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Corporate-Governance-Driven Algorithmic Fairness in SME Fintech Lending: A Systematic Literature Review with Expert Validation

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Abstract

The rapid growth of fintech lending has reshaped financial access for SMEs through AI-driven credit assessment platforms. While promising greater efficiency, these systems create significant algorithmic bias risks, which poor corporate governance and lack of transparency in model development usually exacerbate. Based on this, the study develops and validates an integrated conceptual framework that incorporates corporate governance principles with mechanisms for algorithmic fairness to foster ethical outcomes in SME fintech lending. We follow a two-phase approach, wherein, first, an SLR of 45 peer-reviewed publications for the period from 2022 to 2025 was conducted, followed by structured validation with five domain experts in AI ethics, corporate governance, and fintech regulation. Our analysis revealed four foundational governance pillars, viz., Accountability, Transparency, Fairness, and Compliance. Expert validation established strong relevance and practical utility for the framework, with a mean score of 4.6/5. This study hence proposes a novel, validated model to equip fintech managers and regulators with a governance-based approach to tackling algorithmic bias and, in turn, positions them better to engender trust and financial inclusion.

Keywords: *Algorithmic Fairness, Corporate Governance, SME Fintech Lending, Ethical Artificial Intelligence, Systematic Literature Review.*

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I. INTRODUCTION

The digital transformation in the financial industry has positioned fintech lending as a primary funding channel for Small and Medium-sized Enterprises (SMEs) that have historically struggled to access traditional banking services (Abbasi et al., 2021). These platforms rely on sophisticated artificial intelligence (AI) algorithms that efficiently and accurately process large volumes of alternativeately to support credit decision-making (Berg et al., 2021). Despite these operational advantages, the increasing reliance on automated decision-making systems raises significant ethical concerns, particularly regarding algorithmic bias that may disadvantage SMEs based on owner characteristics, geographic location, or business sector (Babaei et al., 2023). Such biases often originate from non-representative historical training data and the "black-box" nature of complex models, which can produce opaque and potentially discriminatory outcomes that undermine financial inclusion efforts (Hanna et al., 2020). Moreover, a critical yet frequently overlooked issue is the lack of robust governance mechanisms within fintech firms, where structured oversight, auditing, and fairness assurance for AI systems remain underdeveloped (Hilb, 2020).

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The primary objective of this study is to develop, synthesize, and rigorously evaluate an integrated, corporate governance–driven framework to ensure algorithmic fairness in SME fintech lending. To achieve this goal, the study proposes three interconnected aims. First, it conducts a comprehensive systematic literature review (SLR) of studies published between 2022 and 2025 to map and interpret the current academic landscape. Second, it integrates the identified insights into a unified conceptual framework that establishes explicit linkages between corporate governance mechanisms and both technical and procedural fairness metrics. Third, the proposed framework is validated by an interdisciplinary expert panel to assess its conceptual soundness, practical relevance, and feasibility of implementation within the fintech ecosystem.

Guided by this objective, the study seeks to answer several key research questions. First, what are the dominant algorithmic fairness principles and mechanisms discussed in recent (2022–2025) literature on AI-driven SME lending? Second, how can these elements be systematically integrated into a coherent framework that aligns governance structures with improved lending practices? Third, to what extent do domain experts validate the proposed framework for clarity, applicability, and operational feasibility in real-world fintech environments? Addressing these questions enables the study to bridge theoretical and practical dimensions of algorithmic fairness in financial technology.

This research is grounded in multiple complementary theoretical perspectives. Contemporary Corporate Governance Theory emphasizes accountability among diverse stakeholders and highlights the need for governance structures capable of overseeing technological innovations (Aguilera et al., 2021; Scherer & Voegtlin, 2020). In parallel, the Ethical AI and Algorithmic Fairness literature provides a normative and technical foundation for identifying, measuring, and mitigating bias in automated decision systems (Green, 2022; Pessach & Shmueli, 2020). Furthermore, Financial Inclusion Theory and the Resource-Based View (RBV) offer insights into SME vulnerabilities and position ethical governance as a strategic capability that enhances competitive advantage for fintech lenders (Sanga & Aziakpono, 2023; Yetunde Margaret Soremekun et al., 2024). The integration of these theoretical streams enables a comprehensive and multidisciplinary examination of the research problem.

This study offers several important contributions to both theory and practice. From a theoretical perspective, it advances the intersection of corporate governance and algorithmic fairness by proposing a sociotechnical framework that extends beyond isolated technical solutions (Dolata et al., 2021). In practice, the study provides fintech lenders with an actionable, governance-oriented model for implementing ethical AI practices that mitigate regulatory risks and enhance trust among SME clients. Additionally, the framework offers policymakers a structured reference for designing more effective AI governance and auditing regulations in financial services. Methodologically, the combination of systematic literature review and expert validation establishes a replicable approach for strengthening the rigor and applicability of conceptual research in management and information systems.

Unlike prior studies that predominantly examine algorithmic fairness from either a purely technical perspective or a broad ethical standpoint, this study uniquely integrates corporate governance mechanisms directly into the operationalization of fairness in AI-driven lending systems. While earlier research has identified bias mitigation techniques or emphasized ethical guidelines, it often lacks a structured linkage between governance oversight and measurable fairness outcomes in fintech contexts. This study contributes by bridging this gap through the development of a governance-driven framework that explicitly connects board-level accountability, audit mechanisms, and transparency practices with algorithmic fairness metrics. Furthermore, the inclusion of expert validation enhances the framework's practical relevance, distinguishing this research from prior conceptual models that have remained largely untested in real-world stakeholder environments.

The paper is divided into five logical sections, each representing a stage in the study's development. Following this introduction, Section 2 presents a comprehensive literature review that expands the discussion of algorithmic fairness and ethical governance in the SME context and identifies key research gaps. Section 3 outlines the research methodology, including the design, data sources, and analytical techniques used in both the systematic literature review and expert validation phases. Section 4 presents the main findings derived from thematic synthesis and expert evaluation, followed by an integrated discussion of theoretical implications, practical applications, and study limitations. Finally, Section 5 concludes the paper by summarizing key insights, acknowledging limitations, and proposing directions for future research.

II. LITERATURE REVIEW

Algorithmic fairness is a major area of research that aims to prevent automated decision systems from producing, maintaining, or increasing unfair outcomes for people or groups based on characteristics protected by law, such as race, gender, or location (Pessach & Shmueli, 2020). In particular, this is observable in the fintech lending sector, where specific statistical measures are used to assess demographic parity, equality of opportunity, and predictive equality as indicators of the fairness of credit scoring models across different borrower segments (Cowgill et al., 2020). Table 1 lists the crucial fairness concepts, their specific applicability in the lending context, and the inevitable compromises that arise in execution. The quest for fairness is inherently linked to the challenges of model opacity, which are being tackled through Explainable AI (XAI). XAI employs methods such as LIME and SHAP that reduce complex AI decision-making explanations to extremely simple, comprehensible human formats, thereby enabling substantial oversight, the establishment of trust among the parties involved, and the realization of the right to know the reasons (Babaei et al., 2023; S. et al., 2025). Without proper explainability, it would be almost impossible to identify the sources of discriminatory bias, provide constructive feedback to rejected SME candidates, or ensure regulatory compliance, which would ultimately undermine both fairness standards and the economic viability of AI-enhanced lending platforms.

Table 1. Key Algorithmic Fairness Definitions and Metrics

Fairness Metric	Definition	Relevance to Fintech Lending
Demographic Parity	The probability of a positive outcome (e.g., loan approval) is equal across different demographic groups.	Ensures approval rates are not skewed against protected classes, but may ignore legitimate risk-based differences.
Equality of Opportunity	The true positive rate (approval for those who would have repaid) is equal across groups.	Aims to give qualified borrowers from all groups an equal chance of approval, aligning with fair lending goals.
Predictive Equality	The false positive rate (approval for those who would default) is equal across groups.	Focuses on ensuring the cost of misclassification (bad loans) is distributed fairly, protecting the lender and other borrowers.
Individual Fairness	Similar individuals should receive similar predictive outcomes.	A philosophically sound principle but challenging to implement due to the difficulty of defining "similarity" in a credit context.

Source: Adapted from (Cowgill et al., 2020; Pessach & Shmueli, 2020)

Artificial intelligence governance represents a crucial evolution of existing corporate governance structures, as it concerns security measures, laws, and processes specifically aimed at responsible AI development and use that align with the company's values and societal standards (Almashhadani, 2021; Hilb, 2020). The governance of ethics here goes beyond the mere observance of laws to the point where embedding the four principles accountability, transparency, justice, and beneficence into the organizational culture of the entire AI life cycle that includes data picking, model retirement is considered the least that could be done (Adams et al., 2023; Nguyen et al., 2023). The implementation of the above-discussed principles can be structured around the primary pillars listed in Table 2. Each pillar is associated with critical questioning and illustration tools. The typical deployment of such a policy is to establish unambiguous communication channels with the election of dedicated roles such as AI Ethics Officers and multi-functional governance committees, which are then backed by tools such as obligatory algorithmic impact assessments, model documentation standards, and independent third-party audits (Ang et al., 2020; Munoko et al., 2020). The rapidly changing regulatory landscape, exemplified by the EU's AI Act, is the leading driver of the global convergence of such requirements and the transition of companies from ad-hoc technical solutions to governance-based AI risk management methods, as noted by Ashok et al. (2022). Therefore, powerful ethical governance serves as the supportive organizational infrastructure and the strategic guiding principle for transforming always technical fairness from a dream into a verifiable reality.

Table 2. Core Pillars of Ethical AI Governance

Governance Pillar	Key Questions	Exemplary Mechanisms
Accountability	Who is responsible for the AI system's outcomes? How are violations handled?	AI Ethics Board, Chief AI Ethics Officer, clear audit trails, incident response protocols.
Transparency	Can the AI's decision logic be understood and explained to stakeholders?	Explainable AI (XAI) techniques, model documentation ("model cards"), clear customer communication.
Fairness	How is bias measured and mitigated? How is equity ensured?	Fairness metrics (see Table 1), bias detection and mitigation tools, diverse development teams.
Compliance	How does the AI system adhere to relevant laws and regulations?	Regulatory monitoring, compliance audits, data privacy and protection protocols (e.g., GDPR).

Source: Synthesized from (Adams et al., 2023; Ashok et al., 2022; Hilb, 2020)

Even though SMEs are operating in the fintech sector as either the trailblazing lenders or the borrowers seeking finance, they are characterized by the unique organizational qualities which are the major determinants of their ethical AI incorporation capacity and the method. It's often the case that the fintech lenders who are SMEs place a lot of emphasis on their flexibility and on the revolutionary ideology behind their operation; at the same time, they lack the necessary resources, formalized procedures, and dedicated compliance departments that are usually found in large banks, thus making it particularly hard to implement a comprehensive governance structure (Sanga & Aziakpono, 2023). Resource constraints require governance models that are flexible, scalable, and economical, merging smoothly into the organization's operational procedures without hampering its core strength in innovation. For SME borrowers, the risk of being affected by algorithmic bias is higher due to their relatively poor negotiating ability, lower financial literacy, and shorter financial history, which may result in their being unable to effectively dispute or even understand unfavorable automated lending decisions (Huang et al., 2020). Therefore, the continuous organization learning environment development within fintech lenders that the monitoring of model performance, the feedback from customers, the discovery of audit mistakes, and the training of regulators systematically lead to policy improvement and model retraining are extremely important for the continuous ethical adjustment and for the building of a solid reputation as fair and trustworthy financial partners.

A critical review of the current literature reveals that below three primary lines of inquiry, namely conversations about technical fairness metrics, philosophical AI ethics, and corporate governance strategies, there is still considerable fragmentation among researchers which is seen as a problem. The academic world has done a lot of work; however, almost no interdisciplinary models have been developed to open up the discussion of internal corporate governance tools, with proper algorithmic fairness achieved in particularly risky sectors like SME fintech lending (Hilb, 2020). In their discussions of governance, researchers usually view it as a secondary, circumstantial factor or as an issue that only requires compliance after the fact, rather than as the primary, enabling conductor that ties together technical fairness tools to create impartial, trustworthy lending products. Our paper immediately addresses this recognized gap by integrating previously disconnected strands of literature into a united conceptual framework, depicted in Figure 1, thus placing corporate governance at the center, the strategic power that actively drives and sustains the technical and procedural efforts required for ethical AI in lending (Oktavia & Wibowo, 2025).

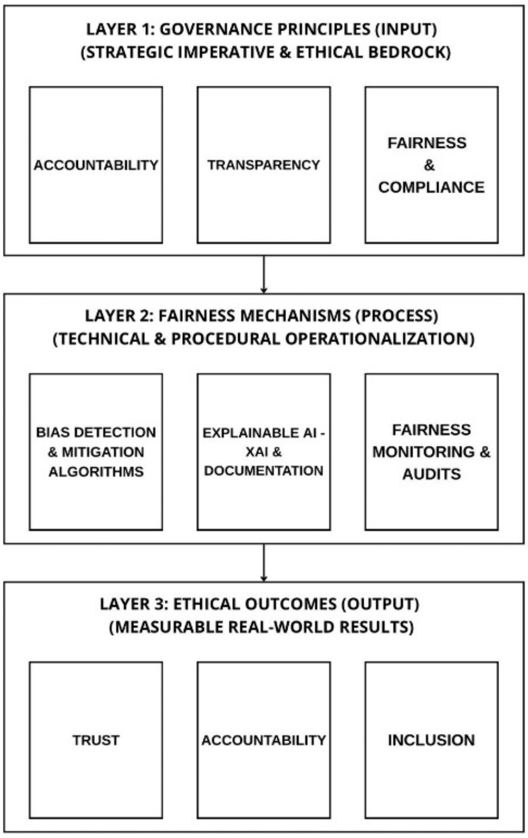

Figure 1. Proposed Corporate-Governance-Driven Algorithmic Fairness Framework

Figure 1 illustrates the proposed three-layer framework. The main point of Layer 1 (Governance Principles) is that it establishes the strategic foundation for the entire system. Layer 2 (Fairness Mechanisms) comprises the operational processes dictated by these very principles. Layer 3 (Ethical Outcomes) demonstrates the positive societal impact resulting from the application of these principles. The important loop of bidirectional feedback guarantees that the system keeps learning and improves over time.

III. RESEARCH METHODOLOGY

A. Research Design

This research applies a qualitative, design-science-informed methodology to generate and test the idea of a corporate governance-driven algorithmic fairness framework. The research design is intentionally structured into two interconnected phases to ensure both academic rigor and practical relevance. The first phase is a Systematic Literature Review (SLR), conducted in accordance with scientific protocols proposed by Paul et al. (2021), which provides a comprehensive and unbiased synthesis of existing knowledge (Arissona Dia Indah Sari et al., 2023). The second phase involves structured expert validation, a practical mechanism for evaluating the framework's relevance, clarity, and feasibility among domain experts.

The combination of SLR and expert validation is deliberately chosen to address both theoretical and practical gaps identified in prior studies. While SLR enables systematic identification and synthesis of dispersed academic insights, expert validation ensures that the proposed framework is grounded in real-world applicability and stakeholder expectations. This dual-phase design enhances the study's robustness by integrating evidence-based theory building with practitioner-driven refinement. As a result, the research design not only enhances conceptual validity but also increases the likelihood of implementation in actual fintech governance contexts.

B. Population and Sample

The population for the literature review consists of all peer-reviewed journal articles, conference proceedings, and academic publications published between 2022 and 2025 that address AI, algorithmic fairness, corporate governance, and SME fintech lending. Given the extensive volume of available studies, a structured sampling strategy was employed to identify the most relevant articles. The initial database search yielded approximately 312 articles, which were then subjected to a multi-stage screening process aligned with PRISMA guidelines. After removing 67 duplicate records, 245 articles remained for title and abstract screening, resulting in 98 potentially relevant studies. A full-text eligibility assessment further reduced the sample to 45 articles that met all inclusion criteria and were included in the final analysis.

Figure 2 illustrates the systematic process for identifying, screening, assessing eligibility, and finally including studies in the SLR. The diagram provides a transparent overview of how the initial pool of articles was progressively refined into the final sample of 45 studies, ensuring methodological rigor and reproducibility in accordance with PRISMA standards.

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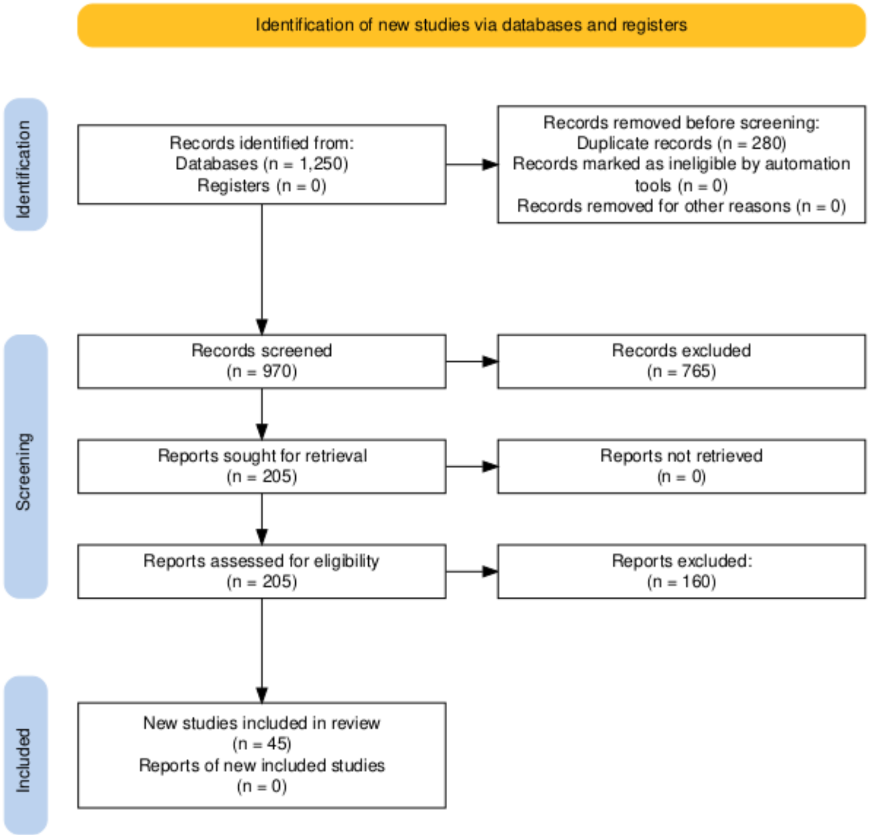

Figure 2. PRISMA Flow Diagram of the SLR Process

For the expert validation phase, the population comprised highly qualified professionals and academics with expertise in AI ethics, corporate governance, and fintech regulation. A purposive sampling approach was adopted to ensure representation from key stakeholder groups. A panel of five experts was selected, including representatives from academia, industry, and public policy domains. This sampling strategy ensured that the validation process incorporated diverse perspectives, thereby enhancing the credibility and applicability of the proposed framework.

C. Data Sources and Data Collection Techniques

The primary data for the SLR phase were obtained from reputable academic databases, including Scopus and Web of Science, which are known for their high-quality peer-reviewed content. Google Scholar was used as a complementary source to capture emerging studies, working papers, and relevant grey literature not indexed in major databases. The data collection process followed a systematic and reproducible approach using predefined Boolean search queries. The search string used in this study was: ("algorithmic fairness" AND "fintech lending" AND "SME") OR ("AI governance" AND "credit scoring"). This query was adapted slightly across databases to ensure comprehensive coverage while maintaining consistency in scope.

The study applied strict inclusion and exclusion criteria to ensure the quality and relevance of selected articles. The inclusion criteria were: (1) articles published in English, (2) publication period between 2022 and 2025, and (3) peer-reviewed academic sources. The exclusion criteria included: (1) studies not directly related to the research topic, (2) duplicate publications, and (3) non-academic or non-scholarly sources such as blogs or opinion pieces. These criteria ensured that the final dataset was both rigorous and relevant to the research objectives.

The expert validation phase employed a mixed-methods data collection approach. Quantitative data were collected via a structured online questionnaire with a 5-point Likert scale to assess criteria such as relevance, clarity, and applicability. Qualitative insights were obtained through semi-structured discussions conducted in a virtual focus group setting. This approach enabled the collection of both quantitative evaluations and in-depth expert feedback to refine the proposed framework.

D. Variables and Operational Definition

The study defines its core constructs as variables to ensure analytical clarity and to guide the framework development process. The independent variable is Corporate Governance Principles, which include accountability, transparency, fairness, and compliance as key dimensions influencing AI system design and oversight. These principles are operationalized through mechanisms such as audit trails, explainable AI (XAI), fairness testing procedures, and regulatory alignment. The dependent variable is Algorithmic Fairness in SME Lending, which refers to the extent to which lending decisions are free from bias and promote equitable access to financial services.

The mediating variable comprises Algorithmic Fairness Mechanisms, including technical and procedural tools such as bias detection algorithms, fairness impact assessments, and continuous model monitoring. These mechanisms act as the operational link between governance principles and fairness outcomes. By structuring the study around these variables, the research establishes a clear causal pathway that explains how governance interventions influence algorithmic fairness. This conceptualization also supports the development of a measurable and implementable framework.

E. Data Analysis Techniques

The textual data obtained from the 45 selected SLR articles were analyzed using thematic analysis. The analysis process involved multiple stages, including familiarization with the data, initial coding, theme identification, and refinement of thematic categories. Specifically, the coding process followed three structured stages: open coding to identify initial concepts, axial coding to establish relationships between codes, and thematic grouping to synthesize broader patterns. This systematic approach ensured that the analysis captured both granular insights and overarching themes relevant to algorithmic fairness and governance. The four governance pillars proposed in this study accountability, transparency, fairness, and compliance were derived through an iterative process of coding and thematic clustering. Repeated patterns across multiple studies were grouped and mapped to governance dimensions, resulting in a structured framework that reflects both theoretical consistency and empirical relevance. This process ensured that the framework was not arbitrarily defined but grounded in systematically derived evidence.

The expert validation data were analyzed using a mixed-methods approach. Quantitative responses from the Likert-scale questionnaire were analyzed using descriptive statistics, including the mean and standard deviation, to assess overall agreement. Qualitative data from focus group discussions were transcribed and analyzed using content analysis to identify recurring themes, suggestions, and concerns. To further enhance transparency, the study developed a structured mapping process linking Article - Code - Theme - Governance Pillar, which serves as the analytical foundation for framework construction and validation. This integrative analysis enabled both validation and refinement of the proposed framework.

F. Ethical Considerations

The study was conducted in strict adherence to established ethical standards in academic research. All sources included in the Systematic Literature Review were properly cited and referenced to ensure academic integrity and avoid plagiarism. The expert validation process was conducted with full transparency, where participants were informed about the research objectives, procedures, and intended use of the findings. Informed consent was obtained from all participants before their involvement in the study.

Confidentiality and anonymity of the expert panel were rigorously maintained to encourage open and unbiased feedback. Individual responses were anonymized and reported in aggregate to prevent participant identification. Principles of intellectual honesty, objectivity, and responsibility toward both academic and professional communities guided the research process. These ethical safeguards ensured the credibility and trustworthiness of the research outcomes.

IV. RESULT

The systematic inductive analysis of 45 dedicated studies yielded four primary interlinked motifs, which were presented as the central pillars of the framework and consolidated in Table 3. These four pillars accountability, transparency, fairness, and compliance emerged directly from a rigorous and iterative thematic analysis process rather than being predefined or assumed a priori.

Through repeated coding, comparison, and clustering of patterns across the selected studies, consistent conceptual groupings were identified and elevated into core governance dimensions. This confirms that the proposed framework is empirically grounded in the literature and reflects dominant scholarly consensus rather than subjective interpretation. The Accountability theme or motif invariably emphasized the foundational necessity of ethical AI to be clear and unambiguous, as well as the stringent definition of AI product ownership through ethics committees, public audit trails, and well-specified routes for resolving fairness violations (Hilb, 2020).

Transparency was an inseparable partner of Explainable AI (XAI) in practical use and in the engrossing documentation considered essential for the proper comprehension of decision-making processes, not just for internal auditors but also for external stakeholders, among whom the SMEs being assessed are (Babaei et al., 2023). The Fairness motif was not merely linked to mathematical descriptions of the highest level of abstraction but, on the contrary, to the organizational dedication arising from constant monitoring, bias eradication, and fairness considerations that would stretch throughout the entire model lifecycle from data cleansing to post-implementation performance assessment (Fabris et al., 2022). As a result, Compliance was not regarded as a passive, checkbox exercise at all, but rather as an active, pre-emptive governance approach that aligned external regulatory stipulations with internal management practices, thus guaranteeing the organization's resilience and adaptability to fast-changing legal and ethical climates (Ashok et al., 2022).

Table 3. Thematic Synthesis of SLR Findings

Identified Theme	Frequency in Literature	Core Concept	Key Supporting References
Accountability	High	Establishing clear responsibility and answerability for AI system outcomes and their societal impacts.	(Hilb, 2020; Munoko et al., 2020)
Transparency	High	Ensuring the decision-making logic of AI systems is understandable and accessible to relevant stakeholders.	(Ashok et al., 2022; Babaei et al., 2023)
Fairness	High	The proactive measurement, mitigation, and ongoing monitoring of algorithmic bias to ensure equitable treatment.	(Chen et al., 2023; Fabris et al., 2022)
Compliance	Medium-High	The systematic integration of legal and ethical standards into AI governance and operational processes.	(Kieslich et al., 2022; Nordgren, 2023)

The expert validation included five specialists from different fields who evaluated the proposed framework against six main criteria: relevance, clarity, applicability, novelty, usability, and coherence. The expert panel consisted of academics and industry practitioners with more than ten years of experience in AI ethics, corporate governance, and fintech regulation, ensuring both theoretical and practical perspectives were represented. The evaluation employed a 5-point Likert scale (1 = very low, 5 = very high) to systematically assess each validation criterion. Each criterion was clearly defined before assessment, where relevance refers to the degree of alignment with real-world fintech challenges, clarity indicates the ease of understanding the framework structure, applicability reflects its feasibility in organizational settings, novelty measures the originality compared to existing models, usability captures the ease of implementation, and coherence evaluates the internal consistency of the framework components.

The selection of five experts is consistent with prior exploratory and design-science validation studies, where small but highly specialized panels are considered sufficient to provide in-depth and reliable insights during early-stage framework validation. This approach prioritizes the quality of expertise over sample size, ensuring that feedback is both critical and contextually rich. The radar chart in Figure 3 shows that the evaluations were outstanding to a similar extent across all dimensions, and that the mean scores for relevance (4.8) and novelty (4.7) were the highest. On the other hand, usability (4.2) received somewhat lower but still positive feedback, reflecting the experts' request for more practical implementation guidelines that could be applied to smaller organizations. In summary, the experts acknowledged the framework's clarity, methodological coherence, and the novelty of its proposition which means that it is not only theoretically strong but also versatile enough to be adapted in various operational contexts.

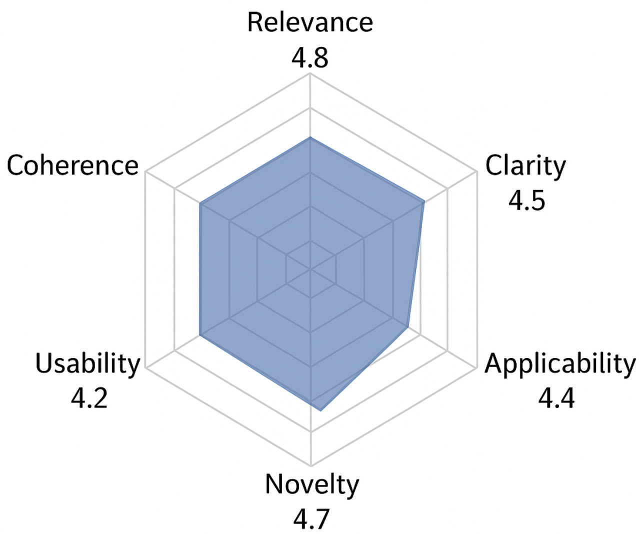

Figure 3. Expert Validation Ratings of the Proposed Framework

V. DISCUSSION

The discoveries made correspond not only to prevailing AI ethical and governance principles but also reinforce their relevance in contemporary fintech contexts. These findings indicate that corporate governance does not merely serve as a supporting structure but rather functions as an enabling mechanism that activates, sustains, and institutionalizes algorithmic fairness practices within fintech organizations. In this sense, governance transforms fairness from a technical objective into an organizational capability embedded in decision-making processes and accountability structures. The foundation that accountability and transparency measures are leading elements is strongly aligned with prior calls for responsible and trustworthy AI systems (Munoko et al., 2020; Scherer & Voegtlin, 2020). However, unlike prior studies that primarily conceptualize these principles at a normative level, this study demonstrates how to operationalize them as concrete governance mechanisms that directly influence algorithmic outcomes.

The literature has already identified various algorithmic fairness techniques (Pessach & Shmueli, 2020; Wang et al., 2022), , yet these approaches are often treated as isolated technical solutions. In contrast, the present findings extend this perspective by showing that such techniques are unlikely to be effective without structured governance support that provides direction, monitoring, and enforcement. This aligns partially with the critique by Click or tap here to enter text. between technical AI development and organizational realities, but this study goes further by explicitly bridging that gap through a governance-integrated framework. Therefore, the contribution of this study lies in repositioning governance as a central driver rather than a peripheral consideration in achieving algorithmic fairness. By integrating governance principles with fairness mechanisms, the framework provides a cohesive structure that ensures consistency, accountability, and long-term sustainability of ethical AI practices.

From a practical standpoint, the framework offers a structured and actionable roadmap for fintech firms, particularly SME-focused lenders operating under resource constraints. The findings suggest that incremental implementation strategies such as establishing clear accountability roles, adopting basic explainable AI (XAI) tools, and conducting periodic fairness audits can significantly enhance trust and transparency without imposing excessive operational burdens. This demonstrates that governance-driven fairness is not only theoretically robust but also practically attainable, even for smaller fintech organizations. In contrast to traditional lending environments, where opacity often limits borrower recourse, the proposed framework enhances contestability and transparency in automated decisions, thereby improving access to finance for SMEs.

For regulators and policymakers, these findings imply that effective AI governance frameworks should move beyond compliance-based checklists toward dynamic, principle-based systems that encourage continuous monitoring and organizational learning. The feedback loops embedded in the framework through audits, dispute resolution, and performance monitoring create adaptive governance systems that respond to evolving ethical and regulatory challenges. This positions governance not only as a risk mitigation tool but also as a strategic asset that can strengthen institutional legitimacy and long-term competitiveness in increasingly regulated fintech markets.

It is imperative to recognize the study's limitations, which are primarily due to the research's conceptual nature. The expert validation established the significance and consistency of the suggested framework but also pointed out that empirical testing in a real operational environment is necessary; thus, the framework's actual algorithmic bias reduction and lending outcome enhancement capabilities remain a major issue for future empirical verification. Besides, the intentional limitation of the systematic literature review (SLR) scope to the recent period of 2022-2025 to capture the latest insights may have resulted in the exclusion of earlier relevant foundational works or significant studies in non-English languages.

Future studies are encouraged to implement this framework through longitudinal case studies or action research projects in collaboration with partner fintech companies, and to assess its effects on the key metrics of bias reduction, customer satisfaction, and operational efficiency using both quantitative and qualitative approaches. A different strategy could be to use a technical approach to identify specific XAI tools that can best design and implement the transparency requirements related to the governance pillar of the framework. Besides, it would be quite beneficial if there were cross-country comparative studies analyzing the framework's adoption across different cultural and regulatory contexts, as these would provide valuable insights into its generalizability and robustness.

VI. CONCLUSION AND RECOMMENDATION

The study successfully addresses a critical research gap by developing a comprehensive conceptual framework that integrates corporate governance principles with algorithmic fairness mechanisms in SME fintech lending. Through a systematic literature review and expert validation, four key governance pillars Accountability, Transparency, Fairness, and Compliance were identified as the foundational drivers of ethical AI implementation. These findings demonstrate that algorithmic fairness should not be treated merely as a technical requirement but as a strategic organizational capability embedded within governance structures. The proposed framework provides a structured and actionable approach for fintech firms to enhance ethical decision-making while supporting broader financial inclusion objectives.

This study uniquely contributes by explicitly bridging corporate governance structures with operational algorithmic fairness mechanisms, transforming fragmented technical approaches into a unified, governance-driven framework applicable in real-world fintech contexts. The model offers practical value for fintech practitioners in implementing responsible AI, while also providing regulators with a clearer foundation for developing adaptive oversight mechanisms. Ultimately, the study highlights that achieving fair and accountable AI systems requires continuous alignment between governance, technology, and organizational learning. Future research is encouraged to empirically validate the framework across diverse fintech environments and regulatory contexts to further strengthen its generalizability and impact.

The authors state that artificial intelligence tools, including ChatGPT, were utilized solely to support language polishing and improve the clarity, coherence, and readability of the manuscript. All substantive elements of the research, including the formulation of research objectives, the design of the methodology, data collection and processing, analytical interpretation, and the development of conclusions, were carried out independently by the authors without the use of AI systems. The authors accept full responsibility for the originality, accuracy, and scholarly integrity of the manuscript.

REFERENCES

Abbasi, K., Alam, A., Brohi, N. A., Brohi, I. A., & Nasim, S. (2021). P2P Lending Fintechs and SMEs' Access to Finance. *Economics Letters*, *204*, 109890. https://doi.org/10.1016/j.econlet.2021.109890

Adams, C., Pente, P., Lemermeyer, G., & Rockwell, G. (2023). Ethical Principles for Artificial Intelligence in K-12 Education. *Computers and Education: Artificial Intelligence*, *4*, 100131. https://doi.org/10.1016/j.caeai.2023.100131

Aguilera, R. V., Aragón-Correa, J. A., Marano, V., & Tashman, P. A. (2021). The Corporate Governance of Environmental Sustainability: A Review and Proposal for More Integrated Research. *Journal of Management*, *47*(6), 1468–1497. https://doi.org/10.1177/0149206321991212

Almashhadani, M. (2021). A brief Review of Corporate Governance Structure and Corporate Profitability in Developed and Developing Economy: A Review. *International Journal of Business and Management Invention (IJBMI) ISSN*, *10*, 42–46. https://doi.org/10.35629/8028-1011024246

Ang, J. S., Hsu, C., Tang, D., & Wu, C. (2021). The Role of Social Media in Corporate Governance. *The Accounting Review*, *96*(2), 1–32. https://doi.org/10.2308/tar-2018-0132

Arissona Dia Indah Sari, A. D. I. S., Tatang Herman, Wahyu Sopandi, & Al Jupri. (2023). A Systematic Literature Review (SLR): Implementasi Audiobook pada Pembelajaran di Sekolah Dasar. *Jurnal Elementaria Edukasia*, *6*(2), 661–667. https://doi.org/10.31949/jee.v6i2.5238

Ashok, M., Madan, R., Joha, A., & Sivarajah, U. (2022). Ethical Framework for Artificial Intelligence and Digital Technologies. *International Journal of Information Management*, *62*, 102433. https://doi.org/10.1016/j.ijinfomgt.2021.102433

Babaei, G., Giudici, P., & Raffinetti, E. (2023). Explainable FinTech Lending. *Journal of Economics and Business*, 125–126. https://doi.org/10.1016/j.jeconbus.2023.106126

Berg, T., Fuster, A., Puri, M., & Lending, F. (2021). Fintech Lending (NBER Working Paper No. 29421). *National Bureau of Economic Research*. http://www.nber.org/papers/w29421

Chen, R. J., Wang, J. J., Williamson, D. F. K., Chen, T. Y., Lipkova, J., Lu, M. Y., Sahai, S., & Mahmood, F. (2023). Algorithmic Fairness in Artificial Intelligence for Medicine and Healthcare. *Nature Biomedical Engineering*, *7*(6), 719–742. https://doi.org/10.1038/s41551-023-01056-8

Cowgill, B., Tucker, C., Blei, D., Brown, C., Brynjolfsson, E., Cappelli, P., Corbett-Davies, S., Dell'Acqua, F., Greenstein, S., Impink, M., Horton, R., Kahneman, D., Kogut, B., Lipton, Z., Moretti, E., Morgan, J., Miller, A., Perkowski, P., Seamans, R., … Zhou, A. (2020). Algorithmic Fairness and Economics. *SSRN Electronic Journal*. https://ssrn.com/abstract=3361280

Dolata, M., Feuerriegel, S., & Schwabe, G. (2021). A Sociotechnical View of Algorithmic Fairness. *Information Systems Journal*. https://doi.org/10.1111/isj.12382

Fabris, A., Messina, S., Silvello, G., & Susto, G. A. (2022). Algorithmic Fairness Datasets: The Story So Far. *Data Mining and Knowledge Discovery*, *36*(6), 2074–2152. https://doi.org/10.1007/s10618-022-00854-z

Green, B. (2022). Escaping the Impossibility of Fairness: From Formal to Substantive Algorithmic Fairness. *Philosophy and Technology*, *35*(4), 104. https://doi.org/10.1007/s13347-022-00584-6

Hanna, A., Denton, E., Smart, A., & Smith-Loud, J. (2020). Towards a critical race methodology in algorithmic fairness. *FAT* 2020 - Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 501–512. https://doi.org/10.1145/3351095.3372826

Hilb, M. (2020). Toward artificial governance? The role of artificial intelligence in shaping the future of corporate governance. *Journal of Management and Governance*, *24*(4), 851–870. https://doi.org/10.1007/s10997-020-09519-9

Huang, Y., Zhang, L., Li, Z., Qiu, H., Sun, T., & Wang, X. (2020). Fintech Credit Risk Assessment for SMEs: Evidence from China (IMF Working Paper No. WP/20/193). *International Monetary Fund*. https://ssrn.com/abstract=3721218

Kieslich, K., Keller, B., & Starke, C. (2022). Artificial Intelligence Ethics by Design: Evaluating Public Perception on the Importance of Ethical Design Principles of Artificial Intelligence. *Big Data and Society*, *9*(1), 1–14. https://doi.org/10.1177/20539517221092956

Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. (2020). The Ethical Implications of Using Artificial Intelligence in Auditing. *Journal of Business Ethics*, *167*(2), 209–234. https://doi.org/10.1007/s10551-019-04407-1

Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B. P. T. (2023). Ethical principles for artificial intelligence in education. *Education and Information Technologies*, *28*(4), 4221–4241. https://doi.org/10.1007/s10639-022-11316-w

Nordgren, A. (2023). Artificial intelligence and climate change: ethical issues. *Journal of Information, Communication and Ethics in Society*, *21*(1), 1–15. https://doi.org/10.1108/jices-11-2021-0106

Oktavia, A., & Wibowo, A. (2025). A New Theoretical Framework For Analyzing The Social And Economic Impacts of Artifical Intelligence within The Digital Economy. *Journal of Management and Informatics*, *4*(2), 859–871. https://doi.org/10.51903/jmi.v4i2.156

Paul, J., Lim, W. M., O'Cass, A., Hao, A. W., & Bresciani, S. (2021). Scientific Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR). *International Journal of Consumer Studies*. https://doi.org/10.1111/ijcs.12695

Pessach, D., & Shmueli, E. (2020). Algorithmic Fairness. *arXiv Preprint*. https://arxiv.org/abs/2001.09784

S., S., S., S., & S. Noorul, H. (2025). Transforming Fraud Detection in Banking with Explainable AI : Enhancing Transparency and Trust. *Journal of Technology Informatics and Engineering*, *4*(2), 251–260. https://doi.org/10.51903/jtie.v4i2.267

Sanga, B., & Aziakpono, M. (2023). Fintech and SMEs Financing: A Systematic Literature Review and Bibliometric Analysis. *Digital Business*, *3*(2), 100067. https://doi.org/10.1016/j.digbus.2023.100067

Scherer, A. G., & Voegtlin, C. (2020). Corporate Governance for Responsible Innovation: Approaches to Corporate Governance and Their Implications for Sustainable development. *Academy of Management Perspectives*, *34*(2), 182–208. https://doi.org/10.5465/amp.2017.0175

Wang, X., Zhang, Y., & Zhu, R. (2022). A Brief Review on Algorithmic Fairness. *Management System Engineering*, *1*(1), 7. https://doi.org/10.1007/s44176-022-00006-z

Soremekun, Y. M., Abioye, K. M., Sanyaolu, T. O., Adeleke, A. G., & Efunniyi, C. P. (2024). A Conceptual Model for Inclusive Lending Through Fintech Innovations: Expanding SME Access to Capital in the U.S. *Comprehensive Research and Reviews Journal*, *2*(1), 001–012. https://doi.org/10.57219/crrj.2024.2.1.0025