Executive Summary

# Cracking the Credit Code: Alternative Data *and* AI for Financial Inclusion

MAY 2026

IFC International Finance Corporation
WORLD BANK GROUP

Photo: © Arne Hoel / World Bank

# Executive Summary

Traditional credit scoring systems often exclude women and underserved borrowers—especially those without formal financial histories or collateral—and this limits their access to credit and ability to grow their businesses and improve their livelihoods. Demand for financing among micro, small, and medium enterprises (MSMEs) far exceeds supply, especially among those run and led by women (WMSMEs), as shown in Figure A (IFC 2024, Findex 2025, FICO 2024).

In response, a new generation of credit scoring models powered by alternative data and artificial intelligence (AI) is redefining credit scoring for borrowers who lack formal credit histories. Yet, the benefits of this shift are uneven—women, informal workers, and microentrepreneurs remain underrepresented in credit portfolios.

FIGURE A

### How the financing gap disproportionally excludes women

**5.7 trillion**
The financing gap for MSMEs rose by $1.3 trillion from 2015 to 2019.

**1.9 trillion**
The financing gap for WMSMEs continues to widen.

**3 billion**
Men and women lacking adequate credit histories.

**1.3 billion**
Men and women without bank accounts.

Women are less likely to apply for credit.

More likely to have applications denied.

Receive smaller amounts or poorer loan terms.

This report aims to inform practitioners and policymakers about ways in which innovations in credit scoring can advance financial inclusion while ensuring fairness and protecting consumers. It was guided by three central issues:

1. **Market Trends:** How are alternative data and artificial intelligence used in credit scoring, particularly across emerging markets?
2. **Gender Inclusion:** To what extent do these models expand women's access to formal credit?
3. **Data and Model Design:** What types of data and modeling approaches underpin these systems, and how might they differ for women borrowers?

This analysis draws on interviews with more than 30 experts in fintech and credit scoring and a global mapping of 448 alternative-credit scoring firms, as detailed in Figure B. It also includes a literature review and borrower-and customer-level insights from the fintech companies Eshandi in Zambia and Vexi in Mexico. Combined, these capture diverse data use, business models, and regional operations, while highlighting emerging partnerships, regulatory developments, and challenges around fairness and transparency.

FIGURE B

Key dimensions used to map the credit scoring ecosystem

**Region of Operation**

**Business Models & Services**
Direct lending, embedded finance, credit scoring, and risk and loan management tools, for example.

**Inclusion**
Do firms refer to women, the underserved, or excluded borrowers in their vision or mission statement?

**Funding Stage & Recent Raises**

**Loan Types Supported**
Financing for MSMEs, personal loans, and buy now, pay later credit, for example.

**Gender Representation in Leadership**
Are founders or senior executives women?

**Alternative Data Types & Sources**
This covers data types, such as transaction patterns, and data sources, such as mobile wallets.

# Five Major Findings

## 1. Alternative credit scoring is expanding and evolving

**Alternative data-driven scoring models aim to broaden access to credit by going beyond traditional metrics such as repayment history and formal income documentation.** Instead, they draw on behavioral, transactional, and digital footprint data, ranging from utility bill payments to gig work records and telecommunication indicators, such as call frequency, recharging of airtime, and mobile money activity, as shown in Figure C.

FIGURE C

## Examples of alternative data

Call/ SMS metadata, app usage, operating system, geolocation


Digital transactions, utility payment, shopping behaviors

Social media connections, login methods, app usage

Artificial Intelligence plays a growing and varied role in these credit scoring models, as shown in Figure D. While some firms fully automate score generation using machine learning (ML), others limit AI to specific tasks such as transaction categorization or fraud detection, often due to regulatory, cost, or explainability constraints. The frontier is dynamic, and credit scoring is no longer a one-size-fits-all approach. It is becoming more modular, context-specific, and embedded into broader digital financial ecosystems.

FIGURE D

## Varying levels of sophistication in models that analyze data

**More analytical sophistication**

### Rule-based System

For example, in Uganda, the Grameen Foundation uses data from group savings ledgers and applies rule-based methods to assess eligibility.

### Hybrid

This includes machine learning-based classification combined with manual adjustments. For example, Manda in Argentina uses natural language processing methods to parse transactions into categories, then applies rule-based thresholds.

### Fully Automated

Fully automated pipelines include those used by Eshandi in Zambia that auto-approve nano loans if proprietary machine learning based scores from mobile money data are greater than 0.9.

**Together, these models enable visibility for women and other underserved borrowers**

Reduce discrimination in credit decision-making.

Offer new pathways for women and informal borrowers.

Increase consistency in driving data-based credit decisions.

## 2. Alternative scoring is taking off but growth is uneven across regions and market segments

**Most mapped fintech firms operate in Europe and North America, but significant traction is visible across East Asia and the Pacific, Africa, and South Asia.** Loan segments range from individuals borrowing $10 to $20 in emergency microcredit to full-fledged small and medium-sized enterprise (SME) financing of $50,000 or more.

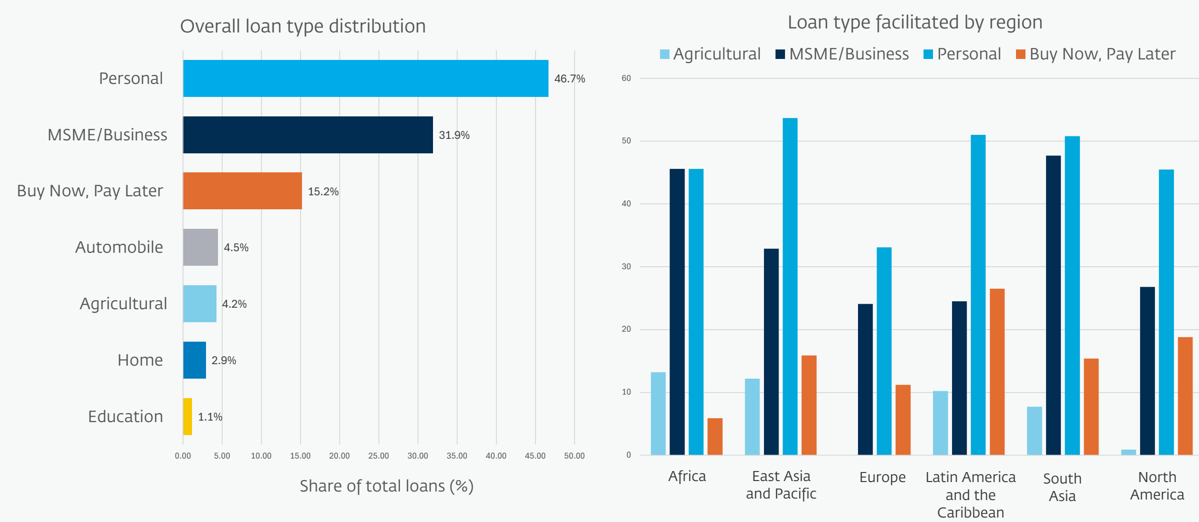
**Transaction data drive most alternative-credit models, with AI used selectively rather than end-to-end.** Transaction data—from mobile money, digital wallets, point-of-sale (POS) systems, and bank statements—is the most common input for non-traditional credit scoring models. In regions like Africa and South Asia, mobile money and digital wallet data are especially prevalent. Other examples of alternative data include utility payments, geolocation, device usage patterns such as phone metadata, and psychometric assessments. While most firms incorporate some form of AI or modeling sophistication—particularly to classify transactions or generate scores—fully autonomous models remain rare. Many providers continue to rely on rule-based or hybrid scoring approaches.

**Context is key—transaction data may seem traditional in one setting and 'alternative' in another.** The value lies in not only where data come from, but how they are processed, segmented, and deployed. Some firms rely on basic financial signals and reframe them through AI models to assess first-time borrowers. Others combine fragmented records and behavioral data into sophisticated scoring systems. Even relatively structured sources—such as bank statements or basic business records—can offer new insights to help evaluate borrowers with limited formal histories, thereby uncovering credit potential that conventional models often miss.

**Personal and MSME loans dominate the product mix among mapped lenders, with buy now, pay later and agri-lending emerging as niches.** As shown in Figure E, personal loans and MSME credit account for 47 percent and 32 percent of offerings, respectively. Just over one third of firms that develop their own credit scores also act as direct lenders, while 60 percent offer scoring and lending software to financial partners as part of a wider suite of products, such as fraud detection, loan management platforms, and financial advisory services.

FIGURE E

Loans offered by mapped fintechs, overall (left) and by region (right)

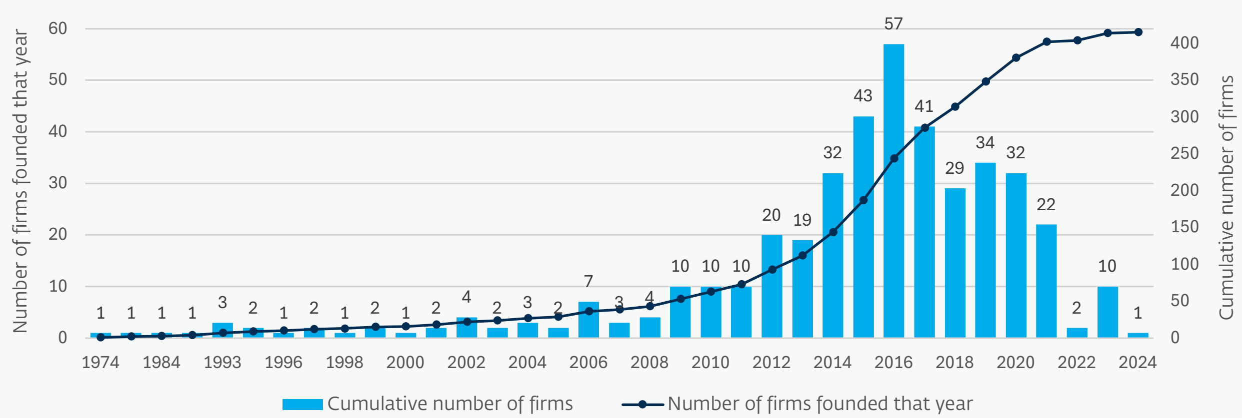



*Source: Firms mapped in alternative credit scoring landscape analysis. N=448 firms*
*Note: Firms can appear in multiple categories as classifications are not mutually exclusive.*

**The ecosystem is young and dynamic, with most mapped firms concentrated at early-venture stages.** As shown in Figure F, over 75 percent of mapped firms were founded in the last decade, and over 70 percent of funded firms raised capital in the three years prior to this report's publication. Series A–C is the most common funding stage. MSME lenders tend to attract more funding. Regionally, North America and Europe dominate mature and well-funded segments, while Africa has more unfunded firms.

FIGURE F

## Year in which mapped fintech firms were founded




*Source: N=415 mapped firms with available founding year data.*
*Note: Bars represent the share of newly-founded firms in that year. The dotted line reflects the total number of firms over time.*

**Alternative-credit scoring methods complement—but do not replace—traditional methods by helping borrowers gain access to greater amounts of credit.** Alternative data and AI-based scoring models increasingly serve as bridges rather than substitutes for traditional lending. For many first-time borrowers—especially women and informal workers—they offer a pathway into the formal credit system by lowering entry barriers and establishing a verifiable repayment history. For those already in the system, these models can help unlock higher loan amounts, better terms, or faster approval cycles by capturing additional indicators of reliability and cash flow. In doing so, they enable lenders to identify creditworthy borrowers who may have been previously overlooked—turning exclusion into opportunity and inclusion into growth.

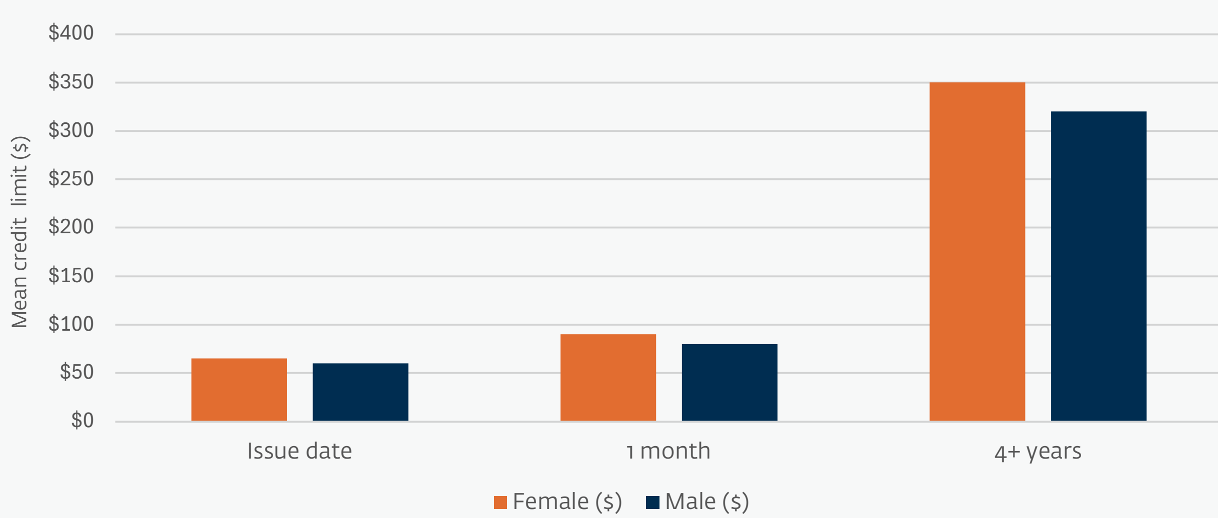
## 3. Gender-inclusive potential is real

**When designed and deployed inclusively, alternative data and AI-driven models can meaningfully expand women's access to credit.** This finding applied to almost every firm interviewed for this report as well as those highlighted in case studies. In many cases, women benefit when new data sources redefine what is considered 'creditworthy,' especially when these models capture cash flows or behavioral indicators that traditional systems overlook. Female borrowers are often overrepresented among successful repayment cases, receive better loan terms, and are already being reached at scale.

**Evidence from multiple markets shows women's reliable repayment habits and growing credit confidence.** In India, Kaleidofin has facilitated over seven million loans, largely to women. Eshandi, a fintech in Sub-Saharan Africa, has disbursed nearly one million loans to women. Borrower-level analysis of Eshandi's mobile money–based scoring model shows that women score slightly higher on machine learning–generated credit scores and are more likely to receive repeat loans, reflecting their consistent repayments and stable financial behavior. In Cameroon, Yellow Factoring reports higher repayment reliability and lower interest rates among women borrowers. In Mexico, survey data from digital credit card provider Vexi revealed that women use digital credit for business expenses more often than men and, over time, receive higher average credit limits, as shown in Figure G. This suggests that fintech-driven products can strengthen both access and confidence in using formal credit.

FIGURE G

### Mean credit card limit, by gender and tenure

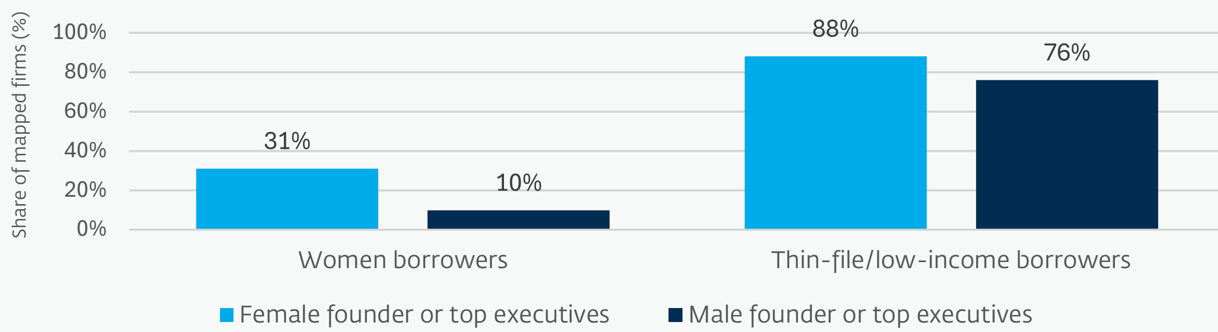



*Source: Customer survey data of over 3000 Vexi borrowers in Mexico*
*Note: $1=18.5 Mexican pesos*

**Despite reliable repayment habits and other outcomes, most models are gender-neutral by design—and inclusion gains are largely incidental.** Gender is rarely used as a predictive variable, and only 12 percent of firms publicly reference women on their website, in their outreach, mission or vision statement, or model framing, as shown in Figure H. While exclusion can sometimes stem from fairness concerns or lean model design, it also reflects missed opportunities. The outcomes suggest that well-designed inclusive scoring can be both effective and commercially viable.

FIGURE H

## Share of mapped firms that publicly reference women or low-income borrowers




*Source: Mapped firms' public communications. N=448 firms*
*Note: Thin-file borrowers have little or no formal credit history and include first-time borrowers, informal sector workers, and those without regular access to banking services.*


Photo: © Daniella Van Leggelo-Padilla / World Bank

## 4. Pathways for women's inclusion are emerging but they require intentional support

**While AI and alternative data can improve access for woman and underserved groups, they also introduce new risks of bias and exclusion.** Biases in training data—such as gaps in women's digital footprints, underrepresentation in credit histories, or the mismeasurement of informal income—can reinforce exclusion if left unaddressed. Proxy variables such as education level, geography, or device type may unintentionally entrench discrimination, even when gender is omitted from models. Explainability and fairness checks are therefore critical to ensure that algorithms expand access.

**Privacy and consent risks are particularly pronounced where women rely on shared phones, have limited digital literacy, or operate in environments with weak data-protection norms.** Without safeguards, models that depend on sensitive or behavioral data may expose women to harm, misclassification, or loss of agency over their information.

**Recent advances in gender-intentional design show that it can deliver both equity and commercial returns**. Fintechs such as Kaleidofin and Eshandi are beginning to test fairness metrics and sex-disaggregated reporting, and the results often reveal that women's repayment performance is as strong or stronger—even where data appear 'thin.' Centering gender in model design and oversight can help maximize benefits for both firms and consumers, but scaling inclusion will require coordinated action among firms, regulators, and data partners.

## 5. Partnerships and regulation are shaping growth

**Alternative credit scoring firms are partnering with banks, credit bureaus, mobile network operators, platforms, and others, to scale access, share risk, and legitimize new scoring approaches.** For example, dominant players like Equifax and TransUnion have acquired niche analytics providers, while banks and mobile operators are using data partnerships to develop embedded credit tools. In India, Kaleidofin has teamed up with established lenders like Federal Bank to scale microloans, while telecom players MTB in Uganda and Safaricom in Kenya have launched credit products using their own data. Still, collaboration remains uneven. During interviews, fintechs noted that traditional institutions, especially those that are larger or more risk-averse, have been slow to adopt or scale alternative models due to concerns ranging from regulatory compliance and data privacy to the opaque nature of AI-based scoring methods.

**Regulatory and operational challenges remain significant, and data privacy, explainability, and gaming risks must be addressed.** Rapid innovation in AI and data use brings its own risks. For example, while some alternative credit score providers partner with licensed lenders to share compliance burdens, others rebrand their tools as analytic services rather than credit scoring to sidestep regulatory scrutiny. Inconsistent data privacy rules, limited consumer consent mechanisms, and varying explainability requirements across markets constrain how models are built and deployed. Without adequate safeguards, model integrity and borrower trust can be undermined by opaque algorithms, unverified data sources, or potential 'gaming' of digital signals. These challenges underscore the need for clear guidance that balances innovation with consumer protection and responsible data use.

# Recommendations:
## Enabling Responsible Innovation and Inclusive Credit at Scale

Alternative data and AI-based credit models have proven potential to expand financial access—especially for women—but scaling them responsibly requires deliberate policy, partnerships, and design choices. Regulators, financial institutions, and industry actors are encouraged to tackle the following priorities:

**1. Create regulatory sandboxes and AI-testing environments to build confidence and oversight.** These regulator-supervised frameworks enable companies to test new algorithmic models in real world conditions—evaluating accuracy, loss estimation, and fairness before rolling them out in the open marketplace. Successful pilots in markets such as Kenya and the Philippines show that empirical evidence from sandboxes can accelerate adoption while also protecting consumers.

**2. Embed fairness testing and bias audits across model lifecycles.** Encourage all financial institutions and fintechs to embed fairness checks—such as approval-rate parity or model explainability benchmarks—into model development and retraining. These processes help detect hidden biases arising from proxy variables, such as location or education, that may disadvantage women or low-income borrowers.

**3. Encourage sex-disaggregated and intersectional reporting to inform and improve model design.** Encourage lenders and credit scorers to collect and report gender-disaggregated outcomes across the credit lifecycle, including applications, approvals, loan size, and repayments. Linking this data with other demographic factors such as geography or employment type can uncover structural barriers and support evidence-based interventions that strengthen fairness.

**4. Encourage traditional lenders to integrate alternative data responsibly and transparently.** Banks and credit bureaus could partner with fintech innovators to layer alternative data—such as transaction or mobile-money records—onto traditional scoring frameworks. Doing so can expand reach without compromising prudential standards, as long as explainability, consent, and audit trails are also in place.

**5. Promote cross-sector data partnerships to expand the visibility of underserved borrowers.** Data-rich entities—such as mobile network operators, utilities, and e-commerce platforms—can play a catalytic role by enabling data-sharing with users' consent through secure application programming interfaces (APIs) that allow different software applications to communicate with each other. Structured partnerships between fintechs, incumbents, and regulators can reveal data-rich but invisible borrower segments, especially women and informal entrepreneurs. Figure I illustrates how open-finance frameworks and responsible AI can enable more inclusive, consent-based credit ecosystems.

**6. Build consumers' digital credit skills and data-literacy to ensure inclusion translates into empowerment.** Complement financial innovation with user awareness programs on data rights, consent, and digital credit management, especially in low-trust or shared-device contexts where women face heightened risks from data misuse or over-indebtedness.

**7. Support open-finance frameworks that combine interoperability, access, and consent.** When paired with algorithmic learning, interoperable data-sharing systems can allow lenders to assess borrowers more holistically while preserving consent and privacy. Clarifying how sensitive attributes such as gender can be shared between platforms, lenders, and regulators—while balancing anti-discrimination rules and fairness-testing—is essential for sustainable and responsible innovation, and will enable AI to learn from more representative datasets.

**Copyright & Disclaimer**

The material in this work is copyrighted. Copying and/or transmitting portions or all of this work without permission may be a violation of applicable law. IFC does not guarantee the accuracy, reliability or completeness of the content included in this work, or for the conclusions or judgments described herein, and accepts no responsibility or liability for any omissions or errors (including, without limitation, typographical errors and technical errors) in the content whatsoever or for reliance thereon.

© International Finance Corporation 2026. Some rights reserved.
2121 Pennsylvania Avenue, N.W.
Washington, D.C. 20433
www.ifc.org

IFC International Finance Corporation WORLD BANK GROUP