
Gender of respondent	-	-	-1.052
(Constant)	-1.657	-3.490	-2.483

Source: Data from a field survey, 2022

Table 9: Canonical discriminant function coefficients for the male, female and pooled loan applicants.

The canonical discriminant function coefficients help to show the variables that contributed significantly to discrimination between two groups (Sajobi et al., 2020). For the male respondents, the results presented in Table 9 showed that the important variables for the z-score value in discriminating the male respondents into creditworthy and non-creditworthy farmers were mostly annual income, with a canonical discriminant function coefficient value of (2.034). Annual income played a very vital role in the discrimination of smallholder male farmers into creditworthy and non-creditworthy groups, alongside the farm size of the farmer (1.134), off-farm income (1.020), level of education (0.973), and accessibility of farmers to their account officers (0.923). Annual income reflects how financial institutions rate financial performance; in addition, off-farm income reflects the importance of income diversification; education also underscores the importance of financial literacy and information on the part of the farmer; and accessibility to an account officer translates to guidance from financial institutions on terms and conditions.

However, annual income (2.780), farming experience (2.083), educational qualification (1.310), and farm size (1.162) were important in discriminating female respondents between groups. This translates to the female farmers financial performance, farming experience, level of training, exposure, and financial literacy, and finally the farmers scale of operation. This shows the complex nature of the credit evaluation process, as several conditions need to be met before credit is extended to an applicant.

Average group discrimination function values

The result of the distribution of the respondents by average group discrimination function values is presented in Table 10 below.

Parameters	Male	Female	Pooled
Non-Creditworthy	-0.684	-1.282	-0.916
Creditworthy	1.323	1.465	1.351
Z-score	0.639	0.183	0.435

Source: Data from a field survey, 2022

Table 10: Average group discrimination function values.

Unstandardized canonical discriminant functions assessed using the group mean

The average group discrimination function values were used to determine whether creditworthiness existed between the farmers. Table 10 displays the mean separation function performances for each category of farmers. This is the same as finding the difference between the function values of the creditworthy farmers and those of the non-creditworthy farmers. Whenever the z-score value exceeds the z-value of each group of farmers, loans are granted to applicants based on their creditworthiness, or vice versa. From the results in Table 10 above, the z-scores of the male, female, and entire (pooled) farmers were 0.639, 0.183, and 0.435, respectively. This implies that loans are granted to applicants based on their creditworthiness. This suggests that not all the farmers received the loan they applied for due to their creditworthiness.

Discriminant analysis classification success results of farmers' creditworthiness

The discriminant analysis classification success result of the creditworthiness of farmers along gender line is obtainable in Table 11.

The Table 11 shows the practical results of using the discriminant model. In the cases utilized to develop the male farmer's model, the model estimated creditworthiness with 82.2% and 88.7% accuracy for the non-creditworthy and creditworthy farmers, respectively. The total correct classification success rate for 180 male loan applicants is recorded as 84.4%. This indicates that the model is mostly accurate. The discriminant analysis success result shows that 62 out of 180 (34.4%) male smallholder farmers who applied for loans are creditworthy based on their socioeconomic characteristics, which is similar to the result of 33.3% derived using the credit score model approach.

Similarly, for the female farmers, the model estimated creditworthiness with 90.6% (87 out of 96) and 88.1% (74 out of 84) accuracy for the non-creditworthy and creditworthy farmers, respectively. The total correct classification success rate for 180 female loan applicants is recorded as 89.4%. The discriminant analysis success result shows that 84 out of 180 (46.7%) female smallholder farmers who applied for loans are creditworthy based on their socioeconomic characteristics, which is similar to the result of 45.5% derived using the credit score model approach.

From the results in the Table 11, 34.4 percent of the male farmers were creditworthy, while

Discriminant Analysis		Male farmers Estimated Group				Female farmers Estimated Group				Pooled farmers Estimated Group			
		Non-Creditworthy	Creditworthy	Total	Accuracy %	Non-Creditworthy	Creditworthy	Total	Accuracy %	Non-Creditworthy	Creditworthy	Total	Accuracy %
Observed Group	Non-Creditworthy	97 (82.2)	21 (17.8)	118 (100.0)	82.2	87 (90.6)	9 (9.4)	96 (100.0)	90.6	184 (86.0)	30 (14.0)	214 (100.)	86.0
	Creditworthy	7 (11.3)	55 (88.7)	62 (100.0)	88.7	10 (11.9)	74 (88.1)	84 (100.0)	88.1	17 (11.6)	129 (88.4)	146 (100.0)	88.4
	Total	104	76	180	84.4	97	83	180	89.4	194	166	360	86.9

Source: Data from a field survey, 2022

Table 11: Discriminant analysis classification success results[abc].

[a] 84.4% of original grouped cases for the male farmers were correctly classified.
[b] 89.4% of original grouped cases for the female farmers were correctly classified.
[c] 86.9% of original grouped cases for the pooled farmers were correctly classified.

46.7 percent of the female farmers were creditworthy, indicating a gap of 12.3% in credit assessment along gender lines.

Summary statistics of sample description

Socioeconomic characteristics of the smallholder farmers by gender (Loan Applicants)

The socioeconomic characteristics of the smallholder farmers by gender that applied for credit in the study area are presented in the Table 12.

The result shows that the average age of male and female respondents was 36 and 34 years, respectively. When pooled together we had a mean age of 35 years. However, the female farmers were seen to be in a more youthful age bracket than their male counterparts. This indicates a very close variation in age profile along gender lines. Implying a youthful population of farmers who would be enterprising and inclined to take loans for productive purposes or for expansion of existing operations. This close age variation of farmers along gender lines underscores the need to design customized loan products and standard assessments of farmers creditworthiness for male and female farmers.

Majority of both male and female respondents (about 67% and 63 %) were married. This implies that both the male and female respondents were settled and should therefore be better positioned to undertake their economic activities profitably responsibly. Ominikari, Onumadu and Nnamerenwa (2017) posited that being married can confer some level of stability to an individual in a household and can put them in a better position to practice their occupation more profitable for the business sustenance and for solving family needs. The results show a close variation in percentage difference of the majority of farmers who are married. This could imply that the gap in marital status of farmers along gender lines may not influence a difference in credit assessment by banks as the lending institutions should maintain uniformity in credit assessments for farmers irrespective of gender differences.

The result also shows that most of the respondents (35.6% of males and 33.3% of females) had primary education. However, 85.6% and 83.9% of the male and female respondents had formal education. This result suggests that a large number of the respondents were educated and therefore

Variables	Male smallholder farmers		Female smallholder farmers		Male and female pooled together	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Age of Farmers (years)						
Average	35.8		33.9		34.6	
Farmers marital status						
Single	50	27.8	55	30.6	105	29.1
Married	120	66.7	113	62.8	233	64.8
Divorced	7	3.9	7	3.9	14	3.9
Widowed	3	1.7	5	2.7	8	2.2
Educational Level						
No formal education	26	14.4	29	16.1	55	15.3
Primary	64	35.6	60	33.3	124	34.4
Secondary	49	27.2	47	26.1	96	26.7
Tertiary	41	22.8	44	24.5	85	23.6
Farming Experience (years)						
Average	7.83		8.22	8.03		
Farm size (ha)						
Average	1.58		1.17		1.37	
Extension Agents						
Yes	106	60.6	109	58.9	215	59.7
No	74	39.4	71	41.1	145	40.3
N	180	100.0	180	100.0	360	100.0

Source: Computed by the researcher from field survey data 2022

Table 12: Socioeconomic characteristics of the smallholder farmers by gender (Loan borrowers).

understood the requirements for accessing credit from the bank. Education is a virtue that is required for a successful business operation; thus, these educated respondents have acquired relevant skills that would be useful in operating their own firms and know how to utilize loans to enhance their business performance. Nnamerenwa et al. (2017) posited that education serves as an important criterion for loan approval and thus gives an edge to any individual with educational qualification over another with no educational qualification.

In addition, the farming experience for male, female and pooled smallholder farmers in the study area were 7.88, 8.22 and 8.03 respectively. The results suggest that most of the smallholder farmers in the study area had some level experience into the business of farming to know how to allocate financial resources for farm expansion. According to Nwaru (2004) expansion in farm business is dependent on the years of farming experience. Lender would prefer to extend credit facilities and loans to experienced farmers (Nnamerenwa et al., 2017). The average farm size is 1.58 ha for males, 1.17 ha for females, and 1.37 ha for all respondents. This implies that the respondents had small farm sizes. According to UNCTAD Commodities and development report (2015) and Chiaka, et al (2022) the average farm size for smallholder farmers in Nigeria is 2.0 hectares and indicates that most respondents were actually smallholder farmers. This implies that male farmers are at an advantage over their female counterparts as farm size could translate to higher revenue generation which could help in loan repayment.

The result further shows that 61% of males, 59% of females, and 60% of all respondents visited agricultural extension agents in the study area. The small-gap percentage of male and female smallholder farmers who visited extension agents shows a fairly identical assignment and suggests similarity in extension information. It would be advisable for financial institutions. Agricultural extension programs tend to advance their level of financial literacy and keep farmers at an advantage when evaluated by microfinance banks.

Conclusions

The objective of this research is to juxtapose the gender differentials in credit assessment by microfinance banks in southeast Nigeria using a hybridized credit scoring approach. Secondly, we analyzed the factors influencing the creditworthiness of smallholder farmers along gender lines, and finally, we presented the summary of the sample description for male and female smallholder farmers in the study area. Several outcomes were attained. One outcome indicated that 34.4% and 46.7% of male and female farmers were identified as creditworthy based on our credit assessment of MFBs farmer applicants, indicating a gap of 12.3% in the assessment of farmers' financial standing using the discriminant analysis, while the CSMSF showed that 33.3% and 45.5% of male and female farmers were grouped as creditworthy based on the credit assessment of MFBs farmer applicants, indicating a gap of 12.2% and an average 12.25% gender discrepancy (using the hybridized credit scoring approach). The gap points to extensive disparity on the basis of gender in credit evaluation, indicating that female farmers are more creditworthy than males, thereby marking a significant divergence from the previous narrative, which frequently portrays male farmers as more creditworthy. Reasons for the improved creditworthiness amongst smallholder female farmers could be as a result of the efficacy of variables used in credit assessment, which provided a penchant for abilities in which women were at an advantage, such as the non-availability of loans in other banks, better banking relationships, and a good previous credit record, among others. In addition, it could be as a result of the increasing level of accessibility to agricultural extension programs, which tends to advance their level of financial literacy and commercial savvy due to societal trends, the rising level of women in leadership positions, and improved educational accessibility.

Other results revealed that annual income, marital status, and farm size strongly influenced the separation between creditworthy and non-creditworthy farmers. While age, loan term, and a history of defaults had a negative impact on discrimination, as a result, suggestions for policy include boosting income diversity and improving gender equality in financing.

In addition, the summary of the sample description showed that the average age of male and female respondents was 36 and 34 years, the majority of both male and female respondents (about 67% and 63%) were married, the mean years of farming experience was 7.83 for males and 8.22 for females, the average farm size was 1.58 hectares for males and 1.17 hectares for females, 85.6% and 83.9% of the male and female respondents had formal education, and 61% of males and 59% of females visited agricultural extension agents in the study area.

We therefore recommend a collaboration between authorities, financial institutions, and extension workers in offering tailored training to both male and female farmers, assisting them in meeting up-to-date credit prerequisites, adopting modified farming techniques, and improving their general preparedness to be accepted for loans in this changing credit evaluation landscape so as to bridge the disparity and promote financial inclusion for farmers irrespective of gender affiliations.

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