5C Credit Analysis, SLIK Utilization, and ICS Readiness Determine MSME Financing Access through Credit Decision

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ABSTRACT

Micro, Small, and Medium Enterprises (MSMEs) are key drivers of economic development but often face financing constraints due to limited collateral, weak credit histories, and information asymmetry. This study examines how 5C credit analysis, Financial Information Service System (SLIK) utilization, and Innovative Credit Scoring (ICS) readiness influence MSME credit decision-making and financing access in Rural Banks in North Sumatra, Indonesia. The study further investigates whether credit decision-making mediates the relationship between these assessment mechanisms and financing access. A quantitative survey was conducted with 290 credit decision-makers, including directors, branch managers, and credit officers. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate direct, indirect, and total effects among the constructs. The findings indicate that 5C credit analysis significantly influences credit decision-making but does not directly impact MSME financing access, with its effect fully mediated through credit decisions. In contrast, SLIK utilization and ICS readiness significantly affect both credit decision-making and financing access, with credit decisions partially mediating these relationships. Credit decision-making serves as the primary mechanism translating institutional assessment into actual financing, highlighting the importance of integrating traditional and digital credit assessment tools to support prudent and inclusive MSME financing in rural banks.

Keywords*: 5C Credit Analysis, Credit Decision-Making, Financing Access, Financial Information Service System, Innovative Credit Scoring, Rural Banks.*

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INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) are central to economic development, particularly in emerging markets where they contribute substantially to employment, income distribution, and regional economic resilience (Tekola & Gidey, 2019; Dasaraju & Tambunan, 2023). Despite their strategic role, MSMEs face persistent structural barriers in accessing formal finance. Limited collateral, inadequate financial documentation, and thin credit histories intensify information asymmetry between borrowers and financial institutions, often resulting in credit rationing and financial exclusion. Consequently, many economically viable MSMEs remain underserved by the formal banking sector (Saputra & Darmawan, 2023; Ofianti et al., 2025).

To mitigate information asymmetry, financial institutions traditionally employ risk-based lending frameworks, notably the 5C credit analysis framework (character, capacity, capital, collateral, and condition of the economy), and utilize credit information systems to enhance screening accuracy (Usanti & Setiawati, 2022; Rajamani et al., 2022; Kaveri, 2024). While these mechanisms are widely institutionalized, their effectiveness is constrained when applied to thin-file or unbanked MSMEs with limited formal financial footprints (Islam et al., 2024; Wang et al., 2025). Credit registries, although designed to

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reduce adverse selection, primarily capture historical formal borrowing data and may inadvertently reinforce exclusion for enterprises without established credit records.

Recent advances in digital finance have introduced Innovative Credit Scoring (ICS), which leverages alternative data and advanced analytics to evaluate creditworthiness beyond conventional financial statements (Saifurrahman & Kasim, 2024; Adebayo, 2025). Although existing studies highlight improvements in predictive accuracy and financial inclusion potential, empirical evidence remains concentrated on fintech-driven models and algorithmic performance. Limited attention has been paid to institutional readiness within conventional banking institutions, particularly smaller banks operating under prudential regulatory frameworks. Drawing on institutional theory, the successful adoption of innovation depends not merely on technological availability but also on organizational capacity, regulatory alignment, governance structures, and human resource competence (Addy et al., 2024).

Despite the growing body of literature on MSME financing and alternative credit assessment, research remains fragmented. Studies by Kowsar et al. (2023) and Abi (2025) examine traditional credit analysis, credit registry utilization, or alternative scoring models independently, without integrating them into a unified analytical framework. More critically, existing models often assume a direct relationship between assessment tools and access to MSME financing, overlooking the internal credit decision-making process that mediates the translation of risk information into actual lending outcomes (Al Maruf et al., 2024). From a financial intermediation perspective, credit allocation is shaped by organizational discretion, policy alignment, and institutional processes, particularly within smaller banking institutions where decision flexibility is relatively pronounced (Al-Slehat et al., 2024; Snyder, 2024; Oualid et al., 2025).

By integrating 5C credit analysis, credit information utilization, and readiness for innovative credit scoring into a single structural model and by positioning credit decision-making as a mediating mechanism, this study advances literature in two important ways. First, it bridges risk management theory and financial inclusion research by explaining how internal evaluation systems influence access to MSME financing. Second, it extends digital credit innovation scholarship by incorporating institutional readiness as a determinant of effective implementation within Rural Banks operating in an emerging market context. This integrative approach offers a more comprehensive understanding of how prudential risk management and inclusive financing objectives can coexist within small-scale banking institutions. This study aims to examine the direct effects of 5C credit analysis, SLIK utilization, and ICS readiness on MSME financing access in Rural Banks in North Sumatra, Indonesia. Furthermore, it seeks to investigate the mediating role of credit decision-making in translating these institutional assessment mechanisms into actual lending outcomes. By integrating these variables into a unified structural framework, the study endeavors to provide empirical evidence on how traditional risk assessment and digital readiness collectively shape inclusive financing practices within small-scale banking institutions.

LITERATURE REVIEW & HYPOTHESIS DEVELOPMENT

The Effects on Credit Decision-Making

Credit decision-making within financial institutions represents a complex evaluative process wherein lenders assess borrower credibility and repayment capacity prior to approving or rejecting financing applications. The quality of these internal decisions is significantly shaped by the robustness of the assessment mechanisms employed. The 5C credit analysis framework, encompassing character, capacity, capital, collateral, and condition of the economy, remains a foundational tool in traditional credit evaluation for MSMEs. Studies by Sondang (2025) and Novirin (2025) highlight that applying the 5C credit analysis enables lenders to systematically assess borrowers' credibility and repayment capacity, providing structured information to support internal credit decisions. Character and capacity evaluations assist financial institutions in predicting borrower

behavior and default risk. Trivedi et al. (2024) and Joenoes et al. (2025) further emphasize that the 5C credit analysis not only helps banks mitigate risk but also supports managerial discretion in approving or rejecting financing requests.

Beyond traditional frameworks, the utilization of formal credit information systems such as SLIK plays a critical role in reducing information asymmetry between banks and MSMEs. Studies by Bakare (2024) demonstrate that access to borrower credit histories and repayment records enables banks to evaluate creditworthiness more accurately, supporting informed internal decision-making. SLIK complements traditional assessment methods with objective financial data, improving the accuracy of default risk predictions and enhancing the overall quality of credit decisions. Furthermore, recent advances in digital finance have introduced ICS, which leverages alternative data and predictive analytics to assess borrower creditworthiness beyond conventional financial statements. Research by Jakob (2023) and Rai (2024) indicates that ICS enhances credit decision-making by allowing banks to quantify risk more accurately and objectively, particularly for MSMEs with limited formal financial records. Supriadi et al. (2025) further assert that implementing ICS enables financial institutions to modernize credit risk assessment and streamline loan origination processes. By incorporating transaction behavior, digital footprints, and repayment patterns, ICS enables lenders to systematically evaluate potential borrowers, thereby improving the reliability and efficiency of internal credit decisions.

H1: 5C credit analysis has a positive effect on credit decisions.
H2: SLIK utilization has a positive effect on credit decisions.
H3: ICS readiness has a positive effect on credit decisions.

The Effects on MSME Financing Access

Internal credit decision-making is recognized as a pivotal factor in determining MSME access to finance. Studies by Widyastuti et al. (2023) and Gustika et al. (2024) indicate that even when high-quality assessment tools and information systems are available, the final lending decision ultimately governs which MSMEs receive credit. Managerial discretion, organizational policies, and formal approval procedures shape how risk evaluations are translated into actual financing outcomes, highlighting the central role of decision-making in credit allocation. The influence of credit decisions on financing access is further supported by studies showing that structured and transparent decision-making frameworks increase both fairness and efficiency in credit distribution (Sukarnasih & Bhegawati, 2024; Charfeddine et al., 2024). Banks with effective internal processes are better able to balance risk management with financial inclusion objectives, ensuring that viable MSMEs are not excluded from formal lending channels.

In addition to the mediating role of credit decisions, several studies suggest that assessment mechanisms may exert direct influence on financing access. The 5C framework indirectly affects MSME financing access by shaping internal lending judgments. Banks that conduct comprehensive 5C credit analysis are better able to differentiate viable MSMEs from high-risk applicants, increasing the likelihood of credit approval for enterprises with strong fundamentals (Chirchir & Jagongo, 2024; Puryani, 2025). Research by Sari and Karsinah (2022) indicates that systematic application of 5C credit analysis enhances transparency and predictability in lending processes, thereby improving the inclusion of small and medium enterprises in formal financial systems. Similarly, SLIK utilization contributes positively to broader MSME financing access by allowing banks to confidently extend credit to previously underserved businesses. Nwachukwu (2024) shows that credit registries and formal reporting mechanisms reduce adverse selection and encourage lenders to serve smaller enterprises. Furthermore, ICS readiness supports MSME financing access by extending formal credit opportunities to previously underserved enterprises. Studies by Rohmana and Wulandari (2025) and Panjaitan and Siahaan (2025) suggest that financial institutions prepared to implement innovative scoring technologies are better able to bridge information gaps, reduce default

risk, and increase confidence in lending to small businesses. Bate'e et al. (2025) provide a multivariate framework demonstrating that financial and strategic determinants, including access to credit, significantly influence MSME performance in developing economies.

H4: Credit decision has a positive effect on MSME financing access.
H5: 5C credit analysis has a positive effect on MSME financing access.
H6: SLIK utilization has a positive effect on MSME financing access.
H7: ICS readiness has a positive effect on MSME financing access.

The Effect of Credit Decision as a Mediator

Credit decision-making acts as a critical mediator in translating institutional assessment mechanisms into MSME financing access. Studies by Dey et al. (2023) and Bi et al. (2024) emphasize that tools such as credit analysis, SLIK, and ICS enhance internal evaluation, but they influence financing outcomes only when integrated into formal decision-making processes. This mediating role ensures that risk assessments, whether traditional or digital, are effectively operationalized to produce tangible lending results.

Research also indicates that mediation through credit decision-making strengthens the relationship between information quality and financial inclusion. For example, integrating SLIK or ICS into credit evaluations enhances MSME access only when credit officers can interpret and apply the data within institutional frameworks (Gyimah et al., 2022). Similarly, the structured application of the 5C credit analysis translates assessment insights into approvals that extend financing to viable enterprises. These findings suggest that while assessment tools provide essential information, internal decision-making is the mechanism that converts institutional inputs into actual MSME financing, underscoring its strategic importance in inclusive credit allocation.

H8: Credit decision mediates the relationship between 5C credit analysis and MSME financing access.
H9: Credit decision mediates the relationship between SLIK and MSME financing access.
H10: Credit decision mediates the relationship between ICS and MSME financing access.

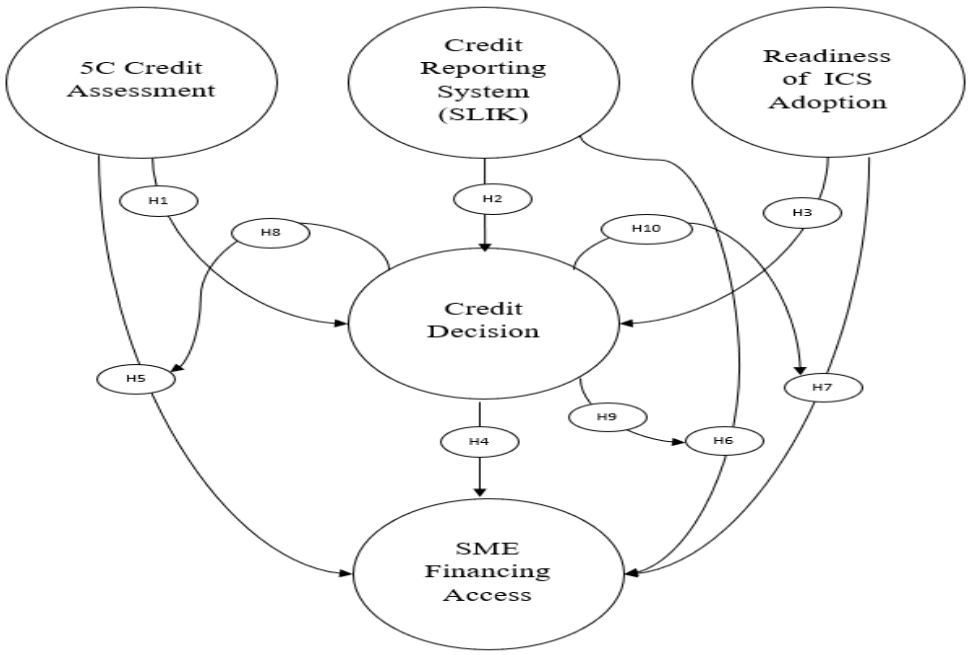

Figure 1. Research Framework

Figure 1 illustrates the conceptual framework of this study, depicting the hypothesized relationships among the five latent constructs. The model positions 5C credit analysis, SLIK utilization, and ICS as exogenous variables influencing MSME financing access, both directly and indirectly, through the mediating role of credit decision-making. The framework comprises seven direct paths (H1–H7) and three indirect mediation paths (H8–H10), providing a structural basis for testing how traditional and digital credit assessment mechanisms translate into actual MSME financing outcomes within rural banks.

RESEARCH METHODS

This study adopts a quantitative explanatory approach to analyze causal relationships among 5C credit analysis, SLIK utilization, Innovative Credit Scoring (ICS) readiness, MSME credit decision-making quality, and MSME financing access in Rural Banks (*Bank Perekonomian Rakyat/Bank Perekonomian Rakyat Syariah* or BPR/BPRS). Using a cross-sectional design, the research aims to explain how internal credit assessment mechanisms and information infrastructure influence financing outcomes. A variance-based Structural Equation Modeling (PLS-SEM) technique was employed due to its predictive orientation, ability to handle complex mediation structures, and minimal distributional assumptions (Hair et al., 2020). The study was conducted in North Sumatra Province, Indonesia, with the institutional credit decision-making function as the unit of analysis. Respondents included credit analysts, account officers, credit committee members, branch managers, and heads of credit divisions directly involved in MSME loan approval processes.

A stratified purposive sampling technique was applied by selecting BPR/BPRS institutions with total assets above IDR 50 billion to ensure adequate institutional capacity and exposure to credit information systems. Respondents were required to have direct involvement in MSME credit decisions, experience using SLIK, and at least one year of professional experience. A total of 290 valid responses were collected from 21 institutions, meeting the minimum sample requirement based on the 5–10 observations per indicator rule for PLS-SEM with 58 indicators. Data were gathered between December 2025 and January 2026 through structured questionnaires using a five-point Likert scale, distributed electronically and through institutional coordination. Two Focus Group Discussions (FGDs) with (*Otoritas Jasa Keuangan*/OJK) representatives, ICS providers, and BPR directors were conducted to enrich contextual interpretation and reduce mono-method bias. Secondary data from regulatory documents, OJK publications, and relevant literature supported construct development.

All constructs were modeled as reflective latent variables adapted from established studies and contextualized to the rural banking environment. The independent variables comprise 5C credit analysis, SLIK utilization, and ICS readiness (capturing technological, organizational, and regulatory dimensions), while credit decision-making quality serves as a mediating variable, and MSME financing access as the dependent variable. Data analysis followed a two-stage PLS-SEM procedure using SmartPLS: assessment of the measurement model (outer loadings, AVE, composite reliability, Cronbach's alpha, Fornell–Larcker criterion, and HTMT) and evaluation of the structural model (R^2, Q^2, f^2). Hypotheses were considered supported when t-values exceeded 1.96 and p-values were below 0.05, ensuring statistical robustness and explanatory validity.

RESULTS

The characteristics of the respondents in this study are presented to provide an overview of the demographic and professional backgrounds of the participants involved in the survey. Understanding the respondent profile is important to ensure that the collected data represent individuals who are directly involved in the credit evaluation and lending decision-making processes within rural banks. The distribution of respondents based on gender, age, level of education, position, and years of professional experience is presented in Table 1.

Table 1. Descriptive Statistics of Respondents

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	213	73.45%
	Female	77	26.55%
Age	< 25 years	10	3.45%
	26-35 years	119	41.03%
	36–45 years	93	32.07%
	46–55 years	57	19.66%
	> 55 years	11	3.79%
Education	Senior High School	40	13.79%
	Diploma	41	14.14%
	Bachelor	204	70.34%
	Master	5	1.72%
Position	Credit Officer/Analyst	127	43.79%
	Branch Manager	54	18.62%
	Directors	22	7.59%
	Head of Lending	22	7.59%
	Sub Head of Marketing	30	10.34%
	Sub Head of Operation	16	5.52%
	ManRisk & Compliance Head	19	6.55%
Years of Experience	< 1 year	10	3.45%
	1–2 years	16	5.52%
	2–3 years	15	5.17%
	3–5 years	29	10.00%
	> 5 years	220	75.86%

Table 1 shows that the characteristics reveal that the majority of respondents are male (73.45%). Most are credit officers/analysts (43.79%) aged between 26 and 35 years, followed by middle-aged (41.03%) with more than five years of experience in MSME financing, suggesting that the data were obtained from individuals with substantial operational expertise in credit evaluation processes. In terms of education, 70.34% of respondents have a bachelor's education, while high school and higher education levels account for 13.79% and 14.14%, respectively.

Table 2. Measurement Model

Construct	Loading Range	AVE	Composite Reliability	Cronbach's Alpha
55 Credit Analysis	0.843 – 0.956	0.683	0.948	0.936
SLIK Utilization	0.857 – 0.931	0.579	0.941	0.932
ICS Readiness	0.932 – 0.961	0.729	0.965	0.958
Credit Decision	0.776 – 0.925	0.613	0.952	0.944
MSME Financing Access	0.837 – 0.943	0.620	0.956	0.949

Table 2 summarizes the measurement model assessment results, including indicator reliability, convergent validity, and construct reliability. The outer loading values range from 0.776 to 0.961, all exceeding the recommended threshold of 0.70, indicating that each indicator adequately reflects its corresponding latent construct. The Average Variance Extracted (AVE) values vary between 0.579 and 0.729, confirming satisfactory convergent validity as each construct explains more than 50% of indicator variance. Furthermore, Composite Reliability (0.941–0.965) and Cronbach's Alpha values (0.932–0.958) are well above the minimum criterion of 0.70, demonstrating strong internal consistency across all constructs, including 5C credit analysis, SLIK utilization, ICS readiness, MSME credit decision-making, and MSME financing access. These findings confirm that the measurement model meets the required validity and reliability standards, supporting further evaluation of discriminant validity and structural model analysis.

Table 3 presents the results of the discriminant validity assessment of the measurement model, which aims to determine whether each construct in the study is empirically distinct from the others. The results show that the square root of the Average Variance Extracted

(AVE) for each construct, indicated by the diagonal values, 5C credit analysis (0.826), SLIK utilization (0.761), ICS readiness (0.854), credit decision (0.805), and MSME financing access (0.788), is greater than the correlations with other constructs. This indicates that each construct explains the variance of its indicators better than the variance shared with other constructs. Therefore, it can be concluded that the measurement model satisfies the discriminant validity criterion, confirming that all constructs are conceptually distinct and

Table 3. Discriminant Validity

Fornell-Larcker Criterion					
Construct	**1**	**2**	**3**	**4**	**5**
1. 5C Credit Analysis	0.826				
2. SLIK Utilization	0.519	0.761			
3. ICS Readiness	0.448	0.662	0.854		
4. Credit Decision	0.547	0.721	0.613	0.805	
5. MSME Financing Access	0.448	0.662	0.578	0.783	0.788
HTMT Ratio					
1. 5C Credit Analysis	—				
2. SLIK Utilization	0.718	—			
3. ICS Readiness	0.607	0.480	—		
4. Credit Decision	0.547	0.649	0.646	—	
5. MSME Financing Access	0.448	0.789	0.578	0.858	—

Table 3 also presents the results of the Heterotrait–Monotrait Ratio (HTMT) test, which is used to assess the discriminant validity among the constructs in the research model. The HTMT value indicates the degree of similarity between different constructs, where a value below the recommended threshold (generally 0.90) suggests that the constructs are empirically distinct. The results show that all HTMT values, including the relationships between 5C credit analysis and SLIK utilization (0.718), 5C credit analysis and ICS readiness (0.607), SLIK utilization and ICS readiness (0.480), SLIK utilization and credit decision (0.649), ICS readiness and credit decision (0.646), credit decision and MSME financing access (0.858), and SLIK utilization and MSME financing access (0.789), are below the recommended threshold. These findings indicate that all constructs demonstrate adequate discriminant validity, confirming that each construct measures a conceptually distinct variable within the research model.

Table 4. Model Fit Assessment

Model Fit Index	**Saturated Model**	**Estimated Model**	**Threshold**	**Result**
SRMR	0.062	0.075	< 0.10	Fit
NFI	0.762	0.751	> 0.90	Marginal

Table 4 summarizes overall model fit evaluated using the Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI). The SRMR values for both the saturated model (0.062) and the estimated model (0.075) are below the recommended threshold of 0.10, indicating a satisfactory level of model fit and a low residual discrepancy between observed and predicted correlations. Although the NFI values remain below the ideal threshold of 0.90, PLS-SEM primarily emphasizes predictive capability rather than absolute model fit. Therefore, the acceptable SRMR values confirm that the proposed structural model adequately represents the empirical data and is suitable for further structural analysis.

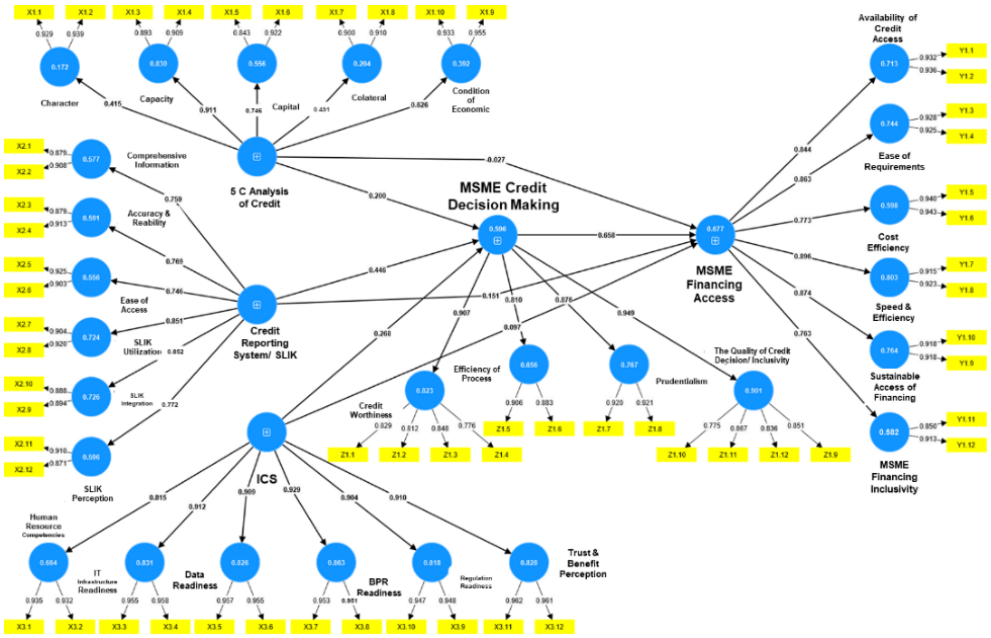

Figure 2. Structural Model

Figure 2 presents the results of the measurement and structural model analysis using PLS-SEM for the five main constructs examined in BPR/BPRS in North Sumatra, Indonesia. All indicators demonstrate satisfactory reliability with loading factors exceeding 0.70, confirming adequate construct representation. The structural model shows moderate to strong explanatory power, with R^2 values of 0.605 for MSME credit decision-making and 0.668 for MSME financing access. The results indicate that MSME credit decision-making plays a significant mediating role in linking 5C credit analysis, SLIK utilization, and ICS readiness to improved MSME financing access within rural banking institutions.

Table 5. Structural Model Evaluation

Endogenous Construct	R^2	Adjusted R^2	Q^2	Predictive Power
Credit Decision Making	0.605	0.601	0.596	Strong
MSME Financing Access	0.668	0.664	0.492	Strong

The structural model evaluation demonstrates substantial explanatory and predictive capability. Table 5 summarizes that credit decision making achieves an R^2 value of 0.605, indicating that 60.5% of its variance is explained by credit analysis, 5C credit analysis, SLIK, and ICS, reflecting moderate-to-strong explanatory power. Meanwhile, MSME financing access records an R^2 value of 0.668, suggesting that nearly two-thirds of the variance is jointly explained by the exogenous constructs and the mediating variable. Furthermore, Q^2 values exceeding 0.35 for both endogenous constructs confirm strong predictive relevance, indicating that the model possesses high out-of-sample predictive accuracy consistent with the predictive orientation of PLS-SEM.

Table 6. Effect Size

Relationship	f^2	Effect Size
5C Credit Analysis → Credit Decision	0.069	Small
5C Credit Analysis → MSME Financing Access	0.001	Small
SLIK → Credit Decision	0.316	Moderate
SLIK → MSME Financing Access	0.028	Small
ICS → Credit Decision	0.112	Small
ICS → MSME Financing Access	0.020	Small
Credit Decision → MSME Financing Access	0.500	Strong

Table 6 summarizes that SLIK utilization demonstrates a moderate effect on credit decision-making (f^2 = 0.316), highlighting its strategic importance in credit evaluation processes. In contrast, 5C credit analysis and ICS readiness exert only small effects on decision formation. Notably, credit decision-making shows a large effect (f^2 = 0.500) on MSME financing access, indicating that lending decisions act as the dominant mechanism translating institutional assessment into financing accessibility. The negligible direct effect of 5C credit analysis on MSME financing access further suggests the presence of an indirect transmission mechanism through the mediating construct.

Table 7. Hypothesis Testing Results

Hypothesis	Path	β	t-statistics	p-value	Result
H1	5C Credit Analysis → MSME Financing Access	-0.026	0.650	0.516	Not Supported
H2	5C Credit Analysis → Credit Decision	0.196	4.064	0.000	Supported
H3	SLIK → MSME Financing Access	0.146	2.398	0.017	Supported
H4	SLIK → Credit Decision	0.468	7.895	0.000	Supported
H5	ICS → MSME Financing Access	0.107	2.169	0.030	Supported
H6	ICS → Credit Decision	0.261	5.168	0.000	Supported
H7	Credit Decision → MSME Financing Access	0.648	11.159	0.000	Supported

The hypothesis testing results indicate that most structural relationships are statistically significant. Table 7 summarizes that SLIK utilization and ICS readiness significantly influence both credit decision-making and MSME financing access, confirming the importance of digital credit information systems and institutional readiness in promoting financing inclusion. Conversely, 5C credit analysis does not directly affect MSME financing access, suggesting that traditional credit assessment alone is insufficient to expand financing accessibility without formal decision endorsement. The strongest relationship is observed between credit decision-making and MSME financing access (β = 0.648), emphasizing the mediating role of institutional lending decisions within the financing ecosystem.

Table 8. Mediation Analysis

Indirect Path	Indirect Effect	p-value	Mediation Type
5C Credit Analysis → Credit Decision → MSME Financing Access	0.127	0.000	Full Mediation
SLIK → Credit Decision → MSME Financing Access	0.304	0.000	Partial Mediation
ICS → Credit Decision → MSME Financing Access	0.169	0.000	Partial Mediation

Mediation analysis confirms that credit decision-making plays a critical intermediary role in translating institutional assessment mechanisms into MSME financing access. Table 8 summarizes that the indirect effect of 5C credit analysis becomes significant only through credit decision-making, indicating full mediation. Meanwhile, SLIK utilization and ICS readiness exhibit partial mediation, as both direct and indirect effects remain significant. These findings demonstrate that MSME financing access is determined not merely by assessment quality or system readiness, but also by how these factors are operationalized through formal credit decision processes.

DISCUSSION

The findings of this study provide important insights into the mechanisms that determine MSME financing access within rural banking institutions. The results indicate that institutional credit assessment tools and information systems influence financing access primarily through the internal credit decision-making process rather than through direct assessment outcomes. The results show that 5C credit analysis significantly affects

credit decision-making but does not directly increase MSME financing access. This suggests that traditional credit assessment functions primarily as an input for internal lending decisions rather than as a direct determinant of financing accessibility. This finding is consistent with Al-Slehat et al. (2024), who emphasize that qualitative credit assessment methods serve as informational tools but must be integrated with institutional decision-making mechanisms to influence lending outcomes.

In contrast, SLIK utilization and ICS readiness play crucial roles in both credit decision-making and MSME financing access. The availability of formal credit information systems improves banks' ability to evaluate borrower reliability and reduce information asymmetry. These results align with Oualid et al. (2025), who highlight that credit registries reduce adverse selection and enhance lending efficiency in developing financial markets. Similarly, Supriadi et al. (2025) assert that implementing ICS enables financial institutions to modernize credit risk assessment and streamline loan origination, thereby improving both efficiency and inclusivity. Bate'e et al. (2025) further support this notion by demonstrating that access to credit serves as a critical strategic determinant of MSME performance in developing economies.

A central contribution of this study lies in its examination of the mediating role of credit decision-making. The mediation analysis confirms that credit decision-making serves as a critical intermediary mechanism that translates institutional assessment systems into tangible MSME financing access. Specifically, the indirect effect of 5C credit analysis on financing access becomes significant only through credit decision-making, indicating full mediation. This implies that traditional credit evaluation frameworks require formal endorsement through structured lending decisions to expand financial inclusion (Al-Slehat et al., 2024).

Meanwhile, SLIK utilization and ICS readiness exhibit partial mediation, as both direct and indirect effects remain statistically significant. These findings demonstrate that MSME financing access is determined not merely by assessment quality or system readiness alone, but rather by how effectively these factors are operationalized through formal credit decision processes. Lending decisions act as the operational bridge through which information from credit analysis, credit registries, and digital scoring systems is translated into actual financing approvals. This reinforces the financial intermediation perspective, which emphasizes that credit allocation is shaped by organizational processes, internal policies, and managerial discretion (Dey et al., 2023; Bi et al., 2024).

This study advances the literature by demonstrating that credit decision-making constitutes the primary mechanism through which assessment tools influence financing outcomes, thereby bridging risk management theory and financial inclusion research. The results suggest that rural banks should focus not only on strengthening assessment tools but more importantly on improving the quality and consistency of internal credit decision-making processes. This may involve enhancing the capacity of credit officers and refining lending policies to accommodate the unique characteristics of MSME borrowers. Furthermore, policymakers should consider initiatives that support the integration of digital credit information systems and innovative scoring technologies within rural banks. Ultimately, effective financial inclusion depends on the seamless integration of robust assessment mechanisms within formal credit decision-making processes, allowing rural banks to balance prudent risk management with broader financial inclusion objectives for MSMEs.

CONCLUSION

This study demonstrates that MSME financing access in rural banking institutions is primarily determined by the internal credit decision-making process, which mediates the effects of institutional assessment mechanisms, including 5C credit analysis, SLIK utilization, and ICS readiness. Traditional credit assessment provides essential information for evaluating borrower credibility, but does not directly expand financing access. In contrast, formal credit information systems and institutional readiness for innovative credit scoring significantly enhance both lending decisions and financing

access, highlighting the critical role of digital tools and organizational preparedness in supporting financial inclusion. These findings underscore that effective financing for MSMEs requires not only quality assessment tools but also their operationalization through structured institutional processes.

The implications of this study suggest that rural banks should focus on strengthening internal decision-making frameworks and integrating both traditional and digital credit assessment tools to improve MSME financing outcomes. The study is limited by its focus on a single geographic region and a specific set of rural banks, which may affect the generalizability of the results. Future research could examine the applicability of the proposed model across different regions or banking segments and explore additional organizational or environmental factors influencing lending decisions. Moreover, investigating the role of fintech partnerships or alternative data sources may provide further insights into enhancing MSME access to finance. The study emphasizes the importance of combining prudent risk management with institutional readiness to achieve inclusive financing in emerging markets.

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