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Determinants of SMEs' Access to Microfinance Credit in Lubumbashi: An Analysis Based on Multinomial Logistic Regression

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Abstract

This quantitative study investigates the factors contributing to the limited access of Small and Medium-sized Enterprises (SMEs) to credit from Microfinance Institutions (MFIs) in Lubumbashi, Democratic Republic of Congo. Using a multinomial logistic regression model on a sample of 69 SMEs, the authors analyze variables such as self-exclusion, interest rates, credit history, collateral, and solvency. The findings indicate that the lack of solid collateral and low solvency are the primary statistically significant determinants hindering credit access.

Keywords

MFIs, Financial Exclusion, SMEs, Microfinance, Multinomial Logistic Regression

1. Introduction

1.1. Context and Observed Phenomenon

In the African context in general, and the Congolese context in particular, small and medium-sized enterprises (SMEs) represent a strategic lever for social and economic progress. In sub-Saharan Africa, according to studies (IFC, 2021; Thorsten et al., 2005), these entities represent approximately 90% of the economic fabric and contribute significantly to job creation and Gross Domestic Product (GDP) growth.

The need to address SME issues is justified in the city of Lubumbashi in the Democratic Republic of Congo (DRC), where they represent a large part of the entrepreneurial fabric. However, their access to bank credit remains limited due to a lack of collateral, regular account activity, and reliable income Bangika et al., 2025). Unlike traditional banks, which prioritize financial profitability over social objectives, Microfinance Institutions (MFIs) are called upon to create more suitable conditions that can facilitate SMEs' access to financing. According to Merroun & Hamiche (2023), SMEs' access to microcredit is an effective lever for addressing the shortcomings of traditional credit. This will strengthen the role of SMEs in economic development (Kabore, 2009) and promote their emergence.

In Lubumbashi, microfinance institutions (MFIs) have dominated the financial market in recent years with the emergence of numerous institutions (TUJENGE, FINCA, IFOD, SMICO, BAOBAB, etc.) to fill the gaps in the traditional banking system. They offer financial services tailored to excluded populations, particularly SMEs and low-income individuals, according to Yunus (1999), under the best possible conditions, while allowing the institutions to cover their operating costs (Conde, 2024). However, several studies (Kapitene, 2019; Kapad et al., 2024) highlight that access to financing for SMEs remains a challenge (**Table 1**), despite the progress made in microfinance as a tool for financial inclusion (Guerin et al., 2010).

Table 1. Evolution of credit granted by MFIs. (In millions of CDF).

Section	2019	2020	2021	2022	2023
Gross customer credit	1,062,667	822,217	2,047,548	2,656,439	6,135,468
SME access rate in %	14.02	11.88	6.85	11.14	6.26

Source: Financial stability report of the central bank of Congo (2023).

Faced with obstacles to accessing credit from MFIs, some SMEs see their growth limited and in some cases, are exposed to the risk of financial failure, which could lead to their closure.

To achieve this objective, 69 contacts of SMEs that had experienced obstacles to accessing financing were surveyed using a questionnaire.

1.2. Literature Review

The concept of financial exclusion is a central phenomenon in the field of economic inclusion, which has sparked the interest of many practitioners and researchers. To date, no definition of financial exclusion has achieved universal acceptance in the research community. It is a multidimensional, multifaceted, and multifactorial phenomenon. The most widespread definition considers financial exclusion as the absence of, or difficulty in accessing, formal financial services (credit, savings, insurance, means of payment). For some authors, it can be defined as the inability of an individual or legal entity to use basic financial services due to economic, geographical, institutional, or social barriers (Sossa, 2011; Gloukoviezoff, 2009).

For other authors, financial exclusion cannot be reduced to the difficulty of accessing financial services but also encompasses the marginalization of low-income populations, who often have no choice but to resort to informal, less secure, and sometimes even more expensive solutions (Figuet & Pinos, 2014). From this perspective, many authors have proposed a definition integrating both dimensions: on the one hand, the absence of or difficulty of accessing formal financial services, and on the other hand, the marginalization of low-income populations. Financial exclusion is a process by which certain segments of the population are excluded from financial services due to mechanisms that constitute an economic barrier, thereby reinforcing inequalities. He highlights the paradox that the development of financial systems, which is supposed to promote financial inclusion, nevertheless contributes to increasing the exclusion of the most vulnerable populations (Servet, 2000; Finca, 2015).

Regarding the definition of an SME, it varies from country to country and region to region, with criteria generally based on the number of employees, turnover, or asset value. In some European Union and OECD countries, an SME is considered to be a company with annual turnover of less than €50 million and fewer than 250 employees (OCDE, 2004). In the DRC, the SME Charter defines these entities as an economic structure belonging to one or more natural or legal persons, with a centralized management structure. It is defined according to the number of employees, turnover, the value of investments required to establish operations, and the management structure (**Table 2**).

Table 2. Criteria for defining SMEs in the DR. Congo.

	Number of employees	Revenue	Investment value	Management method
Micro	1 to 5	\$1 to \$10,000	\$10,000	Concentrate
Small	6 to 50	\$10,001 to \$50,000	\$10,001 to \$1,500,000	Concentrate
Medium	51 to 200	\$50,000 to \$400,000	\$150,001 to \$350,000	Decentralized

Source: Charter for small and medium-sized enterprises and crafts in the DRC.

Based on the main theoretical and empirical contributions around the topic, the results of previous studies reveal several factors contributing to the financial exclusion of certain SMEs in microfinance institutions.

1.2.1. Theoretical Review

Armendariz and Morduch (2010) examined how microfinance can address the problems of information asymmetry and high transaction costs for unbanked populations. The researchers also point out that these mechanisms can sometimes contribute to the financial exclusion of micro-entrepreneurs who need more substantial financing.

According to Allemand (2011), although microcredit, microinsurance, and microsavings enable low-income individuals to participate in the economy, finance income-generating activities, and access essential financial services, microfinance does not always succeed in reaching the most vulnerable individuals. It has limitations.

Nsabimana (2009) concludes that the entry of banks into the microfinance sector in Africa can lead to more professional management and improved performance of MFIs. However, banks tend to prioritize financial profitability over the social objectives fulfilled by MFIs.

Jensen and Meckling (1976) developed a theory called "agency theory." This theory posits that there is an opposing relationship between two agents: on the one hand, the owner of the means of production, generally called the principal (microfinance institutions), and on the other hand, the agent (SMEs) that manages and organizes the principal's means of production at its request. This relationship is very often a source of conflict. Each party seeks to maximize its own interest, which can lead to suboptimal or harmful decisions for the principal. To counteract the agent's opportunistic behavior, the principal incurs costs called agency costs (Jensen & Meckling, 1976). These costs include those related to monitoring the agent, board fees, and so on.

The theory of asymmetric information, developed by Akerlof (1970) and further elaborated by Stiglitz & Weiss (1981), explains that economic agents do not have the same level of information in a contract, creating an imbalance. In the context of credit, this asymmetry between lender and borrower often leads to credit rationing. This manifests in two main forms: adverse selection, where riskier borrowers are favored due to information hidden in the contract, and moral hazard, where borrowers adopt opportunistic behavior after obtaining a loan. These phenomena result in a misallocation of credit and increase risks for financial institutions.

Hicks & Allen (1934) explained in their theory of consumer behavior that individuals make purchasing decisions based on their preferences, prices, and budget constraints, in order to maximize their satisfaction. Applied to SMEs, this theory shows that some choose not to use external credit when the perceived cost is too high.

What about empirical studies?

1.2.2. Empirical Review

In Congo-Brazzaville, in a contribution, Mayoukou & Kertous (2015) question the role of MFIs. These authors confirm that the selectivity of MFIs and high collateral requirements reinforce the self-exclusion of the poorest clients.

In Burundi, Niyuhire (2023) reveals that MFIs reject a significant number of loan applications due to insufficient collateral, information asymmetry, and a lack of managerial capacity.

Massamba (2019) explored how the partnership between the Islamic Bank of Senegal (BIS) and microfinance institutions (MFIs) contributes to improving SME financing. The results show that MFIs' bank placements and share capital improve access to finance.

In Benin, Nakou & Nana (2020) reveal that CSR, perceived as a consistent and binding activity, contributes to both the direct and indirect benefits of MFIs, while supporting financial and social inclusion. On the other hand, studies (Cailloux et al., 2014; Pluskota, 2020) have revealed that the financial exclusion of SMEs is caused by several factors, including: low incomes, lack of collateral, absence of a credit history, and high financial service costs.

In Lubumbashi, the study by Kapad et al. (2024) highlights that the COVID-19 crisis exacerbated these obstacles by further reducing access to financing due to closures and increased caution among financial institutions. Mushigo et al. (2019) conducted a study on the "Relationship between microfinance and the perceived performance of SMEs." Based on a sample of 232 SMEs, the results confirmed that credit, financial education, and an entrepreneurial mindset significantly boost business performance. Furthermore, the positive impact of financial education is only observed when entrepreneurs identify entrepreneurial opportunities.

Unlike the aforementioned studies, this one focuses solely on the reasons why some SMEs in the city of Lubumbashi are unable to access microfinance credit, which has evolved in recent years.

1.3. Problematic

The economic fabric of the DRC remains dominated by SMEs, which play a crucial role in creating jobs and boosting the nation's economic growth. However, their access to credit, through microfinance institutions (MFIs), remains a major challenge. It therefore seems wise to examine this difficulty, which limits their capacity to invest, innovate, and grow, and consequently hinders the country's economic potential. Faced with this situation, it is important to identify and understand the factors that impede SMEs' access to microfinance, which aims to address the shortcomings of the traditional banking system (Armendariz & Morduch, 2010). However, microfinance may continue to exacerbate the situation. This is an undeniable reality and a path to explore and encourage for African economies, particularly the Congolese economy.

Therefore, it is probably desirable to examine the factors explaining this situation: What factors explain the reduced access of SMEs to credit from MFIs in Lubumbashi? Once the research question is clearly defined, we can formulate hypotheses. These will then be subjected to tests in order to either corroborate or falsify them.

1.4. Hypotheses

All of the above leads us to formulate some hypotheses. The limited access of SMEs to microfinance credit is explained by:

- H1: Self-exclusion of SMEs
- H2: Very high interest rates offered by MFIs
- H3: Lack of credit history for SMEs
- H4: Lack of solid collateral to offer to MFIs
- H5: Low degree of solvency of SMEs

The research hypotheses that we have just formulated following our theoretical analysis are represented in the conceptual model below (**Figure 1**).

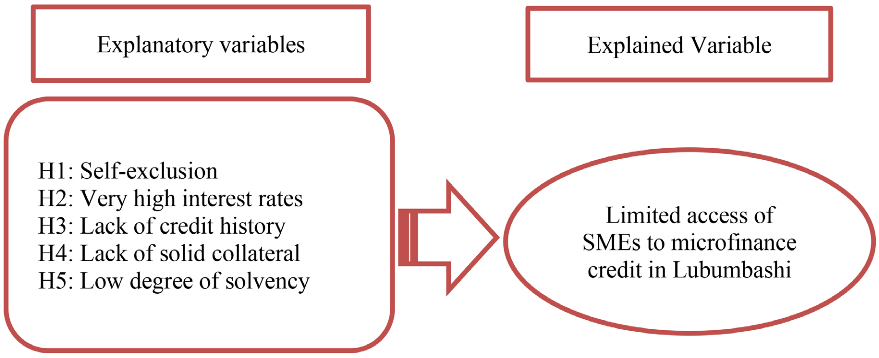

Figure 1. Conceptual model of research.

2. Research Methodology

The objective of this study is to explore the factors explaining the limited access of SMEs to microfinance institution (MFI) credit in the city of Lubumbashi. To this end, our research methodology relied on a quantitative approach. This approach was chosen due to the need to measure the impact of microfinance on reducing the financial exclusion of SMEs, using numerical data and statistical analyses to test our research hypotheses.

2.1. Sample Composition

To construct our sample, we used the non-probability convenience sampling method which, according to Sem & Cornet (2018), is a method by which each member of the population has the same chance of belonging to the sample.

Thus, we estimated the sample size as follows:

$$n = \frac{Z_{\alpha/2}^2 * ps(1-ps)}{e^2} \quad (1)$$

With:

- n : sample size;
- $Z_{\alpha/2}^2$: value of the standard normal distribution raised to the threshold squared;
- ps : proportion observed in the sample;
- e^2 : desired precision squared.

It should be noted that in management sciences, we generally work with a threshold of $\alpha = 5\%$, therefore $z_{\alpha/2} = 1.96$. The proportion is often unknown;

it is generally set at 0.5 (Berthier, 2023). We will estimate our sample size to the nearest 10% ($e = 0.1$).

It should be noted that a population for which the sample size is known (N is known) and the sampling rate is greater than 10% is considered small. Therefore, the sample size will need to be adjusted (Royer & Zarlowski, 2014).

$$\text{Sample Rate}\left(sr\right) = \frac{\text{Sample size}}{\text{Population size}} = \frac{n}{N} \tag{2}$$

If “ sr “ is greater than 10%, the final sample size is equal to that of the classic sample on 1 + the sampling rate (Royer & Zarlowski, 2014).

$$\text{Final sample size} = \frac{n}{1 + sr} \tag{3}$$

If As part of this work, we obtained the population size at the Lubumbashi town hall, and it is equal to 512.

From the above, the sample size is estimated to be:

$$n = \frac{Z_{\alpha/2}^{2} * ps\left(1 - ps\right)}{e^{2}} = \frac{1.96^{2} * 0.5\left(1 - 0.5\right)}{0.1^{2}} = 96.04$$

Where the survey rate: $= \frac{\text{Sample size}}{\text{Population size}} = \frac{n}{N} = \frac{96.04}{512} = 0.1876 > 10\%$

The sampling rate is greater than 10%, meaning we are dealing with a small population. Therefore, we can adjust the sample. This gives us the following adjustment:

$$n = \frac{96.04}{1 + 0.1876} = 80.87 \approx 81$$

Ultimately, this sample theoretically consists of 81 SMEs based in Lubumbashi. However, only 69 SME contacts were included in this study (representing 85% coverage). Regarding the data collection technique, we used a survey. This technique aims to obtain and collect information systematically within a population using a survey questionnaire (Sem & Cornet, 2018). The questionnaire comprises three parts, including: identification of the respondent (the SME owner), identification of the SME, and finally, the reasons for the SME’s lack of access to microfinance credit. The survey was conducted between June 3rd and June 13th, 2025.

2.2. Data Analysis Method: Multinomial Logistic Regression

In this study, we chose multinomial logistic regression as our analytical method. This approach is particularly well-suited for modeling the frequency of SMEs’ limited access to microfinance credit and allowed us to identify the factors influencing the financial exclusion of SMEs in our sample.

Although access to credit is often perceived as binary outcome, the dependent variable is not a simple dichotomy (access vs limited/no access). Multinomial logistic regression is used in this research because the dependent variable comprises more than two response categories. This model is appropriate for capturing the frequency with which SMEs access credit from MFIs.

While this structure might suggest an ordinal scale, the study deliberately adopts multinomial logistic regression in order to treat the categories as nominal. Limited access to credit is measured through a series of categories representing varying degrees of difficulty. The dependent variable therefore captures nuanced levels of credit access experienced by SMEs (Never, Rarely, Sometimes, Often, Always).

As we can understand, the Multinomial logistic regression, also called polytomous regression, is an econometric analysis used when the dependent variable has multiple categories (Rakotomalala, 2015). The dependent variable has K ($K>2$) categories. This regression therefore aims to model the probability of an individual, or an SME, belonging to a category Y_k.

Note:

$$\pi_k(\omega) = P(y(\omega)) = \frac{y_k}{X(\omega)} \tag{4}$$

Under constraint:

$$\sum \pi_k(\omega) = 1$$

With:

- $\pi_k(\omega)$: the probabilities of success;
- $P(y(\omega))$: the probability that an SME belongs to a modality;
- y_k: the modalities of the dependent variable;
- $X(\omega)$: the independent variables

It should be noted that multinomial logistic regression follows a multinomial distribution, which means that it models the probability of obtaining different combinations from a series of independent variables, where each independent variable can lead to one of several possible categories (Rakotomalala, 2015).

However, the idea of the multinomial logit model is to model with respect to the probability ($K-1$), so the choice of the reference modality Y_k is important for the interpretation of the coefficients.

The logit for modality Y_k is written:

$$C_k = \ln\ln \pi_k \pi_k = a_{0,k} + a_{1,k}x_1 + \cdots + a_{j,k}x_j \tag{5}$$

Indeed, the multinomial logit model is an extension of the binary logit model; in order to estimate the coefficients ($K-1$) × ($J+1$), it is necessary to optimize the log-likelihood via the Newton-Raphson algorithm (Rakotomalala, 2015).

The correlation matrix in linear regression is a square matrix that allowed us to identify the correlations between the exogenous variables used to explain the endogenous variable. The correlation coefficient can range from −1 to +1 (Fox, 2015). We performed a multicollinearity analysis. Multicollinearity statistics are used to detect interrelated explanatory variables in our model; multicollinearity is problematic because it distorts the statistical significance of independent variables. The ideal scenario is one where the tolerance is greater than the threshold of 0.1 and the VIF is close to 1, or at least less than 10. Otherwise, we will encounter a multicollinearity problem (Data Science, 2020). The null hypothesis test allowed us to determine if the coefficient is significant. This involves testing the null hypothesis that the coefficient of the regression model for an independent variable is equal to zero. Furthermore, with this test, we seek to verify whether the complete model is significantly more efficient than the independent model (Rakotomalala, 2015).

3. Significant Results

The following section will allow us to examine in detail the results of our study and interpret them in order to better understand their significance and relevance.

3.1. Presentation and Interpretation

In this section, we presented and interpreted the main results of our analysis using multinomial logistic regression with XLSTAT 2025 software. We would like to remind you that for our study, we had to consider the following explanatory variables: self-exclusion, lack of credit history, very high interest rates, lack of solid collateral to offer, and low solvency. We will explain their impact on the explained variable, which is the reduced access of SMEs to microfinance credit.

3.1.1. Correlation Matrix

We found that all correlations are weak, meaning that the explanatory variables are weakly correlated or not redundant with each other as presented by Fox (2015). The strongest correlation observed (0.138) is between credit history and Solvency, but it remains weak and does not indicate significant redundancy, meaning there is no presumption of multicollinearity.

3.1.2. Multicollinearity Analysis

We observe that the VIFs of our variables are less than 10. This means that there is an absence of multicollinearity between the explanatory variables. In other words, we can conclude that the explanatory variables are not correlated in our regression model (**Table 3**).

Table 3. Multicollinearity statistics.

	Self-exclusion	Interest rates	Credit history	Lack of collateral	Solvency
TOL	0.911	0.919	0.873	0.845	0.914
LIVELY	1.097	1.088	1.145	1.184	1.094

Source: Authors, using XLSTAT.

3.1.3. Adjustment Coefficients

From this analysis of the adjustment coefficients, we retain McFadden's Pseudo R^2 because it is the most suitable for multiple logistic regression (Rakotomalala, 2015). To support our McFadden Pseudo R^2, we will add Cox and Snell's Pseudo R^2.

The literature tells us that when McFadden's R^2 is between 0.2 and 0.4, the model is considered acceptable because the fit is good and accurately explains our regression model. As for Cox and Snell's R^2, it ranges from 0 (= the model is not good) to 1 (= the model is good and explanatory) (Rakotomalala, 2015).

Based on our results (**Table 4**), we observe that McFadden's R^2 is 0.700. This indicates that we have an acceptable regression model with good goodness of fit and adequate explanatory power, with a strong presumption of multicollinearity. The Cox and Snell R^2 is 0.767. This leads us to conclude that the variability of the dependent variable is explained by 76.7% by the five explanatory variables.

Table 4. Multicollinearity statistics.

Statistical	Independent	Complete
Observations	69	69
Sum of weights	69,000	69,000
DDL	67	45
−2 Log (Likelihood)	143,638	43,139
R^2 (McFadden)	0.000	0.700
R^2 (Cox and Snell)	0.000	0.767

Source: Authors, using XLSTAT.

3.1.4. Null Hypothesis Test

The likelihood ratio test is a statistical method used to compare the goodness of fit between two models: the restricted model and the complete model (Fisher, 1922). Furthermore, it involves comparing two deviances for the overall and significant evaluation of the model (Rakotomalala, 2015).

According to the likelihood ratio test's decision criterion, if the p-value is less than or equal to the significance level of 0.05, the model is globally significant and the null hypothesis is rejected. In our case, as shown in **Table 5**, the probability of the likelihood ratio test is 0.0001, which is less than the significance level; therefore, we say that the model is globally significant.

The score test or Lagrange test in multinomial logistic regression is a statistical method used to evaluate the importance of explanatory variables in a model (Rao, 1948). In our case, the probability is 0.001, which is less than the significance threshold. We say that at a risk of error of 5%, the model is globally significant because the explanatory variables in our model exert a significant influence on the explained variable.

Table 5. Null hypothesis test: Beta = 0.

Statistical	DDL	Chi²	Pr > Chi²
−2 Log (Likelihood)	22	100,498	**<0.0001**
Score	22	60,217	**<0.0001**

Source: Authors, using XLSTAT.

3.1.5. Type II Analysis

Table 6 above presents all the explanatory variables and their calculated p-values. For an explanatory variable to explain a model, its probability must be less than or equal to the significance threshold. Therefore, based on the results, we note that only two variables, H4 and H5, significantly explain this model: "lack of collateral" (H4) and "low Solvency" (H5). The three other variables—self-exclusion (H1), very high interest rate (H2), and credit history (H3)—do not significantly explain this model because their probabilities (0.420, 0.410, and 0.606, respectively) are greater than the significance threshold.

Table 6. Type II analysis.

Source	DDL	Chi² (Wald)	Pr > Wald	Chi² (LR)	Pr > LR
Self-exclusion	2	1650	0.438	1.737	0.420
Interest rates	6	4455	0.615	13,122	0.410
Credit history	2	0.918	0.632	1.001	0.606
Lack of solid collateral	4	0.142	0.998	39,646	<0.0001
Low Solvency	8	2933	0.938	66,525	<0.0001

Source: Authors, using XLSTAT.

3.2. Model Parameters

The regression model used in the study, usually logistic regression, is often formulated as follows:

$$P\left(Y=1\mid X\right)=\varphi\left(\beta_0+\beta_1X_1+\cdots+\beta_nX_n\right) \tag{6}$$

With:

- $P\left(Y=1\mid X\right)$: represents the probability that the dependent variable Y takes the value 1 (never) given the values of the independent variables *X*.
- $\varphi(\cdot)$: is the cumulative distribution function of the standard normal distribution.
- β_0: is the y-intercept.
- $\beta_1,\beta_2,\cdots,\beta_n$: are the regression coefficients associated with the independent variables $X_1,X_2,\cdots,X_n$.

It corresponds to:

$$\begin{aligned}P\left(\text{Limited access}=1\mid X\right)=\varphi\big(&\beta_0+\beta_1\text{Self-exclusion}+\beta_2\text{Credit history}\\&+\beta_2\text{Interest rate}+\beta_4\text{Collateral}+\beta_5\text{lSolvency}\big)\end{aligned} \tag{7}$$

It is worth noting that the model parameters allow us to test the influence of each variable-modality individually on each of the modalities of the explained variable in relation to the reference variable which for our study is "never" (Rakotomalala, 2015).

Having seen the overall importance of factors related to the lack of collateral and the low degree of solvency of SMEs through their variables in the model, let us now look at how their different modalities contribute to this effect, bearing in mind that the influence may come from a combined effect rather than a single dominant modality.

Based on the results in **Table 7**, we can see that the p-values of the modal variables are above the significance threshold of 0.05. Therefore, we conclude that while some variables contribute significantly to the model (in the Type II analysis), no single specific category has a sufficiently strong impact to explain the reduced access to credit from microfinance institutions (MFIs). This finding is common in models with multiple modalities, as the overall effect results from the combined effect of all categories, but these categories individually may not be significant (Hosmer, Lemeshow, & Sturdivant, 2013).

Table 7. Model parameters.

Modality	Source	Pr > Chi^2
Never	Constant	0.997
	Self-exclusion-0	0.323
	Interest rate-1	0.997
	Interest rate-2	0.896
	Interest rate-3	0.997
	Credit history-0	0.705
	Lack of collateral-1	0.996
	Lack of collateral-2	0.921
	Solvency-1	0.997
	Solvency II	0.997
	Solvency III	0.997
	Solvency-4	1000

Source: Authors, using XLSTAT.

3.3. Validation of Hypotheses

Using the results obtained in the previous section, we have in this section verified all the hypotheses put forward. The aim here is to determine whether or not they explain the limited access of SMEs to microfinance credit.

Following the processing of our data, the results highlighted the factors that explain SMEs' limited and/or difficult access to credit from microfinance institutions (MFIs). **Table 8** summarizes the results.

Table 8. Summary of results.

Dependent variable	Independent variables	Related hypotheses	Results obtained
SMEs have limited access to credit from microfinance institutions.	Self-exclusion of SMEs	H1	−Disproven
	High interest rates	H2	−Disproven
	lack of credit history	H3	−Disproven
	Lack of a solid collateral	H4	**+Confirmed**
	Low solvency level of SMEs	H5	**+Confirmed**

Source: Authors, using XLSTAT.

From the above, our study confirmed that the variables of lack of solid collateral (H3) and low Solvency (H5) explain the limited access of SMEs to microfinance institution (MFI) credit in the city of Lubumbashi. Conversely, the results refute self-exclusion (H1), very high interest rates offered by MFIs (H2), and the lack of a credit history among SMEs (H3).

4. Discussion of Results

These results partly echo the conclusions of Cailloux et al. (2014), Niyuhire (2023), Kapad et al. (2024), according to which the low degree of solvency and the absence of solid guarantee to offer prevent SMEs from accessing microfinance credit.

Our results partly contradict those of other studies (Mayoukou & Kertous, 2015; Pluskota, 2020), which state that self-exclusion, lack of credit history, and very high interest rates offered by MFIs have an impact on the reduced access of SMEs to microfinance credit.

Our results support agency theory, developed by Jensen and Meckling (1976). This theory posits an adversarial relationship between two agents: the principal (microfinance institutions), who owns the means of production, and the agent (SMEs), who manages and organizes the principal's means of production at its request. This relationship is often a source of conflict. To counteract the agent's opportunistic behavior, the principal incurs costs known as agency costs. MFIs implement control mechanisms before granting credit because SME managers often make decisions that favor their own interests regarding the intended use of funds. This leads to poor financial management and, consequently, loan default.

From the perspective of this theory, the requirement for collateral is a control mechanism implemented by microfinance institutions (MFIs) to counter the potential opportunistic behavior of SME managers. To mitigate moral hazard, collateral serves to protect the principal against the risk of capital loss; the fact that low solvency is a major determinant of loan denial reinforces the idea that MFIs seek to minimize their agency costs. Therefore, by prioritizing solvency and collateral, MFIs replicate the selection criteria of the traditional banking system. This demonstrates that, faced with information asymmetry and the management risks inherent in agents (SMEs), Microfinance institutions prioritize the protection of their resources, in accordance with the predictions of agency theory.

5. Limitations of the Study and Suggestions

5.1. Limitations of the Study

The multinomial logistic regression model used has 45 degrees of freedom, meaning that the ratio of observations per parameter is low. This is due to the small final sample size (n = 69). This size increases the risk that variances will not be accurately estimated. This can lead to numerical instability in the model parameters and reduce the statistical power of the econometric model. A study with a larger sample size would be desirable.

This research is strictly limited to the city of Lubumbashi and used a non-probability convenience sampling method. While this approach facilitates access to the field, it has significant limitations in terms of representativeness, as each member of the population did not have a known probability of being selected. Although this spatial framework is relevant to the local context, the economic specificities of this region may not reflect the dynamics at play in other geographical areas of the country. Although the results obtained reflect the reality on the ground, it would theoretically not be significant to generalize the results to all SMEs in the DR. Congo.

5.2. Suggestions

SMEs could consider the following alternatives:

- Strengthen their solvency by adopting more rigorous management, formalizing their activities and keeping simplified but regular accounts;
- Implement alternative forms of guarantee (joint guarantee, allocation of an asset, endorsement by a trusted third party) adapted to local realities;

By taking these suggestions into account, SMEs will be able to facilitate their access to credit from MFIs.

The Congolese state could:

- Develop a truly inclusive financial market, with an entire segment reserved for SMEs in this market;
- Grant tax advantages to investors who will start placing their capital in SME bonds;
- Strengthen the financial infrastructure by creating a national credit register that must be accessible to financial institutions and investors to reduce information asymmetry;

Encourage the creation of public-private investment funds dedicated to SMEs.

6. Conclusion

This research focused on microfinance and ending the financial exclusion of SMEs in Lubumbashi. We were guided by the observation that SMEs are victims of financial exclusion by microfinance institutions in the city of Lubumbashi. In doing so, we addressed the issue of the factors that explain the limited access of SMEs to credit from MFIs in Lubumbashi.

The study favored a quantitative approach based on the analysis of a sample of 69 SMEs in Lubumbashi, using multinomial logistic regression at the 5% significance level. Ultimately, the results confirm two of our hypotheses: the low solvency of SMEs (H5) and the lack of solid collateral to offer to microfinance institutions (H4). These two variables proved highly significant statistically, confirming that traditional banking selection criteria are also very much present in the microfinance sector, which is supposed to fill the gap left by the traditional banking system. In other words, microfinance is not the end of exclusion.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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