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Optimization of Behavioral Scoring for Microcredit by Utilizing E-Commerce Seller Operational Data (Seller Metrics)

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Abstract: This study aims to explore the role of seller metrics on e-commerce platforms in assessing microcredit risk through a Systematic Literature Review (SLR) approach. The study reviewed recent literature from 2020 to 2025 from academic databases such as Scopus, DOAJ, and Google Scholar, using keywords like "seller metrics," "microcredit risk," "credit scoring," and "machine learning." Findings indicate that seller metrics, including long-term payment behavior, transaction frequency, purchase consistency, and seller engagement on digital platforms, significantly enhance the accuracy, stability, and fairness of credit scoring models compared to traditional financial indicators. The integration of alternative data and the application of machine learning models, particularly boosting algorithms, further strengthen predictive capabilities for credit risk. Nonetheless, challenges related to formal validation, algorithmic bias, and model interpretability remain critical. Future research is recommended to develop a comprehensive predictive framework and bias mitigation strategies to support inclusion and fairness in microcredit risk assessment.

Keywords: Seller Metrics, Microcredit Risk, Credit Scoring, Machine Learning, Alternative Data.

Introduction

Microcredit plays a crucial role in strengthening the digital economy by supporting the sustainability of MSMEs, which are a significant sector for the national economy (Mahesh et al., 2022). In the process of digitalization, MSMEs require access to financing to enhance business capacity and optimize the use of e-commerce platforms (Hendrawan et al., 2024). However, limited credit history, financial documents, and collateral remain major obstacles to obtaining formal financing (Munishi et al., 2022). The development of the digital ecosystem creates opportunities to utilize operational data based on online activities as more accurate and real-time indicators of creditworthiness (Wu & Liao, 2025). Therefore, improving the effectiveness of microcredit assessment is crucial to expanding financial inclusion in the digital era.

Although financial institutions have long relied on conventional credit assessment methods, these approaches are increasingly considered inadequate for evaluating the creditworthiness of digital MSME borrowers. Traditional models based on credit history, formal financial statements, and collateral fail to capture the profiles of entrepreneurs who are not yet integrated into the formal financial system (Hardik, 2024). As a result, many e-commerce sellers are classified as high-risk borrowers despite demonstrating stable and sustainable business activities (L. Wang, 2022). The mismatch between actual risk profiles and traditional assessment outcomes creates a significant credit gap, thereby limiting financing access for productive actors in the digital ecosystem. These challenges highlight the need for a risk assessment approach that is more adaptive and sensitive to the operational dynamics of online sellers (Balboa et al., 2024).

The use of alternative data and behavioral scoring approaches has begun to be developed to address the limitations of traditional credit assessment models. Alternative data provides non-conventional information, including digital activity traces that can more accurately reflect the operational characteristics of potential borrowers (Djeundje et al., 2021). Meanwhile, behavioral scoring evaluates creditworthiness through

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actual behavioral patterns, such as transaction consistency and business activity stability (Abi, 2025). Empirical studies show that leveraging digital data can improve risk detection accuracy while expanding financial inclusion for entrepreneurs without formal credit histories (Adewuyi et al., 2020). Therefore, the integration of alternative data and behavioral scoring represents a strategic approach to enhancing the effectiveness of microcredit assessment in the digital economy era.

Seller metrics provide crucial information regarding the financial health and operational efficiency of businesses, thereby enhancing the accuracy of credit risk assessment through indicators such as revenue growth and profitability. When combined with machine learning models, including Smote-RF-CatBoost achieving over 95% accuracy, risk prediction precision improves significantly (A. Wang et al., 2023). Hybrid approaches, such as AHP-SVM, also demonstrate high performance up to 96% (Amalia et al., 2025), while deep learning models with attention mechanisms help explain the impact of each metric on prediction outcomes (Guo et al., 2023). Nevertheless, quantitative data still need to be complemented by qualitative factors to ensure a more holistic credit assessment.

Exploration of seller metrics on e-commerce platforms as real-time risk indicators remains limited, despite the growing body of research on credit scoring and fintech lending. Most studies continue to focus on traditional financial indicators and have yet to leverage operational e-commerce data that can more accurately reflect sellers' financial conditions, such as sales trends, customer reviews, and inventory levels (Crosato et al., 2023). Integrating these data with AI models, including LSTM, has been shown to improve risk prediction accuracy compared to conventional methods (Chen & Long, 2023) and enables more precise market segmentation based on sellers' operational performance (Bouvard et al., 2022). Nonetheless, its utilization still faces challenges such as data privacy, governance, and the need to consider broader economic factors to ensure comprehensive risk assessment.

The need for integrated research and cohesive scoring technologies is increasingly urgent, as existing approaches remain fragmented and inconsistent. (Supriyadi & Bahagiati, 2024) emphasize that the legal framework for fintech remains "fragmented," with regulations scattered across multiple domains, while (Hensher et al., 2021) observe a similar pattern in health application evaluations, with 430 highly variable assessment criteria. Scoring technologies have also developed rapidly, ranging from the application of machine learning in credit assessment (Michael, 2020) to sensor-based scoring in martial arts (Ihsan et al., 2024), yet many of these approaches remain unstandardized. (Aslan et al., 2024) further highlight the lack of external validity and consistency across various risk assessment tools. Consequently, the main challenge lies in formulating an integrated, valid, and widely applicable scoring framework.

Based on these various gaps, this study aims to optimize behavioral scoring for microcredit by leveraging seller metrics on e-commerce platforms through a systematic literature review approach. Specifically, the research seeks to identify and categorize the most relevant operational metrics of sellers, assess the consistency and effectiveness of modeling methods used in previous studies, evaluate the external validity and interpretability of predictive models, and examine data governance issues and their practical implications. Accordingly, this study is expected to formulate a more standardized, accurate, and applicable scoring framework to support the expansion of financing access for micro-entrepreneurs within the e-commerce ecosystem.

Method

The primary objective of this study is to optimize the utilization of seller metrics as the basis for developing behavioral scoring in microcredit, using a Systematic Literature Review (SLR) approach to identify relevant concepts, methods, and empirical findings. The literature search was conducted systematically through databases such as Google Scholar, Scopus, and DOAJ, using keywords including "behavioral scoring," "microcredit," "e-commerce seller metrics," and "risk assessment." Literature published between 2020 and 2025 was prioritized to ensure the analysis reflects the latest developments in risk assessment technology and the use of operational seller data on digital platforms.

The inclusion criteria encompass studies that examine the use of behavioral or operational data in credit risk assessment, particularly within the context of microcredit or e-commerce platforms. Exclusion criteria included articles that were conceptually irrelevant, lacked a clear scientific methodology, or did not provide extractable data. During the selection stage, articles meeting the inclusion criteria were analyzed in depth, and key data were manually extracted, including research objectives, methodological approaches, primary variables, and main findings supporting qualitative analysis. The collected data were subsequently analyzed to identify patterns, differences in approaches, and research gaps related to the utilization of seller metrics as the foundation for behavioral scoring models. The overall research procedure is illustrated in Figure 1.

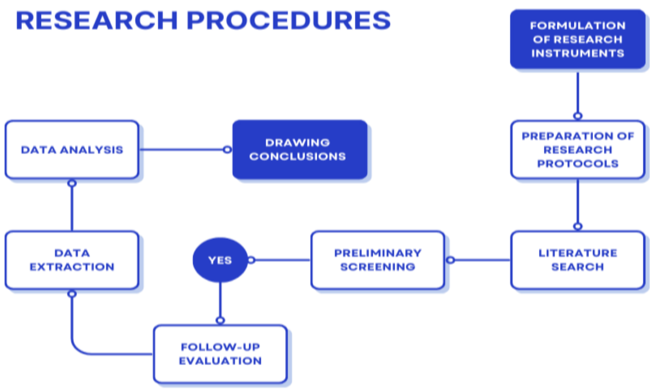

Figure 1. Research Procedure

Figure 1 illustrates the research procedure, which begins with the formulation of a research instrument specifically focused on utilizing seller metrics as the basis for developing behavioral scoring in microcredit risk assessment. The next step involves preparing a research protocol that includes establishing inclusion and exclusion criteria and identifying literature sources from databases such as Google Scholar, Scopus, and DOAJ. The literature search is conducted systematically using keywords such as "behavioral scoring," "microcredit," "seller metrics," "e-commerce risk assessment," and "alternative data for credit scoring." The search results are then screened based on titles and abstracts to eliminate articles that are not relevant to seller operational data and risk assessment models. Articles that pass the initial screening are reviewed in full to ensure compliance with the established inclusion criteria. Subsequently, key data from the selected articles are extracted and analyzed to identify findings related to the use of behavioral and operational data in credit scoring, the predictive models employed, and implementation challenges. The results of this analysis form the basis for mapping research trends, identifying knowledge gaps, and formulating recommendations for optimizing behavioral scoring based on seller metrics to enhance the accuracy and effectiveness of microcredit risk assessment.

Result and Discussion

The research findings you presented can generally be categorized into four main areas: (1) seller metrics as credit risk indicators, (2) alternative data and digital behavior for credit scoring, (3) machine learning model performance in credit risk prediction, and (4) the effectiveness of gradient boosting and boosted decision trees in credit risk modeling. Each area includes researchers focused on similar topics and provides key insights, such as the use of online transaction behavior, high-frequency transaction data, alternative data, fairness-aware credit scoring, predictive model performance, and the effectiveness of boosting algorithms in enhancing credit risk assessment accuracy.

Table 1. Focus and Insights on Research Findings According to Eligibility Criteria

No	Field / Focus	Authors in the Same Field	Insights / Research Variables
1	Seller Metrics as Microcredit Risk Indicators	Qiao et al. (2024); Yang (2024); Binwen (2023); Amalia et al. (2025)	Long-term payment behavior; high-frequency transaction data; consumer financial metrics in the e-commerce ecosystem; 5C principles and expert involvement for risk mitigation; dynamics of seller transaction behavior.
2	Alternative Data & Digital Behavior in Enhancing Credit Scoring	Amornkitvikai et al. (2022); Tabianan & Velu (2022); Gao et al. (2023); Mustafa et al. (2022); Kilay & Simamora (2022)	Digital transaction intensity; customer purchase consistency; seller engagement level; perception of online transaction risk; impact of e-commerce services on MSME performance; preliminary validation of seller metrics as credit risk predictors.
3	Alternative Data to Improve Credit Risk Model Accuracy	Id et al. (2024); Çallı (2021); Kyeong et al. (2021)	Social network data (default status), regional economic indicators, banking system log data, non-traditional data; improvement in AUC and discriminatory power of credit assessment models.
4	Machine Learning for Credit Scoring & Credit Risk	Lam (2024); Marín (2024); Moldovan (2023); Giang et al. (2024)	Alternative data for underbanked groups; Hamiltonian neural networks for out-of-time prediction; fairness-aware models; bias mitigation in credit scoring; adaptive models based on transactional behavior.
5	ML Model Performance: Gradient Boosting, Random Forest, XGBoost, LightGBM	Xu (2024); Nguyen (2025)	GBM AUC 0.87; accuracy 92%; Random Forest AUC 0.85; boosting models (XGBoost, LightGBM) reach 98% accuracy; logistic regression significantly lower; challenges with class imbalance.
6	Effectiveness of Gradient Boosting & Boosted Decision Trees	Han & Id (2024); Bastos (2022); Çallı (2021)	Gradient boosting with oversampling achieves AUC 0.9649, MCC 0.8104, F1 0.9072; boosted decision trees are competitive; significant improvement over traditional models; supports trend toward non-traditional data and advanced modeling.

Types of seller metrics on e-commerce platforms that have been proven relevant, significant, or potentially usable as indicators of risk in microcredit.

Seller metrics on e-commerce platforms play an important role as financial risk indicators in the context of microcredit, as they reflect the stability and operational behavior of sellers. Analysis of long-term payment behavior, including extended payment patterns and their aggregation at the merchant level, has been shown to improve the accuracy of risk profiling (Qiao et al., 2024). In addition, the use of high-frequency transaction data allows for dynamic risk measurement based on trends and periodicity in seller performance (Yang, 2024), while the integration of consumer financial metrics within the e-commerce ecosystem provides insights into seller reliability and payment behavior (Binwen, 2023). Creditworthiness evaluation through the application of the 5C principles and expert involvement further enhances the accuracy of risk classification and credit mitigation (Amalia et al., 2025). However, overreliance on quantitative data may overlook relevant qualitative factors, indicating that risk analysis should be designed in a more comprehensive manner.

Several studies indicate that a number of seller metrics on e-commerce platforms have potential for use in microcredit risk assessment, although their validation remains limited. The intensity of digital transactions, such as the percentage of sales conducted through online platforms, has been shown to be relevant in reflecting seller performance (Yot (Amornkitvikai et al., 2022), while customer behavior factors including purchase frequency and consistency are also considered to contribute to assessing business stability (Kayalvily (Tabianan & Velu, 2022). Seller engagement on digital platforms (Gao et al., 2023) as well as aspects of trust and perceived risk in online transactions (Mustafa et al., 2022) are also viewed as potential indicators. Additionally, e-commerce services in general are known to positively impact MSME performance (Kilay & Simamora, 2022). However, these studies have not yet produced a verified framework that directly establishes these metrics as microcredit risk indicators, highlighting the need for further research to assess their predictive reliability.

Various research findings indicate that several seller metrics on e-commerce platforms have significant relevance and potential as risk indicators in microcredit. The most prominent metrics include long-term payment behavior, reflecting the seller's financial discipline; transaction intensity and stability, which indicate operational cash flow strength; and high-frequency transaction data, allowing dynamic risk monitoring. Additionally, operational quality measures such as return rates, order cancellations, and order fulfillment speed also reflect operational health affecting creditworthiness. Customer behavior factors, including repeat purchase frequency, consistency of demand, and consumer ratings and reviews, provide insights into the stability of seller revenue. Seller engagement with digital platform features and trust indicators in online transactions further enrich the risk signals. Nevertheless, formal validation of these metrics for direct use in microcredit assessment remains limited, highlighting the need for further research to ensure predictive reliability and integration into more comprehensive risk models.

Seller metrics can improve the accuracy, stability, or fairness of credit scoring models compared to traditional financial indicators.

Seller metrics have the potential to enhance the accuracy, stability, and fairness of credit scoring models compared to traditional financial indicators, as they can leverage alternative data and more adaptive machine learning techniques. The use of non-conventional data, such as transaction histories and payment behaviors, has been shown to produce more precise credit assessments, particularly for groups underserved by formal banking systems (Lam, 2024). Advanced machine learning models, including Hamiltonian neural networks, also demonstrate superior out-of-time predictive performance, making them more resilient under changing economic conditions (Marín, 2024). In addition, the application of bias mitigation techniques and fairness-aware models helps improve assessment fairness by identifying and correcting inequities in traditional scoring systems (Moldovan, 2023; Giang et al., 2024). Nevertheless, the use of alternative data must be continuously monitored, as it may introduce new biases, and credit scoring models should be regularly evaluated to prevent reinforcing existing inequalities.

Several studies demonstrate that the utilization of alternative data sources can enhance the accuracy of credit scoring models beyond conventional financial indicators. Findings by Id et al., (2024) show that incorporating variables such as default status within social networks and regional economic assessments improves the predictive performance of models, achieving an AUC of 0.79360. The shift toward using non-traditional data is also emphasized by Çallı, (2021), who highlight the significant potential for improving prediction accuracy. Further empirical evidence is provided by (Kyeong et al., 2021), where integrating banking system log data increased credit ranking discrimination by 1.84 percentage points compared to traditional credit bureau-based assessments. Although these studies do not specifically address "seller metrics," they collectively indicate that diverse alternative data sources can substantially contribute to enhancing the accuracy and reliability of credit scoring models.

Seller metrics have the potential to enhance the accuracy, stability, and fairness of credit scoring by providing a more real-time and detailed view of sellers' operational performance compared to traditional financial indicators. Metrics such as transaction volume, order fulfillment consistency, return rates, and customer ratings capture business dynamics that reflect actual risk, enabling more precise and responsive predictions to changing conditions. The use of these data also expands credit assessment access for micro-entrepreneurs who lack formal credit history, thereby improving fairness. However, implementation still requires careful oversight to prevent new biases and ensure that the models remain valid and accountable.

Which analytical or machine learning models are most commonly used to process seller metrics for credit risk assessment, and how do their performances compare.

The development of seller metrics for credit risk assessment increasingly relies on machine learning (ML) models, which have been shown to outperform traditional statistical methods. Several studies indicate that boosting-based algorithms, particularly Gradient Boosting Machine (GBM), achieve high performance with an AUC of 0.87 and accuracy of 92%, supported by the strong performance of Random Forest with an AUC of 0.85 and accuracy of 90% (Xu, 2024). Models such as XGBoost and LightGBM have even been reported to reach up to 98% accuracy in predicting defaults, highlighting the superiority of boosting algorithms in handling complex data (Nguyen, 2025). In contrast, traditional models like Logistic Regression show lower performance with an AUC of 0.78 and accuracy of 86%, while Decision Trees achieve only an AUC of 0.72, indicating their limitations in dynamic credit risk environments (Xu, 2024). Nevertheless, the use of ML still faces challenges such as data imbalance and model interpretability, which must be carefully addressed to ensure its effective and reliable application.

Several studies indicate that boosted decision trees and gradient boosting are the most effective machine learning approaches for processing seller metrics in credit risk assessment. Han & Id, (2024) demonstrated that applying oversampling techniques to gradient boosting models yielded very high performance, with an AUC of 0.9649, MCC of 0.8104, and F1 Score of 0.9072. Similarly, Bastos, (2022) found that boosted decision trees remain a competitive method in credit scoring modeling. Although traditional logistic regression is still widely used, machine learning models show significant performance improvements; Han & Id, (2024) reported increases of 19.33% in AUC, 71.56% in MCC, and 85.33% in F1 Score compared to conventional approaches. Furthermore, Çallı, (2021) noted a paradigm shift toward the use of non-traditional data and advanced modeling techniques, further highlighting the effectiveness of machine learning models in predicting credit risk.

Boosting-based machine learning models, such as GBM, XGBoost, and LightGBM, have proven to be the most effective in processing seller metrics for credit risk assessment, as they can capture complex and non-linear data patterns more accurately than traditional methods. This approach demonstrates higher predictive performance, including more stable accuracy and AUC, especially on datasets with class imbalance. The use of oversampling techniques further enhances the models' ability to detect potential defaults. However, challenges arise in terms of interpretability, necessitating model explanation strategies to ensure transparency and accountability in credit risk assessment applications.

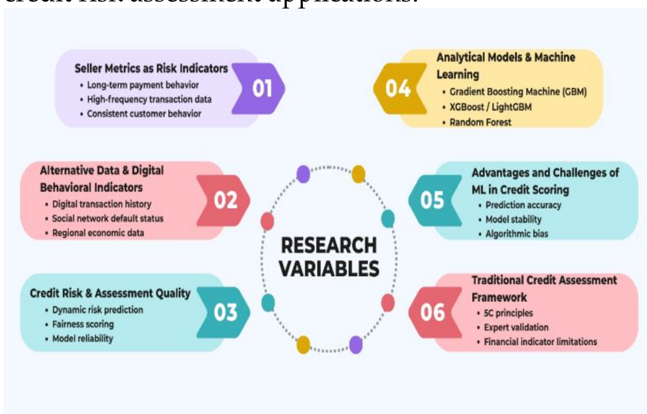

Figure 2. Development of Research Variables

Figure 2 illustrates the development of research variables concerning the role of seller metrics in microcredit risk assessment on e-commerce platforms. Seller metrics provide critical insights into seller performance, including long-term payment behavior, high-frequency transaction patterns, and customer purchasing consistency, which significantly affect the accuracy and reliability of credit risk evaluations. The integration of alternative data, such as digital transaction history, social network default status, and regional economic conditions, enhances predictive power and fairness in credit scoring models. Advanced machine learning models, including Gradient Boosting Machine, XGBoost, LightGBM, and Random Forest, demonstrate superior performance in dynamic risk prediction compared to traditional methods, although challenges such as algorithmic bias and model interpretability remain. Additionally, the application of traditional credit assessment principles, including the 5C framework and expert validation, continues to provide foundational guidance, highlighting the importance of balancing quantitative and qualitative data to ensure comprehensive risk evaluation and equitable access to microcredit.

Conculsion

Based on research findings, seller metrics on e-commerce platforms have proven relevant for enhancing the accuracy, stability, and fairness of credit scoring in microcredit, with variables such as long-term payment patterns, transaction frequency, purchase consistency, and seller engagement being significant. The integration of alternative data and advanced machine learning models, particularly boosting algorithms, demonstrates superior risk prediction compared to traditional methods. However, gaps remain, including limited formal validation, insufficient studies across varying economic and demographic conditions, and challenges related to algorithmic bias and model interpretability. Therefore, urgent research is needed to develop predictive frameworks based on seller metrics, evaluate model performance on diverse datasets, and design bias mitigation strategies to ensure fairness, accountability, and broader inclusion in microcredit.

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