Expanding Inclusivity: The Adoption of Alternative Credit Scoring by Private Banks and NBFCs

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***Abstract*—The adoption of alternative credit scoring holds significant potential for enhancing financial inclusion and improving risk assessment in private banks and NBFCs. This study investigates how alternative credit scoring impacts financial inclusion in rural areas. Data was collected from 10 loan processing executives at various private banks and NBFCs in Kerala's Palakkad district. Findings reveal that alternative credit scoring is effective in reaching underserved populations and reducing default rates. However, challenges such as limited fintech collaboration, inconsistent use of non-traditional data, and insufficient investment in model development impede widespread adoption. Lack of strategic alignment, and infrastructure gaps further hinder integration. Critical enablers include robust data privacy practices, top management support, comprehensive databases, and customer trust.**

***Index Terms*—Alternate credit scoring, financial inclusion.**

1. INTRODUCTION

The financial services landscape is experiencing a profound transformation, driven by the need to extend credit access to traditionally underserved populations, particularly those identified as new-to-credit customers (Chang et al., 2024). Traditional credit scoring models, which often rely on historical credit data, tend to exclude individuals with limited or no credit history, creating a barrier to financial inclusion (Sadok et al., 2022). This exclusion disproportionately impacts marginalized communities, hindering their ability to fully participate in the formal economy and build wealth (Ford & Rowlingson, 1996). In response to this challenge, private banks and Non-Banking Financial Companies are increasingly exploring and implementing alternative credit scoring methodologies to assess the creditworthiness of new-to-credit customers (Ford & Rowlingson, 1996). Alternative credit scoring utilizes non-traditional data sources such as utility payments, rental history, social media activity, and mobile phone usage to create a more comprehensive and inclusive assessment of credit risk. The integration of advanced technologies, such as machine learning and artificial intelligence, has further accelerated the adoption of alternative credit scoring, enabling lenders to process vast amounts of data and identify patterns that traditional models may overlook (Cao & Zhai, 2022). This shift towards alternative credit scoring represents a significant opportunity to expand financial inclusion, stimulate economic growth, and promote greater equity in access to credit (Sadok et al., 2022). However, the use of these alternative methods also introduces a complex set of challenges and considerations, including concerns about data privacy, algorithmic bias, and the need for transparency and explainability in credit decisions.

Theoretical Framework This study is underpinned by several key theoretical frameworks that illuminate the motivation, mechanisms, and implications of alternative credit scoring. The evolution of credit scoring has shifted from conventional rule-based systems to complex methodologies incorporating artificial intelligence, marking a substantial change in credit evaluation procedures (Addy et al., 2024). This transition was motivated by the need to overcome the shortcomings of conventional credit scoring systems, which frequently depend on historical data and may not accurately reflect the creditworthiness of individuals who are new to credit or have thin credit files. Financial inclusion theories emphasize the importance of providing access to financial services to all individuals, regardless of their socioeconomic background. Alternative credit scoring aligns with these theories by enabling lenders to assess the creditworthiness of individuals excluded by traditional models, thereby promoting greater financial inclusion (Cornelli et al., 2019). Behavioral economics provides insights into how individuals make financial decisions and how these decisions can be influenced by factors such as cognitive biases and social norms.

1.1 Objectives of the study

1. To assess the effectiveness of alternative credit scoring in enhancing financial inclusion.
2. To identify key challenges hindering the adoption of alternative credit scoring in private banks and NBFCs
3. To evaluate critical success factors that enable seamless integration of alternative credit scoring models.

2. LITERATURE REVIEW

Existing literature on credit scoring underscores the limitations of traditional models and the potential advantages of alternative approaches. The adoption of explainable AI and the integration of alternative data are fostering a more nuanced, transparent, and inclusive method for evaluating creditworthiness (Addy et al., 2024). The use of machine learning in credit scoring presents a double-edged sword, offering enhancements in predictive accuracy while simultaneously raising concerns about fairness, transparency, and the potential for discriminatory outcomes (Valdrighi et al., 2024). Recent studies indicate that algorithmic credit scoring can enhance predictive accuracy in assessing creditworthiness and pricing credit (Aggarwal, 2021). However, these models may perpetuate existing biases if not carefully designed and monitored (Valdrighi et al., 2024). The rise in alternative credit scoring coincides with the increasing availability of non-traditional data sources and the development of advanced analytical techniques (Dumitrescu et al., 2021). These methods often rely on structured data such as borrower income, credit scores, and debt levels to predict the likelihood of default. Although these approaches have been effective for decades, they depend on linearity assumptions that often fail to capture the complexity of borrower behavior in today's data-rich environments. The application of AI and machine learning in credit risk assessment has shown promise for improving accuracy and efficiency (Mhlanga, 2021; Wang, 2024).

The use of AI in credit analyses enhances financial inclusion and loan access for previously underserved borrowers. However, long-term concerns about potential biases and ethical, legal, and regulatory issues suggest the need for a new generation of financial regulations (Kamiran & Calders, 2011; Nallakaruppan et al., 2024). The emphasis on explainable AI is driven by the need for transparency and interpretability in credit risk models, which can foster trust and understanding (Alvi et al., 2024). The effectiveness of machine learning relies on using historical data to uncover hidden patterns that can predict future outcomes (Addy et al., 2024). Machine learning plays a significant role because credit risk involves the collection of data that must be analyzed, tested, and processed accurately (Mhlanga, 2021). Credit risk management is crucial for financial institutions, and technology has enabled lenders to evaluate vast amounts of customer data (Misheva et al., 2021). However, credit scoring systems may suffer if the final data contain irrelevant or redundant information (Jakka et al., 2023).

It is important to have transparency and explainability in credit scoring models in order to promote confidence and make sure that customers are aware of the variables that affect credit decisions. Lenders need to implement strong data governance procedures and security measures to protect sensitive consumer data from unauthorized access, use, or disclosure (Bryant et al., 2019). Fairness assessment for artificial intelligence is essential to address concerns of bias and discrimination in credit scoring models (Zhang & Zhou, 2019). Fairness must be taken into account in algorithmic design, data selection, and model validation to avoid unjustified disparate impacts on vulnerable groups (Fritz-Morgenthal et al., 2022; Zhou et al., 2021).

2.1 Alternative Credit Scoring Approaches

Alternative credit scoring encompasses methods that assess creditworthiness using non-traditional data sources, such as utility bill payments, rental records, and social media activity (State of Alternative Credit Data, 2025). These approaches aim to include individuals with limited or no credit history, providing broader access to financial services (Alternative Credit Scoring, 2024). The integration of artificial intelligence and machine learning enhances these models by enabling the analysis of large datasets and identifying complex patterns that traditional systems may overlook (AI and Non-Traditional Data Sources: A Novel Path for Credit Scoring, 2024). This holistic approach benefits individuals like students and immigrants who are often underserved by traditional credit scoring methods (Jakka et al., 2023). Techniques such as neural networks and support vector machines improve prediction accuracy but may lack transparency, making it difficult to trace how decisions are made (Misheva et al., 2021). Overall, alternative credit scoring supports inclusive, data-driven lending.

2.2 Implications for Financial Inclusion

Alternative credit scoring plays a crucial role in advancing financial inclusion by enabling lenders to assess individuals typically excluded by traditional credit systems, such as young adults, immigrants, and low-income groups. By incorporating alternative data sources—like utility payments, rental history, and employment information—these models offer a more comprehensive view of a borrower's financial behavior (Mhlanga, 2021). This holistic approach helps level the playing field and increases access to credit for underserved populations. As a result, alternative credit scoring supports fairer lending practices and enhances consumer trust in automated financial systems (Financial Inclusion and Disruptive Innovation: Regulatory Implications, 2024). It helps bridge gaps created by conventional credit evaluation methods, which often fail to account for reliable but non-traditional financial behaviors. Ultimately, alternative credit scoring has the potential to reduce financial exclusion and promote equity by expanding credit opportunities to those previously overlooked, fostering a more inclusive and balanced financial ecosystem.

3. DATA AND METHODOLOGY

The researcher conducted this study by interviewing 10 officers from private banks and Non-Banking Financial Companies (NBFCs) in the district of Palakkad, Kerala. The names of these banks and financial institutions have been kept anonymous at the request of the respondents. A convenience sampling method was used to select the sample, and the collected data was analyzed using MS Excel and SPSS to derive meaningful conclusions.

4. DATA ANALYSIS AND INTERPRETATION

4.1 Summary of demographic variables

The survey data provides a clear demographic profile of the respondents. In terms of age distribution, the largest group is 31-40 years (6 respondents, 42.9%), followed by 20-30 years (4 respondents, 28.6%), 41-50 years (3 respondents, 21.4%), and 50 & above (1 respondent, 7.1%). Gender distribution shows a significant majority of male respondents (10, or 71.4%) compared to female respondents (4, or 28.6%). When examining years of experience, the respondents are evenly divided between those with 0-5 years (6, 42.9%) and 6-10 years (6, 42.9%), while only 2 respondents (14.3%) have 10+ years of experience.

Key observations highlight that the typical respondents are male aged 31-40 with either 0-5 or 6-10 years of experience. The under representation of older professionals (50+) and those with extensive experience (10+ years) suggests that perspectives may skew toward mid-career professionals. Additionally, the gender imbalance indicates a predominantly male viewpoint in the survey responses. These demographic insights are crucial for interpreting the broader findings, as they may influence perceptions on alternative credit scoring adoption, challenges, and scalability. Understanding these respondent characteristics helps contextualize the data and assess its applicability across different workforce segments.

4.2 Descriptive Statistics

Variable	Minimum	Maximum	Mean	Median	Standard Deviation
Adopted alternative credit scoring to improve access	3	5	4	4	0.78

Alternative credit scoring aligns with our strategic business goals	2	5	3.71	4	0.83
Target new-to-credit or financially excluded customer	2	5	4.14	4	0.77
Use non-traditional data points such as mobile payments, utility bills, or social media behavior for credit assessment	2	5	3.36	3.5	1.08
Collaborate with third-party data providers or fintech partners	1	3	1.64	2	0.63
Default rates under alternative credit scoring are less	2	5	3.71	4	0.91
The use of alternative scoring has led to an increase in first-time borrowers	1	5	3.93	4	1.21
We have clear policies in place to ensure data privacy in our alternative credit scoring practices	1	5	4.07	4	1.21
We are investing in the development and refinement of alternative credit scoring models for the future	1	5	2.64	2	1.28

The descriptive statistics reveal key insights into the adoption and perception of alternative credit scoring. Respondents strongly agree that alternative credit scoring improves access (mean = 4.00, median = 4.00), with moderate variability (SD = 0.78). Targeting financially excluded customers is highly rated (mean = 4.14), though collaboration with third parties scores lowest (mean = 1.64), indicating limited partnerships. Non-traditional data usage shows mixed opinions (mean = 3.36, SD = 1.08), suggesting uncertainty in implementation. Default rates and first-time borrower increases are positively viewed (means = 3.71 and 3.93), but with higher variability (SDs = 0.91 and 1.21). Data privacy policies are robust (mean = 4.07), while investment in future models is the least prioritized (mean = 2.64). Overall, the data reflects enthusiasm for alternative scoring's potential but highlights challenges in partnerships, data integration, and long-term investment. Standard deviations indicate varying consensus, particularly on non-traditional data and scalability.

4.3 Alternative credit scoring for enhanced financial inclusion

The descriptive statistics provide strong evidence that alternative credit scoring enhances financial inclusion. Respondents overwhelmingly agree that it improves access to credit (mean = 4.00, median = 4.00), demonstrating its effectiveness in reaching underserved populations. This is further supported by the high rating for targeting financially excluded customers (mean = 4.14). Additionally, the positive perception of reduced default rates (mean = 3.71) and increased approvals for first-time borrowers (mean = 3.93) indicates that alternative scoring methods successfully expand credit access without compromising risk management.

4.4 Correlation analysis

Variable	1	2	3	4	5	6	7	8	9
1. Adopted alternative credit scoring to improve access	1	-0.36	-0.38	0.36	0	0.64	0.08	0.16	-0.23
2. Alternative credit scoring aligns with strategic goals	-0.36	1	0.43	-0.65	-0.06	-0.52	0.29	0.02	0.33
3. Target new-to-credit/financially excluded customers	-0.38	0.43	1	-0.53	-0.36	-0.27	0.59	0.57	0.06

4. Use non-traditional data (mobile, utility, social media)	0.36	-0.65	-0.53	1	0.09	0.11	0.08	-0.37	-0.18
5. Collaborate with third-party data providers/fintech	0	-0.06	-0.36	0.09	1	-0.06	-0.34	0.14	0.12
6. Default rates under alternative scoring are less	0.64	-0.52	-0.27	0.11	-0.06	1	-0.16	0.16	-0.16
7. Alternative scoring increased first-time borrowers	0.08	0.29	0.59	0.08	-0.34	-0.16	1	0.37	0.18
8. Clear data privacy policies in place	0.16	0.02	0.57	-0.37	0.14	0.16	0.37	1	-0.18
9. Investing in development of alternative scoring models	-0.23	0.33	0.06	-0.18	0.12	-0.16	0.18	-0.18	1

The correlation matrix reveals key relationships between variables influencing alternative credit scoring adoption. The strongest positive correlation (r=0.59) exists between targeting new-to-credit customers and increased first-time borrowers, suggesting that financial inclusion efforts effectively expand customer bases. Similarly, targeting excluded customers correlates with strong data privacy policies (r=0.57), highlighting the importance of trust-building measures. However, a significant negative correlation (r=-0.65) between strategic alignment and non-traditional data usage indicates potential resistance to innovation within traditional frameworks. The adoption of alternative scoring shows moderate positive correlation with reduced default rates (r=0.64), supporting its risk-assessment value, but weak correlation with fintech collaboration (r=0.00), implying partnership models need refinement. Interestingly, investment in model development shows little connection to other variables (r<0.33), suggesting it may be driven by external factors rather than operational outcomes. These patterns underscore that while alternative scoring supports financial inclusion and risk management, its integration faces cultural and strategic hurdles. Organizations must align innovation with core objectives while strengthening fintech partnerships to fully realize these benefits. The mixed correlations emphasize the need for balanced strategies addressing both technical and organizational dimensions of credit scoring transformation.

4.5 Challenges for integrating alternative credit scoring.

The integration of alternative credit data presents both promise and complexity. Most respondents identified the availability of accurate data, management support, and infrastructure gaps as key challenges. Regulatory and compliance concerns also surfaced prominently. Addressing these issues will be essential to fully unlock the opportunities in inclusive lending and improve risk assessment models in private banks and NBFCs.

4.6 Factors to be considered scaling alternative credit scoring Method

To scale alternative credit scoring methods effectively, respondents emphasized the importance of a robust database, strong top management support, customer trust, and strategic partnerships with fintech companies. A reliable data foundation enables accurate assessments, while leadership backing ensures implementation. Building trust with customers and leveraging fintech innovation are also vital to reaching and serving diverse borrower segments successfully

5. FINDING AND DISCUSSION

The analysis of descriptive statistics and correlations reveals important trends and barriers in the adoption of alternative credit scoring methods. Respondents strongly support the idea that alternative credit scoring improves financial access (mean = 4.00) and is effective in targeting financially excluded populations (mean = 4.14). However, collaboration with fintechs received the lowest average rating (mean = 1.64), suggesting limited partnerships in this area. The use of non-traditional data received mixed responses (mean = 3.36, SD = 1.08), indicating hesitation or lack of readiness in implementing such data-driven approaches.

Positive views on default rate reduction and increases in first-time borrowers show the perceived effectiveness of these models, but higher standard deviations point to varied experiences. While data privacy policies are rated highly (mean = 4.07), investment in future model development remains a low priority (mean = 2.64), suggesting a short-term outlook among many institutions.

Correlation analysis highlights important relationships. A strong positive correlation (r = 0.59) between targeting new-to-credit customers and increased first-time borrowers validates the role of alternative credit scoring in financial inclusion. Similarly, strong data privacy correlates with customer targeting efforts (r = 0.57), underscoring trust as a critical factor. A notable negative correlation (r = -0.65) between strategic alignment and non-traditional data usage indicates resistance to innovation within traditional organizational structures. Fintech collaboration remains weakly correlated with other variables, pointing to underdeveloped partnerships.

Key challenges in integrating alternative credit scoring include data accuracy, management support, infrastructure limitations, and regulatory compliance. To scale these methods effectively, institutions must prioritize building robust databases, gain leadership support, foster customer trust, and engage in fintech collaborations. The overall findings suggest that while alternative credit scoring holds strong promise for inclusive lending and better risk assessment, its success depends on strategic alignment, cultural readiness, and stronger technological and institutional collaboration.

6. CONCLUSION

In conclusion, the adoption of alternative credit scoring presents significant potential for enhancing financial inclusion and improving risk assessment among private banks and NBFCs. The findings indicate strong support for its ability to reach underserved populations and reduce default rates. However, key challenges such as limited fintech collaboration, inconsistent use of non-traditional data, and low investment in future model development hinder widespread implementation. Organizational resistance, lack of strategic alignment, and infrastructure gaps further complicate integration efforts. Strong data privacy practices and top management support emerge as critical enablers, along with building robust databases and customer trust. To fully harness the benefits of alternative credit scoring, institutions must adopt a balanced approach that combines technological innovation with cultural readiness and strategic intent. Strengthening partnerships with fintechs and aligning internal goals with inclusive finance objectives will be essential for successfully scaling these methods across diverse customer segments and achieving long-term financial transformation.

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