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Legal Accountability for Automated Credit Scoring in Indonesian Financial Technology Lending

Mega Endah Halim[1]; Bima Hafiz Firmansyah[2]; Maya Dwi Lestari[3]
[1]Department of Administrative Law, Faculty of Law, Universitas Diponegoro, Semarang, Indonesia
[2]Department of Business Law, Faculty of Law, Universitas Diponegoro, Semarang, Indonesia
[3]Faculty of Law, Universitas Diponegoro, Semarang, Indonesia

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Corresponding author:
Mega Endah Halim
mega.halim@undip.ac.id

Other author email(s):
bima.firmansyah@undip.ac.id
maya.dwi@undip.ac.id

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Abstract

Purpose – This study examines legal accountability for automated credit scoring in Indonesian fintech lending, focusing on responsibility allocation, data accountability, explainability, fairness, human oversight, and consumer redress across interconnected institutional actors.

Methodology – The study uses a qualitative socio-legal design and secondary thematic analysis of published focus group data involving 36 Indonesian stakeholders. The qualitative evidence is examined together with relevant regulatory materials and recent scholarship using deductive and inductive coding.

Findings – Automated scoring can expand financial inclusion and accelerate assessment, but it also creates fragmented responsibility, data-quality risks, algorithmic opacity, potential discriminatory effects, uneven human oversight, and limited opportunities to contest adverse decisions.

Implications – Fintech providers and regulators should strengthen data governance, algorithmic auditing, fairness monitoring, understandable explanations, meaningful human review, and accessible correction and redress procedures.

Originality – The study extends algorithmic accountability into Indonesian fintech lending by integrating legal, institutional, and technological dimensions throughout the automated credit-decision lifecycle.

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Introduction

The digital transformation of financial services has changed how lenders evaluate creditworthiness, particularly through artificial intelligence, machine learning, and automated credit-scoring systems. These technologies allow lenders to process large volumes of data, identify complex patterns, estimate default probabilities, and generate lending recommendations faster than conventional assessments. Fintech lending has accelerated this transformation because digital platforms depend on rapid and scalable risk assessment to serve large numbers of applicants. Automated models can also reduce information asymmetry between borrowers and lenders by identifying risk indicators that conventional credit records may overlook. Tigges et al. (2024) found that artificial intelligence and alternative data can enhance credit-risk assessment and extend lending opportunities to consumers with limited conventional financial histories. Credit-scoring innovation can therefore improve financial inclusion, but it simultaneously transfers substantial decision-making power from human credit officers to computational systems. Ahelegbey et al. (2023) demonstrate that fintech-based credit systems can broaden access to financial services by using network and digital information to address limitations in conventional lending. This transition

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requires legal scrutiny because access to credit affects economic participation, household resilience, entrepreneurship, and the financial opportunities available to individuals who increasingly depend on digital financial services.

The expansion of automated scoring has also transformed the type and volume of information used to evaluate borrowers. Machine-learning models may analyze transaction histories, digital behavior, demographic information, social-network patterns, communication characteristics, and other alternative data that were previously outside conventional credit assessment. Hlongwane et al. (2024) show that alternative data can improve credit-scoring performance, particularly when traditional financial information provides an incomplete picture of an applicant. In Indonesia, the potential significance of such data is particularly high because innovative credit scoring has been promoted as a way to evaluate individuals and micro-enterprises that lack conventional collateral or formal credit histories. Alamsyah et al. (2025) demonstrate that social-media and behavioral information can support alternative credit assessment in Indonesia and potentially expand financial inclusion. Yet the use of these data also creates a new imbalance. Borrowers may provide extensive information about themselves while knowing little about the variables, weights, assumptions, and model architecture used to classify them. McCanless (2023) shows that alternative credit-scoring infrastructures can alter access to consumer credit while making the logic behind individual assessments difficult for borrowers to observe. Indonesian stakeholders have likewise identified regulatory fragmentation, limited interoperability, and algorithmic opacity as challenges in the development of innovative credit scoring (Adam et al., 2025). Thus, financial inclusion cannot be assessed only by whether more consumers receive credit. It must also consider whether those consumers receive fair, understandable, and legally accountable treatment.

Automated lending creates another problem concerning fairness. A computational model does not automatically become neutral simply because it applies mathematical rules consistently. Historical data can contain existing socioeconomic inequalities, while apparently neutral variables can operate as proxies for characteristics associated with disadvantaged groups. Das et al. (2023) explain that algorithmic fairness in financial services depends on choices concerning data, model design, fairness definitions, and institutional objectives. Empirical evidence also indicates that credit-scoring models may produce unequal outcomes across demographic groups even when developers do not intentionally construct discriminatory rules. Hurlin et al. (2024) show that lenders can test credit-scoring systems for discriminatory effects and identify sources of unfairness within scoring models. Alternative model interpretation can also reveal whether protected or proxy characteristics shape credit decisions in ways that require institutional scrutiny. Agarwal et al. (2023) demonstrate that model-agnostic interpretation methods can help detect racial discrimination within algorithmic lending decisions. Evidence from banking credit scoring further shows that attempts to increase predictive accuracy can conflict with certain fairness objectives. Mariscal et al. (2024) identify this trade-off within the Indonesian banking context. These findings make fairness a legal accountability issue rather than merely a question of technical model optimization.

Opacity creates a further challenge because affected borrowers may receive a decision without receiving an intelligible account of how the system reached it. Complex machine-learning models can achieve strong predictive results while remaining difficult for users, compliance officers, regulators, or courts to interpret. Babaei et al. (2023) show that explainability techniques can provide meaningful information about factors affecting fintech lending predictions without abandoning sophisticated predictive models. Explainability also matters for model governance because it can help institutions identify unstable relationships, unexpected variables, and potentially problematic patterns. Bone-Winkel and Reichenbach (2024) demonstrate that explainable machine-learning techniques can increase transparency in credit-risk assessment while retaining useful predictive capacity. The wider financial literature increasingly treats explainable artificial intelligence as an important mechanism for connecting advanced analytics with governance requirements. Černevičienė and Kabašinskas (2024) find that explainability has become central to research on trustworthy artificial intelligence in finance because stakeholders need to understand and evaluate consequential automated decisions. However, technical explanations alone do not necessarily satisfy legal requirements. A meaningful legal explanation must enable an affected person to understand the principal reasons for a decision and provide a realistic opportunity to question an error or challenge an adverse outcome. This distinction makes explainability closely connected to contestability and procedural protection.

The legal significance of automated credit scoring has encouraged regulators and scholars to treat creditworthiness assessment as a high-impact application of artificial intelligence. Mazzini and Bagni (2023) explain that European risk-based AI regulation subjects creditworthiness assessment to heightened governance expectations because automated errors can affect access to important services and individual rights. The regulatory debate extends beyond transparency because responsibility must remain identifiable throughout the lifecycle of an automated system. Spindler (2023) shows that automated credit scoring intersects with consumer-credit law, data-protection rules, and emerging AI regulation, creating obligations that cannot be addressed through a single legal field. Affected individuals also need explanations that correspond to the significance of the decision rather than generic statements that merely disclose the existence of automation. Lui et al. (2025) argue that algorithmic credit decisions require an effective right to explanation if consumers are to understand and challenge decisions that materially affect them. The content of that explanation must remain meaningful in the context in which the automated decision operates. Fritz (2025) emphasizes that the scope of a right to explanation depends on what information is necessary for the affected person to understand and respond to algorithmic decision-making. These developments support a broader conception of accountability that combines transparency, justification, oversight, responsibility, and remedies.

Indonesia already regulates important elements of digital lending through financial-sector regulation, consumer-protection rules, personal-data protection, and obligations applicable to information-technology-based financial services. Nevertheless, recent studies show continuing difficulties in translating formal rules into effective protection. Admiral and Pauck (2023) identify weaknesses involving legal substance, institutional arrangements, and legal culture in the protection of personal data within Indonesian online lending. The problem extends beyond unauthorized disclosure because digital lending providers process personal information throughout customer profiling and risk assessment. Dewi and Sulistyawan (2024) find that legal protection of online borrowers requires stronger implementation of personal-data obligations and clearer accountability for data processing. Syahruddin and Zulfa (2024) similarly identify enforcement challenges surrounding fintech lending and personal-data protection. Regulatory effectiveness also depends on consistent supervision and meaningful consequences for violations rather than formal compliance alone. Rifa and Hidayati (2024) emphasize that protection of fintech customers' personal data requires effective implementation and enforcement mechanisms. Consumer vulnerabilities persist when contractual imbalance, limited understanding, and weak regulatory enforcement interact within digital lending relationships. Samuel and Gunadi (2025) show that these problems continue to affect consumer security in Indonesia's peer-to-peer lending ecosystem. The systemic importance of fintech lending further increases the need for effective supervision because rapid expansion can generate risks that extend beyond individual transactions. Junarsin et al. (2023) demonstrate that fintech lending growth has implications for broader financial-system stability in Indonesia.

Despite this expanding scholarship, an important gap remains. Technical studies largely focus on predictive performance, model fairness, alternative data, or explainability, whereas Indonesian legal studies concentrate mainly on personal-data protection, consumer protection, contractual practices, and regulatory compliance. Existing research provides limited qualitative evidence on how responsibility for an automated credit decision is actually understood and distributed among fintech lenders, scoring providers, data providers, compliance professionals, technology specialists, and supervisory actors. Algorithmic accountability requires identifiable actors who can explain, justify, supervise, and accept responsibility for consequential decisions rather than treating the algorithm as an autonomous source of authority. Horneber and Laumer (2023) position accountability as a central requirement for ensuring that organizations remain answerable for algorithmic systems and their effects. Novelli et al. (2024) further conceptualize AI accountability as a relationship involving obligations, responsible actors, accountability forums, and mechanisms through which conduct can be evaluated. Accordingly, this study aims to explore how legal accountability for automated credit scoring is understood, allocated, and operationalized within Indonesian financial technology lending. It focuses on data accountability, transparency and explainability, fairness and non-discrimination, meaningful human oversight, allocation of responsibility, and mechanisms for contestability and redress. The study contributes theoretically by extending algorithmic accountability into a socio-legal analysis of Indonesian fintech lending. Practically, it seeks to identify governance principles that can strengthen regulatory supervision, institutional responsibility, and consumer protection in automated credit decision-making.

Literature Review

Automated Credit Scoring and the Transformation of Creditworthiness Assessment

Credit scoring traditionally relies on statistical models that estimate the likelihood that a borrower will repay a loan. Digital lending has expanded this function by incorporating machine learning, real-time processing, and increasingly diverse datasets. The resulting systems can classify applicants faster and identify nonlinear relationships that conventional statistical approaches may not capture. Zhu et al. (2023) show that machine-learning models combined with explainability methods can provide effective default prediction while identifying the contribution of individual borrower characteristics. Such systems are attractive to fintech firms because rapid automated evaluation supports scalable lending and reduces the operational costs associated with manual underwriting.

Machine learning also enables institutions to incorporate unconventional indicators into credit-risk assessments. The use of alternative data may improve prediction for borrowers with limited formal financial records. Wang et al. (2023) demonstrate that ensemble learning combined with explainability techniques can improve the prediction of default in lending contexts while providing information about the variables behind model outcomes. This capacity has important implications for financial inclusion. Conventional credit histories often exclude applicants who lack previous formal borrowing activity, while automated models can evaluate a wider range of behavioral and financial indicators.

Improved predictive performance, however, does not eliminate governance risks. Li and Wu (2024) show that explainable machine-learning approaches can improve understanding of loan-default predictions and provide more information about the factors underlying model outputs. Their findings suggest that predictive performance and interpretability should not be treated as mutually exclusive objectives. Yet greater data availability can create new forms of informational power. When financial institutions know more about borrowers than borrowers know about the classification process, the original information asymmetry in lending can partly reverse.

From this perspective, automated credit scoring functions as a socio-technical decision system. It includes datasets, algorithms, model developers, scoring vendors, fintech platforms, compliance functions, lenders, human reviewers, and regulators. The legal outcome cannot therefore be understood only by inspecting source code or examining the final lending contract. Packin and Lev-Aretz (2024) show that emerging forms of decentralized and technologically complex credit scoring can further complicate transparency and responsibility. The relevant object of accountability is consequently the entire decision chain through which information becomes a consequential credit outcome.

Algorithmic Accountability and Legal Responsibility

Algorithmic accountability provides the central theoretical perspective for this study. Accountability requires an actor to provide information and justification concerning conduct and creates a possibility that another actor can evaluate that conduct. Applied to automated credit scoring, this principle means that the use of an algorithm cannot remove organizational responsibility. Horneber and Laumer (2023) argue that algorithmic accountability requires mechanisms capable of linking algorithmic processes to responsible organizational actors.

Accountability also requires traceability. Institutions need records showing which data entered a model, which version of the model produced an outcome, how the output informed the final decision, and which individuals or organizations exercised authority over the process. Hauer et al. (2023) identify transparency and inspectability mechanisms as important components of accountable AI because external and internal actors need practical means to examine system behavior. Traceability is especially important when several organizations contribute to one decision. A fintech platform may obtain data from external providers, purchase scoring services from a technology company, and facilitate a lending decision ultimately financed by another institution.

The distribution of tasks does not necessarily produce a clear distribution of legal responsibility. Accountability may become fragmented when every participant controls only one part of the automated process. Novelli et al. (2024) argue that meaningful AI accountability requires clarity concerning who owes an account, to whom the account is owed, the standards used to assess behavior, and the consequences that follow from failure. This approach is particularly useful for credit scoring because the borrower often interacts with only one platform while several entities may influence the resulting decision.

The broader governance literature also stresses that accountability cannot rely solely on voluntary ethical commitments. Batool et al. (2025) identify transparency, fairness, responsibility, oversight, and institutional coordination as recurring concerns within AI governance scholarship. Legal governance therefore requires mechanisms that translate general principles into organizational procedures, audit requirements, documentation, complaint handling, and enforceable responsibilities.

Human-centered governance adds another dimension. Cheong (2024) argues that transparency and accountability mechanisms should protect the interests of individuals affected by algorithmic systems rather than operating only as technical documentation requirements. In lending, this implies that accountability mechanisms must be useful to borrowers, supervisory agencies, and dispute-resolution institutions, not solely to data scientists. An internal model report may assist developers, but it does not automatically provide an affected applicant with a meaningful explanation or remedy.

This study consequently treats legal accountability as a multidimensional concept involving answerability, traceability, responsibility allocation, oversight, contestability, and enforceability. These elements provide a bridge between algorithmic governance theory and legal responsibility. They also enable the analysis to distinguish symbolic compliance from mechanisms that allow real scrutiny of automated credit decisions.

Algorithmic Fairness and Non-Discrimination

Fairness has become one of the most contested issues in automated lending because different mathematical definitions of fairness can produce different results. A model can satisfy one fairness metric while failing another. Chen et al. (2024) demonstrate that assessments of fairness in credit ratings can change according to the composition and size of the population being evaluated. This finding shows that institutions cannot declare a model fair merely because it performs well on an aggregate dataset.

Credit-scoring models can generate unfairness through multiple pathways. Historical lending records may reflect earlier social or institutional inequalities. Variables that appear neutral may correlate strongly with protected or vulnerable characteristics. Model optimization can also prioritize aggregate accuracy without considering unequal error rates among groups. Garcia et al. (2024) identify these mechanisms as central concerns in research on algorithmic discrimination within the credit domain.

Technical interventions can mitigate some forms of unfairness, but they require explicit institutional decisions about which fairness objectives matter. Moldovan (2023) demonstrates that fair credit-scoring methods can incorporate fairness constraints while maintaining useful predictive performance. This finding challenges the assumption that lenders must always choose between accurate credit assessment and fair treatment.

Standardization remains difficult because fairness also has normative and legal dimensions. Genovesi et al. (2024) argue that fairness evaluation in creditworthiness assessment requires interdisciplinary analysis rather than a purely mathematical approach. A metric that appears technically appropriate may not reflect the relevant legal understanding of discrimination, equality, or proportionality.

Recent reviews confirm that fairness interventions operate at different stages of the machine-learning lifecycle. de Castro Vieira et al. (2025) show that bias mitigation may occur through data preprocessing, model-level interventions, or post-processing adjustments. Effective governance therefore requires continuous monitoring rather than a one-time fairness test performed before deployment.

These findings support the treatment of fairness as part of legal accountability. Institutions should be able to demonstrate how they identify potential discrimination, select relevant fairness criteria, investigate disparities, document mitigation measures, and respond when harmful patterns appear. Wang et al. (2024) emphasize that regulatory responses to algorithmic discrimination require attention to both technical processes and enforceable legal standards. Fairness therefore becomes a responsibility that must remain attributable to organizational actors.

Explainability, Transparency, and Contestability

Transparency provides information about the existence and operation of an automated system, while explainability focuses more specifically on making the reasons for an output understandable. The two concepts overlap but serve different purposes. Weber et al. (2024) show that explainable AI has become increasingly important in finance because financial decisions involve regulatory obligations, risk management, stakeholder trust, and high-impact consequences.

Explainability methods can operate at global or individual levels. Global explanations describe how a model generally behaves, whereas local explanations identify the factors that contributed to a particular outcome. Individualized explanations are especially relevant when an applicant seeks to understand why a specific loan request was rejected or priced differently. Babaei and Giudici (2024) demonstrate that explainable machine learning can provide additional insight into fairness problems in credit lending and can support the identification of factors associated with unequal outcomes.

Legal explainability should not be reduced to the production of a technical output. Taylor (2024) argues that the value of an explanation depends on its capacity to answer the informational needs underlying the right to explanation. A list of feature-importance scores may help an engineer but remain incomprehensible to an ordinary borrower. A legally meaningful explanation must therefore consider the audience and the purpose for which the information is provided.

The stakes of the decision also matter. Credit rejection can affect an individual's ability to finance education, housing, business activities, emergency expenses, or productive investment. An explanation should consequently provide enough information for the affected person to identify relevant errors and determine whether a decision should be reviewed. The right to an explanation becomes practically useful only when linked to contestability.

Contestability refers to the ability to question an automated decision, present relevant information, correct inaccurate data, request meaningful human review, and seek appropriate redress. Fritz (2025) demonstrates that determining the proper scope of algorithmic explanations requires attention to the practical function that explanation serves. This connection means that transparency without an effective response mechanism can remain procedurally weak.

Automated credit scoring should therefore provide an accountability chain from decision to explanation, from explanation to contestation, and from contestation to review or remedy. Without this chain, organizations can disclose the existence of artificial intelligence while preserving the practical opacity of individual decisions.

Human Oversight and Responsibility Allocation

Human oversight frequently appears as a safeguard against harmful automated decision-making. However, the mere presence of a human actor does not guarantee meaningful oversight. A reviewer who routinely accepts algorithmic recommendations without the information or authority required to question them does not provide substantive protection. Accountability requires oversight arrangements that allow humans to understand relevant model outputs, recognize potential errors, and intervene when necessary.

This issue becomes particularly important when organizations rely on third-party scoring providers. Responsibility may be dispersed between the entity that develops the model and the entity that uses its output. The user institution might claim that it cannot explain proprietary model architecture, while the developer might argue that it does not make the final lending decision. Such fragmentation can create an accountability gap.

Regulatory approaches increasingly attempt to prevent this problem by assigning obligations across different participants in the AI lifecycle. Mazzini and Bagni (2023) demonstrate that risk-based AI regulation emphasizes documentation, risk management, data governance, oversight, and monitoring for high-impact systems. These obligations illustrate an important principle for fintech lending: outsourcing a technical component should not result in outsourcing accountability.

The legal analysis must therefore distinguish between technical responsibility and decision responsibility. Technical responsibility concerns data engineering, model development, testing, maintenance, security, and performance monitoring. Decision responsibility concerns whether and how model outputs influence lending outcomes. Organizational and legal accountability must connect these responsibilities so that affected individuals do not encounter a chain in which every participant attributes the problem to another participant.

Indonesian Fintech Lending and the Regulatory Accountability Gap

Indonesia provides an important setting for examining automated credit-scoring accountability because fintech lending combines rapid technological innovation with a major policy interest in financial inclusion. The sector has expanded access to digital financing, but its growth has also produced disputes concerning personal data, consumer rights, contractual practices, and supervisory effectiveness. The national regulatory framework addresses personal-data protection, financial-sector consumer protection, electronic systems, and technology-based lending, but these rules developed from regulatory domains that do not always conceptualize algorithmic decision-making in the same manner.

Existing Indonesian research has primarily addressed the protection of data before, during, or after fintech transactions. Admiral and Pauck (2023) show that weaknesses in legal substance, institutional structure, and legal culture can undermine effective protection in online lending. This perspective remains important because automated credit scoring relies on extensive data processing.

Data protection, however, does not answer every accountability question. Data can be lawfully collected but still be inaccurate, poorly representative, or used in a model that creates unfair outcomes. Dewi and Sulistyawan (2024) show the importance of clear legal protection for borrowers whose personal information is processed through online lending platforms. Automated scoring adds a further layer because harm may result from an inference drawn from data rather than from unauthorized disclosure itself.

The interaction between financial supervision and personal-data governance also raises institutional questions. Syahruddin and Zulfa (2024) identify legal challenges surrounding personal-data violations within Indonesian fintech lending. Algorithmic credit scoring may intensify these difficulties because supervision must examine not only whether data processing has a lawful basis but also how the resulting analytical systems affect consumers.

Enforcement remains another concern. Rifa and Hidayati (2024) show that the effectiveness of data-protection rules in fintech lending depends on implementation, supervision, and meaningful sanctions. Similar considerations apply to algorithmic accountability. Formal obligations to manage risk or protect consumers offer limited protection when regulators or institutions lack mechanisms to inspect automated decision processes.

Consumer-protection scholarship also points to persistent power imbalances in digital lending. Samuel and Gunadi (2025) identify concerns involving standard agreements, data misuse, consumer understanding, and enforcement. Automated scoring can deepen this imbalance if borrowers cannot determine how a platform translated their personal information into a credit decision.

The emerging Indonesian literature on innovative credit scoring provides evidence that these concerns are no longer theoretical. Adam et al. (2025) find that stakeholders perceive algorithmic opacity and regulatory fragmentation as barriers to the responsible development of innovative credit scoring. These findings indicate that Indonesia requires an accountability framework that connects technology governance with existing legal protections.

Research Gap and Conceptual Framework

Existing scholarship can be divided into three broad streams. The first examines the predictive capabilities of machine learning and alternative data. The second investigates fairness, bias, explainability, and technical governance. The third analyzes consumer protection, data protection, and fintech regulation. Each stream provides essential knowledge, but their intersection remains underdeveloped in the Indonesian context.

Technical credit-scoring research commonly treats accountability problems as issues that can be improved through model design. Yet technical correction does not determine which actor bears legal responsibility when a model causes an adverse outcome. Legal fintech studies, by contrast, often focus on rights and regulatory obligations without examining how responsibilities move across data and algorithmic supply chains.

The gap is especially evident at the level of institutional practice. There is limited qualitative evidence explaining how Indonesian stakeholders understand who should be responsible when an automated credit score relies on inaccurate data, generates a discriminatory effect, cannot be meaningfully explained, receives inadequate human review, or produces an outcome that a borrower seeks to challenge. Addressing this gap requires examining law as both a formal normative structure and an institutional practice.

The study therefore develops a conceptual framework consisting of six interrelated dimensions: data accountability, transparency and explainability, fairness and non-discrimination, meaningful human oversight, responsibility allocation, and contestability and redress. Data accountability concerns legality, accuracy, relevance, provenance, and responsibility for information used in assessment. Transparency and explainability concern the ability to trace and communicate the basis of outcomes. Fairness concerns the monitoring and mitigation of unjustified disparate effects. Human oversight concerns the authority of human actors to examine and intervene. Responsibility allocation concerns the distribution of duties among lenders, scoring providers, and data providers. Contestability and redress concern the borrower's ability to correct information, challenge a decision, obtain review, and access an effective remedy.

Together, these dimensions conceptualize legal accountability as a continuous process rather than an obligation that arises only after harm occurs. The process begins with data collection and model development, continues through deployment and lending decisions, and extends to explanation, monitoring, review, dispute resolution, and regulatory supervision. This framework provides the analytical foundation for investigating how formal legal expectations interact with the actual governance of automated credit scoring in Indonesia.

Research Methods

Research Design

This study employs a qualitative socio-legal research design to examine legal accountability for automated credit scoring in Indonesian financial technology lending. The design combines secondary qualitative analysis of published focus group discussion data with legal and regulatory document analysis. A socio-legal approach is appropriate because the research question concerns not only the content of legal rules but also how responsibility, transparency, fairness, and oversight are understood within the institutional practices surrounding automated credit assessment. The study therefore treats automated credit scoring as a socio-technical legal process in which data infrastructures, scoring providers, lenders, regulators, and affected consumers interact.

The empirical component does not claim primary interviews conducted by the present authors. Instead, the study reanalyzes a published qualitative dataset reported by Adam et al. (2025), which directly examined the development of innovative credit scoring in Indonesia. This approach allows the research to use verifiable stakeholder evidence while maintaining methodological transparency concerning the origin of the data. The secondary analysis is guided by the legal-accountability framework developed in the literature review rather than reproducing the thematic objectives of the source study.

Secondary Qualitative Data and Informant Selection

The principal qualitative dataset consists of eight focus group discussions conducted in Jakarta between September and October 2024 and reported by Adam et al. (2025). The source study involved 36 participants selected purposively because of their professional involvement in innovative credit scoring, financial services, data governance, financial inclusion, or regulation. The participant pool comprised six data controllers, nine data processors, eleven data users, five representatives of regulatory or government institutions, and five academics. The original study reported that participants had at least two years of relevant professional experience and that thematic saturation was reached after consecutive discussions no longer produced substantially new themes.

The present study includes the published FGD material because it provides direct stakeholder evidence on data availability, infrastructure, scoring practices, regulation, algorithmic opacity, financial inclusion, and institutional barriers in Indonesia. It excludes statements that cannot be linked to the documented participant categories or the published thematic record. Informant codes are retained exactly as reported in the source material to preserve anonymity and avoid creating identities that are not supported by the original dataset.

Legal and Documentary Materials

Document analysis complements the secondary FGD evidence. The legal materials include Indonesian rules relevant to financial-sector technology, alternative credit rating, consumer protection, personal-data governance, electronic systems, and technology-based lending. Particular attention is given to the regulatory transition formalized through POJK No. 29 of 2024 concerning Pemeringkat Kredit Alternatif because it provides a specific institutional framework for alternative credit-rating providers. Secondary materials include peer-reviewed scholarship from 2023 to 2025 concerning automated credit scoring, algorithmic accountability, fairness, explainability, fintech regulation, and qualitative analysis.

The documentary analysis focuses on provisions and scholarly interpretations relating to data responsibility, transparency, risk management, consumer rights, institutional obligations, human oversight, supervision, complaints, and remedies. The legal materials are used to establish the normative expectations against which stakeholder concerns are interpreted. They are not treated as interchangeable with the empirical data. Instead, the analysis compares formal obligations with the institutional problems identified in the FGD evidence.

Data Analysis

The study applies thematic analysis to the published qualitative material and documentary evidence. Cernasev and Axon (2023) describe thematic analysis as a systematic method for identifying and interpreting patterns in qualitative data. The analysis uses a hybrid deductive and inductive strategy. Deductive categories are derived from the conceptual framework, namely data accountability, transparency and explainability, fairness and non-discrimination, meaningful human oversight, responsibility allocation, and contestability and redress. Inductive coding is used to capture issues emerging from the FGD evidence that are not fully represented by the initial categories, including the economic cost of alternative data and institutional dependence on external providers.

The analytical process follows repeated familiarization with the source material, extraction of relevant stakeholder statements, coding, comparison across participant categories, development of thematic relationships, and socio-legal interpretation. Naeem et al. (2023) emphasize the importance of maintaining a clear progression from raw qualitative material to codes, themes, and conceptual interpretation. The present analysis therefore retains the connection between each empirical theme and the informant codes or stakeholder groups reported in the original publication. Contradictory or divergent perspectives are preserved where they reveal accountability gaps rather than being removed in favor of consensus.

Reflexive interpretation is used to distinguish the present study's legal-accountability analysis from the original study's financial-inclusion focus. Hole (2024) stresses that thematic analysis requires methodological clarity about the researcher's interpretive role. For this reason, the study explicitly identifies when a conclusion results from reanalysis rather than from a direct claim made by the source authors. The unit of analysis is the accountability process surrounding automated credit scoring, from data acquisition and scoring to lending decisions, explanation, review, and regulatory supervision.

Trustworthiness and Ethical Considerations

Trustworthiness is strengthened through source triangulation and stakeholder-category comparison. Published FGD evidence is compared with regulatory materials and peer-reviewed scholarship to identify convergence, contradiction, and implementation gaps. Perspectives attributed to data controllers, processors, users, regulators, and academics are compared rather than treated as a single institutional position. Saunders et al. (2023) show that transparent movement between source data, coding, and themes strengthens the rigor of qualitative analysis, particularly in applied multidisciplinary research.

Because the study uses published and anonymized secondary qualitative data, it does not recruit new participants or collect new personal information. Ethical responsibility therefore centers on accurate representation of the source dataset, preservation of participant anonymity, avoidance of fabricated quotations or identities, and clear acknowledgment of the original data source. The study reproduces only limited excerpts where necessary for analysis and otherwise paraphrases the published findings. This approach ensures that empirical claims remain traceable while respecting the confidentiality protections applied in the original research.

Results and Discussion

Empirical Data Source and Informant Profile

The findings show that automated credit scoring in Indonesian financial technology lending operates within a complex institutional network rather than through a single decision maker. The empirical basis for this analysis derives from the published qualitative dataset of Adam et al. (2025), which involved eight focus group discussions conducted in Jakarta between September and October 2024 with 36 participants. The participants represented five stakeholder groups, namely six data controllers, nine data processors, eleven data users, five representatives of regulatory or governmental institutions, and five academics. This composition provides a broad institutional perspective because automated credit scoring depends on the interaction of organizations that collect alternative data, organizations that process data into scores, financial institutions that use those scores, regulators that supervise the process, and academics who evaluate its implications. Reanalysis of these data through the lens of legal accountability produced six central themes: fragmented responsibility, data accountability, explainability, fairness and non-discrimination, meaningful human oversight, and contestability and redress. These themes show that the primary legal problem does not arise simply from the use of artificial intelligence. It arises from the difficulty of determining which actor must provide an explanation, correct inaccurate information, review an adverse result, and bear responsibility when automated credit scoring affects a borrower unfairly.

The original FGD design also provides important contextual information for interpreting the findings. The discussions followed a semi-structured format and examined the perceived benefits of innovative credit scoring, supporting infrastructure, regulation, data management, implementation barriers, and future governance strategies. The source study reports that participants were selected purposively based on direct professional relevance and had at least two years of related experience. This means that the dataset captures institutional knowledge from actors positioned at different points in the credit-scoring chain rather than general public opinion. The present study retains the anonymized informant codes used in the publication and does not infer personal identities that the source did not disclose.

Table 1. Composition of Informants

Informant Group	Number	Institutional Characteristics	Relevance to the Study
Data controllers	6	Telecommunications, utilities, e-commerce, and organizations controlling alternative data	Data availability, consent, accuracy, and data-sharing responsibility
Data processors	9	ICS providers, fintech developers, and credit bureaus	Algorithm development, scoring, model governance, and explainability
Data users	11	Banks, fintech lenders, cooperatives, and microfinance institutions	Application of scores to lending decisions and human review
Regulators/government	5	Financial and government supervisory institutions	Licensing, oversight, consumer protection, and regulatory coordination
Academics	5	Researchers and experts in fintech and financial inclusion	Independent assessment of fairness, inclusion, and governance
Total	**36**		

Source: Adapted from the FGD participant composition reported by Adam et al. (2025).

Table 2. Selected Informant Profiles Used in the Analysis

Code	Institutional Profile	FGD	Date	Main Issue Represented
SP	Indonesian fintech association representative	FGD-1	25 September 2024	Financial inclusion and borrowers without formal credit history
SW	Financial institution/cooperative representative	FGD-2	2 October 2024	Comparison between SLIK and alternative scoring
RW	Fintech/financial institution representative	FGD-2	2 October 2024	Automation, alternative data,

Code	Institutional Profile	FGD	Date	Main Issue Represented
				cost, and data governance
BH	Financial institution representative	FGD-2	2 October 2024	Digital infrastructure
AS	Academic/microfinance expert	FGD-4	11 October 2024	Accuracy, behavioral information, and inclusion
HW	Data processor/credit bureau representative	FGD-4	11 October 2024	Data availability, cost, and model-development constraints
CL	Academic	FGD-4	11 October 2024	Differentiation of data and regulatory treatment
EMR	Academic	FGD-4	11 October 2024	Digital infrastructure gaps
SN	Financial Services Authority representative	FGD-5	16 October 2024	Fraud detection and financial inclusion
IRS	Government representative	FGD-6	18 October 2024	Data protection and expansion of credit access
TAW	Financial institution/state-owned bank representative	FGD-8	30 October 2024	Data security and faster credit assessment
AKS	Financial institution representative	FGD-8	30 October 2024	Algorithmic accountability and regulatory gaps
PKN	Financial institution representative	FGD-8	30 October 2024	Data quality and reliability of credit scoring

Source: Reconstructed from the empirical FGD reporting of Adam et al. (2025). Informant codes and institutional categories remain anonymized as in the source publication.

Fragmented Responsibility Across the Automated Credit-Scoring Ecosystem

The first major finding concerns the fragmentation of responsibility across the automated credit-scoring chain. The FGD data show that an automated credit decision may involve several independent organizations before it reaches the borrower. Data controllers may supply telecommunications, utility, e-commerce, or other behavioral information. Data processors or innovative credit-scoring providers transform these data into indicators, classifications, or credit scores. Financial institutions then use the resulting scores together with other information to assess eligibility, determine credit limits, price risk, or reject an application. The borrower, however, generally interacts only with the lender or fintech platform. This creates an important asymmetry because the consumer experiences the credit decision as a single outcome even though the decision may be produced through several organizational and technological layers. The structure becomes legally problematic when each actor regards responsibility as limited to its own technical function. A data provider may argue that it merely supplies information, a scoring company may claim that it only produces an analytical output, and the lender may argue that it relies on an external scoring mechanism. Such separation can make it difficult for borrowers to determine where an error originated and which institution must provide a remedy.

The FGD evidence also indicates that the growth of innovative credit scoring is increasing the number of institutional relationships involved in digital lending. Participants described collaborations among fintech companies, financial institutions, credit bureaus, technology providers, and organizations controlling alternative data. This expanding network increases the efficiency of credit assessment but simultaneously complicates the allocation of accountability. The issue is particularly significant where lenders use several sources of risk information. SW, for example, described how conventional credit information can indicate that an applicant is acceptable while alternative information may reveal a different risk pattern. This means that a final decision can result from the interaction of SLIK information, alternative data, a proprietary scoring model, and internal lending rules. In such a structure, simply identifying the lender as the final contracting party does not fully explain who is responsible for the substantive basis of the automated assessment. The findings therefore indicate that accountability requires a clear institutional map connecting data acquisition, model development, model validation, score generation, decision use, explanation, human review, and complaint resolution.

This result strengthens the argument of Horneber and Laumer (2023) that algorithmic accountability requires organizational actors to remain answerable for systems they design, procure, or use. The Indonesian fintech context demonstrates that responsibility can be distributed without being allowed to disappear. Novelli et al. (2024) similarly explain that accountability requires identifiable actors, applicable standards, a forum capable of evaluating conduct, and consequences when obligations are not met. Applied to automated credit scoring, this means that outsourcing technical functions should not remove the responsibility of the institution using those functions to make consequential decisions. A fintech lender should remain capable of explaining the role played by external scoring providers and data suppliers, while scoring providers should remain responsible for the reliability, validation, and documented operation of their models. The findings therefore support a layered accountability model in which each participant bears responsibility for the part of the automated decision process that it controls, while the institution communicating the lending outcome retains a direct duty toward the borrower.

Data Accountability as the Foundation of Automated Credit Decisions

The second major finding is that data accountability forms the foundation of responsible automated credit scoring. The FGD participants repeatedly emphasized that the reliability of an automated score depends on the quality, diversity, accuracy, and relevance of the underlying information. PKN highlighted the importance of reliable data when credit-scoring systems are used to assess individuals who lack conventional financial histories, while HW identified difficulties in obtaining sufficiently diverse and validated datasets. These concerns are particularly important in Indonesia because innovative credit scoring seeks to evaluate individuals who may not have extensive banking records. Alternative data can therefore become highly influential in determining whether a person is considered creditworthy. Yet the same flexibility that creates opportunities for financial inclusion can create risks when data are inaccurate, outdated, incomplete, or interpreted outside their original context.

The empirical material shows that the accountability problem begins before any algorithm produces a score. Alternative credit assessment may use utility-payment behavior, telecommunications activity, e-commerce transactions, digital behavior, or other records that were not originally created for lending decisions. The legal question is therefore not limited to whether the consumer consented to data processing. It also concerns whether the information is sufficiently accurate and relevant to support a consequential financial judgment. For example, utility information associated with a household may not always describe the financial behavior of the individual applicant. Similarly, digital activity can be influenced by factors unrelated to creditworthiness. If these distinctions are ignored, the scoring model may convert contextual or imperfect information into a seemingly objective risk classification. The problem becomes more serious when borrowers do not know which data categories have materially influenced their result.

The findings therefore extend existing Indonesian literature on personal-data protection. Admiral and Pauck (2023) demonstrate that online lending remains affected by weaknesses involving legal substance, institutional structures, and legal culture. Their analysis mainly concerns protection against misuse or unauthorized processing. Automated credit scoring introduces an additional dimension because harm can arise even when the data are lawfully acquired. A lender may comply with formal data-processing requirements while relying on information that is inaccurate, weakly related to creditworthiness, or unsuitable for the population being assessed. Dewi and Sulistyawan (2024) likewise emphasize the importance of borrower protection in online lending, but the present findings suggest that effective protection should include not only control over access to personal data but also the right to challenge the accuracy and relevance of data used to generate automated financial inferences.

Data accountability should therefore include several operational obligations. Institutions should document the origin of material data, assess their reliability, establish procedures for correcting inaccuracies, monitor changes in data quality, and determine responsibility when information supplied by a third party affects a credit decision. These mechanisms are necessary because explainability becomes ineffective when the data underlying the explanation cannot be verified. A lender may accurately explain that an applicant was classified as high risk due to a particular variable, but the explanation provides little legal protection if the variable itself is incorrect. The findings consequently show that data accountability must precede algorithmic accountability. A responsible scoring system must be able to demonstrate not only how a model processed information but also why the information entering that model was appropriate, accurate, and legally defensible.

Economic and Infrastructure Barriers Affect Responsible Scoring

A further finding concerns the financial and infrastructural costs associated with alternative data. The FGD participants did not portray innovative credit scoring as an automatically inexpensive solution. RW explained that institutions may have to pay for external information, including utility-related data, while HW described the broader costs of technology procurement, system integration, cybersecurity, model development, and maintenance. These costs matter because they affect which institutions can develop sophisticated internal scoring capabilities and which must depend heavily on external providers. Large financial institutions may possess the resources to purchase diverse datasets, employ specialized data scientists, maintain validation teams, and negotiate detailed contracts with technology vendors. Smaller lenders and microfinance institutions may have far fewer resources and may therefore rely on limited information or externally produced scores that they cannot independently examine in depth.

The published FGD record provides a concrete illustration of the economic dimension of alternative data. RW stated, "We pay IDR 350 per data point to PLN" (Adam et al., 2025). The statement demonstrates that data acquisition can create direct marginal costs in addition to the fixed costs of model development and technical infrastructure. The significance of this evidence is not the nominal amount alone, but the fact that alternative data markets can shape which institutions have access to broad and reliable information. If responsible scoring depends on diverse data, validation, and continuous monitoring, unequal access to those resources may produce uneven governance capacity across the lending ecosystem.

This economic dimension has important implications for legal accountability. If access to high-quality data and sophisticated validation systems requires substantial financial investment, responsible algorithmic governance may develop unevenly across the market. Institutions with limited resources may lack the capacity to perform extensive bias testing, model validation, or independent auditing. They may also become more dependent on proprietary scoring providers. Such dependence can create an accountability problem when lenders use a score in a consequential decision but lack detailed knowledge of how the external provider produced it. The consumer may then approach the lender for an explanation while the lender possesses only limited information beyond the final risk classification.

The findings therefore indicate that regulation should consider institutional capability rather than assuming that all market participants have equal technological resources. Governance requirements should remain sufficiently strong to protect borrowers, but supervisory mechanisms may need to distinguish between organizations developing scoring models and organizations merely using them. Clear contractual obligations between scoring providers and users become especially important in this context. Providers should supply enough information to support validation, explanation, monitoring, and dispute resolution. Lenders should not be permitted to rely on contractual confidentiality as a reason for being unable to explain material factors influencing an adverse credit decision. Economic efficiency cannot justify an accountability structure in which the technical logic of a decision becomes inaccessible to the institution legally responsible for communicating that decision.

The Gap Between Technical Transparency and Meaningful Explainability

The next major theme is the gap between technical transparency and meaningful explainability. The FGD evidence identifies algorithmic opacity as one of the principal challenges surrounding innovative credit scoring in Indonesia. Participants recognized that complex scoring systems can improve prediction and accelerate lending decisions, but they also noted that sophisticated models can make it more difficult for consumers, compliance officers, and regulators to understand why a particular outcome occurred. AKS raised concerns about gaps related to explainability, bias mitigation, and algorithmic accountability. This issue becomes especially important where an applicant is rejected, assigned a lower credit limit, or offered less favorable conditions based substantially on an automated score.

The findings indicate that institutions need to distinguish between explanations designed for technical experts and explanations designed for affected borrowers. A data scientist may understand feature importance, model coefficients, SHAP values, or other technical representations, but these forms of information may not help an ordinary consumer understand why a loan was denied. Babaei et al. (2023) demonstrate that explainable machine-learning techniques can make fintech lending predictions more interpretable by identifying variables that influence model outputs. However, the present findings suggest that technical interpretability should be translated into a form that supports legal understanding. The consumer does not need access to source code or every mathematical parameter. The consumer needs to know which principal factors materially affected the decision, whether those factors came from conventional or alternative data, and what steps can be taken if the information is inaccurate.

This distinction supports the broader literature on explainable artificial intelligence. Weber et al. (2024) show that explainability has become increasingly important in finance because automated decisions combine technical complexity with significant regulatory and social consequences. Taylor (2024) further argues that explanations should be assessed according to the informational purpose they serve. In credit scoring, the purpose is not merely to demonstrate that a model exists. The explanation should allow an applicant to understand why an adverse result occurred and whether there are grounds for correction or review. An explanation that provides only a generic statement such as 'the application did not meet internal scoring criteria' does not meaningfully reduce the information asymmetry between the institution and the consumer.

The findings therefore support the concept of actionable explainability. Actionable explainability requires an explanation that can lead to a practical response. It should enable the borrower to identify the major adverse factors, correct relevant factual inaccuracies, and request reconsideration where appropriate. This approach protects legitimate proprietary interests because it does not require complete disclosure of model architecture. At the same time, it prevents institutions from using trade secrecy or technical complexity to avoid explaining decisions that significantly affect consumers. Explainability should thus function as a bridge between automated prediction and procedural fairness rather than as a purely technical feature of artificial intelligence.

Algorithmic Fairness and the Risk of Hidden Discrimination

The findings also reveal significant concern about fairness and the possibility of indirect discrimination. Automated credit scoring often appears neutral because the same computational process is applied to every applicant. Yet identical mathematical treatment does not guarantee fair outcomes. The model learns from historical or observational data that may already contain socioeconomic inequalities. Variables that appear neutral can also correlate with characteristics associated with vulnerable groups. Geographic location, patterns of device use, employment instability, or forms of digital behavior may function as indirect indicators of socioeconomic status even when legally protected characteristics are not explicitly used.

The FGD participants' concerns about data diversity and representativeness are particularly relevant to this issue. HW emphasized challenges in accessing sufficiently varied and reliable data. If a training dataset represents some populations more accurately than others, the resulting model may perform unevenly across groups. This can create different error rates for applicants whose characteristics are underrepresented in the historical data. A scoring system may therefore be statistically accurate overall while still generating systematically less reliable predictions for specific groups.

This finding corresponds with Hurlin et al. (2024), who show that credit-scoring models can produce discriminatory outcomes and that lenders can use statistical tests to identify unfairness. Das et al. (2023) similarly explain that algorithmic fairness depends on data choices, model design, and institutional definitions of fairness. The present qualitative findings add an important legal dimension. If institutions possess technical tools capable of detecting systematic disparities, fairness cannot reasonably be treated as an unknowable side effect of automation. Institutions using automated scoring should actively monitor whether the model produces unjustified differences in treatment.

Fairness is nevertheless more complex than selecting a single mathematical indicator. Chen et al. (2024) demonstrate that fairness assessments can change according to population composition and the metric selected. Mariscal et al. (2024) also show that efforts to mitigate bias in credit scoring can involve trade-offs with predictive performance. These findings mean that fairness requires institutional judgment rather than automated measurement alone. Financial institutions need to document why particular fairness criteria were selected and how those criteria correspond to legal principles of equality and non-discrimination.

The findings therefore support continuous fairness governance. Model testing should occur before deployment, after significant model updates, and periodically during operation. Institutions should examine subgroup outcomes, proxy variables, error distributions, and changes in borrower populations. Genovesi et al. (2024) argue that fairness evaluation in creditworthiness assessment requires interdisciplinary analysis because technical metrics alone cannot resolve legal and ethical questions. The Indonesian fintech context reinforces this argument. Fairness should be treated as an ongoing accountability obligation that connects technical monitoring with legal standards rather than as a one-time certification that a model is bias free.

Human Oversight Must Involve Genuine Authority to Intervene

Another major theme concerns the role of human oversight. The empirical evidence indicates that institutions use innovative credit scores in different ways. Some lenders treat automated scores as one factor among several, while other digital lenders rely more heavily on automation to accelerate onboarding and credit assessment. RW and TAW described the ability of automated systems to process alternative information rapidly, which creates clear operational benefits. Yet the increased efficiency of automation raises an important legal question: what role remains for human judgment when the model produces an adverse or questionable result?

The findings suggest that the presence of a human actor should not automatically be interpreted as effective oversight. Human review can become merely formal if employees routinely accept the algorithmic recommendation, lack access to the relevant information, or do not possess authority to override the result. This creates a risk of automation bias, where machine-generated outputs are assumed to be objective or superior and are therefore accepted without adequate examination. In such circumstances, the organization may claim that a human made the final decision even though the automated score effectively determined the outcome.

Meaningful human oversight requires at least four elements. The reviewer must have access to sufficient information about the factors influencing the model. The reviewer must possess adequate knowledge to identify unusual or potentially problematic outcomes. The reviewer must have enough time to assess disputed cases rather than merely confirm a recommendation. Most importantly, the reviewer must have authority to depart from the automated result when there is a justified reason to do so. Without these conditions, human involvement provides little substantive protection to borrowers.

The finding is consistent with risk-based approaches to artificial intelligence governance. Mazzini and Bagni (2023) show that high-impact AI regulation increasingly emphasizes human oversight, documentation, and risk management. In the Indonesian lending context, this principle is especially important when consumers challenge inaccurate information, present exceptional circumstances, or allege unfair treatment. Automated systems may efficiently process large numbers of routine cases, but exceptional or contested decisions require a meaningful route back to human judgment. The role of human oversight is therefore not to replace automation but to ensure that automation does not become immune from institutional responsibility.

Regulation Has Become More Specific but Decision-Level Accountability Remains Developing

The findings must also be interpreted in light of Indonesia's evolving regulatory environment. The original FGD discussions took place during a period when innovative credit scoring was moving from experimentation toward more formal supervision. POJK No. 29 of 2024 subsequently established a specific framework for Pemeringkat Kredit Alternatif, covering institutional requirements, governance, business activities, supervision, and compliance. This development provides greater legal certainty for organizations offering alternative credit-rating services and confirms that automated or alternative scoring has become an increasingly formal component of Indonesia's financial infrastructure.

The empirical findings nevertheless show that institutional authorization does not resolve every accountability issue. Licensing can determine which organizations may operate as alternative credit-rating providers, but it does not by itself guarantee that every individual credit decision is understandable, fair, contestable, and traceable. The FGD participants identified continuing concerns about data quality, interoperability, algorithmic opacity, bias, and fragmented responsibility. These concerns indicate that the next stage of regulatory development should focus increasingly on decision-level accountability.

Decision-level accountability asks what happens when a specific borrower receives an adverse result. It requires institutions to identify the data involved, explain the material factors, determine whether an external provider influenced the decision, offer meaningful human review, and correct problems when they are identified. This is a more demanding form of accountability than institutional registration because it evaluates the operation of the scoring system in individual cases.

The finding also reinforces Spindler's (2023) observation that automated credit scoring intersects with several regulatory domains at once. Financial supervision, consumer protection, data protection, and AI governance cannot function effectively as isolated regulatory silos. Indonesia's evolving framework therefore requires coordination among relevant authorities and clear expectations concerning how overlapping obligations apply to automated credit decisions. An institution should not be able to satisfy one regulatory requirement while leaving a borrower without meaningful protection under another.

Contestability and Redress Remain Central Weaknesses

The final substantive theme concerns contestability and redress. The empirical material indicates that consumers may not fully understand which data are being used or how those data affect their credit score. This informational disadvantage becomes especially problematic when the scoring result produces an adverse lending outcome. Without meaningful information, borrowers cannot distinguish between a legitimate risk assessment and a decision influenced by inaccurate data, inappropriate variables, or model error.

Contestability requires more than the existence of a customer-service channel. A complaint mechanism is meaningful only when it can trigger substantive reconsideration. The findings suggest that an effective process should include several linked stages. The consumer should first receive notification when automated scoring materially influences an adverse decision. The consumer should then receive an understandable explanation identifying the main factors involved. If the relevant information is inaccurate, the consumer should have a clear procedure for requesting correction. Where the consumer disputes the interpretation of the information or the fairness of the decision, meaningful human review should be available. If an error or violation is established, the process should provide an appropriate remedy.

This sequence is particularly important because each component depends on the others. A right to correction has limited value when the borrower does not know which data affected the score. A right to explanation has limited value when no mechanism exists to review the result. Human review has limited value when the reviewer lacks authority to change the decision. Redress therefore requires an integrated procedural architecture rather than isolated consumer-protection obligations.

Samuel and Gunadi (2025) identify continuing power imbalances and consumer-protection challenges within Indonesia's peer-to-peer lending ecosystem. Automated credit scoring can deepen these imbalances because decision-making becomes more technically complex and less visible to borrowers. Rifa and Hidayati (2024) likewise emphasize that legal protection depends on effective implementation and enforcement rather than the existence of formal rules alone. The present findings support this view. Algorithmic accountability becomes meaningful only when consumers can translate formal rights into practical procedures capable of changing an incorrect or unfair outcome.

Synthesis of the Empirical Findings

The combined findings demonstrate that legal accountability for automated credit scoring should be understood as a continuous governance process. It begins with decisions about which data to collect and continues through data validation, model construction, model testing, deployment, score generation, institutional interpretation, consumer communication, human review, and dispute resolution. Failure at any stage can influence the final lending outcome. The most important analytical implication is therefore that accountability cannot be reduced to the moment when a lender approves or rejects an application.

Table 3. Empirical Accountability Matrix

Empirical Finding	Main Informant Evidence	Accountability Issue	Primary Actors	Required Governance Response
Alternative scoring can broaden access to credit	SP, AS, SN	Inclusion and responsible risk assessment	Fintech providers, lenders, regulators	Proportionate and inclusive scoring standards
Multiple scoring sources can produce different risk signals	SW	Traceability of decision inputs	Lenders, scoring providers	Documented weighting and decision logic
Data quality directly affects scoring reliability	PKN, HW	Data accountability	Data controllers, processors	Provenance, validation, and correction procedures
Access to alternative data involves significant costs	RW, HW	Institutional capacity	Data providers, lenders, government	Transparent and proportionate data-access arrangements
Data sharing creates privacy and security concerns	TAW, IRS	Data governance and liability	Controllers, processors, regulators	Clear allocation of data-sharing responsibility
Complex models create opacity	AKS, CL	Explainability	Scoring providers, lenders	Actionable explanations and model auditability

Empirical Finding	Main Informant Evidence	Accountability Issue	Primary Actors	Required Governance Response
Limited data diversity can create bias	HW, AKS	Fairness and non-discrimination	Model developers, scoring providers, lenders	Continuous fairness testing
Automation accelerates lending assessment	RW, TAW	Human dependence on algorithms	Financial institutions	Substantive human oversight
Responsibility is distributed across several organizations	Cross-group findings	Fragmented accountability	All institutional participants	Formal accountability mapping
Consumers have limited visibility into scoring processes	Cross-group findings	Contestability and redress	Lenders, scoring providers, regulators	Explanation, correction, review, and remedy

Source: Secondary thematic analysis of the FGD evidence reported by Adam et al. (2025).

Theoretical Implications

The findings contribute to algorithmic accountability theory by demonstrating that accountability in automated credit scoring is simultaneously distributed, process-based, and relational. It is distributed because multiple actors contribute to the decision. It is process-based because legal risk can emerge at different stages of the automated credit lifecycle. It is relational because different actors owe different forms of accountability to borrowers, regulators, institutional partners, and other stakeholders. This structure helps explain why conventional models centered on a single decision maker can become inadequate when data, scoring, and lending functions are divided among several organizations.

The first theoretical implication is that distributed responsibility should not result in diluted responsibility. The presence of multiple institutions does not reduce the need for clear accountability. Instead, it increases the need to specify responsibilities more precisely. Data controllers should remain responsible for the quality and lawful provision of information. Model developers and scoring providers should remain responsible for validation, documentation, fairness testing, and technical reliability. Lenders should remain responsible for how scores influence credit decisions and for communicating with affected borrowers. Regulators should establish enforceable expectations connecting these responsibilities.

The second implication is that accountability should be evaluated across the full lifecycle of an automated decision. Traditional legal analysis often focuses on the final contractual relationship between lender and borrower. Automated systems require a broader perspective because the legal quality of the final decision depends on upstream technical and organizational processes. A fair final procedure cannot easily compensate for fundamentally unreliable data, just as accurate data cannot compensate for a discriminatory model or ineffective complaint mechanism.

The third implication concerns information asymmetry. Traditional credit scoring seeks to reduce uncertainty faced by lenders. Automated scoring can successfully reduce that asymmetry by increasing the information available about applicants. However, the findings show that it can create a reverse informational asymmetry. Financial institutions gain increasingly detailed knowledge about consumers while consumers know less about the analytical process used to classify them. This new imbalance means that explainability and contestability are not peripheral ethical concerns. They are necessary mechanisms for restoring procedural balance within digital lending relationships.

Practical and Regulatory Implications

The practical implication of the findings is that fintech providers and financial institutions should establish a documented accountability architecture for automated credit scoring. Internal policies should identify who is responsible for data quality, model validation, fairness monitoring, explanation, human review, complaint handling, and corrective action. These responsibilities should not remain implicit because ambiguity becomes especially problematic when several external vendors contribute to the scoring process.

Contracts with third-party scoring providers should also include accountability obligations. Providers should supply sufficient information to allow financial institutions to assess model reliability, understand major factors influencing scores, investigate disputes, and comply with supervisory requirements. Commercial confidentiality should remain protected, but it should not prevent lenders from providing legally meaningful explanations to consumers.

The findings also indicate that regulators should strengthen expectations concerning algorithmic auditing and documentation. Supervision should examine not only whether an institution is legally authorized to provide alternative scoring but also whether its models can be traced, tested, monitored, and explained. Fairness assessment should become a recurring governance obligation rather than a voluntary technical exercise.

Consumer-protection procedures should be strengthened by connecting explanation with review. When automated scoring materially contributes to an adverse lending decision, the borrower should receive sufficient information to understand the principal reasons. Clear mechanisms should allow correction of inaccurate information and meaningful reconsideration of disputed decisions. Human review should involve genuine authority rather than simply repeating the automated output.

Overall, the findings show that responsible automated credit scoring cannot be defined solely by high predictive accuracy, rapid processing, or expanded financial inclusion. These benefits remain important, but they must operate within a governance system that preserves legal accountability. The critical question is therefore not whether Indonesia should use innovative credit-scoring technologies. The more important question is whether every consequential automated credit decision can be traced to responsible actors, explained in understandable terms, tested for unfair effects, reviewed by competent humans, and corrected when it produces an inaccurate or unjust outcome. Strengthening these mechanisms would allow Indonesia to pursue financial innovation while maintaining meaningful protection for borrowers within an increasingly automated lending environment.

Conclusion

This study concludes that legal accountability for automated credit scoring in Indonesian financial technology lending depends on the ability to connect data processing, algorithmic assessment, institutional decision-making, and consumer protection within a single accountable governance chain. The findings show that responsibility is distributed among data controllers, scoring providers, fintech lenders, financial institutions, and regulators, but this distribution should not dilute legal responsibility. Six dimensions emerge as essential to accountable automated lending: data accountability, transparency and explainability, fairness and non-discrimination, meaningful human oversight, clear responsibility allocation, and effective contestability and redress. The study also shows that automated credit scoring can improve financial inclusion and accelerate risk assessment, yet these benefits create new legal risks when alternative data are inaccurate, scoring models are opaque, responsibility is fragmented, or borrowers cannot meaningfully challenge adverse decisions. Theoretically, the study extends algorithmic accountability into the Indonesian fintech context by demonstrating that accountability is not confined to the final lending outcome but operates throughout the entire decision lifecycle. It also identifies a reverse form of information asymmetry in which financial institutions gain increasingly detailed knowledge about borrowers while borrowers have limited knowledge of how their data are transformed into consequential credit assessments.

The findings have practical and policy implications for fintech providers, scoring companies, financial institutions, and regulators. Institutions using automated credit scoring should establish explicit responsibility for data quality, model validation, fairness monitoring, consumer explanation, human review, and corrective action, including when scoring functions are provided by third parties. Regulatory development should move beyond institutional authorization toward decision-level accountability by strengthening requirements for traceability, algorithmic auditability, understandable explanations, ongoing fairness assessment, and accessible mechanisms for correcting and reviewing disputed credit outcomes. These measures can support technological innovation without weakening borrowers' procedural and legal protection. Future research should extend this analysis through primary interviews with borrowers, fintech practitioners, regulators, and technology providers, as well as comparative studies across different types of digital lenders and credit-scoring arrangements. Such research would deepen understanding of how formal accountability standards operate in practice and how automated credit governance can adapt as Indonesia's digital financial ecosystem continues to evolve.

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Author Contributions

Conceptualization: Mega Endah Halim, Bima Hafiz Firmansyah
Data curation: Maya Dwi Lestari
Formal analysis: Mega Endah Halim, Maya Dwi Lestari
Investigation: Bima Hafiz Firmansyah, Maya Dwi Lestari
Methodology: Mega Endah Halim, Bima Hafiz Firmansyah
Project administration: Maya Dwi Lestari
Supervision: Mega Endah Halim
Validation: Mega Endah Halim, Bima Hafiz Firmansyah
Visualization: Maya Dwi Lestari
Writing - original draft: Mega Endah Halim, Bima Hafiz Firmansyah, Maya Dwi Lestari
Writing - review and editing: Mega Endah Halim, Bima Hafiz Firmansyah, Maya Dwi Lestari
All authors contributed to the preparation of the manuscript, reviewed the final version, and approved the manuscript for publication. All authors agree to be accountable for the integrity and accuracy of the work.

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Conflict of Interest

The authors declare that they have no financial, professional, institutional, or personal conflicts of interest that could have influenced the research process, interpretation of the findings, or preparation of this manuscript.

Statement on the Use of Artificial Intelligence

Artificial intelligence-assisted tools were used solely to support the preparation and refinement of the manuscript. Claude AI was used to assist with language organization and textual refinement, DeepL was used to support English-language translation and linguistic clarity, and Grammarly was used for grammar, spelling, punctuation, and readability checks. These tools were not used to generate, alter, fabricate, or manipulate research data, interview evidence, findings, or conclusions. The authors critically reviewed, verified, and revised all AI-assisted outputs and retain full responsibility for the accuracy, originality, interpretation, and integrity of the final manuscript.

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