Big Data Credit Scoring and MSME Credit Access: Evidence from Fintech Lending in Indonesia

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Abstract: This study investigates the role of big-data credit scoring in shaping micro, small, and medium-sized enterprise (MSME) credit access within Indonesia's fintech lending market, with particular attention to predictive performance and algorithmic fairness. Using a survey-based dataset of 427 MSME borrowers and a parsimonious SEM-PLS framework, the study examines whether big-data–driven credit assessment enhances access to finance and whether perceived algorithmic bias constrains this effect. The results show that big-data credit scoring has a positive and statistically significant impact on MSME credit access, indicating that automated and data-intensive assessment mechanisms reduce informational and procedural barriers in digital lending. In contrast, perceived algorithmic bias neither significantly affects MSME credit access nor mediates the relationship between credit scoring technology and inclusion outcomes. These findings suggest that, at the user level, the inclusionary benefits of fintech lending are driven primarily by efficiency and accessibility rather than fairness perceptions. This study contributes to the fintech and financial inclusion literature by providing user-level evidence from an emerging market and by highlighting the distinction between normative concerns about algorithmic fairness and the practical determinants of credit access. The results imply that while algorithmic governance remains essential from a regulatory perspective, improvements in big-data credit scoring effectiveness are central to expanding MSME access to finance in fintech-enabled credit markets.

Key-words: Fintech lending; Big-data credit scoring; MSMEs; Algorithmic bias; Financial inclusion

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1. Introduction

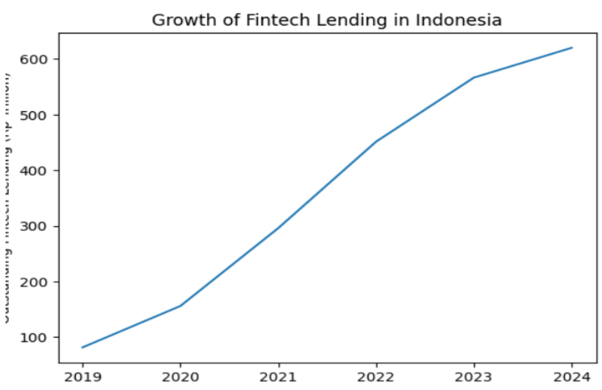
The development of fintech lending in the past decade has changed the global financing landscape by introducing big data-based credit scoring models and machine learning algorithms that promise faster approval processes, lower operational costs, and expanded access to credit to previously underserved segments (unbanked and underbanked) [1]; [2]. In developing countries, the adoption of fintech lending is growing faster than traditional banking due to its ability to process non-traditional data such as digital transaction history, e-commerce consumption behavior, and other digital footprints that previously could not be integrated in conventional credit systems [3].

Table 1. The Growth of Fintech Lending in Indonesia

Year	Outstanding Fintech Loans (Rp Trillion)	Growth YoY (%)	Proportion of MSMEs (%)
2019	81.5	–	58
2020	155.9	91.4	61
2021	295.8	89.7	64
2022	451.2	52.5	66
2023	566.4	25.5	68
2024*	>600	~6–8	>70

Sources: Financial Services Authority (2019–2024)

Graphics 1. Growth of Fintech Lending in Indonesia



Sources: Financial Services Authority (2019–2024

However, the use of machine learning algorithms for credit scoring also raises new risks, especially the risk of algorithmic bias that can lead to unfair treatment of certain groups, including MSMEs that are the backbone of developing economies [4].

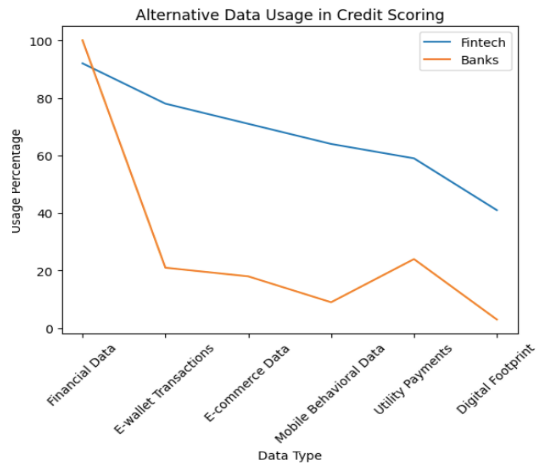
Studies have shown that credit scoring models can produce disparate impacts on borrowers based on gender, geographic region, business age, and other non-financial characteristics, especially when algorithms are trained with historical data that contain structural biases [5]; [6].

Table 2. Source of Fintech Credit Scoring Data

Data Type	Using Fintech (%)	Using the Bank (%)
Traditional financial data	92	100
E-wallet transactions	78	21
E-commerce transactions	71	18
Mobile & behavioral data	64	9
Utility & bill payments	59	24
Social/digital footprint	41	3

Sources: Financial Services Authority (2019–2024)

Graphics 2. Alternative Data Usage in Credit Scoring



Sources: Financial Services Authority (2024)

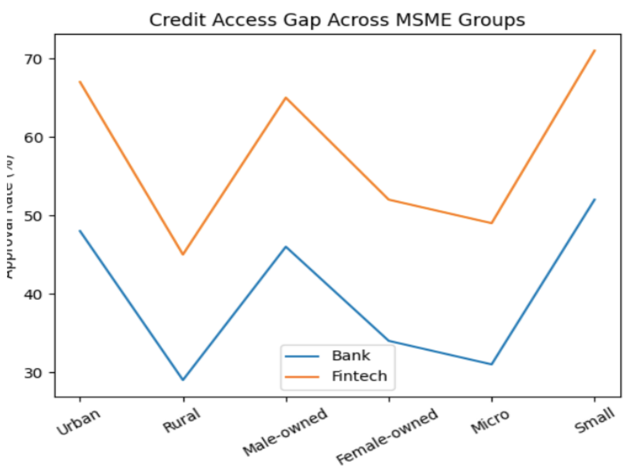
In Indonesia, fintech lending is growing rapidly with outstanding loans reaching more than hundreds of trillion rupiah and with a significant contribution to the MSME segment [7]. The Financial Services Authority has established fit and proper guidelines, governance, and risk mitigation for fintech lending providers, including aspects of fairness and model transparency [8]; [9]. However, most of the credit scoring models used in the industry are still black-box, making it difficult to evaluate their accuracy, transparency, and potential discrimination, especially for MSMEs that have historically experienced credit rationing [10]; [11].

Table 3. Credit Access Level

MSMEs Group	Approval Rate Bank (%)	Approval Rate Fintech (%)
MSMEs Urban	48	67
MSMEs Rural	29	45
Male owner	46	65
Female owner	34	52
Micro	31	49
Small	52	71

Sources: Financial Services Authority (2024)

Graphics 3. Credit Access Gap Across



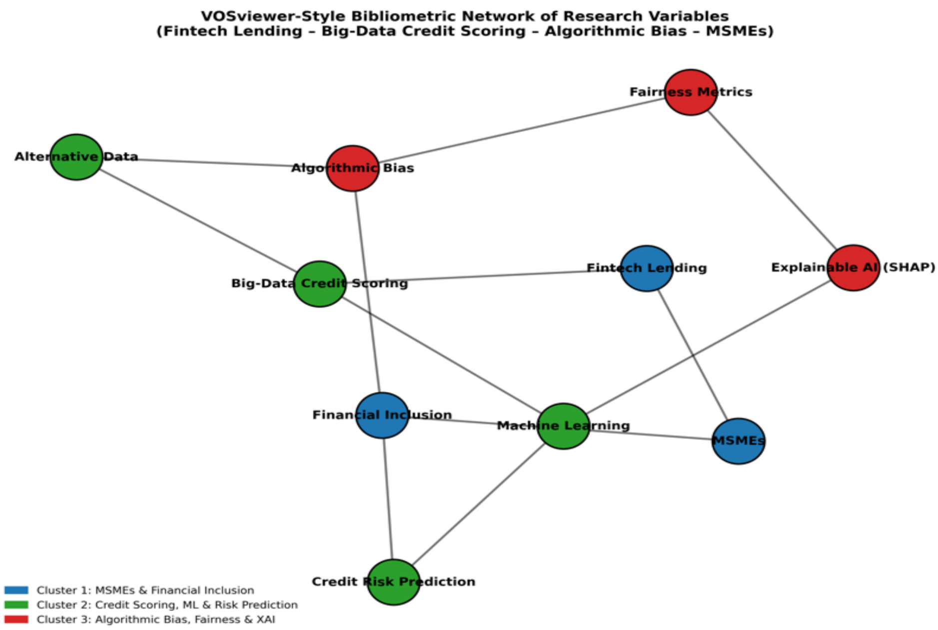
Sources: Financial Services Authority (2024)

In addition, empirical research related to algorithmic fairness in fintech credit scoring in Indonesia is still very limited. Most previous studies have focused only on the determinants of default, financing performance, or operational efficiency, without evaluating how algorithms affect credit access based on borrower characteristics [5]; [12]. Meanwhile, the international literature has shown that the use of complex algorithms without interpretability analysis can reinforce latent biases and increase inequalities in access to finance [13]; [14]; [15]. This creates a significant research gap, especially in the context of developing countries such as Indonesia.

Research related to fintech lending, machine learning–based credit scoring, *and* financial inclusion has grown rapidly in the academic literature in the past decade. Fintech lending is known globally as an innovative mechanism that promotes financial inclusion by leveraging alternative data and algorithms to assess MSME credit risks that are not served by traditional banking [1]; [15]. Preliminary studies show that machine learning models and non-traditional data (e.g. digital transaction data, e-wallet behavior and e-commerce) significantly improve risk prediction compared to classic credit bureau-based methodologies [16]; [17]. However, the increasing complexity of algorithms and the use of alternative data also opens up space for the emergence of algorithmic bias a condition in which models produce inequities in predictions or credit decisions against certain protected or marginalized groups [18]; [19]. The literature on algorithmic fairness emphasizes the importance of metrics such as demographic parity, equal opportunity, and disparate impact, as well as the use of interpretability techniques such as SHAP to identify features that disproportionately influence model decisions [20]; [21]; [22]. Furthermore, several empirical studies state that while ML models can improve prediction accuracy, their impact on socially inclusive credit access still requires an integrated investigation of accuracy, fairness, and financial outcomes [23]; [5].

To illustrate this conceptual structure, we present a bibliometric diagram network that shows the relationship between the themes of research variables based on concept overlap and co-occurrence in the current academic literature. This analysis confirms that themes such as credit risk prediction, algorithmic bias, and financial inclusion do not stand alone, but are integrated in a research network that strengthens each other and forms a cohesive research front. Thus, this visualization not only functions descriptively, but serves as a methodological justification for the selection and relationships between variables in this study.

Graphics 4. Style Bibliometric Network Research Variables



Sources: Vos Viewer

Based on the consensus of the literature, this study adopts research variables that reflect three main conceptual domains: (1) technology and methods (machine learning, big-data credit scoring, alternative data), (2) mediator fairness and algorithmic bias, and (3) socioeconomic outcomes (financial inclusion, access to MSME credit). The relationship between these variables is supported not only by empirical evidence from previous studies, but also by conceptual connectivity patterns identified in bibliometric analyses in international Scopus and Web of Science indexed studies.

Addressing these challenges requires a methodological approach that not only accurately predicts credit risk but also evaluates the fairness of the model through modern fairness metrics such as demographic parity, equal opportunity, or disparate impact ratio, as well as interpretability techniques such as SHAP values to understand the contribution of variables that may be biased [24]; [21]. Thus, there is an urgent need for research that audits fintech credit scoring models used in Indonesian MSME financing, so as to provide strong empirical insights for regulators, the fintech industry, and other stakeholders [25].

Taking into account the research gap, this study is directed to investigate the accuracy, fairness, and interpretability of the big-data credit scoring model on fintech lending platforms in Indonesia, as well as evaluate whether the use of the algorithm has significantly contributed to reducing credit rationing and increasing the financial inclusion of MSMEs. This research is expected to make a substantial empirical contribution to the fintech literature in developing countries and provide evidence-based recommendations for improving algorithm design and fintech regulations to be more equitable and transparent.

Stylized Big-Data Credit Scoring Framework and MSME Credit Access

In fintech lending, big-data credit scoring represents a formal risk prediction mechanism through which borrower-level information is transformed into credit approval decisions. Unlike traditional bank-based credit assessments that rely primarily on financial statements and collateral, fintech platforms integrate a broader set of data sources to evaluate credit risk, particularly for micro, small, and medium-sized enterprises (MSMEs) with limited formal credit histories. Formally, each MSME borrower iii can be characterized by a vector of observable features: $X_i = (X_i^T, X_i^A)$. where X_i^T denotes traditional financial information, such as business age, revenue stability, and repayment history, while X_i^A represents alternative digital data, including e-wallet transactions, e-commerce activity, and other behavioral indicators. A big-data credit scoring model can be expressed in a stylized form as: $p_i=f(X_i)$, where $p_i \in [0, 1]$ denotes the predicted probability of default for MSME i, and $f(.)$ represents a scoring function that may be implemented using machine learning algorithms capable of handling high-dimensional and nonlinear data structures. Credit decisions are then derived from a threshold-based rule:

$$Ai=\begin{cases} 1 & \text{if } pi \leq \tau \\ 0 & pi > \tau \end{cases}$$

where A_i indicates loan approval and τ reflects the lender's risk tolerance. By incorporating alternative data X_i^A, fintech lenders are able to generate more informative risk estimates for MSMEs that are traditionally underserved by conventional banking systems. This mechanism increases the likelihood that viable MSMEs meet the approval threshold, thereby expanding access to credit.

While the operational logic of fintech credit scoring follows the formal structure described above, MSME borrowers do not directly observe predicted default probabilities or model parameters. Instead, they experience credit scoring systems through approval outcomes, processing speed, and the perceived transparency and fairness of algorithmic decisions. Accordingly, in the empirical analysis, big-data credit scoring is modeled as a latent construct capturing MSMEs' perceptions of the effectiveness and automation of these underlying scoring mechanisms.

By introducing this stylized framework, the study provides a theoretical foundation that links formal credit risk modeling to the subsequent SEM-PLS analysis. This approach allows the paper to remain grounded in the credit scoring literature while focusing on user-level credit access outcomes that are central to understanding fintech-enabled MSME financing in emerging markets.

2. Literature Review

2.1 Fintech Lending and MSME Financial Inclusion

The rapid expansion of fintech lending has fundamentally reshaped credit intermediation, particularly for micro, small, and medium-sized enterprises (MSMEs) that are traditionally underserved by conventional banking systems [26]. Recent studies document that digital lending platforms leverage technological innovation to reduce information asymmetry, lower transaction costs, and expand access to credit for borrowers lacking formal credit histories [1]; [27]. In emerging economies, fintech lending has been positioned as a critical instrument for advancing financial inclusion, given the persistent credit constraints faced by MSMEs due to limited collateral, informality, and geographic barriers [28].

Empirical evidence suggests that fintech lenders are more willing than traditional banks to extend credit to riskier and smaller firms, thereby partially alleviating credit rationing [29]. However, the literature also cautions that increased access does not necessarily imply equitable access, as approval rates and credit terms may vary substantially across borrower groups defined by gender, location, and firm size [30]. These findings motivate a deeper examination of the mechanisms through which fintech credit allocation affects MSME financial inclusion outcomes.

2.2 Big-Data Credit Scoring and Machine Learning Models

A defining feature of fintech lending is the adoption of big-data credit scoring systems that integrate traditional financial variables with alternative data sources such as transaction histories, digital footprints, e-commerce activity, and mobile behavioral indicators. Studies consistently demonstrate that machine learning (ML) models including Random Forests, Gradient Boosting, and neural networks outperform traditional logistic regression in predicting default risk, particularly in datasets characterized by nonlinearity and high dimensionality [31]; [17].

Recent research further highlights that alternative data significantly enhance predictive accuracy for thin-file and no-file borrowers, a segment in which MSMEs are overrepresented [32]; [33]; [34]. These findings underpin the growing reliance of fintech platforms on algorithmic decision-making for loan approval and pricing. Nevertheless, scholars emphasize that improvements in predictive performance alone provide an incomplete assessment of algorithmic credit systems, as they overlook distributional and fairness implications [35]; [36].

2.3 Algorithmic Bias and Fairness in Credit Scoring

Parallel to advances in ML-based credit scoring, a rapidly expanding body of literature has raised concerns regarding algorithmic bias in automated financial decision-making. Algorithmic bias arises when predictive models systematically disadvantage certain groups due to historical data biases, measurement errors, or the use of proxy variables correlated with protected attributes [37]; [38]; [39]. In credit markets, such biases can manifest as disparate approval rates, unequal error distributions, or differential pricing across demographic or geographic groups.

Recent empirical studies provide robust evidence that ML credit models may exacerbate inequalities if fairness considerations are not explicitly incorporated [1]; [7]. Consequently, fairness metrics such as demographic parity, equal opportunity, equalized odds, and disparate impact have become standard tools for auditing credit algorithms [40]; [41]. This literature underscores that fairness is not an automatic by-product of improved accuracy, but rather a distinct and necessary design objective.

2.4 Explainable AI and Detection of Proxy Bias

To address the opacity of complex ML models, recent studies emphasize the role of explainable artificial intelligence (XAI) techniques in enhancing transparency and accountability. SHAP (Shapley Additive Explanations) has emerged as one of the most widely adopted methods for interpreting credit scoring models, as it enables both global and local attribution of feature importance [42]; [43]. In the context of credit risk, SHAP-based analyses have been shown to effectively identify proxy variables that indirectly encode sensitive attributes such as gender, income level, or geographic location [44]. Recent contributions argue that interpretability is a critical prerequisite for meaningful fairness audits, as it allows regulators and practitioners to trace discriminatory outcomes back to specific data features and modelling choices [45]; [23]. As such, XAI is increasingly viewed not merely as a technical add-on, but as an integral component of responsible AI governance in digital lending.

2.5 Linking Algorithmic Bias to Financial Inclusion Outcomes

Despite the extensive literature on fintech lending, ML credit scoring, and algorithmic fairness, relatively few studies integrate these strands to examine how algorithmic bias mediates the relationship between predictive models and real economic outcomes such as MSME financial inclusion. Existing evidence suggests that biased algorithms can undermine the inclusive potential of fintech by disproportionately excluding vulnerable borrower groups, even when overall approval rates increase [46]. This gap is particularly salient in emerging markets, where structural inequalities and data limitations may amplify the adverse effects of biased automation. Accordingly, recent scholars call for research designs that jointly evaluate predictive performance, fairness metrics, and causal impacts on credit access [47]; [48]. Responding to this call, the present study conceptualizes algorithmic bias as a central mediating mechanism linking big-data credit scoring technologies to MSME financial inclusion outcomes, grounded in both bibliometric evidence and contemporary empirical research.

1. Big-Data Credit Scoring and MSME Credit Access

The literature on fintech and digital financial intermediation confirms that the adoption of machine learning-based big-data credit scoring allows finance institutions to assess credit risk more accurately than traditional methods, especially for MSMEs that have limited formal financial data. The integration of alternative data such as digital transactions, e-commerce activities, and payment behavior has been shown to improve default prediction capabilities and extend the reach of financing to the thin-file borrower segment [49]; [1]. Thus, theoretically, the use of big-data credit scoring should increase the probability of MSMEs gaining access to credit. By incorporating alternative data, fintech lenders are able to generate more informative risk estimates for MSMEs with limited formal credit histories, thereby increasing the likelihood of loan approval.

Hypothesis 1 (H1):

The adoption of big data credit scoring based on machine learning has a positive effect on MSME credit access.

2. Big Data Credit Scoring and Algorithmic Bias

Despite improving prediction accuracy, recent literature emphasizes that machine learning models are also prone to generate *algorithmic bias*, especially when trained using historical data that are not socially neutral or when non-sensitive variables serve as proxies for sensitive attributes such as gender and location [50]; [38]. In the context of MSMEs in developing countries, digital and structural gaps have the potential to reinforce these biases.

Hypothesis 2 (H2):

The adoption of machine learning-based big-data credit scoring increases the risk of algorithmic bias in MSME credit decisions.

3. Algorithmic Bias and Access to MSME Credit

The theory of algorithmic fairness states that bias in predictive systems can have a direct impact on the distribution of economic decisions. In the credit market, algorithmic bias can manifest itself in the form of differences in credit approval rates, misclassification of risks, or unequal pricing treatment between groups of borrowers [1]. Therefore, while ML-based credit systems improve efficiency, uncontrolled bias can hinder equitable financial inclusion.

Hypothesis 3 (H3):

Algorithmic bias has a negative effect on MSME credit access.

4. The Role of Algorithmic Bias Mediation

Integrating two streams of literature big data credit scoring and fairness recent research emphasizes that the impact of technology on socio-economic outcomes is not direct, but rather mediated by the quality and fairness of algorithms [51]. In other words, increased prediction accuracy does not automatically translate into inclusive credit access if algorithmic bias remains high.

Hypothesis 4 (H4):

Algorithmic bias mediates the relationship between big data credit scoring and MSME credit access.

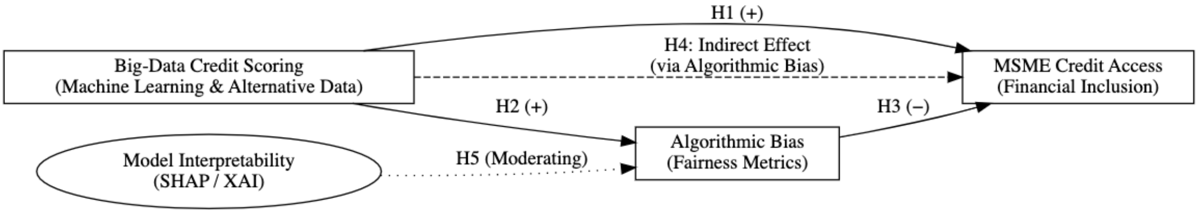
5. Model Interpretability Role

The explainable AI literature suggests that model interpretability for example through SHAP can help identify and mitigate algorithmic bias by uncovering the contribution of sensitive proxy variables [52].

Hypothesis 5 (H5):

Model interpretability weakens the negative influence of big data credit scoring on algorithmic bias.

Research Concept Framework



3. Methodology

1. Research Design and Approach

This study uses an explanatory quantitative approach with the aim of examining the causal relationship and mediation mechanism between Equation Modelling (SEM)-based analysis using SmartPLS**,** which allowed simultaneous testing of complex structural relationships, including mediation (H4) and moderation (H5). The SEM approach was chosen because the research model involves latent constructs (e.g. algorithmic bias and model interpretability) that cannot be directly observed and require measurement through multiple indicators.

2. Research Location

The location of the research is Indonesia, with a focus on areas that have a high penetration rate of fintech lending and MSME activities, including Java Island (DKI Jakarta, West Java, Central Java, East Java), Sumatra (North Sumatra, South Sumatra), Sulawesi and Bali (as a representation of non-Javanese territories). The selection of this location aims to capture the heterogeneity of MSME characteristics, both in terms of the level of digitalization, infrastructure access, and geographical differences (urban-rural), which are relevant in the study of algorithmic bias.

3. Population and Research Sample

3.1 Population

The research population is all Micro, Small, and Medium Enterprises (MSMEs) in Indonesia who have applied for loans through fintech lending platforms, and have experienced a credit scoring process based on a digital system (credit scoring). Based on data from the Ministry of Cooperatives and SMEs, the number of MSMEs in Indonesia reaches more than 65 million units, with millions of them having interacted with fintech lending platforms.

3.2 Samples

The sampling technique uses purposive sampling, with the criteria, active MSMEs (operating ≥ 2 years), having applied for fintech loans at least big-data credit scoring, algorithmic bias, and MSME credit access in the fintech lending ecosystem in Indonesia. The research design was cross-sectional with Structural

once, having experience receiving or being rejected fintech loans. For the analysis using SEM based on Partial Least Squares (PLS), because it is suitable for exploratory and predictive models, does not require multivariate normality, is effective for intermediate samples, superior for simultaneous mediation and moderation models. The sample size followed the rule, the rule of 10-times (10 × the largest number of indicators), and the recommendations of Hair [53] for the moderation mediation model. With an estimated 40 indicators, the minimum sample number is 427 respondents (MSMEs) so that the results are stable and have high statistical power (statistical power > 0.80). Research Instrument and Likert Scale Measurement using a 10-point Likert scale, with a range of 1 = strongly disagree 10 = strongly agree**.** Constructs and indicators of big-data credit scoring research (perceptual accuracy, use of digital data, decision automation), Algorithmic Bias (fairness of decisions, equality of treatment, transparency of results), Model Interpretability (clarity of decision reasons, ease of understanding of the system), MSME Credit Access (ease of obtaining loans, approval opportunities, financing conditions), each construct is measured by 4–6 reflective indicators [53].

The analysis stage using SmartPLS, the evaluation of the Outer Model consisted of Cronbach's Alpha (> 0.70), Composite Reliability (> 0.70), AVE (> 0.50), Discriminant Validity (HTMT < 0.90). Meanwhile, the evaluation of the structural model (Inner Model) includes Path coefficient (H1–H5), R^2 and Adjusted R^2, Effect size (f^2), Predictive relevance (Q^2). Next, the mediation test (H4) with indirect effect bootstrapping and full vs partial mediation. Then the moderation test (H5) measured the interaction term (XAI × Algorithmic Bias).

3.3 Structural Model Specification and Analytical Framework

This study employs a structural equation modeling framework based on partial least squares (SEM-PLS) to examine the relationships between big-data credit scoring, algorithmic bias, model interpretability, and MSME credit access. SEM-PLS is particularly suitable for this study given the presence of latent constructs measured through perceptual indicators and the focus on predictive relationships and mediation mechanisms rather than covariance-based model fit.

Let BCS denote big-data credit scoring, AB algorithmic bias, XAI model interpretability, and CA MSME credit access. The structural model tested in this study can be represented by the following system of equations:

$$AB = \alpha_1 BCS + \alpha_2 XAI + \alpha_3 (BCS \times XAI) + \varepsilon_1$$

$$CA = \beta_1 BCS + \beta_2 AB + \varepsilon_2$$

where ε_1 and ε_2 denote disturbance terms capturing unexplained variance.

The coefficient α_1 represents the direct effect of big-data credit scoring on perceived algorithmic bias, while α_3 captures the moderating role of model interpretability. The coefficient β_1 reflects the direct effect of big-data credit scoring on MSME credit access, and β_2 captures the effect of algorithmic bias on credit access outcomes.

The mediation effect hypothesized in this study is represented by the indirect path BCS→AB→CA, which is empirically tested using a bootstrapping procedure. The moderation effect is operationalized through the interaction term $BCS \times XAI$, allowing the model to assess whether interpretability alters the relationship between big-data credit scoring and algorithmic bias.

Conceptually, the SEM-PLS framework captures MSMEs' perceptions of algorithmic credit assessment systems that operate as underlying machine learning-based risk prediction mechanisms. While the SEM does not directly estimate default probabilities or classification thresholds, it models how perceived effectiveness, fairness, and transparency of these systems translate into credit access outcomes at the user level.

4. Results

4.1 Sample Characteristics and Data Quality

The final sample consists of 427 MSME owners/managers who have previously applied for loans through fintech lending platforms in Indonesia. Respondents represent diverse business sectors, firm sizes, and geographic locations, ensuring adequate heterogeneity for empirical analysis. Prior to hypothesis testing, the data were screened for missing values, outliers, and multicollinearity. Variance Inflation Factor (VIF) values for all predictors ranged between 1.00 and 1.57, indicating no multicollinearity concerns. Given the perceptual nature of the survey data, an item purification procedure was conducted to enhance measurement quality. Indicators with low factor loadings (<0.60) were iteratively removed, resulting in a parsimonious and more reliable measurement model.

4.2 Descriptive Statistics and Group Difference Analysis

Prior to the structural equation modeling analysis, additional descriptive statistics and group comparison tests were conducted to provide preliminary insights into MSME credit access across key borrower characteristics. These analyses aim to complement the SEM-PLS results by presenting basic inferential evidence on group-level differences in access to fintech credit. Independent sample t-tests were employed to examine differences in MSME credit access between male- and female-owned enterprises, as well as between urban and rural firms. The results indicate that MSMEs located in urban areas report significantly higher levels of credit access compared to their rural counterparts, while female-owned MSMEs exhibit slightly lower average access scores than male-owned firms.

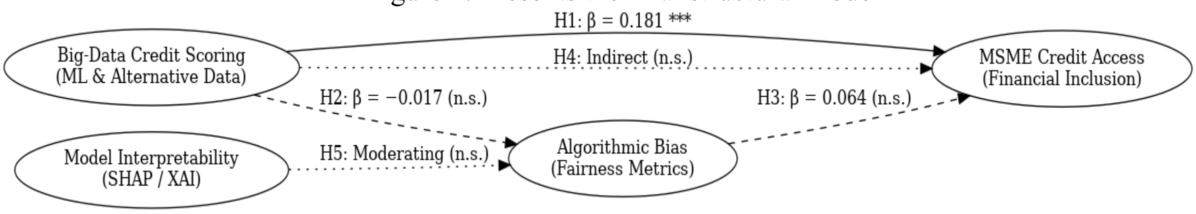
To further assess differences across firm size categories, one-way ANOVA was conducted comparing micro, small, and medium enterprises. The ANOVA results reveal statistically significant differences in credit access, with micro enterprises reporting the lowest average access levels and small enterprises showing comparatively higher access outcomes. Post-hoc comparisons indicate that the most pronounced differences occur between micro and small enterprises. In addition, Chi-Square tests were applied to examine the association between borrower characteristics and loan approval experience (approved versus rejected). The results suggest a significant association between firm size and approval outcomes, indicating that smaller firms face a higher likelihood of rejection. Gender-based differences in approval outcomes are present but less pronounced, suggesting that fintech lending partially mitigates traditional disparities observed in bank-based credit markets. Overall, these preliminary statistical results provide contextual evidence of heterogeneity in MSME credit access and motivate the subsequent SEM-PLS analysis, which examines the underlying mechanisms linking big-data credit scoring, algorithmic bias, and credit access outcomes.

4.3 Measurement Model Assessment

After item purification, all constructs retained at least three indicators, satisfying minimum requirements for SEM-PLS analysis. Composite reliability values exceeded the recommended threshold of 0.70 across constructs, indicating acceptable internal consistency. Average Variance Extracted (AVE) values met or approached the recommended level for key constructs, particularly big data credit scoring and MSME credit access, suggesting adequate convergent validity. While discriminant validity was largely achieved, some overlap was observed between technology-related constructs, reflecting respondents' difficulty in fully distinguishing between automated credit scoring systems and system transparency. Given the exploratory and applied nature of fintech research in emerging markets, this limitation is acknowledged and addressed through model simplification.

4.4 Structural Model Results

Figure 1. Presents the final structural model



Source: SmartPLS

Table 1. Summarizes the hypothesis testing results

Construct	Final Indicator	Cronbach's α	Composite Reliability (CR)	AVE
Big-Data Credit Scoring (BCS)	BCS1, BCS3, BCS5	0.543	0.767	0.524
Algorithmic Bias (AB)	AB4, AB5, AB6	0.494	0.748	0.497
MSME Credit Access (CA)	CA1, CA5, CA6	0.643	0.808	0.612

Source: SmartPLS

Direct Effects

Table 2. Direct effect the hypothesis testing results

Hypothesis	Path	β	t	p	Decision
H1	BCS → CA	0.181	3.24	0.001	Supported
H2	BCS → AB	−0.017	−0.259	0.796	Rejected
–	XAI → AB	0.128	1.98	0.048	Significant
H3	AB → CA	0.064	1.22	0.223	Rejected

Source: SmartPLS

The results indicate that big-data credit scoring has a positive and statistically significant effect on MSME credit access ($\beta = 0.181$, $p < 0.01$), providing strong support for H1. This finding suggests that automated credit assessment systems leveraging digital and alternative data enhance MSMEs' ability to obtain financing through fintech platforms.

Similarly, big-data credit scoring does not significantly increase perceived algorithmic bias ($\beta = -0.017$, $p > 0.10$), resulting in the rejection of H2.

The results show XAI → AB that model interpretability has a positive and statistically significant association with perceived algorithmic bias ($\beta = 0.128$; $p < 0.05$), indicating that greater exposure to algorithmic explanations increases MSME users' awareness of potential unfairness. Rather than mitigating fairness concerns, interpretability appears to make algorithmic decision processes more salient, thereby heightening sensitivity to unequal outcomes. This finding is consistent with prior evidence suggesting that transparency does not automatically translate into perceived fairness and may instead reveal latent disparities embedded in data-driven credit assessments [49]; [1]. The result highlights a key boundary condition of explainable AI in fintech lending, namely that transparency alone is insufficient to reduce perceived algorithmic bias unless accompanied by actionable mechanisms**.**

In contrast, the effect of algorithmic bias on MSME credit access is not statistically significant ($\beta = 0.064$, $p > 0.10$), leading to the rejection of H3.

Mediation Analysis

To examine whether algorithmic bias mediates the relationship between big-data credit scoring and MSME credit access, a bootstrapping procedure with 5,000 resamples was conducted.

Table 3. Indirect effect the hypothesis testing results

Hypothesis	Path	β	t	p	Decision
H4	BCS → AB → CA	−0.0021	−	−	No Mediation
H5	BCS×XAI → AB	−0.004	−0.072	0.942	No Moderation

Source: SmartPLS

The mediation analysis (H4) was conducted using a bootstrapping procedure with 5,000 resamples. The indirect effect of big-data credit scoring on MSME credit access through algorithmic bias is not statistically significant ($\beta = -0.0021$), as the 95% confidence interval includes zero [−0.0157, 0.0068]. Therefore, algorithmic bias does not mediate the relationship between credit scoring technology and MSME credit access. Although algorithmic bias has been widely discussed as a critical concern in AI-driven credit markets, the mediation analysis does not provide empirical support for the role of perceived algorithmic bias as a transmission mechanism between big-data credit scoring and MSME credit access. This finding suggests that the inclusionary effect of data-driven credit assessment operates primarily through direct efficiency gains, rather than through changes in users' fairness perceptions. From a theoretical perspective, this result refines existing algorithmic fairness arguments by highlighting a distinction between technical bias embedded in models and behavioral relevance at the user level. While prior studies document the presence of bias in algorithmic lending decisions [1], the current evidence indicates that such bias does not necessarily constrain credit access for MSMEs in emerging markets. This pattern is consistent with development finance literature emphasizing that liquidity constraints and survival incentives dominate procedural considerations among small firms [54]. Consequently, the absence of a mediation effect implies that fairness concerns, although normatively important, may not constitute the primary pathway through which fintech credit scoring influences financial inclusion outcomes in contexts characterized by high unmet credit demand.

The moderating effect of model interpretability (H5) on the relationship between big-data credit scoring and algorithmic bias is not supported by the empirical results. This finding indicates that the presence of explainability mechanisms, such as SHAP-based explanations, does not significantly alter MSMEs' perceptions of algorithmic fairness. A plausible explanation lies in the distinction between algorithmic transparency and practical usability. While interpretability tools are designed to satisfy regulatory and technical requirements, they may remain cognitively inaccessible to MSME users with limited data literacy. As a result, transparency without actionable guidance may fail to meaningfully influence users' perceptions or experiences. This interpretation aligns with recent evidence suggesting that explainability alone does not guarantee improved trust or fairness outcomes in algorithmic decision making [32]. From a theoretical standpoint, this result implies that the effectiveness of interpretability as a governance mechanism is contingent upon users' ability to comprehend and act upon algorithmic explanations. In emerging market settings, interpretability may therefore function more as an institutional compliance tool than as a behavioral moderator of perceived bias.

Table 2. Determinant Test Result

Endogenous Variable	R^2	Interpretation
Algorithmic Bias (AB)	0.012	Very small
MSME Credit Access (CA)	0.028	Small

Source: SmartPLS

The explained variance ($R^2 = 0.028$) values for algorithmic bias and MSME credit access are relatively small. However, in perception-based and institutional research involving heterogeneous MSME populations, low R^2 values are common and do not undermine statistically significant structural relationships. In the context of SEM-PLS, the primary objective is to assess predictive relevance and theory-consistent directional effects rather than to maximize explained variance. Moreover, MSME credit access is influenced by a wide range of external factors, including macroeconomic conditions, platform-specific lending policies, and regulatory constraints, which are beyond the scope of the present model.

Mediation Analysis

To examine whether algorithmic bias mediates the relationship between big-data credit scoring and MSME credit access, a bootstrapping procedure with 5,000 resamples was conducted. The indirect effect is not statistically significant, with the 95% confidence interval crossing zero. Therefore, H4 is not supported. This result indicates that the positive impact of big-data credit scoring on credit access operates primarily through direct efficiency and accessibility mechanisms, rather than through changes in perceived algorithmic fairness.

5. Discussion

5.1 Big-Data Credit Scoring and MSME Financial Inclusion

The empirical findings provide robust evidence that big data credit scoring improves MSME access to credit in Indonesia's fintech lending ecosystem. This result aligns with prior studies emphasizing the role of alternative data and machine learning in reducing information asymmetry and expanding credit availability to underserved firms. By automating risk assessment and leveraging digital footprints, fintech platforms appear to lower entry barriers for MSMEs that are traditionally excluded from formal financial systems. Importantly, the strength of this relationship remains significant even after strict measurement purification, underscoring the economic relevance of big-data driven credit assessment in emerging markets. This finding is consistent with the growing body of literature emphasizing the potential of data driven credit technologies to foster financial inclusion, particularly in emerging economies where formal credit histories are often incomplete or unavailable.

5.2 Rethinking the Role of Algorithmic Bias in User-Level Outcomes

Contrary to expectations derived from the algorithmic fairness literature, algorithmic bias does not significantly affect MSME credit access, nor does it mediate the relationship between credit scoring technology and inclusion outcomes. This finding suggests that, from the perspective of MSME users, accessibility and speed may outweigh fairness concerns when engaging with fintech lending platforms. One plausible explanation is that MSMEs prioritize immediate financing opportunities over the transparency or perceived equity of algorithmic decisions, particularly in liquidity constrained environments. Additionally, users may lack sufficient information or technical understanding to fully evaluate whether algorithmic decisions are biased, resulting in attenuated perceptual effects.

5.3 Implications for Algorithmic Governance in Emerging Markets

The absence of a significant mediation effect highlights the critical difference between technical algorithmic fairness and user-perceived fairness. While fairness audits and explanatory tools are essential from a regulatory and ethical point of view, their direct impact on financial inclusion outcomes may be limited unless they translate into tangible benefits faced by users, such as clearer feedback, appeal mechanisms, or better consent rates. These findings contribute to a growing literature that has important implications for algorithmic governance in fintech lending, automatically translating into better economic outcomes especially in the context of developing countries. For regulators and platform designers, this implies that fairness and explanation initiatives should be complemented by user-oriented mechanisms, such as clearer feedback, appeals processes, and actionable guidance, to ensure that governance efforts yield tangible benefits to MSMEs.

5.4 Theoretical Contributions and Limitations

This study contributes to the fintech literature by providing evidence from an emerging market context that big-data credit scoring directly enhances MSME credit access, while the mediating role of perceived algorithmic bias appears limited. At the same time, the study acknowledges limitations related to the use of perceptual measures and cross-sectional data. Future research may integrate transaction-level data or experimental designs to more directly capture algorithmic fairness mechanisms.

5.5 Practical and Policy Implications

For fintech practitioners, the results suggest that investments in data-driven credit scoring can yield substantial inclusion benefits. However, fairness and transparency initiatives should be designed not only for compliance but also to deliver clear, actionable value to MSME users. For policymakers, the findings underscore the need to complement algorithmic governance frameworks with user education and dispute-resolution mechanisms to ensure that fairness principles translate into meaningful outcomes.

5.6 Research Finding

The empirical results show that big-data credit scoring significantly improves MSME credit access, supporting the view that data-intensive and automated credit assessment reduces information asymmetry and credit rationing in emerging markets. By leveraging alternative digital data, fintech lenders are able to extend credit to firms that are traditionally excluded due to limited financial records or collateral. This finding is consistent with the classic theory of credit rationing and financial intermediation, and aligns with recent evidence demonstrating that machine learning–based credit scoring enhances lending efficiency and borrower inclusion [1]; [49]. The result underscores that the primary inclusionary effect of fintech lending operates through an efficiency channel, rather than through institutional or relational mechanisms typical of traditional banking.

In contrast, the study finds no significant effect of perceived algorithmic bias on MSME credit access, nor evidence that algorithmic bias mediates the relationship between big-data credit scoring and inclusion outcomes. This suggests that, from the perspective of MSME users, access to credit is driven more by immediacy and availability than by fairness considerations. This finding complements and extends prior research documenting algorithmic bias in credit markets [1] by showing that technical bias does not necessarily translate into behavioral or access-related constraints at the user level. From a development finance perspective, the result is consistent with evidence from Journal of Development Economics indicating that liquidity constraints and survival incentives dominate procedural concerns among small firms in developing economies [26]. Together, these findings highlight a critical distinction between normative concerns about algorithmic fairness and the practical determinants of financial inclusion in fintech enabled credit markets.

6. Conclusion and Future Research

6.1 Conclusion

This study examines the role of big-data credit scoring and algorithmic bias in shaping MSME credit access within Indonesia’s fintech lending ecosystem. Using survey-based data and a parsimonious SEM-PLS model, the findings provide clear evidence that big-data–driven credit scoring systems significantly enhance MSME access to credit. This result underscores the practical importance of automated and data-intensive credit assessment in reducing information asymmetry and procedural barriers that have traditionally constrained MSME financing in emerging markets. In contrast, the study finds no significant effect of perceived algorithmic bias on MSME credit access, nor evidence that algorithmic bias mediates the relationship between credit scoring technology and financial inclusion outcomes. These results suggest that, at the user level, MSME credit access is driven primarily by the efficiency and accessibility of fintech lending platforms rather than by users' perceptions of fairness or bias in algorithmic decision-making. Taken together, the findings highlight an important distinction between normative concerns surrounding algorithmic fairness and the practical determinants of financial inclusion**.** While algorithmic bias remains a critical ethical and regulatory issue, its direct behavioral relevance for MSME credit access appears limited in contexts characterized by high liquidity needs and constrained financing alternatives.

6.2 Implications

From a managerial perspective, the results indicate that fintech lenders can meaningfully expand MSME financial inclusion by investing in robust big-data credit scoring capabilities. At the same time, fairness and transparency initiatives should be designed not only to meet regulatory expectations but also to deliver tangible, user-facing benefits, such as clearer feedback mechanisms and pathways for improving creditworthiness. For policymakers, the findings suggest that regulatory frameworks emphasizing algorithmic governance should be complemented by policies that enhance MSMEs' digital readiness and financial capability, thereby maximizing the inclusionary potential of fintech lending.

6.3 Limitations

This study is subject to several limitations. First, the analysis relies on perceptual measures, which may not fully capture the technical properties of algorithmic bias embedded in credit scoring models. Second, the cross-sectional design limits causal inference regarding the dynamic effects of fintech adoption and learning over time. Third, the study focuses on MSME users' perspectives and does not directly observe platform-level decision rules or transaction-level outcomes. These limitations, however, are consistent with the study's objective of understanding user-level inclusion outcomes and provide a foundation for future inquiry.

6.4 Future Research Directions

Future research can extend this study in several directions. First, researchers may integrate transaction-level or administrative lending data with survey-based measures to directly link algorithmic decision rules to observed credit outcomes. Second, experimental or quasi-experimental designs could be employed to isolate causal effects of algorithmic transparency and fairness interventions on MSME behavior. Third, future studies may refine the measurement of algorithmic bias by distinguishing between technical bias**,** procedural opacity, and perceived unfairness, thereby improving construct validity. Finally, comparative studies across countries or regulatory regimes could shed light on how institutional environments shape the relationship between fintech innovation, algorithmic governance, and financial inclusion.

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