International Journal of Social Science and Economic Research

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

Comparative Analysis of Alternative Credit Scoring Models: Expanding Access and Identifying Limitations

Ruhaan Munjuluri

Livingston high school USA

DOI: 10.46609/IJSSER.2025.v10i08.034 URL: https://doi.org/10.46609/IJSSER.2025.v10i08.034

Received: 10 August 2025 / Accepted: 28 August 2025 / Published: 4 September 2025

ABSTRACT

Background: *Access to credit remains a fundamental barrier to financial inclusion, with millions worldwide excluded from traditional banking systems due to inadequate credit histories. This study investigates whether alternative credit scoring models effectively expand credit access for underserved populations while examining the constraints that limit their equitable application across different markets.*

Methodology/Principal Findings: *A comparative analysis was conducted of three leading fintech companies—Upstart, Tala, and Kaleidofin—using publicly available financial reports, impact assessments, and peer-reviewed literature. The analysis evaluated credit approval rates, borrower demographics, default rates, and customer outcomes. Results demonstrate that alternative credit scoring models significantly increase credit access. Upstart's AI-driven model approves 44.28% more borrowers than traditional models, with 28.8% of loans directed to low-to-moderate-income communities. Tala has served over 7.5 million borrowers globally, with 63% being first-time digital borrowers and 84% reporting improved quality of life. Kaleidofin serves 7.55 million customers (98% women), achieving 20-30% higher approval rates than traditional bureaus while maintaining portfolio-at-risk below 2%. Collectively, these models have reached approximately 18 million previously excluded borrowers. However, effectiveness is constrained by significant limitations: extensive data collection requirements raising privacy concerns, persistent algorithmic fairness challenges despite bias mitigation efforts, and regulatory barriers limiting international scalability.*

Conclusions/Significance: *While alternative credit scoring models demonstrate substantial success in expanding financial inclusion, their transformative potential requires coordinated efforts to address underlying challenges. This includes developing comprehensive regulatory frameworks balancing innovation with consumer protection, implementing robust bias mitigation*

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

strategies, investing in digital infrastructure, and fostering international regulatory cooperation. The study's findings indicate that achieving equitable financial systems depends not only on technical capabilities but also on the broader ecosystem of policies and infrastructure investments supporting responsible implementation.

Keywords: alternative credit scoring, data privacy, financial inclusion, fintech, Kaleidofin, regulation, Tala, Upstart

Introduction

Access to credit serves as a fundamental pillar of financial inclusion, enabling individuals to invest in education, start businesses, and build economic stability. Yet millions worldwide remain excluded from traditional banking systems due to inadequate credit histories or systemic barriers. This exclusion perpetuates cycles of economic marginalization, particularly affecting underserved populations including rural communities, women, young adults, and minorities who face significant obstacles in accessing traditional credit services.

Traditional credit scoring models, which rely heavily on conventional credit bureau data and established financial histories, systematically exclude individuals who lack extensive credit records. This creates a paradox where those who most need access to credit are often denied it due to insufficient credit history. Research consistently demonstrates that barriers to credit access include complex application procedures [1], inadequate financial infrastructure, educational limitations, and institutional biases that disproportionately affect marginalized communities. Abu and Issahaku [2] highlight that many farmers lack access to essential credit provisions, attributing this to institutional failures and the necessity for government intervention. Moreover, Sekyi et al. [3] indicate that increasing age can reduce the probability of credit access, as older individuals are often seen as higher-risk borrowers by financial institutions.

The emergence of alternative credit scoring models represents a promising innovation in addressing these persistent barriers. Companies such as Upstart, Tala, and Kaleidofin have pioneered approaches that leverage non-traditional data sources, including mobile phone usage patterns, social network analytics, utility payment histories, and transaction behaviors to assess creditworthiness. Upstart was founded in 2012 by former Google executives to make it easier for people to get loans by using AI to better understand their real financial situation, especially for those who don't have traditional credit histories [4]. These models employ machine learning algorithms and advanced analytics to evaluate borrowers who would otherwise be excluded from traditional lending systems, potentially expanding financial access to previously underserved populations. Hlongwane et al. [5] demonstrate that incorporating alternative data such as social network influence, regional economic metrics, and local population characteristics can lead to

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

more accurate credit assessments compared to traditional scoring models reliant solely on conventional credit bureau data.

However, the implementation of alternative credit scoring is not without challenges. Concerns regarding data privacy, algorithmic fairness, and regulatory compliance present significant obstacles to widespread adoption. The potential for these models to inadvertently perpetuate existing biases or create new forms of discrimination requires careful examination. Aitken [6] raises concerns about how the unbanked are categorized and the potential for algorithmic bias to reinforce socio-economic barriers rather than mitigate them. Additionally, regulatory frameworks have yet to fully address the complexities introduced by alternative data sources and machine learning algorithms in credit assessment [7].

Research Question and Hypothesis

This study investigates whether alternative credit scoring models effectively expand credit access for underserved populations. Specifically, the research examines the hypothesis that while the implementation of alternative credit scoring models leads to increased credit approval rates for underserved populations, their effectiveness in expanding equitable access to credit is constrained by issues related to data privacy, algorithmic fairness, and regulatory barriers that limit scalability and equitable application across different markets.

Significance of the Study

Understanding the effectiveness and limitations of alternative credit scoring models is crucial for several reasons. First, financial inclusion catalyzes poverty alleviation and economic empowerment, enabling individuals to pursue entrepreneurial activities and improve their socioeconomic status [8]. Second, addressing credit access disparities can promote gender equality and social justice by reducing systemic barriers that disproportionately affect marginalized groups [9]. Finally, as financial technology continues to evolve, establishing frameworks for responsible innovation in credit assessment becomes essential for fostering inclusive economic growth while protecting consumer rights and ensuring equitable access to financial services.

Literature Review

Traditional Credit Scoring Systems: Limitations and Exclusionary Practices

Traditional credit scoring systems, exemplified by widely-used models such as FICO and CIBIL, where FICO is primarily used in the US, while CIBIL is India's credit scoring system, operate on the fundamental premise that past credit behavior serves as the most reliable predictor of future

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

creditworthiness. These systems primarily rely on established credit histories, creating a systematic exclusion of individuals without prior credit accounts, commonly referred to as "thin-file borrowers" [7]. This exclusion represents a significant barrier to financial inclusion, as individuals who may possess both the capacity and willingness to repay loans are nonetheless denied opportunities based solely on the absence of a formal credit history.

The scope of this exclusion is substantial and affects diverse demographic groups. Young adults entering the financial system for the first time, recent immigrants lacking domestic credit histories, individuals who have primarily relied on cash transactions, and those who have been geographically or economically excluded from traditional banking services all face systematic disadvantage under conventional scoring models. Lessmann et al. [7] demonstrate that while conventional methods prove effective for assessing established borrowers with extensive credit histories, they fundamentally fail to accommodate the unique circumstances of thin-file individuals, thereby limiting overall credit market access and perpetuating cycles of financial exclusion.

Beyond the issue of data availability, traditional credit scoring models face significant technical limitations that constrain their effectiveness in contemporary financial landscapes. Addy et al. [10] argue that conventional scoring methods, particularly those relying on logistic regression and similar statistical techniques, struggle to adapt to the complex, nonlinear relationships present in modern financial data. These traditional approaches often miss critical risk indicators that more sophisticated analytical methods could capture, thereby failing to provide accurate assessments of creditworthiness for diverse borrower populations.

Lessmann et al. [8] demonstrate that while conventional methods prove effective for assessing established borrowers with extensive credit histories, they fundamentally fail to accommodate thin-file individuals, thereby limiting overall credit market access. Beyond data availability issues, Addy et al. [9] argue that conventional scoring methods struggle to adapt to complex, nonlinear relationships present in modern financial data.

The Rise of Alternative Credit Scoring Models

The emergence of alternative credit scoring models represents a paradigmatic shift in how financial institutions assess creditworthiness, moving beyond traditional credit bureau data to incorporate diverse information sources that provide more comprehensive insights into borrowers' financial behaviors and capabilities. Hlongwane et al. [5] found that credit scoring models using alternative data—such as mobile phone activity, educational background, and local economic factors—performed significantly better than models relying only on traditional credit histories. Specifically, these models achieved an area under the curve (AUC) score of 0.79360.

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

In this case, AUC measures how well a model can distinguish between creditworthy and non-creditworthy borrowers. A score closer to 1.0 means higher accuracy. By incorporating overlooked variables such as social network default rates, regional economic indicators, and local demographics, the model achieved an AUC of 0.79360 on the Kaggle Home Credit dataset—indicating a 79.36% probability of correctly distinguishing creditworthy from non-creditworthy borrowers and outperforming models based solely on credit bureau data.

Mobile phone usage patterns have emerged as particularly valuable alternative data sources for credit assessment, offering insights into borrowers' financial behaviors, stability, and social connections. Óskarsdóttir et al. [11] examine how mobile phone data and social network analytics can significantly enhance credit scoring effectiveness, particularly for populations often labeled as "credit invisible." Their findings reveal that mobile phone usage patterns, combined with social connectivity metrics, provide valuable predictive insights that enable financial institutions to assess creditworthiness more accurately than traditional methods alone.

Educational background represents another valuable alternative data source that can provide insights into borrowers' long-term financial prospects and stability. Djeundje et al. [12] focus on the predictive accuracy of models that utilize non-traditional data including educational history, psychometric variables, and demographic information. Their results indicate that these models significantly outperform those relying exclusively on conventional credit history, demonstrating the capacity of alternative data to improve risk predictions substantially.

Empirical Evidence: Effectiveness and Challenges

Empirical research provides substantial evidence supporting the effectiveness of alternative credit scoring models in expanding access to credit for underserved populations. The integration of alternative data sources has demonstrated measurable improvements in both predictive accuracy and inclusivity across diverse markets and demographic groups. Hlongwane et al. [5] focus specifically on the effectiveness of integrating alternative data sources such as social network default status and regional economic ratings with traditional credit scoring models. Their empirical findings reveal that these integrated models significantly improve credit scoring accuracy while enabling lenders to better assess the creditworthiness of thin-file borrowers who are typically excluded by traditional systems.

Several limitations were identified in this study. Data availability was limited, particularly concerning borrower outcomes and long-term impacts, as access to detailed, granular data was constrained. Regional differences posed challenges as the models operate in diverse geographical contexts, which may affect their applicability and performance. Model comparability was

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

complicated by differences in data collection methods, scoring algorithms, and evaluation metrics, which posed challenges in direct comparisons.

A particularly critical limitation—underscored across multiple studies—is the persistent risk of bias in alternative credit scoring models, even when explicit discrimination is absent. These biases manifest in several ways:

First, proxy bias arises when seemingly neutral variables—such as ZIP code, mobile phone usage, or education level—encode deeply rooted structural inequalities. Barocas and Selbst [13] and Ledford et al. [14] note that ZIP codes, for example, often act as proxies for race due to historical patterns of redlining and residential segregation, leading to unintended discriminatory outcomes even when protected characteristics are not used explicitly. Second, label bias is introduced when models are trained on past outcomes influenced by human decisions. Mehrabi et al. [15] show that if training data reflects past discriminatory lending practices, the model is likely to inherit and reinforce these patterns, thereby perpetuating systemic exclusions. Third, sample size and representational bias occur when underrepresented or "credit invisible" groups are inadequately captured in training data. For instance, Blattner and Nelson [16] demonstrate that traditional credit scores systematically misrepresent creditworthiness for Black and Hispanic borrowers due to sparse or skewed data histories. Fourth, intersectional bias refers to the compounding of disadvantages faced by individuals at the intersection of multiple marginalized identities. Kim et al. [17] reveal that such individuals often fall through the cracks of group-level fairness tests, experiencing higher error rates and exclusion. While technical approaches—such as fairness-aware algorithms, debiasing procedures, and post-hoc adjustments—can mitigate these issues to a degree, scholars increasingly argue that some forms of bias are irreducible [18]. Eubanks [19] asserts that algorithmic outputs inevitably reflect societal inequalities baked into historical data, rendering perfect neutrality impossible. Barocas et al. [20] contend that risk modeling in financial services is not a neutral exercise but a value-laden one requiring human judgment, transparency, and oversight. Accordingly, while algorithmic fairness tools are vital, they must be accompanied by regulatory frameworks, participatory design methods, and ongoing auditing practices to ensure just outcomes.

Theoretical Frameworks: Financial Inclusion and Algorithmic Fairness

The theoretical understanding of financial inclusion has evolved significantly beyond simple access to financial services to encompass broader concepts of economic empowerment, social equity, and sustainable development. Fan and Zhang [21] provide important theoretical insights into the relationship between financial inclusion and entrepreneurship, developing models that demonstrate how expanding financial inclusion reduces information asymmetry and transaction costs in credit markets. Their theoretical framework illustrates how improved access to credit

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

empowers entrepreneurs, particularly among economically disadvantaged individuals, by reducing barriers to business formation and growth.

The development of theoretical frameworks for algorithmic fairness in credit scoring represents a critical area of academic inquiry with significant practical implications for the design and implementation of alternative credit scoring models. Adegoke et al. [22] provide a comprehensive theoretical analysis examining the fairness implications of credit scoring models for financial inclusion, social equity, and economic mobility. Their framework recognizes that existing model biases can perpetuate systemic inequities in lending practices, thereby hindering marginalized populations' ability to achieve homeownership and financial security.

3. Methodology

Comparative Analysis Framework

This study employs a comparative analysis to evaluate three alternative credit scoring models: Upstart, Tala, and Kaleidofin. Each model utilizes distinct methodologies to assess creditworthiness, incorporating alternative data sources and machine learning algorithms. The comparative approach allows for an examination of how these models perform across various metrics, including approval rates, borrower demographics, fairness, regulatory compliance, and scalability.

Data Collection

Data for this analysis were collected from a combination of primary and secondary sources. For Upstart, accessible investor communications and third-party reviews were consulted to obtain information on approval rates, borrower demographics and scale. An inclusive-lending report indicated that Upstart's model approves 44.28 % more borrowers than a traditional model and directs 28.8 % of its loans to low-to-moderate-income borrowers [4]. Additional coverage noted that by mid-2024 Upstart had partnered with more than 100 banks to provide over US $39 billion in loans to more than 3 million customers [4].

For Tala, the 2022 Global Impact Report compiled by 60 Decibels was the primary data source. It provides detailed insights into customer demographics, loan usage and outcomes. The report states that more than 7.5 million people have borrowed through Tala's smartphone app and that the average Net Promoter Score is 68 [23]. Survey results show that 63 % of borrowers were able to access a digital loan like Tala for the first time, 84 % reported improved quality of life and 88 % reported improved ability to meet a major expense [23].

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

For Kaleidofin, the analysis drew on CGAP's 2024 focus note and corporate disclosures. These sources report that Kaleidofin serves over 7.55 million customers, draws on data from more than 30 million unique customers, and has underwritten more than US $4.7 billion in loans using its ki score system [24]. They also document that 98 % of Kaleidofin's clients are women, 70 % were new to services like Kaleidofin's, and that the platform's models achieve 20–30 % higher approval rates than standard credit bureaus while maintaining a PAR 90 below 2 % [24].

Additionally, academic studies and industry reports were reviewed to understand the broader context of alternative credit scoring models. The study incorporated detailed customer impact data from Tala's 2022 Global Impact Report, which included 1,008 phone interviews with Tala's digital-loan borrowers across Kenya, Mexico, the Philippines, and India [23].

Criteria for Evaluation

The evaluation of each model was based on four primary criteria. Expansion of access was measured by loan approval rates and the inclusion of underserved populations. Fairness was assessed through the model's ability to mitigate biases and ensure equitable outcomes across different demographic groups. Regulatory compliance was evaluated based on adherence to relevant financial regulations and data privacy laws. Scalability was determined by the model's capacity to expand operations across different regions and adapt to varying market conditions.

Limitations

Several limitations were identified in this study. Data availability was limited, particularly concerning borrower outcomes and long-term impacts, as access to detailed, granular data was constrained. Regional differences posed challenges as the models operate in diverse geographical contexts, which may affect their applicability and performance. Moreover, model comparability was complicated by differences in data collection methods, scoring algorithms, and evaluation metrics, as well as by context-specific features that influence borrower behavior and financial infrastructure. These variations make direct comparisons across geographies and institutions inherently difficult, limiting the generalizability of findings and the transferability of best practices across different credit markets.

Findings and Discussion

Comparative Performance Analysis

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

Table 1: Comprehensive Comparison of Alternative Credit Scoring Models

Metric	Upstart	Tala	Kaleidofin
Market Focus	US consumer loans	Emerging market microloans	India microfinance (rural women)
Customers Served	3+ million	5+ million	7.55+ million
Primary Demographics	Mixed demographics	70% low-income	98% women customers
Financial Inclusion Impact	28.8% LMI communities	65% first-time digital loan users	70% new to formal financial services
Customer Satisfaction	Not disclosed	Net Promoter Score: 68	Not disclosed
Approval Rate Improvement	44.28% vs traditional	13% of traditionally rejected applicants	80% for first-time underserved
Loans Underwritten	$2.1B (Q1 2025)	$1B+ cumulative	$4.7B+ based on ki score
Default Rate	Varies	Varies	Not disclosed
Data Points Analyzed	1,600+	10,000+	30+ million
Automation Rate (percentage of credit or loan application decisions made automatically)	92%	90%	AI/ML decisioning
Geographic Reach	Primarily US	Kenya, Mexico, India, and the Philippines	India + Southeast Asia expansion

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

Metric	Upstart	Tala	Kaleidofin
Unique Innovation	Embedding algorithms	Multi-market validation	Rural women empowerment

Note. Data compiled from Upstart [4], Tala [14], 60 Decibels [13], and CGAP [15].

Expansion of Access: Quantified Evidence of Increased Credit Access

The analysis provides compelling evidence that alternative credit scoring models significantly expand access to credit for underserved populations. Upstart's artificial intelligence model approves 44.28 % more borrowers than a traditional model and directs 28.8 % of its loans to low- and moderate-income communities [4]. By mid-2024, the platform had partnered with more than 100 banks and facilitated over US$39 billion in lending to more than 3 million customers, illustrating the scale of its reach [4].

Tala's impact in emerging markets is also substantial. The 2022 Global Impact Report notes that more than 7.5 million people have borrowed through Tala's smartphone app and that the average Net Promoter Score across markets is 68 [23]. A 60 Decibels survey found that 63 % of borrowers were able to access a digital loan like Tala for the first time—44 % in Kenya—and that 78 % could not easily find a good alternative to Tala's services [23]. Borrowers reported significant positive outcomes: 84 % said their quality of life improved and 88 % said their ability to meet a major expense improved; 94 % trust Tala with their personal information, 76 % report increased confidence, 58 % understand all loan terms and conditions, 80 % report improved ability to face major expenses and 77 % report improved financial management [23]. These metrics underscore Tala's role in reaching first-time digital-loan users and providing meaningful benefits beyond credit access.

Kaleidofin's results reinforce the effectiveness of alternative credit models in India's informal sector. The company serves more than 7.55 million customers, approximately 98 % of whom are women, and has underwritten more than US $4.7 billion in loans using its ki score system [24]. A CGAP-commissioned assessment found that 70 % of Kaleidofin's clients were new to services like Kaleidofin's, indicating that a large share were accessing formal financial services for the first time [24]. Kaleidofin's credit models deliver 20–30 % higher approval rates than standard credit bureaus and maintain a portfolio-at-risk (PAR 90) below 2 %, demonstrating both inclusive reach and prudent risk management [24].

Alternative data sources drive improved access across all three companies. Upstart reports that it leverages a wide range of personal and financial attributes—such as education, employment

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

history, income, and cash-flow data—to build its credit models, but it does not publicly disclose a specific number of data points [4]. Tala's Android application collects more than 10,000 data points from mobile phone usage patterns, transaction behaviour and social interactions to build a financial identity within seconds [25]. Kaleidofin's ki score draws on data from more than 30 million unique customers, analysing behavioural and transactional patterns at scale to enable more accurate credit assessment for borrowers without formal credit histories [24].

The combined impact of these three companies demonstrates the scalable potential of alternative credit scoring. Together, they reach roughly 18 million borrowers—more than 3 million through Upstart, over 7.5 million through Tala and more than 7.55 million through Kaleidofin—illustrating the large number of previously excluded individuals now able to obtain credit [4], [23], [24]. Comprehensive default-rate data for all three companies were not available; thus no generalisation about default rates is offered here.

Limitations: Confirmed Constraints on Effectiveness

Despite documented successes in expanding credit access, the analysis reveals significant limitations that constrain the effectiveness and scalability of alternative credit scoring models. These limitations align closely with the study's hypothesis regarding the constraining factors of data privacy, algorithmic fairness, and regulatory barriers.

The convergence of these three critical limitations creates compound challenges that extend beyond simple operational hurdles. Each constraint not only operates independently but also interacts with and amplifies the others, creating a complex web of barriers to scale. For instance, data privacy regulations directly limit the types and amounts of information that can be collected for credit assessment, which in turn affects the models' ability to make fair and accurate decisions across diverse populations. Similarly, regulatory fragmentation across jurisdictions means that a model optimized for one market may require substantial modification—or may be entirely non-compliant—in another, preventing the standardization necessary for cost-effective scaling.

Most significantly, these limitations disproportionately impact the very populations that alternative credit scoring aims to serve. Underserved communities often operate in markets with weaker digital infrastructure, face higher risks of algorithmic discrimination due to historical biases in training data, and may lack the regulatory protections necessary to ensure fair treatment. This creates a fundamental tension: while alternative credit scoring models have demonstrated their ability to expand access within certain parameters, the systemic constraints they face prevent them from achieving the universal financial inclusion they promise. The following analysis examines each of these limitations in detail, demonstrating how they

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

collectively restrict the transformative potential of alternative credit scoring despite its documented successes.

Data Privacy and Security Concerns

All three companies acknowledge significant challenges related to data privacy and the extensive collection of personal information required for their models. Upstart, for instance, collects consumer data with what it describes as "strict adherence to data privacy laws" and states that consumers give "explicit consent" for data collection [4]. However, this framework largely reflects compliance within the United States, where regulatory oversight—though improving—remains fragmented compared to global benchmarks. Public disclosures do not specify a precise number of data points used by Upstart's model; instead, the company notes that it draws on a broad range of variables such as education, employment and cash-flow history. This opacity raises concerns about the breadth and sensitivity of the data collected, particularly when it includes behavioural, educational and employment-related information.

A critical question is whether such practices align with international data protection regimes like the European Union's General Data Protection Regulation (GDPR), which mandates stricter rules around data minimization, user control, and the processing of sensitive information. For example, GDPR imposes rigorous standards on data subject rights (e.g., the right to erasure and portability), limitations on automated profiling, and obligations around cross-border data transfers—many of which are less developed in U.S. law [26]. Similarly, countries across Africa, Latin America, and Asia have adopted divergent and evolving standards under national laws [27]. These jurisdictional discrepancies raise questions about how scalable or transferable Upstart's data practices are in emerging markets, where regulatory environments may demand stronger consumer protections or impose different operational constraints. Companies operating globally must therefore navigate not just technological and credit risk, but also the geopolitical risk of compliance misalignment in an era of increasingly complex data governance.

Tala faces more complex privacy challenges due to its multi-jurisdictional operations. The company collects data from mobile phones, including text messages, call logs, and transaction history [25], across Kenya, the Philippines, Mexico, and India, regions with varying data protection laws and regulatory sophistication. While Tala requires users to explicitly consent to data use [25], the extensive nature of mobile data collection raises concerns about privacy violations and potential misuse of sensitive personal information.

Kaleidofin operates in India's evolving data protection landscape, using alternative data, including mobile phone usage, transaction history, and digital footprints through its 30+ million data point analysis system [24]. The company complies with Know Your Customer and Anti-

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

Money Laundering guidelines [28], but operates in a regulatory environment where comprehensive data protection frameworks are still developing, creating potential vulnerabilities for consumer privacy.

Algorithmic Fairness and Bias Challenges

Despite active efforts to address bias, all three companies acknowledge ongoing challenges with algorithmic fairness that could perpetuate or create new forms of discrimination. Upstart actively tests its artificial intelligence models for bias and implements measures to eliminate discriminatory outcomes [4], but the company's reliance on educational and employment data may inadvertently favor certain demographic groups. The use of behavioral data from online activity could systematically disadvantage populations with limited digital engagement or different online behavior patterns.

Tala "continuously audits its models to ensure fairness" and works to prevent "gender, income, or geographic biases" [25], but the company's reliance on mobile phone usage patterns and social behaviors may reflect socioeconomic disparities rather than creditworthiness. The challenge is particularly acute in emerging markets where mobile usage patterns may correlate with factors like education, income, or cultural background, potentially creating indirect discrimination.

Kaleidofin "regularly audits its artificial intelligence models to ensure equitable outcomes" [24], but faces the challenge that alternative data may not capture the full context of financial behavior in underserved communities. The company's focus on women and rural communities may help address some biases, but the use of digital footprints and spending patterns through 30+ million data points could disadvantage populations with limited digital literacy or different financial management practices [24].

Regulatory and Scalability Barriers

Regulatory complexity significantly constrains the scalability of alternative credit scoring models, particularly for international expansion. Upstart faces challenges when expanding into new markets due to regulatory differences and varying compliance requirements across different jurisdictions [4]. The company must navigate varying regulatory landscapes that can delay market entry and operational expansion, limiting its ability to serve global underserved populations.

Tala encounters "regulatory hurdles in emerging markets" that can delay scaling operations, especially in regions with less clear financial regulations [25]. The company operates across multiple countries with different regulatory frameworks, creating compliance complexity and

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

operational challenges. Additionally, Tala faces infrastructure limitations in target markets with "less developed financial infrastructures" [25] that constrain operational effectiveness.

Kaleidofin's expansion into Southeast Asia faces regulatory complexity as the company must adapt to different compliance requirements across emerging markets [24]. The company's focus on rural communities encounters infrastructure barriers where technological connectivity and digital literacy gaps affect adoption and scalability.

Infrastructure and Technology Dependencies

The effectiveness of alternative credit scoring models depends heavily on technological infrastructure that may be limited in underserved regions. All three companies require sophisticated technology infrastructure and depend on data availability and quality that may be constrained in rural or economically disadvantaged areas. Upstart's 92% automation rate [4] and Tala's 90% automated processing [25] demonstrate the technology dependence that may limit accessibility in regions with poor connectivity.

Digital literacy gaps affect adoption, particularly in Kaleidofin's target markets, where rural populations may lack familiarity with digital financial services. The cultural resistance to digital financial services represents an additional barrier that must be addressed through education and trust-building initiatives.

Regulatory Environment: Opportunities and Challenges

Table 2 Regulatory Environment and Compliance Challenges

Aspect	Upstart	Tala	Kaleidofin
Primary Jurisdiction	United States	Multi-jurisdictional	India
Regulatory Maturity	Established CFPB oversight	Varied across 4 markets	Developing RBI framework
Data Privacy Compliance	CCPA, state laws	Multiple national frameworks	Emerging Indian data protection

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

Expansion Challenges	Interstate compliance variation	Regulatory inconsistency	Regional infrastructure gaps
Consumer Protection	Established framework	Varied oversight quality	Evolving guidelines
Key Constraint	State-by-state requirements	Cross-border complexity	Infrastructure dependencies

Note. Regulatory analysis based on Upstart (2025), Tala (2022), and CGAP (2024).

The regulatory landscape presents both opportunities for innovation and significant challenges for scaling alternative credit scoring models. The analysis presented in Table 2 reveals varying approaches to regulatory oversight across different markets, with implications for model effectiveness and expansion.

Regulatory sandboxes and digital infrastructure provide opportunities for responsible innovation. Mujaddidi and Mehta [29] highlight how regulatory sandboxes facilitate innovation while ensuring consumer protection and market stability. By allowing startups to test new credit models, these sandboxes enable firms to develop scalable solutions without immediate, extensive regulatory compliance burdens. Digital public infrastructure, such as India's digital identity systems, facilitates data collection and risk assessment, ultimately leading to enhanced credit offerings for underserved communities [30].

However, the lack of consistent global regulations creates significant challenges. Onay and Öztürk [31] emphasize the regulatory challenges posed by extensive data usage in alternative credit models, noting that financial institutions must navigate complex regulations concerning data privacy and consumer rights. The evolving landscape necessitates exploration of how credit scoring systems can comply with established anti-discrimination laws and privacy regulations while remaining effective.

Data privacy and security concerns represent paramount regulatory challenges. Yan [32] discusses the implications of using sophisticated models that utilize personal data, noting that regulatory frameworks must adapt to safeguard consumer privacy while facilitating innovation in credit scoring methods. The balance is particularly delicate in developing markets where regulatory frameworks may be less robust, creating potential vulnerabilities for consumer protection.

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

Testing the Hypothesis: Comprehensive Assessment

The empirical evidence strongly supports both components of the study's hypothesis regarding alternative credit scoring models' impact on financial inclusion. The dual nature of the findings—simultaneously demonstrating remarkable success in expanding credit access while revealing fundamental constraints on equitable implementation—presents a nuanced picture of the current state and future potential of alternative credit scoring.

The data reveals a clear pattern across all three companies studied: alternative credit scoring models consistently outperform traditional systems in reaching previously excluded populations, yet each encounters similar structural barriers that prevent full realization of their inclusive potential. This pattern is not coincidental but rather reflects inherent tensions between the innovative capabilities of these models and the complex realities of global financial systems. The evidence suggests that while technological innovation in credit assessment has advanced significantly, as demonstrated by Hlongwane et al. [5] and Óskarsdóttir et al. [11], the regulatory, ethical, and infrastructural frameworks necessary to support these innovations have not evolved at the same pace, as noted by Onay and Öztürk [31] and Yan [32].

Furthermore, the strength of the evidence varies across different metrics and contexts. The quantitative improvements in approval rates and customer reach are unambiguous and substantial—with increases ranging from 20% to over 44% compared to traditional models [4], [24]. However, the qualitative aspects of inclusion, such as long-term borrower outcomes, sustainable financial improvement, and genuine economic empowerment, remain less clearly documented. This disparity in evidence quality itself supports the hypothesis that while alternative credit scoring achieves measurable expansion in credit access [23], [24], its effectiveness in creating equitable and sustainable financial inclusion faces significant limitations that require more comprehensive investigation and systemic solutions, as highlighted by multiple researchers [6], [22], [29].

Confirmed: Increased Credit Approval Rates

The quantitative data provide evidence that alternative credit scoring models improve approval rates for underserved populations. Upstart's AI-driven model approves 44.28 % more borrowers than a traditional model, and 28.8 % of its loans go to borrowers from low-to-moderate-income communities [4]. Kaleidofin reports that its credit models deliver 20–30 % higher approval rates than standard credit bureaus [24]. No comparable approval-rate statistic for Tala relative to banks was found in the available impact studies, so direct comparisons are not possible.

The scale of impact is significant. Upstart has partnered with more than 100 banks to provide over US $39 billion in loans to more than 3 million customers [4], while Tala's smartphone app

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

has been used by more than 7.5 million people [23] and Kaleidofin serves over 7.55 million customers [24]. Taken together, these figures indicate that the three companies collectively reach roughly 18 million borrowers, demonstrating substantial market impact.

Data from 60 Decibels reveal that 63 % of Tala borrowers were first-time digital loan users and 84 % reported improved quality of life, while Kaleidofin's clients are predominantly women (98 %) and 70 % were new to services like Kaleidofin's [24]. These metrics underscore targeted impact on excluded groups and positive borrower outcomes. Comprehensive default-rate data were not accessible across all three companies; thus claims about uniform 4–5 % default rates could not be verified and are omitted.

The analysis did not find accessible evidence supporting claims about Tala achieving 50 % higher approval rates or Upstart operating at near-breakeven. Where publicly available data were lacking, such assertions were removed.

Confirmed: Effectiveness Constrained by Predicted Limitations

The analysis equally confirms that effectiveness is significantly constrained by the hypothesized limiting factors. Data privacy constraints are evident across all three companies, which acknowledge extensive data collection requirements—from tens of thousands of mobile-phone data points for Tala to behavioural and transaction histories for Kaleidofin's more than 30 million clients—and face varying degrees of privacy regulatory complexity across their operating markets [25], [24]. Upstart does not publish a specific data-point count but uses a broad range of personal and financial attributes, raising parallel concerns about the sensitivity of the data being collected. Multi-jurisdictional operations particularly challenge Tala's ability to maintain consistent privacy standards across the four countries it serves [25].

Algorithmic fairness challenges are persistent, with each company reporting ongoing bias monitoring and mitigation efforts, confirming that algorithmic fairness represents a continuing challenge requiring continuous attention. The risk of reproducing historical biases or creating new forms of discrimination through alternative data usage remains a significant concern across all three models.

Regulatory barriers to expansion are explicitly acknowledged by all three companies, with international scaling identified as particularly challenging due to varying compliance requirements and less developed regulatory frameworks in target markets. Scalability limitations are documented through infrastructure dependencies, digital literacy gaps, and technology requirements that constrain the ability to reach all underserved populations, particularly in rural or economically disadvantaged regions with limited connectivity.

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

Implications and Recommendations

Policy Implications

The findings have significant implications for policymakers seeking to promote financial inclusion while protecting consumer rights. Regulatory frameworks should be developed to support responsible innovation in alternative credit scoring while maintaining appropriate consumer protections. This includes establishing clear guidelines for alternative data usage, implementing standardized fairness testing requirements, and creating regulatory sandboxes that allow controlled experimentation with new credit assessment methodologies.

International regulatory coordination is essential for scaling alternative credit scoring models across borders. Documented challenges with multi-jurisdictional compliance—particularly regarding divergent data protection laws, algorithmic transparency requirements, and consumer consent standards—suggest that a harmonized regulatory framework could significantly facilitate the broader deployment of these models. Such alignment would support more efficient cross-border implementation of financial inclusion initiatives while ensuring ethical data practices and equitable lending standards. Existing efforts, such as the United Nations Conference on Trade and Development (UNCTAD) initiative on global data privacy law disparities, highlight the importance of transparent benchmarking and intergovernmental collaboration in reconciling national privacy laws with global financial technology practices [27]. Similarly, the World Bank's Identification for Development (ID4D) program outlines best practices for data protection and privacy as part of broader digital identity and credit infrastructure systems [33]. These forums offer actionable blueprints for policymakers seeking to integrate privacy protection with credit innovation.

Complementing regulatory efforts, investment in digital infrastructure represents a foundational policy priority for scaling credit access. In many underserved regions, limited internet penetration, data availability, and digital literacy significantly hinder the effectiveness of algorithm-driven credit scoring tools. Government initiatives aimed at expanding broadband access, mobile device adoption, and consumer digital education can enhance the reach, equity, and predictive performance of alternative credit models. Without such infrastructure support, even the most advanced credit scoring technologies may fall short in addressing the very populations they aim to empower.

Investment in digital infrastructure represents a critical policy priority for unlocking the full potential of alternative credit scoring models in underserved and emerging markets. Documented infrastructure limitations—including poor connectivity, limited digital literacy, and weak identity verification systems—continue to constrain both the reach and efficacy of these models.

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

Government efforts to invest in broadband access, mobile-first service design, and digital upskilling can substantially improve the inclusivity and predictive accuracy of AI-driven lending systems.

A pivotal component of this broader infrastructure agenda is the advancement of Digital Public Infrastructure (DPI)—the foundational layers of digital identity, payments, and data exchange systems that enable secure, inclusive digital ecosystems. DPI not only underpins modern credit systems but also enables interoperable, privacy-preserving data flows across public and private sectors. Key coordination efforts in this space are gaining momentum. For instance, the United Nations Development Programme (UNDP) has called for global alignment around DPI principles such as open standards, interoperability, and ethical data governance as a means to scale digital inclusion and public services [34]. The Organisation for Economic Co-operation and Development (OECD) similarly emphasizes DPI's potential to serve as a public good, facilitating equitable access to digital financial services while safeguarding individual rights through accountable governance structures [35].

These initiatives underscore that building resilient credit infrastructures is not solely a private-sector challenge, but a multi-stakeholder undertaking that must be supported by robust policy frameworks and public investment. For alternative credit models to deliver on their promise of financial inclusion, they must be embedded in broader ecosystems where digital public infrastructure is prioritized as both a technical and social imperative.

Industry Recommendations

Financial institutions should implement comprehensive bias monitoring and mitigation strategies throughout the model development lifecycle rather than treating fairness as an afterthought. This includes regular algorithm auditing, diverse data representation, and ongoing fairness testing across different demographic groups.

Investment in digital infrastructure and financial literacy programs is crucial for maximizing the reach of alternative credit scoring models. The documented infrastructure limitations suggest that industry collaboration with governments and development organizations could help address connectivity and digital literacy barriers that constrain access in underserved regions.

The development of privacy-preserving analytics techniques represents a critical industry priority as alternative credit models increasingly rely on expansive and often sensitive datasets. Given the extensive data collection practices documented across all three companies—including the use of social, behavioral, and device-level data—ensuring that these processes uphold robust privacy protections is essential not only for regulatory compliance but also for maintaining consumer trust. Traditional data collection and modeling methods expose lenders to substantial privacy

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

risks, especially when applied in jurisdictions with strong data protection laws or in cross-border lending scenarios.

A growing body of work explores Privacy-Enhancing Technologies (PETs) as a solution to this tension between utility and privacy. Techniques such as federated learning, homomorphic encryption, differential privacy, and secure multi-party computation allow for machine learning models to be trained or operated on sensitive data without exposing the raw information itself [36]. These methods enable firms to derive insights or score applicants while retaining data minimization principles and reducing re-identification risks.

The OECD has recently highlighted the strategic importance of PETs in enabling privacy-by-design frameworks that align with evolving legal and ethical standards for AI systems [36]. Similarly, a 2024 white paper from the Information Systems Audit and Control Association (ISACA) outlines the operationalization of PETs within industries handling highly sensitive information, such as finance and healthcare. It emphasizes that integrating PETs requires not only technical innovation but also organizational governance, cross-functional coordination, and stakeholder education [37].

Given that alternative credit scoring models often rely on highly granular and potentially biased data inputs, PETs offer a compelling pathway to balance innovation with accountability. Financial institutions and fintech developers should view these technologies not as regulatory burdens, but as core architectural components of future-proof credit infrastructure.

Future Research Directions

Long-term impact studies are needed to understand whether improved credit access through alternative scoring translates into sustained financial inclusion and improved economic outcomes. Current research focuses primarily on approval rates and short-term impacts, but longer-term studies could provide insights into the true effectiveness of these models in promoting economic empowerment.

Comparative effectiveness research across different alternative data sources and methodological approaches could help identify best practices for optimizing alternative scoring model design for different contexts and populations. Cross-cultural algorithm development research could investigate methods for creating culturally adaptive credit scoring methodologies suitable for diverse markets.

Conclusion

This study provides compelling evidence that alternative credit scoring models, as exemplified by Upstart, Tala and Kaleidofin, can significantly expand access to credit for underserved

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

populations. Upstart's model approves 44.28 % more borrowers than a traditional model and channels 28.8 % of its loans to low-to-moderate-income communities [4]. Kaleidofin reports that its ki score delivers 20–30 % higher approval rates than standard credit bureaus [24], while comparable approval-rate statistics for Tala relative to banks were not available. In aggregate, the three companies reach roughly 18 million borrowers—more than 3 million through Upstart, over 7.5 million through Tala and over 7.55 million through Kaleidofin—demonstrating substantial scale in extending credit to previously excluded individuals [4], [23], [24]. Survey data from Tala's impact study provide empirical validation of positive customer outcomes, with 84 % of borrowers reporting improved quality of life and 88 % reporting improved ability to meet a major expense [23].

However, the research equally confirms that the effectiveness of these models in expanding equitable access to credit is constrained by significant limitations related to data privacy, algorithmic fairness and regulatory barriers. These constraints limit the scalability and universal application of alternative credit scoring across different markets and populations. Data privacy challenges are acute because the models rely on extensive and sensitive datasets: Tala's platform collects more than 10 000 mobile-phone data points per customer, and Kaleidofin's ki score is trained on data from more than 30 million unique customers [25], [24]. Upstart's disclosures do not specify a precise number of data points but acknowledge broad use of personal and financial attributes, raising similar privacy concerns. Algorithmic fairness concerns persist despite ongoing bias-monitoring efforts, and regulatory barriers create significant constraints on international expansion and scalability, particularly for multi-jurisdictional operations such as Tala's presence in four different geographical markets.

The findings suggest that while alternative credit scoring models represent a promising innovation for expanding financial inclusion, their transformative potential can only be fully realized through coordinated efforts to address underlying challenges. This requires developing comprehensive regulatory frameworks that balance innovation with consumer protection, implementing robust bias mitigation strategies, investing in digital infrastructure and literacy programs, and fostering international cooperation on regulatory standards.

As alternative credit scoring models continue to evolve, their success in creating more equitable and accessible financial systems will depend not only on their technical capabilities but also on the broader ecosystem of policies, regulations, and infrastructure investments that support their responsible implementation. The evidence from this study indicates that these models offer significant promise for democratizing credit access, but achieving this potential requires sustained commitment to addressing the systemic challenges that currently constrain their effectiveness.

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

The ultimate goal of financial inclusion—ensuring that all individuals have access to appropriate financial services that enable economic participation and empowerment—remains achievable through alternative credit scoring, but only if stakeholders work collaboratively to preserve its demonstrated benefits while addressing its full spectrum of limitations. These include both well-documented challenges—such as algorithmic bias, data privacy concerns, and regional disparities in model applicability—and less frequently acknowledged or undocumented issues, such as the absence of long-term borrower outcome data, insufficient transparency in model design, difficulties in cross-context model comparability, and the persistent risk of irreducible bias embedded in proxy variables. Many of these limitations remain under-researched, unregulated, or poorly defined in industry standards, hindering the full realization of inclusive credit systems. Bridging this gap requires a commitment not only to innovation, but to critical scrutiny, standardized evaluation, and cross-sectoral coordination to ensure these models advance both efficiency and equity in global financial systems.

Acknowledgements

This paper was prepared as part of an independent research project in collaboration with Professor Priya Nagraj from William Paterson University, Data Science Lead Daniel Alvarez, and mentorship from BlackRock Managing Director Abhinav Uttam.

Correspondence concerning this article should be addressed to Ruhaan Munjuluri, Email: ruhaanmunjuluri@gmail.com.

References

1. Abdallah, A. (2016). Does credit market inefficiency affect technology adoption? Evidence from sub-saharan africa. Agricultural Finance Review, 76(4), 494-511. https://doi.org/10.1108/afr-05-2016-0052

2. Abu, B., & Issahaku, H. (2017). Financial inclusion and agricultural commercialization in ghana: An empirical investigation. Agricultural Finance Review, 77(4), 524-544. https://doi.org/10.1108/afr-02-2017-0007

3. Sekyi, S., Abu, B., & Nkegbe, P. (2017). Farm credit access, credit constraint and productivity in ghana. Agricultural Finance Review, 77(4), 446-462. https://doi.org/10.1108/afr-10-2016-0078

4. Upstart.(2025). Upstart Q1 2025 earnings report. Upstart.

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

5. Hlongwane, R., Ramaboa, K., & Mongwe, W. (2024). Enhancing credit scoring accuracy with a comprehensive evaluation of alternative data. PLoS One, 19(5), e0303566. https://doi.org/10.1371/journal.pone.0303566

6. Aitken, R. (2017). 'All data is credit data': Constituting the unbanked. Competition & Change, 21(4), 274-300. https://doi.org/10.1177/1024529417712830

7. Lessmann, S., Baesens, B., Seow, H., & Thomas, L. (2015). Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research. European Journal of Operational Research, 247(1), 124-136. https://doi.org/10.1016/j.ejor.2015.05.030

8. Pandey, A., Kiran, R., & Sharma, R. (2022). Investigating the impact of financial inclusion drivers, financial literacy and financial initiatives in fostering sustainable growth in north india. Sustainability, 14(17), 11061. https://doi.org/10.3390/su141711061

9. Akinrotimi, A., Adeyemi, I., Oladoyin, O., & Olubunmi-Ajayi, T. (2024). Assessment of gender inclusion in credit utilization among farmers in ondo state, nigeria. Asian Journal of Advances in Agricultural Research, 24(11), 40-48. https://doi.org/10.9734/ajaar/2024/v24i11562

10. Addy, W., Ajayi-Nifise, A., Bello, B., Tula, S., Odeyemi, O., & Falaiye, T. (2024). AI in credit scoring: A comprehensive review of models and predictive analytics. Global Journal of Engineering and Technology Advances, 18(2), 118-129. https://doi.org/10.30574/gjeta.2024.18.2.0029

11. Óskarsdóttir, M., Bravo, C., Sarraute, C., Vanthienen, J., & Baesens, B. (2019). The value of big data for credit scoring: Enhancing financial inclusion using mobile phone data and social network analytics. Applied Soft Computing, 74, 26-39. https://doi.org/10.1016/j.asoc.2018.10.004

12. Djeundje, V., Crook, J., Calabrese, R., & Hamid, M. (2021). Enhancing credit scoring with alternative data. Expert Systems With Applications, 163, 113766. https://doi.org/10.1016/j.eswa.2020.113766

13. Barocas, S., & Selbst, A. D. (2016). Big data's disparate impact. California Law Review, 104(3), 671-732.

14. Ledford, C., Cantor, B., Sephton, N., & Tilly, C. (2020). The geography of unequal recovery. Federal Reserve Bank of San Francisco Community Development Research Brief.

15. Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. ACM Computing Surveys, 54(6), 1-35.

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

16. Blattner, L., & Nelson, S. (2021). How costly is noise? Data and disparities in consumer credit. arXiv preprint arXiv:2105.07554.

17. Kim, M. P., Ghorbani, A., & Zou, J. (2023). Multiaccuracy: Black-box post-processing for fairness in classification. Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency.

18. Binns, R. (2018). Fairness in machine learning: Lessons from political philosophy. Proceedings of Machine Learning Research, 81, 149-159.

19. Eubanks, V. (2017). Automating inequality: How high-tech tools profile, police, and punish the poor. St. Martin's Press.

20. Barocas, S., Hardt, M., & Narayanan, A. (2019). Fairness and machine learning: Limitations and opportunities. fairmlbook.org.

21. Fan, Z., & Zhang, R. (2017). Financial inclusion, entry barriers, and entrepreneurship: Evidence from china. Sustainability, 9(2), 203. https://doi.org/10.3390/su9020203

22. Adegoke, T., Ofodile, O., Ochuba, N., & Akinrinola, O. (2024). Evaluating the fairness of credit scoring models: A literature review on mortgage accessibility for under-reserved populations. GSC Advanced Research and Reviews, 18(3), 189-199. https://doi.org/10.30574/gscarr.2024.18.3.0104

23. 60 Decibels. (2022). Tala global impact study. 60 Decibels & Tala. https://tala.co/wp-content/uploads/2023/03/Impact-Report-2022.pdf

24. CGAP. (2024). Fintech and MSE resilience: Kaleidofin impact assessment. CGAP/60 Decibels. https://www.cgap.org/sites/default/files/publications/Focus%20Note_Fintech%20and%20MSE%20Resilience_Final.pdf

25. Tala. (2022). Tala financial inclusion report 2022. Tala. https://tala.co/wp-content/uploads/2023/03/Impact-Report-2022.pdf

26. DLA Piper. (2024). Data protection laws of the world. https://www.dlapiperdataprotection.com/

27. UNCTAD. (2024). Data protection and privacy legislation worldwide. https://unctad.org/page/data-protection-and-privacy-legislation-worldwide

ISSN: 2455-8834

Volume:10, Issue:08 "August 2025"

28. Kaleidofin. (2022). Kaleidofin privacy policy. Kaleidofin. https://www.kaleidofin.com/privacy-policy

29. Mujaddidi, M., & Mehta, A. (2024). Regulatory framework of p2p lending in india: Market stability and financial inclusion implications. International Journal of Management and Economics Invention, 10(06). https://doi.org/10.47191/ijmei/v10i6.01

30. Asiamah, T., Steel, W., & Ackah, C. (2021). Determinants of credit demand and credit constraints among households in ghana. Heliyon, 7(10), e08162. https://doi.org/10.1016/j.heliyon.2021.e08162

31. Onay, C., & Öztürk, E. (2018). A review of credit scoring research in the age of big data. Journal of Financial Regulation and Compliance, 26(3), 382-405. https://doi.org/10.1108/jfrc-06-2017-0054

32. Yan, J. (2024). How the use of alternative information in risk management fintech platforms influences sme lending: A qualitative case study. Qualitative Research in Financial Markets, 17(1), 1-20. https://doi.org/10.1108/qrfm-08-2023-0198

33. World Bank. (2024). ID4D data protection and privacy guide. https://id4d.worldbank.org/guide/data-protection-and-privacy-laws

34. UNDP. (2024). Digital public infrastructure. https://www.undp.org/digital/digital-public-infrastructure

35. OECD. (2024). Digital public infrastructure for digital governments. https://www.oecd.org/en/publications/digital-public-infrastructure-for-digital-governments_ff525dc8-en.html

36. OECD. (2024). Privacy-enhancing technologies. https://www.oecd.org/en/topics/sub-issues/privacy-enhancing-technologies.html

37. ISACA. (2024). Exploring practical considerations and applications for privacy-enhancing technologies. https://www.isaca.org/resources/white-papers/2024/exploring-practical-considerations-and-applications-for-privacy-enhancing-technologies

