

ARTICLE

LEVERAGING ARTIFICIAL INTELLIGENCE IN MICROFINANCE IN THE GLOBAL SOUTH:

REGULATORY INSIGHTS INTO AI-BASED CREDIT UNDERWRITING

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ABSTRACT

Microfinance has emerged as a key financial inclusion tool aimed at underserved populations, mainly in the Global South. However, it continues to face persistent structural challenges, particularly high operational costs, limited scalability, and mixed outcomes in poverty alleviation. Against this backdrop, this Article explores the integration of artificial intelligence (AI) into microfinance in the Global South, focusing on the use of machine learning for data-driven credit underwriting, which presents both a transformative opportunity and a profound regulatory challenge.

AI promises to enhance efficiency, accuracy, scalability, and financial inclusion, particularly through the use of alternative, non-financial data. At the same time, it introduces significant risks, including algorithmic bias, proxy discrimination, privacy violations, opacity in decision-making, and the erosion of accountability. These risks are especially acute in microfinance, where borrowers are often economically vulnerable, lack financial and digital literacy, and have limited recourse to legal protections.

This Article critically assesses the global regulatory landscape for AI, comparing comprehensive frameworks such as the European

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Union's and South Korea's AI Acts, with lighter or sectoral approaches in countries like the United States, the United Kingdom, Japan, and India. Acknowledging the practical and political limitations of adopting broad AI legislation in many developing jurisdictions, it argues for a sector-specific regulatory response.

This Article calls upon microfinance regulators to take the lead by imposing a set of minimum ethical principles on microfinance institutions. These principles include: respect for human rights, fairness, transparency, explainability, meaningful human oversight, privacy protection, and institutional accountability. Embedding these principles into supervisory frameworks, while tailoring them to the sector's unique context, may enable microfinance institutions to harness the transformative potential of AI while advancing their core mission of financial inclusion and social empowerment.

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I. INTRODUCTION

Microfinance has been heralded as a powerful tool for fostering financial inclusion and promoting economic development among underserved populations.¹ Originating in the 1970s with the pioneering work of the Grameen Bank and other early microfinance institutions (“MFIs”),² the sector has grown to encompass a wide array of financial services aimed at low-income individuals who lack access to traditional banking.³ However, despite its success in providing small loans, savings accounts, money remittance services, and insurance products to millions, the microfinance sector faces significant challenges, including high operational costs that often result in high-interest rates for

1. P.J. Christabell & Raj A. Vimal, *Financial Inclusion in Rural India: The Role of Microfinance as a Tool*, 2 J. HUM. & SOC. SCI. 21, 21 (2015); Chalil Krishnan, *Microfinance for Financial Inclusion and Women Empowerment*, 2 INT’L J. BUS. ECON. & MGMT. RES. 135, 135 (2011); Jayati Ghosh, *Microfinance and the Challenge of Financial Inclusion for Development*, 38 CAMBRIDGE J. ECON. 993, 993 (2014).

2. Milford Bateman, *The Rise and Fall of Muhammad Yunus and the Microcredit Model* 1 (Int’l Dev. Stud., Working Paper No. 001, 2014), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2385190 [<https://perma.cc/2PJ5-9EDP>].

3. Robert Cull & Jonathan Morduch, *Microfinance and Economic Development* 3 (World Bank Pol’y Rsch., Working Paper No. 8252, 2017), <https://documents1.worldbank.org/curated/en/107171511360386561/pdf/WPS8252.pdf> [<https://perma.cc/JXY9-XVWV>].

borrowers, inefficiencies, and limited scalability.⁴ Furthermore, the impact of microfinance on poverty alleviation and financial inclusion is debated.⁵

One of the most significant developments in the financial sector in recent years has been the introduction of artificial intelligence (“AI”). The integration of AI into finance has brought transformative changes to the industry. With its capacity to analyze vast datasets, identify patterns, and make complex automated decisions, AI holds considerable promises for financial services, including consumer lending and credit underwriting.⁶ Similarly, AI has the potential to play a transformative role in the microfinance sector.

AI integration within microfinance offers both opportunities and risks. While AI can enhance financial inclusion by improving risk assessment and expanding credit access to previously excluded populations,⁷ it also introduces significant challenges. These include algorithmic discrimination, opaque decision-making, data misuse, and the potential erosion of accountability.⁸ These risks are particularly acute in the microfinance context, where borrowers are often economically disadvantaged, lack financial and digital literacy, and operate in informal economies with limited recourse to legal or institutional protections.⁹

4. Milford Bateman & Ha-Joon Chang, *Microfinance and the Illusion of Development: From Hubris to Nemesis in Thirty Years*, 1 WORLD ECON. REV. 13, 13 (2012); Cull & Morduch, *supra* note 3, at 9–30; Sushama Sharma, *The Role of Microfinance in Empowering Women Entrepreneurs in Rural India*, 5 IJRAR 327, 333–35 (2018), <https://www.ijrar.org/papers/IJRAR19D5966.pdf> [<https://perma.cc/7DF6-QM4D>].

5. BEATRIZ ARMENDÁRIZ DE AGHION & JONATHAN MORDUCH, *THE ECONOMICS OF MICROFINANCE* (1st ed. 2005); Ingrid Harvold Kvangraven & Paulo L. Dos Santos, *Financial Inclusion and its Discontents*, PRIVATE DEBT PROJECT 1 (2016), <https://privatedebtproject.org/view-articles/financial-inclusion-and-its-discontents-16> [<https://perma.cc/FP44-J6T8>]; Bateman & Chang, *supra* note 4, at 13.

6. See Ashima Narang, Priyanka Vashisht & Shalini Bhaskar Bajaj, *Artificial Intelligence in Banking and Finance*, 12 INT’L J. INNOVATIVE RSCH. COMPUT. SCI. & TECH. 130, 130 (2024); R. Jesse McWaters, *The New Physics of Financial Services: Understanding How Artificial Intelligence is Transforming the Financial Ecosystem*, WORLD ECONOMIC FORUM 18 (Aug. 2018), <https://www.weforum.org/reports/the-new-physics-of-financial-services-how-artificial-intelligence-is-transforming-the-financial-ecosystem> [<https://perma.cc/H7W3-2DEW>].

7. See *infra* Part II.

8. See *infra* Part III.

9. See *infra* Part III.

The objective of this Article is to explore the appropriate regulatory framework for AI-driven microfinance underwriting. The analysis seeks to propose a model that accounts for the unique characteristics of the microfinance sector. The profound asymmetry between MFIs and their customers demands a regulatory response tailored to their specific vulnerabilities. At the same time, overly stringent regulation may hinder technological development and limit the sector's growth potential. The proposed framework aims to strike a careful balance between safeguarding consumer and human rights and fostering responsible innovation. By addressing these objectives, this study aims to contribute to the ongoing discourse on the role of technology in financial inclusion and to provide practical insights for policymakers, practitioners, and researchers in the field.

The Article proceeds as follows: Part II provides the background for the discussion, offering a concise overview of the current microfinance ecosystem. It addresses the successes in promoting financial inclusion and economic development, while also considering the challenges that microfinance still faces. The following two parts examine the promises and perils of employing AI in consumer credit underwriting, with particular attention to its application in microfinance. Part III explores the transformative potential of AI, while Part IV addresses the attendant risks and challenges.

Building on this analysis, Part V examines the appropriate regulatory framework for algorithmic credit underwriting in the microfinance sector. It addresses two central questions: First, whether such underwriting should be subject to regulation; and second, what form an effective and contextually appropriate regulatory approach should take. This Part further advances policy recommendations for regulators, proposing the imposition of a set of minimum ethical standards on MFIs, tailored to the specific vulnerabilities and needs of microfinance borrowers.

Part VI concludes by contending that harnessing AI's benefits in microfinance requires a tailored and proportionate regulatory framework, alongside the institutionalization of core ethical principles, robust consumer protection, and respect for human rights, in order to mitigate risks and ensure the responsible and inclusive deployment of this technology.

II. MICROFINANCE

Microfinance emerged in the late 20th century to address the lack of access to traditional banking services among low-income populations.¹⁰ The concept gained prominence through the work of Professor Muhammad Yunus and the establishment of the Grameen Bank in Bangladesh in 1976. Yunus's innovative approach involved providing small, collateral-free loans to impoverished entrepreneurs, particularly women, empowering them to start businesses and generate sustainable income.¹¹ The success of the Grameen Bank model inspired the establishment of numerous MFIs globally, tailored to their specific domestic markets.¹²

Over time, the scope of microfinance expanded to include other financial services such as savings, insurance, payments, and remittances.¹³ The early successes in Bangladesh and India demonstrated microfinance's potential to alleviate poverty and foster economic development, attracting support from international development organizations, governments, and private investors, further fueling its growth.¹⁴

Today, microfinance is a diverse and dynamic field encompassing a range of institutions, from small NGOs to large commercial banks. The global microfinance market size accounted for US\$239.09 billion in 2025, and is anticipated to hit around US\$266.13 billion in 2026 and up to US\$406.39 billion in 2030.¹⁵ In 2023, it served more than 142 million borrowers.¹⁶

10. See Christabell & Vimal, *supra* note 1 (examining credit exclusion in rural India and analyzing how microfinance can facilitate inclusion, as it is uniquely positioned in reaching out to the rural poor among low-income populations); Krishnan, *supra* note 1, at 137; Ghosh, *supra* note 1, at 1203–04.

11. See Bateman, *supra* note 2, at 2.

12. See *id.*; PATRICK MEAGHER, MICROFINANCE REGULATION IN DEVELOPING COUNTRIES: A COMPARATIVE REVIEW OF CURRENT PRACTICE (2002) (demonstrating how policymakers across different developing countries had to design unique microfinance regulatory frameworks tailored to their specific domestic markets).

13. Christabell & Vimal, *supra* note 1, at 34.

14. See Cull & Morduch, *supra* note 3, at 6–12; Bateman, *supra* note 2, at 5.

15. See THE BUSINESS RESEARCH COMPANY, MICROFINANCE MARKET REPORT 2026 (Mar. 2026), <https://www.thebusinessresearchcompany.com/report/microfinance-global-market-report> [<https://perma.cc/SGL8-NZRW>].

16. See IMPACT FINANCE BAROMETER 5 (4th ed. 2024), https://www.convergences.org/wp-content/uploads/2024/09/BFI-2024_VF1NAL_EN_compressed.pdf [<https://perma.cc/79EV-63N8>].

Microfinance landscapes vary by region. In Latin America and Africa, MFIs primarily serve mixed urban and rural populations, while in Asia they focus on rural areas.¹⁷ MFIs offer both group and individual loans, with group loans more common for larger loans.¹⁸ While microcredit is primarily intended for self-employment projects, loans are also provided for consumption, debt repayment, and other social needs.¹⁹ Despite differences in operational models, these institutions share the common goal of providing financial services to those excluded from traditional banking.

Microfinance is a regulated field in a vast majority of countries around the world. However, the way it is regulated can vary greatly. Most developing countries have some form of regulation for MFIs to ensure consumer protection, financial stability, and orderly growth of the sector.²⁰ As to developed countries, some have specific legislation on microcredit, while others regulate MFIs under existing laws governing financial institutions.²¹

In most countries, the primary regulator in charge of microfinance is the central bank.²² Some countries have established dedicated regulatory bodies specifically for

17. See Cecile Lapenu & Manfred Zeller, *Distribution, Growth, and Performance of the Microfinance Institutions in Africa, Asia, and Latin America: A Recent Inventory*, 26 SAVINGS & DEV. 87, 108 (2002).

18. See MARIA LEHNER, GROUP VERSUS INDIVIDUAL LENDING IN MICROFINANCE 2, 14 (Univ. Munich Discussion Paper No. 2008-24, 2008) (MFIs prefer group loans when the loan amount is large, when refinancing costs are high, or when competition is low).

19. See D. Nagayya & D.K. Rao, *Microfinance and Support Organisations in the Southern States of India*, 36 SMALL ENTERS. DEV. MGMT. & EXTENSION J. 1, 2 (2009).

20. See PATRICK MEAGHER, MICROFINANCE REGULATION IN DEVELOPING COUNTRIES: A COMPARATIVE REVIEW OF CURRENT PRACTICE, (IRIS Ctr., Univ. of Md. 2002), <https://www.findevgateway.org/sites/default/files/publications/files/mfg-en-paper-microfinance-regulation-in-developing-countries-a-comparative-review-of-current-practice-2002.pdf> [<https://perma.cc/86DP-NP83>].

21. See, e.g., EUR. COMM'N, THE REGULATION OF MICROCREDIT IN EUROPE (2007), <https://ec.europa.eu/docsroom/documents/3669/attachments/1/translations/en/renditions/pdf> [<https://perma.cc/338C-A54Z>].

22. See, e.g., CENTRAL BANK OF NIGERIA, GUIDELINES FOR THE REGULATION AND SUPERVISION OF MICROFINANCE BANKS IN NIGERIA (2020), <https://www.cbn.gov.ng/out/2020/fprd/mfb%20regulation%20draft%20merged.pdf> [<https://perma.cc/386P-GHFW>] (Nigeria); The Microfinance Act, 2006 (Act No. 19/2006) (Kenya), <https://www.centralbank.go.ke/wp-content/uploads/2016/08/Microfinance-Deposit-Taking-Microfinance-Institutions-Regulations.pdf> [<https://perma.cc/B9S7-BWZU>]; RESERVE BANK OF INDIA, REGULATORY FRAMEWORK FOR MICROFINANCE LOANS DIRECTIONS (2022), <https://fidcindia.org.in/wp-content/uploads/2022/03/RBI-MFI-MASTER-DIRECTIONS-14-03-22.pdf> [<https://perma.cc/U5SE-9DL5>] (India).

microfinance supervision.²³ Indonesia employs a multi-agency approach where the Financial Services Authority (OJK) is the primary supervisor of MFIs activities, working alongside Bank of Indonesia. The regulatory framework uses size and type of deposit-taking as main criteria for regulation and supervision.²⁴

Notwithstanding its successes, microfinance faces significant challenges. High operational costs are a major barrier. The expenses related to reaching remote customers, conducting due diligence, and maintaining personal interactions are substantial.²⁵ These costs often result in high-interest rates for borrowers, which can undermine the goal of poverty alleviation.²⁶

Scalability is another pressing issue. While some MFIs have achieved significant growth, many struggle to expand sustainably due to limited access to capital, regulatory constraints, and competition from other financial service providers.²⁷ The reliance

23. For example, in Bangladesh, the Microcredit Regulatory Authority (MRA) was established under the Microcredit Regulatory Authority Act of 2006. *See* MICROCREDIT REGULATORY AUTHORITY (2026), <https://mra.gov.bd/pages/static-pages/6922db5f933eb65569e09c20> [<https://perma.cc/UAF6-B6WZ>] (Bangladesh). In Uganda, the Microfinance Regulatory Authority (UMRA) was established in 2017 under the Tier 4 Microfinance Institutions and Money Lenders Act of 2016. *See* MINISTRY OF FIN., PLAN. AND ECON. DEV., UGANDA MICROFINANCE REGULATORY AUTHORITY (2026), <https://archive.finance.go.ug/content/uganda-microfinance-regulatory-authority> [<https://perma.cc/22P6-RZYH>] (Uganda).

24. *See* KPMG, NEW INDONESIAN “BRANCHLESS BANKING” AND MICROFINANCE LAWS—A CATALYST FOR MICROFINANCE GROWTH? 12 (2015), <https://assets.kpmg.com/content/dam/kpmg/pdf/2016/07/id-ksa-financial-inclusion-indonesia.pdf> [<https://perma.cc/V34Y-APBR>].

25. *See* Niels Hermes, Robert Lensink & Aljar Meesters, *Outreach and Efficiency of Microfinance Institutions*, 39 *WORLD DEV.* 938, 939 (2011); MD Hamid Uddin et al., *Why do Microfinance Institutions Charge Higher Interest Rates than Banks? The Role of Operating Costs*, 70 *FIN. RSCH. LETTERS* 1 (2024) (describing microfinancing as labor-intensive and therefore characterized by high operational costs inherent to the business model).

26. Uddin et al., *supra* note 25, at 2; Niels Hermes & Robert Lensink, *Microfinance: Its Impact Outreach and Sustainability*, 39 *WORLD DEV.* 875, 878 (2011). According to some estimates, the interest rates on some loans were as high as 195%. *See* Kvangraven & Dos Santos, *supra* note 5.

27. *See* Alfred Song, *Financial Sustainability of Microfinance Institutions in Sub-Saharan Africa: Challenges and Solutions*, 1 *RSCH. BEACON* J. 17 (2024) (examining the effects of access to capital, operational efficiency, regulatory constraints, and client repayment behaviors on the financial sustainability of MFIs); Hermes, Lensink & Meesters, *supra* note 25 at 948.

on donor funding and subsidies also raises questions about the long-term sustainability of many MFIs.²⁸

Customers' over-indebtedness has emerged as a critical concern. In some regions, the rapid expansion of microcredit has led to multiple borrowing, where customers take loans from several MFIs simultaneously, leading to unsustainable debt levels.²⁹ The lack of comprehensive credit information systems in many developing countries hampers effective risk assessment and management.³⁰

Moreover, the impact of microcredit on poverty alleviation is debated. While there are numerous success stories, some studies suggest that the benefits are not uniformly distributed and may not always lead to significant improvements in income or quality of life. Critics argue that without addressing broader structural issues such as education, healthcare, and infrastructure, microcredit alone cannot achieve substantial and lasting poverty reduction.³¹

The next part seeks to investigate whether artificial intelligence can address the challenges and difficulties outlined above and improve the microlending ecosystem.

28. See Jonathan Morduch, *Smart Subsidy for Sustainable Microfinance*, 6 FIN. FOR POOR 1, 8 (2005).

29. See Jessica Schicks, *Microfinance Over-Indebtedness: Understanding its Drivers and Challenging the Common Myths* (Centre Emile Bernheim, Université Libre de Bruxelles Working Paper No. 10/048, 2010), <https://www.findevgateway.org/sites/default/files/publications/files/mfg-en-paper-microfinance-over-indebtedness-understanding-its-drivers-and-challenging-the-common-myths-2010.pdf> [<https://perma.cc/2XZA-JESH>]; Jessica Schicks, *The Definition and Causes of Microfinance Over-Indebtedness: A Customer Protection Point of View*, 41 OXFORD DEV. STUD. 95, 95–116 (2013); Shahadat Hossain, *Is Commercialization of Microfinance Responsible for Over-Indebtedness? The Case of Andhra Pradesh Crisis*, 4 J. ECON. & SUSTAINABLE DEV. 142, 145–48 (2013).

30. See Jill E. Luoto, Craig McIntosh & Bruce Wydick, *Credit Information Systems in Less Developed Countries: A Test with Microfinance in Guatemala*, 55 ECON. DEV. & CULTURAL CHANGE 313, 314 (2007); Valerie Rozycki, *Credit Information Systems for Microfinance: A Foundation for Further Innovation* (Centre for Micro Finance Working Paper Series, 2006), https://www.ifmrlead.org/wp-content/uploads/2015/OWC/12_rozycki-foundation.pdf. Cf. Maayan Perel & Ruth Plato-Shinar, *AI-Based Consumer Credit Underwriting: The Role of a National Credit Database, in THE USE OF ARTIFICIAL INTELLIGENCE IN THE FINANCIAL SECTOR: OPPORTUNITIES AND REGULATORY CHALLENGES* 151 (Nydia Remolina & Aurelio Guerraz-Martinez eds., 2023).

31. ARMENDÁRIZ DE AGHION & MORDUCH, *supra* note 5, at 4; Kvangraven & Dos Santos, *supra* note 5, at 10; Bateman & Chang, *supra* note 4, at 5.

*III. AI-BASED CREDIT UNDERWRITING—
POTENTIAL ADVANTAGES
FOR MICROFINANCE*

A. AI-Based Credit Underwriting

AI encompasses a broad spectrum of technologies designed to emulate human cognitive functions, such as learning, problem-solving, making predictions based on data, and decision-making. At its core, AI involves the creation of algorithms and models that enable machines to perform tasks that typically require human intelligence.³²

The financial services sector has been at the forefront of AI adoption, leveraging these technologies to enhance efficiency, reduce costs, and improve decision-making processes. AI applications have significantly transformed the industry, offering new ways to process and analyze vast amounts of data swiftly and accurately.³³

One of the most significant breakthroughs in the application of AI in finance is in credit underwriting, namely, the decision-making process regarding the provision of credit to a customer.³⁴ A major component of credit underwriting is the assessment of the customer's credit risk (i.e., the likelihood of default). This assessment primarily relies on two types of information: negative information regarding the customer's non-compliance with his

32. See V. REILLON, EUROPEAN PARLIAMENT BRIEFING, UNDERSTANDING ARTIFICIAL INTELLIGENCE 1 (2018), [https://www.europarl.europa.eu/RegData/etudes/BRIE/2018/614654/EPRS_BRI\(2018\)614654_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/BRIE/2018/614654/EPRS_BRI(2018)614654_EN.pdf) [<https://perma.cc/F8G5-AGJW>]; Li Deng, *Artificial Intelligence in the Rising Wave of Deep Learning: The Historical Path and Future Outlook [Perspectives]*, 35 IEEE SIGNAL PROCESSING MAG. 172, 172 (2018).

33. See DOUGLAS W. ARNER ET AL., *Regulating Artificial Intelligence in Finance and Other Regulated Industries*, in THE USE OF ARTIFICIAL INTELLIGENCE IN THE FINANCIAL SECTOR: OPPORTUNITIES AND REGULATORY CHALLENGES 294 (Nydia Remolina & Aurelio Guerraz-Martinez eds., 2023); Cao Longbing, *AI IN FINANCE: A REVIEW* 1 (2020), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3647625 [<https://perma.cc/5MNU-4SRM>]; KPMG, *THE GENERATIVE AI ADVANTAGE IN FINANCIAL SERVICES* (2023), <https://kpmg.com/us/en/articles/2023/kpmg-generative-ai-consumer-financial-services-non-gated.html> [<https://perma.cc/Z33Q-LS4J>]; MCKINSEY & CO., *CAPTURING THE FULL VALUE OF GENERATIVE AI IN BANKING* (2023), <https://www.mckinsey.com/industries/financial-services/our-insights/capturing-the-full-value-of-generative-ai-in-banking> [<https://perma.cc/8QAQ-6QH5>].

34. See Nikita Aggarwal, *The Norms of Algorithmic Credit Scoring*, 80 CAMBRIDGE L. J. 42, 43 (2021).

financial obligations and positive information indicating compliance with such obligations.³⁵ The accuracy of credit risk assessments derives from the type and scope of data collected, analyzed and used by credit providers to make their predictions.³⁶

In recent years, lenders have increasingly deployed AI models to assess credit risk. These models process vast amounts of data from a wide array of sources, drawing not only on traditional financial records but also on alternative data, such as social media activity, smartphone usage, and web browsing behavior, which offer insights into borrowers' lifestyles and behavioral patterns.³⁷ AI systems further incorporate diverse formats of information, including images, audio files, videos, and data from smart devices using Internet of Things ("IoT") technology, to generate indicators of creditworthiness. In addition, psychometric and behavioral data, such as online interaction patterns, personality traits, and cognitive assessments, have also proven to be strong predictors of repayment ability.³⁸

The growing diversity of data sources has significantly enhanced the predictive power of AI-based underwriting models, enabling more accurate and individualized assessments of credit risk.³⁹ Indeed, the accuracy and efficiency of predictive models depends on the four V's of the input data: volume, variety, velocity, and veracity.⁴⁰ Lenders increasingly develop and refine algorithmic credit underwriting systems that rely on sophisticated

35. MICHAEL A. TURNER & ROBIN VARGHESE, THE ECONOMIC CONSEQUENCES OF CONSUMER CREDIT INFORMATION SHARING: EFFICIENCY, INCLUSION, AND PRIVACY 4 (Pol'y & Econ. Rsch. Council, 2010), [https://one.oecd.org/document/DSTI/ICCP/IE/REG\(2010\)3/en/pdf](https://one.oecd.org/document/DSTI/ICCP/IE/REG(2010)3/en/pdf) [<https://perma.cc/RJ74-N4QF>]; Amir E. Khandani et al., *Consumer Credit Risk Models via Machine Learning Algorithms*, 34 J. BANKING. & FIN. 2767, 2768, 2770 (2010).

36. TURNER & VARGHESE, *supra* note 35, at 6; Khandani et al., *supra* note 35, at 18.

37. Tobias Berg et al., *On the Rise of FinTechs: Credit Scoring Using Digital Footprints*, 33 REV. FIN. STUD. 2845, 2846 (2020); Daniel Björkegren & Darrell Grissen, *Behavior Revealed in Mobile Phone Usage Predicts Credit Repayment*, 34 WORLD BANK ECON. REV. 618, 625 (2020).

38. See Nizan Geslevich Packin & Yafit Lev-Aretz, *On Social Credit and the Right to be Unnetworked*, 2 COLUM. BUS. L. REV. 339, 360 (2016); Saul Fine, *Character Counts: Psychometric-Based Credit Scoring for Underbanked Consumers*, 17 J. OF RISK & FIN. MANAGEMENT 422 (2024) (demonstrating the efficacy of psychometric-based credit scores for predicting future loan defaults among underbanked consumers).

39. Berg et al., *supra* note 37, at 1845; Björkegren & Grissen, *supra* note 37, at 618; Aggarwal, *supra* note 34, at 46.

40. Donna Xu et al., *A Survey on Multi-Output Learning*, 31 IEEE TRANSACTIONS ON NEURAL NETWORKS & LEARNING SYS. 2409, 2409 (2019).

machine learning (“ML”) techniques capable of analyzing and processing large volumes of data.⁴¹

A similar transformative shift has recently become evident in microfinance. Traditional credit scoring models have relied heavily on limited and often outdated financial data, such as income statements, collateral, and credit history. These models pose significant limitations, especially for low-income individuals who lack formal financial documentation or have minimal credit histories, a phenomenon that has led to the exclusion of many potential borrowers from accessing financial services.

However, recently, MFIs have started to use AI-driven credit scoring models, leveraging alternative data sources and advanced analytical techniques.⁴² Their AI models process vast amounts of data from various non-traditional sources, such as mobile phone usage, social media activity, transaction histories, and even behavioral patterns. For instance, algorithms can identify patterns in mobile phone usage that correlate with financial behavior, such as call and text frequency, or mobile money transactions which are common in many developing countries.⁴³ By analyzing these data points, MFIs can perform a more comprehensive and accurate assessment of an individual’s creditworthiness.

B. Advantages of AI-Based Credit Underwriting

AI-based underwriting offers several advantages that may benefit MFIs, their borrowers, and the overall economy.

41. Hussein A. Abdou & John Pointon, *Credit Scoring Statistical Techniques and Evaluation Criteria: A Review of the Literature*, 18 INTELLIGENT SYS. ACCT. FIN. & MGMT. 1, 20 (2011).

42. HELOISA CANDELLO ET AL., MICROBANKING: BRINGING CREDIT TO UNDERREPRESENTED COMMUNITIES BY ENHANCING LOCAL FINANCIAL PRACTICES WITH AI, in REFRAMING DIVERSITY IN AI: REPRESENTATION, INCLUSION AND POWER (Achille Fokoue et al. eds., 2021), https://ceur-ws.org/Vol-2812/RDAI-2021_paper_8.pdf [<https://perma.cc/DF3D-SHRQ>]; Apostolos Ampountolas et al., *A Machine Learning Approach for Micro-Credit Scoring*, 9 RISKS 50, 51 (2019).

43. Allan Mugambi et al., *Mobile-Money Benefits and Usage: The Case of M-PESA*, 16 IT PRO. 16, 16–21 (2014).

1. Efficiency

The capabilities of AI make the process of consumer credit underwriting more efficient.⁴⁴ Empirical evidence provides ample support to this proposition. The application of algorithmic decision-making in credit scoring reduces both the cost and the time of acquiring the relevant data capable of assessing the consumer's creditworthiness. Big Data techniques extract, sort, and analyze the relevant data in a speedy manner, replacing the slow and costly process of meeting consumers in-person and documenting their financial information manually.⁴⁵

This efficiency gain is particularly important in microfinance, where loans are issued in small amounts and at high volumes; the low unit value of each loan makes manual underwriting economically unviable, while AI enables scalable, low-cost credit assessment. Additionally, borrowers in microfinance markets often lack formal documentation or credit histories, which further slows down traditional underwriting and increases administrative costs, challenges that AI systems can bypass by leveraging alternative data sources.

2. Accuracy

ML models significantly improve the accuracy of credit risk prediction compared to traditional logistic models.⁴⁶ Predictive analytics enables lenders to anticipate borrower behavior, assess default probability, and proactively manage risk.⁴⁷ These models identify unexpected correlations, such as links between mobile phone usage or online activity and creditworthiness, and adapt to local economic or behavioral changes.⁴⁸ ML also reduces the

44. Diederick van Thiel & W. Fred van Raaij, *Artificial Intelligence Credit Risk Prediction: An Empirical Study of Analytical Artificial Intelligence Tools for Credit Risk Prediction in a Digital Era*, 19 J. ACCT. & FIN. 150, 151–52 (2019).

45. Berg et al., *supra* note 37; Andreas Fuster et al., *Predictably Unequal? The Effects of Machine Learning on Credit Markets*, 77 J. FIN. 5, 7 (2022); Julapa Jagtiani & Catharine Lemieux, *The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the Lending Club Consumer Platform 1* (Fed. Rsrv. Bank of Phila., Working Paper No. 18-15, 2018), <https://ssrn.com/abstract=3178461> [<https://perma.cc/36WF-2W8G>].

46. Fuster et al., *supra* note 45, at 9; Jagtiani & Lemieux, *supra* note 45.

47. Liran Einav et al., *The Impact of Credit Scoring on Consumer Lending*, 44 RAND J. ECON. 249, 250 (2013).

48. Berg et al., *supra* note 37; Aggarwal, *supra* note 34.

relative weight of any single data point by processing vast datasets, thereby lowering the margin of error.⁴⁹

This enhanced accuracy is especially important in microfinance, where borrowers often lack comprehensive financial records and exhibit diverse, non-standard financial behaviors. In such contexts, AI's ability to analyze large, varied datasets and detect subtle patterns leads to more reliable credit risk assessments than traditional methods.

3. Scalability

As discussed in Part II, the high operational costs and scalability challenges of microfinance give rise to concerns about the long-term sustainability of many MFIs. AI technologies can help lenders scale their lending operations more effectively by automating various processes and reducing the need for manual intervention.⁵⁰ Sophisticated automation not only enhances efficiency but also allows lenders to serve a larger number of customers without compromising on quality or accuracy. This scalability is crucial for lenders aiming to expand their reach and impact.

In addition, advanced analytics tools can analyze loan portfolios, customer behavior, and market trends in real time, enabling lenders to optimize their strategies, identify growth opportunities, and address challenges proactively.⁵¹ By harnessing the power of data and AI-driven insights, lenders can enhance their competitiveness and adaptability in a rapidly evolving financial landscape.⁵²

49. Aggarwal, *supra* note 34.

50. Aditya Arora, *AI-Driven Revolution in Credit Underwriting: Technical Implementation and Impact Analysis*, 23 *GLOB. J. ENG'G & TECH. ADVANCES* 403, 408 (2025).

51. Atharva Tripathi, *Data-Driven Predictive Analytics for Loan Portfolio Management: Proactive Decision-Making*, 13 *INT'L J. CREATIVE RSCH. THOUGHTS* 916 (2025) (demonstrating how data-driven predictive analytics can enhance the effectiveness of loan portfolio management).

52. Chunxiao Li et al., *The Effect of AI-Enabled Credit Scoring on Financial Inclusion: Evidence from One Million Underserved Population*, 48 *MIS Q.* 1, 3–4 (2024); Ranjit Bose, *Advanced Analytics: Opportunities and Challenges*, 109 *INDUS. MGMT. & DATA SYS.* 155, 156 (2009).

4. Financial Inclusion

The use of AI for credit underwriting may expand credit eligibility and increase financial inclusion. Several studies have shown that the rise of AI models that analyze alternative (non-financial) data to predict creditworthiness assists underserved populations.⁵³ Certain segments of the population, particularly those from low-income, less-educated, and ethnic minority backgrounds, have historically suffered from disproportionately low credit scores, not due to an inherent inability to repay, but because of limited or non-existent credit histories.⁵⁴ This structural disadvantage, often manifesting as “thin-file” or “credit invisible” status, restricts access to mainstream lending. The integration of non-financial or alternative data into credit underwriting processes offers a potential remedy, enabling more accurate assessments of creditworthiness. By leveraging such data, lenders may expand credit eligibility and extend financial services to individuals who are otherwise excluded from the credit system.⁵⁵ Indeed, in 2019, the American Consumer Financial Protection Bureau (“CFPB”) found that the application of ML to alternative data resulted in a rise of 27 percent in credit approval rates.⁵⁶

The potential of AI systems to enhance financial inclusion is particularly significant in microfinance, which inherently targets underserved populations who struggle to access financial services within the traditional system. Furthermore, algorithmic decision-

53. COMM. ON GLOB. FIN. SYS. & FIN. STABILITY BD., *FINTECH CREDIT: MARKET STRUCTURE BUSINESS MODELS AND FINANCIAL STABILITY IMPLICATIONS* 3–6 (2017), <https://www.fsb.org/wp-content/uploads/CGFS-FSB-Report-on-FinTech-Credit.pdf>, [<https://perma.cc/W28C-LZVT>]; Marco Di Maggio et al., *Invisible Primes: Fintech Lending with Alternative Data*, (Harv. Bus. Sch., Working Paper 22-024, 2021), https://www.hbs.edu/ris/Publication%20Files/22-024_80dc9115-69cc-4564-99c6-3a937f275d31.pdf [<https://perma.cc/9YWM-KVA5>].

54. OMAR KHAN, *FINANCIAL INCLUSION AND ETHNICITY: AN AGENDA FOR RESEARCH AND POLICY ACTION* 13 (2008).

55. MICHAEL A. TURNER ET AL., *A NEW PATHWAY TO FINANCIAL INCLUSION: ALTERNATIVE DATA, CREDIT BUILDING, AND RESPONSIBLE LENDING IN THE WAKE OF THE GREAT RECESSION* 12 (Pol’y & Econ. Rsch. Council, 2012), <https://www.perc.net/wp-content/uploads/2013/09/WEB-file-ADI5-layout1.pdf> [<https://perma.cc/D9U7-D6BD>].

56. Patrice Alexander Ficklin & Paul Watkins, *An Update on Credit Access and the Bureau’s First No-Action Letter*, CONSUMER FIN. PROT. BUREAU BLOG (Aug. 6, 2019), <https://www.consumerfinance.gov/about-us/blog/update-credit-access-and-no-action-letter/> [<https://perma.cc/U93M-QSJL>].

making may mitigate human bias and taste-based discrimination, as models are typically blind to protected personal attributes.⁵⁷

Besides advantages related to the underwriting process itself, AI also offers additional benefits concerning the loan provision process and its ongoing management, as will be detailed in the next sections.

5. Streamlining Customer Onboarding

Onboarding refers to the process by which new users are introduced to the platform and become verified customers. Onboarding encompasses compliance measures such as anti-money laundering (“AML”) checks, Know Your Customer (“KYC”) procedures, and sanctions screening. It also requires obtaining the customer’s consent to the platform’s terms and conditions and privacy policy, as well as setting up the user’s account preferences such as notification settings and security options.⁵⁸

Onboarding can be labor-intensive, time-consuming, and prone to errors, especially in regions with limited infrastructure and documentation. However, AI technologies can significantly streamline the onboarding process. Natural Language Processing (“NLP”) algorithms can automate AML and KYC processes by extracting and analyzing information from documents, reducing the need for manual data entry and verification, thus enhancing accuracy.⁵⁹ Moreover, biometric verification, such as facial or voice recognition and fingerprint scanning, allows for quick and accurate identification of clients avoiding the need for any document.

The seamless and user-friendly experience for customers may encourage more individuals to engage with microfinance services. Biometric verification and AI-driven processes enable lenders to

57. Shannen Balogh & Carter Johnson, *AI Can Help Reduce Inequity in Credit Access But Banks Will Have to Trade off Fairness for Accuracy—For Now*, BUS. INSIDER (June 30, 2021), <https://www.businessinsider.com/ai-lending-risks-opportunities-credit-decisioning-data-inequity-2021-6> [https://perma.cc/5U4B-T97P]; Robert Bartlett et al., *Consumer Lending Discrimination in the Fintech Era*, 143 J. FIN. ECON. 30, 31 (2022).

58. Samantha Rohn, *CX in Banking: How to Guide Customers & Eliminate Friction*, WHATFIX BLOG (Jan. 8, 2026), <https://whatfix.com/blog/customer-experience-in-banking/> [https://perma.cc/AX58-2RBH].

59. Miren Karmele García et al., *Digital Onboarding in Finance: A Novel Model and Related Cybersecurity Risks*, 1 OPEN RSCH. EUR. 149, 153 (2022), <https://open-research-europe.ec.europa.eu/articles/1-149> [https://perma.cc/BYL2-LSV3].

onboard clients in remote locations that otherwise would not have been able to join, thus enhancing financial inclusion.⁶⁰

The use of AI in customer onboarding also minimizes the risk of fraud by enabling real-time analysis of transaction data to identify suspicious activities and anomalous patterns.⁶¹ Swift fraud detection helps minimize financial losses that can disproportionately impact MFIs, strengthening the overall integrity and stability of the microfinance sector.

6. Personalized Services and Customer Interaction

AI is a key player in the new trend of personalized services, analyzing customer behavior, preferences, and needs to enable lenders to offer customized loans.⁶²

The primary goal for lenders in adopting personalization is to increase profits, retain customers, attract new clients, and improve competitiveness. However, personalization also offers significant advantages to customers: personalization enables the tailoring of communication methods (including language and local dialect), the level of explanation and guidance, and the manner of performing digital actions to each individual customer. It allows for the sending of personal alerts, such as reminders for loan repayment dates, and offers individual value propositions—products or services adapted to their personal circumstances. This is particularly relevant in microfinance, where borrowers often come from diverse linguistic and cultural backgrounds and face unique financial challenges, making personalized communication and

60. Vijay Thokal & Purushottam R. Patil, *Review and Analysis of the Literature: Artificial Intelligence-Based Digital Transformation of Automated Customer Onboarding*, 59 ENG'G PROCS. 234, 240 (2023).

61. Aakash Chotrani et al., *AI in Fraud Detection: Evaluating the Efficacy of Artificial Intelligence in Preventing Financial Misconduct*, 20 J. ELEC. SYST. 1332, 1335 (2024); Philip O. Shoetan & Babajide Tolulope Familoni, *Transforming Fintech Fraud Detection with Advanced Artificial Intelligence Algorithms*, 6 FIN. & ACCT. RSCH. J. 602, 603 (2024); Shubham Singh Kirar et al., *Role of AI in Financial Industry to Detect and Prevent Fraud*, 8 INT'L J. SCI. RSCH. ENG'G & MGMT. 1, 2 (2024); Narang, Vashisht & Bajaj, *supra* note 6, at 131–32.

62. DELOITTE, *THE FUTURE OF RETAIL BANKING: THE HYPER-PERSONALISATION IMPERATIVE* 4 (2020), <https://www.deloitte.com/uk/en/Industries/financial-services/research/hp-future-of-retail-banking.html> [<https://perma.cc/22HR-2J33>]; RAFAL CEGIELA ET AL., *JUST FOR YOU: THE ROUTE TO HYPER-PERSONALIZATION IN BANKING* 4 (Boston Consulting Grp., 2022), <https://media-publications.bcg.com/Just-For-You-The-Route-to-Hyper-personalization-in-Banking.pdf> [<https://perma.cc/JPT6-DGH5>]; Narang, Vashisht & Bajaj, *supra* note 6, at 131.

tailored financial solutions essential for effective engagement and repayment.

AI also enhances the efficiency and effectiveness of handling customer complaints. AI systems can categorize and prioritize issues, provide automated responses through chatbots, and escalate complex cases to human agents with full context.⁶³ Additionally, AI tracks complaint resolution timelines and analyzes trends to identify recurring problems, enabling continuous improvement in service quality and customer satisfaction.⁶⁴

Finally, AI may contribute to improving financial literacy among customers. AI-driven platforms can offer personalized financial advice, educational resources, and budgeting tools, helping borrowers make informed financial decisions and avoid over-indebtedness. These tools may lead to better financial management and improved economic outcomes.⁶⁵

In summary, by leveraging AI, MFIs can enhance their services, expand their reach, and contribute to the broader goal of financial inclusion and economic development. By providing access to credit and other financial services, AI-powered microfinance empowers clients to pursue entrepreneurial activities, improve their livelihoods, and achieve financial independence.

IV. AI-BASED CREDIT UNDERWRITING — CHALLENGES FOR MICROFINANCE

Notwithstanding the significant opportunities AI presents for microfinance, it also raises serious fundamental rights concerns, which are especially troubling given the vulnerability of the microfinance population.

A. Bias and Discrimination

A significant concern with AI models is their susceptibility to biases, which may result in discriminatory practices, perpetuating

63. See Lingli Wang et al., *Voice-based AI in Call Center Customer Service: A Natural Field Experiment*, 32 *PROD. & OPERATIONS MGMT.* 1002, 1002–18 (2023).

64. See J. Aruna et al., *Intelligent Complaint Tracker*, 7 *INT'L J. MULTIDISC. RSCH.* 1, 3–5 (2025).

65. Nitin Kulshrestha et al., *AI Based Enhancing Financial Literacy and Personal Investment Decisions*, 2 *ADVANCES IN CONSUMER RSCH.* 2214, 2223 (2025).

existing inequalities, and excluding vulnerable populations from accessing financial services. Even if the raw data used for developing and training the model does not involve the deliberate use of prohibited criteria (such as race, color, or gender), bias may nevertheless occur, resulting in discriminatory outcomes.⁶⁶ Indeed, several studies that focused on algorithmic credit scoring have indicated discriminatory results in relation to ethnic minorities,⁶⁷ women,⁶⁸ and the LGBTQ community.⁶⁹ Discrimination may manifest not only in the decision to grant credit per se, but also in its pricing, namely the applicable interest rate.⁷⁰

This phenomenon of indirect discrimination—or disparate impact—in credit underwriting may occur for various reasons. First, historical data used to develop and train AI models may reflect societal biases or socioeconomic disparities. If these biases are not addressed, the AI systems will perpetuate them, resulting in discriminatory outcomes.⁷¹ For instance, in the United States, African American and Hispanic people have historically faced discrimination and difficulties in obtaining loans from banks, often leading them to take subprime loans with high-interest rates,

66. Katja Langenbucher, *Responsible AI-Based Credit Scoring—A Legal Framework*, 31 EUR. BUS. L. REV. 527, 549, 553–55 (2020); Katja Langenbucher & Patrick Corcoran, *Responsible AI Credit Scoring—A Lesson from Upstart.com*, in DIGITAL FINANCE IN EUROPE: LAW REGULATION AND GOVERNANCE 141, 151–52, 163–64 (Heikki Marjosola & Emiliós Avgouleas eds., 2021); Salon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CALIF. L. REV. 671, 677–93 (2016); Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 4, 13–14 (2014); Talia B. Gillis, *The Input Fallacy*, 106 MINN. L. REV. 1175, 1177–84, 1192–94, 1213–17 (2022).

67. Will Douglas Heaven, *Bias isn't the Only Problem with Credit Scores—And No AI Can't Help*, MIT TECH. REV. (June 17, 2021), <https://www.technologyreview.com/2021/06/17/1026519/racial-bias-noisy-data-credit-scores-mortgage-loans-fairness-machine-learning> [<https://perma.cc/QB2T-ZUVL>]; Fuster *et al.*, *supra* note 45, at 9–10.

68. *Generated Credit Scoring Increases Women's Chance of Credit Acceptance*, FINEXTRA (Nov. 21, 2019), <https://www.finextra.com/newsarticle/34750/gendered-credit-scoring-increases-womens-chance-of-credit-acceptance> [<https://perma.cc/XV2U-GC7Z>].

69. Cyrus Mostaghim, *Constructing the Yellow Brick Road: Preventing Discrimination in Financial Services Against the LGBTQ+ Community*, 11 MICH. BUS. & ENTREPRENEURIAL L. REV. 63, 108–13 (2021).

70. Talia B. Gillis, “Price Discrimination” Discrimination, 15 HARV. BUS. L. REV. 99, 103–04, 123–24 (2025).

71. Amy J. Schmitz, *Secret Consumer Scores and Segmentations: Separating Consumer ‘Haves’ from ‘Have-Nots’*, 2014 MICH. ST. L. REV. 1411, 1411–12 (2014); Sandra G. Mayson, *Bias In Bias Out*, 128 YALE L.J. 2218, 2218–24 (2019).

resulting in elevated default rates. An underwriting model that incorporates subprime loans as a negative factor impacting credit scores essentially perpetuates this historical discrimination.⁷²

Second, certain raw data which seems neutral, may yet serve as an indicator for prohibited criteria—a phenomenon referred to in the literature as “proxy discrimination.”⁷³ For example, by focusing on a customer’s residential address, the algorithm can infer whether the customer belongs to an ethnic minority group who tends to reside in certain areas. Another proxy is the number of years of education, which is ostensibly used to assess the borrower’s earning capacity, but in practice reflects their socioeconomic status.⁷⁴

Third, the way in which the input is analyzed and processed may influence outcomes, as different machine learning methods may either mitigate or exacerbate the risk of statistical discrimination.⁷⁵

The risk of bias and discrimination is particularly severe in microfinance, where lending decisions affect disadvantaged, demographically diverse populations. For instance, if an AI-driven credit scoring model is biased against a particular ethnic group, individuals from that group may be unfairly denied loans or offered less favorable terms. This can exacerbate financial exclusion and hinder economic development efforts.

72. LISA RICE & DEIDRE SWESNIK, DISCRIMINATORY EFFECTS OF CREDIT SCORING, NAT’L FAIR HOUS. ALL. (2012), <https://nationalfairhousing.org/wp-content/uploads/2017/04/NFHA-credit-scoring-paper-for-Suffolk-NCLC-symposium-submitted-to-Suffolk-Law.pdf> [<https://perma.cc/JP4Y-WLU7>].

73. Dominique Williams, *Problem Solved?: Is the Fintech Era Uprooting Decades Long Discriminatory Lending Practices?*, 23 TUL. J. TECH. & INTELL. PROP. 159, 174–75 (2021); Anya E.R. Prince & Daniel Schwartz, *Proxy Discrimination in the Age of Artificial Intelligence*, 105 IOWA L. REV. 1257, 1260–61 (2020); Gillis, *supra* note 66, at 1200, 1225, 1232–33.

74. Aryn Bussey, *Educational Redlining? The Use of Education Data in Underwriting Could Leave HBCU and MSI Graduates in the Dark*, PROTECT BORROWERS (July 24, 2019), <https://protectborrowers.org/educational-redlining-the-use-of-education-data-in-underwriting-could-leave-hbcu-and-msi-graduates-in-the-dark> [<https://perma.cc/5F84-BLES>].

75. Michael Veale & Reuben Binns, *Fairer Machine Learning in the Real World: Mitigating Discrimination Without Collecting Sensitive Data*, 4(2) BIG DATA & SOC’Y 1, 1–5, 12 (2017), <https://arxiv.org/abs/1610.08452> [<https://perma.cc/SQ4H-VW3F>]; Muhammad Bilal Zefar et al., *Fairness Beyond Disparate Treatment & Disparate Impact: Learning Classification Without Disparate Mistreatment*, PROC. 26TH INT’L WORLD WIDE WEB CONF. 1171, 1171–74 (2017), <https://arxiv.org/abs/1610.08452> [<https://perma.cc/B2Z5-Q5EP>].

B. Violation of Privacy

As was mentioned in Part III, modern AI credit underwriting systems collect and analyze vast amounts of personal data, far beyond traditional financial metrics. In microfinance contexts, this may include alternative data such as social media activity, online shopping behavior, utility payments, mobile phone usage patterns, and location data;⁷⁶ biometric information used for identity verification;⁷⁷ and behavioral analytics such as digital footprints from website registrations, app usage, and online engagement patterns.⁷⁸ All of these practices may result in the continuous monitoring of personal behaviors well beyond financial transactions, leading to surveillance creep.

The collection of such extensive datasets raises fundamental privacy concerns, particularly for vulnerable microfinance populations with limited digital literacy who may not fully understand data collection practices and their implications. Microfinance customers often lack the technical knowledge to understand complex consent mechanisms, leading to situations where personal information is gathered and used for purposes beyond the original loan application. Social media data, for instance, is typically not originally collected with credit reporting in mind, yet it frequently ends up being used by credit reporting service providers without explicit consent.⁷⁹

Because of power imbalances, borrowers may feel pressured to accept privacy-invasive terms they would otherwise reject due

76. Anastasiya Shitikova, *How to Boost Predictive Power Using Digital Footprints*, RISKSEAL (Aug. 6, 2024), <https://riskseal.io/blog/how-to-improve-credit-scoring-using-digital-footprints> [https://perma.cc/L5KM-9H2Y].

77. *Financial Data Consent Trends: Biometric Data and Dynamic Permissions in 2025*, SECURE PRIV. (Apr. 5, 2025), <https://secureprivacy.ai/blog/financial-data-consent-trends-biometric-data-dynamic-permissions-2025> [https://perma.cc/2449-5TGP]; Sarah Lee, *Biometric Banking Trends: Securing Finance Over Next 5 Years*, NUMBERANALYTICS (Mar. 28, 2025), https://www.numberanalytics.com/blog/biometric-banking-trends-future-finance#google_vignette [https://perma.cc/C25N-D9MF].

78. Berg et al., *supra* note 37, at 1846–47.

79. *Use of Alternative Data to Enhance Credit Reporting to Enable Access to Digital Financial Services by Individuals and SMEs Operating in the Informal Economy—Guidance Note*, GLOB. P'SHIP FOR FIN. INCLUSION (June 28, 2018), https://www.gpfi.org/sites/default/files/documents/Use_of_Alternative_Data_to_Enhance_Credit_Reporting_to_Enable_Access_to_Digital_Financial_Services_ICCR.pdf [https://perma.cc/GY8R-6KYP].

to their need for financial services.⁸⁰ The lack of alternatives may exacerbate this problem, as AI-driven microfinance may be the only available source of credit in many areas, limiting borrowers' ability to choose more privacy-friendly options.

The increasing use of biometric authentication in microfinance also creates unique privacy risks.⁸¹ Unlike passwords or PINs, biometric data represents immutable personal characteristics that cannot be changed if compromised. This permanence creates significant responsibility for institutions collecting such data, as breaches can have lifetime consequences for affected individuals.⁸²

Finally, given that MFIs routinely engage with multiple third-party service providers for functions such as identity verification, borrowers are often unaware of which entities have access to their personal information or the purposes for which it is being utilized.⁸³

C. Opacity

A fundamental challenge to the credibility and legitimacy of complex AI systems is their inherent opacity (i.e., the difficulty in understanding how they function and make decisions).

Many AI models, particularly those based on advanced machine learning techniques, are highly complex, making it challenging to articulate their underlying logic. Programmers set the objectives of the model, but they do not determine the method for achieving the solution.⁸⁴ In addition, ML models learn from massive datasets by detecting statistical patterns rather than applying interpretable logic, leading to predictions that may be accurate but are difficult to trace using conventional standards. As

80. Chidimma Maria-Gorretti Umeaduma & Adeniyi Adedapo I, *AI-Powered Credit Scoring Models: Ethical Considerations, Bias Reduction, and Financial Inclusion Strategies*, 6 INT'L J. RSCH. PUBL'N & REVS. 6647, 6654–56 (2025).

81. SECURE PRIV., *supra* note 77.

82. *Face/Off: The Future of Biometric Data vs. Consumer Privacy*, SYRENIS (June 21, 2024), <https://syrenis.com/resources/blog/the-future-of-biometric-data-vs-consumer-privacy> [<https://perma.cc/YJK3-G9Y3>].

83. *Why Data Protection and Privacy are Crucial in Digital Lending*, BRANKAS (July 3, 2024), <https://blog.branks.com/why-data-protection-and-privacy-are-crucial-in-digital-lending> [<https://perma.cc/83YV-GUCA>].

84. Gina-Gail S. Fletcher & Michelle M. Lee, *The Future of Accountability in the Financial Markets*, 24 VAND. J. ENT. & TECH. L. 289, 301 (2022).

a result, these models are often opaque even to the experts who build them, a phenomenon that has been referred to as “black box.”⁸⁵

Beyond the difficulty to understand how the model operates, there is an additional yet related concern: the lack of ability to provide a clear explanation for how a specific decision was reached in an individual case.⁸⁶ This situation further complicates the issue, as it hinders the ability to audit, justify, and account for a decision, thus raising significant concerns about fairness, consumer protection, and human rights.

In the context of credit, this opacity presents acute challenges, given the critical role credit plays in individuals’ economic security, life opportunities, and social inclusion. When credit denial is based on models whose functioning cannot be meaningfully explained, and no comprehensible rationale can be provided for the decision, it undermines due process, limits individuals’ ability to contest outcomes, and renders traditional mechanisms of consumer redress ineffective.

The consequences are not merely individual but also institutional. Financial institutions deploying opaque AI tools may find themselves unable to justify or defend their practices to regulators, courts, or the public. This not only creates legal exposure under data protection, anti-discrimination, and consumer rights regimes, but may also risk reputation in an industry that relies on public trust and credibility.

Moreover, many MFIs operate with a dual mandate of financial sustainability and social impact.⁸⁷ The “black box” nature of these systems can undermine the social mission by making it impossible to ensure fair treatment of marginalized customers. This becomes particularly acute when serving populations that depend on these services for basic economic survival. In microfinance, even small loan decisions can have life-altering

85. Maayan Perel & Niva Elkin-Koren, *Black Box Tinkering: Beyond Disclosure in Algorithmic Enforcement*, 69 FLA. L. REV. 181, 184–85 (2017); Yavar Bathaee, *The Artificial Intelligence Black Box and the Failure of Intent and Causation*, 31 HARV. J.L. & TECH. 889, 891 (2018); Wim De Mulder, Joke Baeck & Peggy Valcke, *Explainable Black Box Models*, in INTELLIGENT SYSTEMS AND APPLICATIONS 573, 574 (2022).

86. See De Mulder, Baeck & Valcke, *supra* note 85.

87. See *Microfinance*, COUNCIL OF EUR. DEV. BANK (June 24, 2024), <https://coebank.org/en/project-financing/sectors/microfinance> [<https://perma.cc/ES4E-4TVZ>].

consequences for borrowers and their families. A denied microloan might prevent a small business from starting, a family from accessing healthcare, or children from attending school.⁸⁸ The inability to explain why such critical decisions were made compounds the harm and erosion of trust.

V. THE NEED FOR TAILORED AI REGULATION IN MICROFINANCE

A. Comparative Perspectives on AI Regulatory Frameworks

The various risks associated with AI-based credit underwriting, as described in Part IV, prompt the question of whether, and to what extent, regulatory intervention is required for AI-based microfinance underwriting.

In respect of AI in general, different jurisdictions have developed varying approaches to AI regulatory policy.⁸⁹

The European Union has assumed a leading global role in AI governance with the adoption of the AI Act in 2024: the first comprehensive and legally binding framework for the regulation of AI (“EU AI Act”).⁹⁰ The EU AI Act adopts a horizontal regulatory approach, meaning it applies uniformly across all sectors and industries.⁹¹ This cross-sectoral scope reflects the European

88. DEVELOPAFRICA, *Microfinance—A Lifetime for the Impoverished*, <https://www.developafrica.org/microfinance-lifeline-impoverished> [<https://perma.cc/2E7V-JALE>]; WORLD VISION, *Economic Empowerment*, <https://www.worldvision.org/our-work/economic-empowerment> [<https://perma.cc/BCK6-8CMW>] (last visited Mar. 30, 2026).

89. INT’L CTR. OF EXPERTISE IN MONTREAL ON A.I. (CEIMIA), *A COMPARATIVE FRAMEWORK FOR AI REGULATORY POLICY: PHASE 2* (2024), https://ceimia.org/wp-content/uploads/2024/06/a-comparative-framework-for-ai-regulatory-policy_phase-2-report.pdf [<https://perma.cc/83P6-W8GZ>]; Yoshija Walter, *Managing the Race to the Moon: Global Policy and Governance in Artificial Intelligence Regulation—A Contemporary Overview and an Analysis of Socioeconomic Consequences*, 4 *DISCOVER A.I.* 14, sec. 3.2–3.5 (2024).

90. Regulation 2024/1689 of the European Parliament and of the Council of 13 June 2024 Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act), 2024 O.J. (L 1689) 1 [hereinafter *The EU AI Act*].

91. *Id.* recitals 3–4.

Union's commitment to addressing the broad societal impacts of AI and ensuring consistency in legal protections.⁹²

At the core of the EU AI Act is a risk-based classification system that imposes varying degrees of regulatory obligations depending on the potential risks posed by an AI system. Among the most heavily regulated are high-risk AI systems, which include those used in credit underwriting and financial decision-making.⁹³ These systems, given their potential to affect individuals' access to essential financial services, are subject to a detailed set of legal obligations and technical requirements designed to ensure accountability, fairness, and reliability. These include: comprehensive risk management systems to identify, monitor, and mitigate potential harms;⁹⁴ robust data governance requirements, ensuring that training data are relevant, representative, and free from bias;⁹⁵ transparency and documentation obligations, including detailed technical documentation and record-keeping that facilitate auditability and regulatory oversight;⁹⁶ human oversight mechanisms, ensuring that meaningful human judgment remains in the loop and that automated decisions can be challenged;⁹⁷ technical robustness and accuracy standards, aimed at ensuring the system performs reliably under expected conditions and is resilient to manipulation or failure;⁹⁸ and fundamental rights impact assessments prior to deployment, which require providers to assess and document how the system might affect privacy, non-discrimination, and other EU fundamental rights.⁹⁹ Violations of the EU AI Act are subject to severe fines.¹⁰⁰

92. Philipp Hacker, *AI Regulation in Europe: From the AI Act to Future Regulatory Challenges*, OXFORD HANDBOOK OF ALGORITHMIC GOVERNANCE AND THE LAW (Ifeoma Ajunwa & Jeremias Adams-Prass eds., forthcoming 2025).

93. The EU AI Act, art. 6; Martin Ebers, *Truly Risk-based Regulation of Artificial Intelligence—How to Implement the EU's AI Act*, 16 EUR. J. OF RISK REG. 684, 686–87 (2024); Wagner et al., *Navigating the Upcoming European Union AI*, 41 IEEE SOFTWARE 19, 19–21 (2024).

94. The EU AI Act, art. 9.

95. *Id.* art. 10.

96. *Id.* art. 11–13.

97. *Id.* art. 14.

98. *Id.* art. 15.

99. *Id.* art. 27.

100. The EU AI Act, art. 99.

Alongside the EU AI Act, significant safeguards relevant to the use of AI are enshrined in a separate legal instrument: the General Data Protection Regulation (“GDPR”).¹⁰¹ Notably, the GDPR grants individuals the right to obtain “meaningful information” about the logic involved in automated decision-making, as well as the significance and envisaged consequences of such processing.¹⁰²

These safeguards aim to balance technological innovation with protection of individual rights, reflecting the EU’s broader digital strategy rooted in ethical and human-centered AI development. The framework ensures that AI systems used in sensitive contexts, including those that influence access to credit, are deployed in a way that is transparent, accountable, and aligned with democratic values.

A similar approach was adopted in South Korea, where the *Basic Act on Artificial Intelligence Development and Establishment of a Foundation for Trustworthiness* (“AI Framework Act”) establishes a comprehensive legal framework for AI.¹⁰³ The stated purpose of the AI Framework Act is to protect citizens’ rights and dignity, improve quality of life, and strengthen national competitiveness.¹⁰⁴

The Act imposes specific obligations on both developers and deployers of “high-impact” AI systems in critical sectors, which also include credit underwriting systems.¹⁰⁵ These include

101. Regulation 2016/679 of the European Parliament and of the Council of 27 April 2016 on the Protection of Natural Persons with Regard to the Processing of Personal Data and on the Free Movement of Such Data (General Data Protection Regulation), 2016 O.J. (L 119) 1.

102. Marco Almada & Nicolas Petit, *The EU AI Act: Between the Rock of Product Safety and the Hard Place of Fundamental Rights*, 62 COMMON MKT. L. REV. 85, 87 (2025).

103. See Basic Act on the Development of Artificial Intelligence and Establishment of Trust, Act No. 20676, Jan. 21, 2025 (S. Kor.); see also *AI Basic Act Explorer*, AI BASIC ACT OF THE REPUBLIC OF KOREA (2025), <https://aibasicact.kr/explorer/> [<https://perma.cc/TH7Q-8JYK>].

104. Sakshi Shivhare & Kwang Bae Park, *South Korea’s New AI Framework Act: A Balancing Act Between Innovation and Regulation*, FUTURE OF PRIV. FORUM (Apr. 18, 2025), <https://fpf.org/blog/south-koreas-new-ai-framework-act-a-balancing-act-between-innovation-and-regulation> [<https://perma.cc/P4UB-DJB8>]; Hwan Kyoung Ko, *Artificial Intelligence—Trends and Developments*, CHAMBERS AND PARTNERS (May 22, 2025), <https://practiceguides.chambers.com/practice-guides/artificial-intelligence-2025/south-korea/trends-and-developments> [<https://perma.cc/2LDQ-YCNY>].

105. Avi Gesser et al., *South Korea Enacts New AI Law*, DEBEVOISE & PLIMPTON DATA BLOG (Mar. 24, 2025), <https://www.debevoisedatablog.com/2025/03/24/south-korea-enacts-new-ai-law> [<https://perma.cc/VEU7-MD49>].

establishing and operating a risk management plan; establishing a plan to provide explanation for AI-generated results within technical limits, including key decision criteria and an overview of training data; establishing user protection measures; ensuring human oversight and supervision; documenting measures taken to ensure AI safety and reliability; and more. Violations may result in fines, although they are moderate compared to the EU AI Act.¹⁰⁶

Another jurisdiction that has opted to regulate artificial intelligence through primary legislation is Japan, which introduced the *Act on the Promotion of Research, Development and Utilization of Artificial Intelligence Technologies* (Japanese AI Act) in March 2025.¹⁰⁷ However, the Japanese approach is completely different than that of the European Union or South Korea. The Japanese government's ambition, outlined in a 2024 whitepaper, is to make Japan the world's "most AI-friendly country."¹⁰⁸

While introducing a basis for binding AI regulation, the Act builds on Japan's longstanding soft law approach to AI governance, relying on non-binding government guidelines, multi-stakeholder cooperation, and the promotion of voluntary business initiatives over hard law regulation. The Act embodies the Japanese government's broader philosophy of agile governance in digital regulation, which posits that in rapidly evolving fields like AI, rigid regulation may quickly become obsolete and hinder innovation.¹⁰⁹

Based on this approach, the Japanese AI Act does not provide detailed obligations, rights, or enforcement mechanisms. Instead, it invites all stakeholders—businesses, academic institutions and citizens—to "endeavour to cooperate" with government AI policies and strategies that aim to foster AI advancement.¹¹⁰ This cooperation constitutes a non-binding "reasonable efforts"

106. Shivhare & Park, *supra* note 104.

107. Act on the Promotion of Research, Development, and Utilization of Artificial Intelligence Technologies, Act No. 53/2025 (Japan).

108. JAPAN LDP HEADQUARTERS FOR THE PROMOTION OF DIGITAL SOC'Y PROJECT TEAM ON THE EVOLUTION AND IMPLEMENTATION OF AIS, AI WHITE PAPER 2024—NEW STRATEGIES IN STAGE II—TOWARD THE WORLD'S MOST AI-FRIENDLY COUNTRY 4–5 (2024), <https://www.tairam.jp/AI%20White%20Paper%202024.pdf> [<https://perma.cc/YMG7-QU44>].

109. Dominic Paulger, *Understanding Japan's AI Promotion Act: An "Innovation-First" Blueprint for AI Regulation*, FUTURE OF PRIV. FORUM (July 5, 2025), <https://fpf.org/blog/understanding-japans-ai-promotion-act-an-innovation-first-blueprint-for-ai-regulation> [<https://perma.cc/K4C7-LMLK>].

110. *Id.*

obligation common in Japanese legislation, and is therefore not enforceable as a legal duty.¹¹¹ The Act contains no sanctions for non-compliance.

The Japanese AI Act is accompanied by *AI Guidelines for Business*¹¹² demonstrating a human-centric approach by requiring that AI development and deployment in Japan align with ethical principles such as fairness, protection, transparency, and accountability.¹¹³

A different pro-innovation approach can be observed in countries that have chosen to forgo primary AI legislation altogether, instead adopting industry-led frameworks aimed at keeping pace with technological advancements without constraining technological progress. The United States, for example, has deliberately chosen to avoid comprehensive AI-specific federal legislation. While various bills have been proposed, focusing on promoting responsible development through fairness, transparency, and accountability mechanisms, none have successfully passed into law.¹¹⁴ President Biden's *Executive Order on Safe, Secure, and Trustworthy Artificial Intelligence*, which set standards such as protecting user privacy, advancing equity and civil rights, and safeguarding consumers and workers from AI-

111. *Id.*

112. Press Release, Ministry of Econ., Trade & Indus. & Ministry of Internal Affs. & Commc'ns (Japan), *AI Guidelines for Business Ver 1.0 Compiled* (Apr. 19, 2024), https://www.meti.go.jp/english/press/2024/0419_002.html [<https://perma.cc/NH4J-7EPQ>].

113. Shunsuke Nagae, *Understanding the New AI Operator Guidelines in Japan*, CLIFFORD CHANCE (June 5, 2024), <https://www.cliffordchance.com/insights/resources/blogs/talking-tech/en/articles/2024/06/understanding-the-new-ai-operator-guidelines-in-japan.html> [<https://perma.cc/UG39-DRF2>].

114. *See, e.g.*, WHITE HOUSE OFF. OF SCI. & TECH. POL'Y, BLUEPRINT FOR AN AI BILL OF RIGHTS: MAKING AUTOMATED SYSTEMS WORK FOR THE AMERICAN PEOPLE (2022), <https://bidenwhitehouse.archives.gov/wp-content/uploads/2022/10/Blueprint-for-an-AI-Bill-of-Rights.pdf> [<https://perma.cc/V2NL-C8GM>] (outlining five core principles for the development and use of automated systems: safe and effective systems, algorithmic discrimination protection, data privacy, notice and explanation, and human intervention); Artificial Intelligence Accountability Act, H.R. 3369, 118th Cong. (2023–2024) (mandating the National Telecommunications and Information Administration [NTIA] to study and report on accountability measures for AI systems, including many of which perform or support ADM functions); Algorithmic Accountability Act of 2023, H.R. 5628, 118th Cong. (2023) (mandating that companies conduct impact assessments for ADM systems and augmented critical decision processes and proposing the creation of a public repository at the Federal Trade Commission).

enabled harms,¹¹⁵ was rescinded by President Donald Trump within hours of assuming office in January 2025. In its place, a new Executive Order, *Removing Barriers to American Leadership in AI*, aims to sustain and enhance US global AI dominance by suspending or revising existing actions and regulations that may hinder rapid AI development and deployment, favoring instead a “light-touch” approach that relies on market forces and industry self-regulation.¹¹⁶ The AI Action Plan from July 2025 implements the Executive Order by pursuing three main pillars: accelerating innovation, building infrastructure, and leading in international diplomacy and security.¹¹⁷

With no comprehensive federal regulation in place, multiple states have proactively enacted legislation to govern the use of AI systems, incorporating ethics and safety measures.¹¹⁸ As a result, a diverse and evolving array of state-level rules and requirements has emerged across the country. However, this regulatory landscape may be significantly attenuated in the wake of the Presidential Executive Order of December 2025.¹¹⁹ By advancing uniform federal standards and authorizing the challenge or preemption of state regulations, the Order consolidates AI oversight at the federal level and curtails states’ ability to enact independent or more stringent rules.

The United Kingdom is another example of a flexible, industry-driven approach. In January 2025, the UK government launched the *AI Opportunities Action Plan*¹²⁰ to make the United

115. See Exec. Order No. 14,110, Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence, 88 C.F.R. 75191 (Nov. 1, 2023).

116. See Exec. Order No. 14,179, Removing Barriers to American Leadership in Artificial Intelligence, 90 Fed. Reg. 8741 (Jan. 31, 2025).

117. THE WHITE HOUSE, WINNING THE RACE – AMERICA’S AI ACTION PLAN (2025), <https://www.whitehouse.gov/wp-content/uploads/2025/07/Americas-AI-Action-Plan.pdf> [https://perma.cc/92X9-G5SH].

118. For a state-by-state tracker, see BCLP, *US State-by-State AI Legislation Snapshot*, BCLP LAW (2026), <https://www.bclplaw.com/en-US/events-insights-news/us-state-by-state-artificial-intelligence-legislation-snapshot.html> [https://perma.cc/G6D7-HLVM]; see also *From California to Kentucky: Tracking the Rise of State AI Laws in 2025*, WHITE & CASE (May 27, 2025), <https://www.whitecase.com/insight-alert/california-kentucky-tracking-rise-state-ai-laws-2025> [https://perma.cc/K7NV-4FMP].

119. Exec. Order No. 14,365, Ensuring a National Policy Framework for Artificial Intelligence, 90 Fed. Reg. 58499 (Dec. 16, 2025).

120. DEP’T FOR SCI., INNOVATION & TECH., AI OPPORTUNITIES ACTION PLAN, 2025, CP 1241 (U.K.), <https://www.gov.uk/government/publications/ai-opportunities-action-plan/ai-opportunities-action-plan> [https://perma.cc/534N-3XAT].

Kingdom a global AI leader by investing in AI infrastructure, attracting top talent, and driving widespread AI adoption across both public and private sectors. The regulatory framework of this plan is built on five core principles: safety, security, and robustness; appropriate transparency and explainability; fairness; accountability and governance; and contestability and redress.¹²¹ These principles are designed to ensure responsible and innovative AI development by promoting public trust, supporting sector-specific oversight,¹²² and encouraging flexible, outcome-focused governance rather than imposing rigid, one-size-fits-all rules.

In summary, these divergent regulatory approaches underscore the absence of a global consensus on how best to govern AI, creating an uncertainty that directly affects sector-specific regulation. This regulatory ambiguity raises important questions regarding the appropriate framework for governing the use of AI in microfinance contexts.

In countries where binding legislation has not yet been enacted, particularly those in which microfinance is prevalent, two key questions emerge. First, should algorithmic credit underwriting be subject to regulation in the microfinance sector? And if so, what would constitute an appropriate and effective regulatory framework?

B. Should Algorithmic Credit Underwriting Be Regulated in the Microfinance Sector?

The first question essentially concerns the choice between two regulatory approaches: a passive approach, which preserves the existing legal framework; and an active approach, which seeks to establish a new regulatory regime.

The passive approach offers several advantages. First, in the absence of legal and regulatory constraints, a *laissez-faire* environment emerges, allowing market participants to operate

121. *Id.*

122. For regulatory implementation principles, see DEP'T FOR SCI, INNOVATION & TECH., IMPLEMENTING THE UK'S AI REGULATORY PRINCIPLES: INITIAL GUIDANCE FOR REGULATORS (2024) (U.K.), https://assets.publishing.service.gov.uk/media/65c0b6bd63a23d0013c821a0/implementing_the_uk_ai_regulatory_principles_guidance_for_regulators.pdf [https://perma.cc/G8UP-MWYX].

freely and foster innovation in the sector.¹²³ Second, passivity does not imply regulatory inaction. Policymakers may utilize the interim to observe the sector's practical development, assess whether intervention is warranted, and subsequently adopt tailored regulation informed by accumulated experience.¹²⁴

However, the passive approach is not without its drawbacks. Most significantly, the lack of oversight and regulation may leave consumers, particularly vulnerable ones, without adequate protection, thereby undermining public trust in the system.¹²⁵ Moreover, given that microfinance lending is conducted by a diverse array of institutions—from tightly regulated banks to non-bank entities not subject to similar scrutiny—regulatory arbitrage may arise, enabling actors to exploit inconsistencies in oversight.¹²⁶ Finally, the absence of a regulatory framework does not inherently lead to innovation or progress. It may result in legal and regulatory uncertainty, deterring new entrants, investors, and consumers from entering the field.¹²⁷

The active approach, by contrast, involves the establishment of a dedicated regulatory framework specifically designed to govern the innovative new practice.¹²⁸ Tailored regulation seeks to address the diverse needs of stakeholders, balance competing interests, and provide structured mechanisms for managing risks.¹²⁹ By fostering clarity and predictability, tailored regulation may incentivize market entry and promote sectoral development. It may also facilitate the adoption of uniform rules applicable to all market participants, thereby offering a coherent and comprehensive response to the evolving landscape.

123. Douglas W. Arner, Janos N. Barberis & Ross P. Buckley, *The Evolution of FinTech: A New Post-Crisis Paradigm?*, 47 GEO. J. INT'L L. 1271, 1284, 1307 (2016).

124. Douglas W. Arner, Janos N. Barberis & Ross P. Buckley, *FinTech, RegTech, and the Reconceptualization of Financial Regulation*, 37 NW. J. INT'L L. & BUS. 371, 403 (2016).

125. Dirk A. Zetsche et al., *Regulating a Revolution: From Regulatory Sandboxes to Smart Regulation*, 23 FORDHAM J. CORP. & FIN. L. 31, 44, 50–52 (2017); Oscar Borgogno & Giuseppe Colangelo, *Regulating FinTech: From Legal Marketing to the Pro-Competitive Paradigm*, 1, 8 (2020), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3563447 [<https://perma.cc/3GZA-V4FC>].

126. Arner, Barberis & Buckley, *supra* note 124, at 403.

127. Aurelio Gurrea-Martinez & Nydia Remolina, *Global Challenges and Regulatory Strategies to Fintech*, 36 BANKING & FIN. L. REV. 39, 54 (2021).

128. *Id.* at 63–66.

129. *Id.* at 64.

Nevertheless, the active approach is also subject to criticism. First, there is no guarantee that the new legal framework will achieve its intended objectives. Second, sufficient domestic experience may not yet exist to support the design of an appropriate regulatory regime. Lessons drawn from foreign jurisdictions may also prove inapplicable, given significant differences in legal systems, economic structures, and institutional arrangements. Most critically, in light of rapid technological developments, the newly adopted framework may soon become obsolete, particularly if it is embedded in primary legislation, which is often difficult to amend.¹³⁰

Determining the appropriate regulatory approach to algorithmic underwriting in microfinance is far from straightforward. Before committing to either model, one must carefully examine the objectives of regulation, the characteristics of the market, the needs of relevant stakeholders, the risks inherent in the activity, past challenges, prevailing financial and commercial practices, and the existing legal and regulatory culture.

In light of the above considerations, this paper argues that the growing use of algorithmic systems in microfinance underwriting necessitates dedicated regulatory oversight.¹³¹ As credit plays a foundational role in enabling investment, consumption, and financial stability, especially for underserved populations targeted by microfinance, its regulation is critical. An unregulated approach is both untenable and unjustifiable given the significant risks associated with AI-driven credit assessments, including the potential for human rights violations and the exclusion of vulnerable borrowers.

130. On the growing gap between emerging technologies and the law, see Gary E. Marchant, *The Growing Gap Between Emerging Technologies and the Law*, in *THE GROWING GAP BETWEEN EMERGING TECHNOLOGIES AND LEGAL-ETHICAL OVERSIGHT: THE PACING PROBLEM* 19 (Gary E. Marchant, Braden R. Allenby & Joseph R. Herkert eds., 2011); Wulf Kaal, *What Happens When Technology Is Faster Than the Law?*, CLS BLUE SKY BLOG (Sep. 22, 2016), <https://clsbluesky.law.columbia.edu/2016/09/22/what-happens-when-technology-is-faster-than-the-law/> [https://perma.cc/XBT7-8RLN]; Anna Butenko & Pierre Larouche, *Regulation for Innovativeness or Regulation of Innovation?*, 7 L. INNOVATION & TECH. 52, 66 (2015).

131. For an approach advocating proactive, dynamic, and responsive intervention in Fintech, see Mark D. Fenwick, Wulf A. Kaal & Erik P.M. Vermeulen, *Regulation Tomorrow: What Happens When Technology Is Faster than the Law?*, 6 AM. U. BUS. L. REV. 561 (2017); see also Wulf A. Kaal, *Dynamic Regulation of the Financial Services Industry*, 48 WAKE FOREST L. REV. 791, 818–20 (2014).

The challenge lies in developing a regulatory mechanism that effectively mitigates risks without compromising the benefits and potential of algorithmic underwriting or stifling innovation. It is crucial to find a balance where risk reduction measures safeguard ethical standards and human rights, while still fostering technological advancements and maintaining the efficiency and accuracy that algorithmic underwriting promises.

C. The Regulatory Framework for Credit Underwriting in the Microfinance Sector

Having concluded that AI-based credit underwriting in the microfinance sector warrants regulatory oversight, a subsequent and equally critical question arises: What constitutes the appropriate regulatory framework for its governance?

Given the complexity of enacting primary AI legislation, and the reality that many jurisdictions where microfinance is most prevalent are unlikely to adopt such legislation in the near term, this Article advocates for a sector-specific and proportionate regulatory framework that accounts for the distinctive features and social mission of microfinance. In other words, it is imperative that microfinance regulators take proactive measures to directly oversee AI-driven credit underwriting.

Regulatory intervention at the sectoral level can be implemented more expediently than primary legislation, and offers the agility needed to keep pace with rapid technological developments. Financial regulators, equipped with domain-specific expertise and a deep understanding of market dynamics and actors, are particularly well-positioned to craft tailored and effective regulatory frameworks. Moreover, such regulation allows for greater flexibility and adaptability over time. Notably, even in jurisdictions that have adopted or plan to adopt comprehensive AI legislation, the role of financial regulators remains essential in operationalizing and concretizing general statutory principles within the specific context of credit underwriting.

Indeed, in conventional banking, financial regulators in various jurisdictions have already acknowledged the need for oversight and issued directives that apply to AI-driven credit

underwriting.¹³² These are often framed as “guidelines” or “recommendations,” granting lenders substantial discretion in their application and emphasizing ethical principles.¹³³ A similar approach should be adopted for microfinance, with content adapted to the sector’s specific characteristics and needs.

Based on these considerations, this Article urges microfinance regulators to establish minimum standards for the ethical use of AI tailored to the specific needs and realities of microfinance customers. On the one hand, such standards would provide a clear framework and direction for MFIs. On the other hand, they would preserve sufficient flexibility to allow institutions to adapt implementation according to their operational contexts and capacities. The next sections detail the key elements of these proposed standards.

1. Respect for Human Rights

The implications of AI on human rights and their foundational values—dignity, freedom, equality and privacy—have been extensively documented in the general literature on AI-driven decision-making.¹³⁴ Therefore, the first principle designed to

132. See, e.g., CONSUMER FIN. PROT. BUREAU, *CFPB Issues Guidance on Credit Denials by Lenders Using Artificial Intelligence* (Sep. 19, 2023), <https://www.consumerfinance.gov/about-us/newsroom/cfpb-issues-guidance-on-credit-denials-by-lenders-using-artificial-intelligence> [<https://perma.cc/X7NY-C77Z>] (outlining the US requirements for lenders to provide specific and accurate reasons for adverse actions, such as credit denials, when using AI or complex models); BUNDESANSTALT FÜR FINANZDIENSTLEISTUNGS AUFSICHT [BAFIN] [FEDERAL FINANCIAL SUPERVISORY AUTHORITY], *BIG DATA AND ARTIFICIAL INTELLIGENCE: PRINCIPLES FOR THE USE OF ALGORITHMS IN DECISION-MAKING PROCESSES* (2021) (Ger.), https://www.bafin.de/SharedDocs/Downloads/EN/Aufsichtsrecht/dl_Prinzipienpapier_BDAI_en.html [<https://perma.cc/7HW4-3UBN>]; MONETARY AUTH. OF SING., *PRINCIPLES TO PROMOTE FAIRNESS, ETHICS, ACCOUNTABILITY AND TRANSPARENCY (FEAT) IN THE USE OF ARTIFICIAL INTELLIGENCE AND DATA ANALYTICS IN SINGAPORE’S FINANCIAL SECTOR* (2018) (Sing.), <https://www.mas.gov.sg/~media/MAS/News%20and%20Publications/Monographs%20and%20Information%20Papers/FEAT%20Principles%20Final.pdf> [<https://perma.cc/5L7Q-48LQ>]; H.K. MONETARY AUTH., *HIGH-LEVEL PRINCIPLES ON ARTIFICIAL INTELLIGENCE* (2019) (H.K.), <https://www.hkma.gov.hk/media/eng/doc/key-information/guidelines-and-circular/2019/20191101e1.pdf> [<https://perma.cc/A396-HB8E>].

133. Nydia Remolina, *The Role of Financial Regulators in the Governance of Algorithmic Credit Scoring* (SMU Ctr. for AI & Data Governance, Rsch. Paper No. 2, 2022), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4057986 [<https://perma.cc/MUG2-ZPYK>].

134. Barocas & Selbst, *supra* note 66, at 677–93; Citron & Pasquale, *supra* note 66; Michal Kosinski, David Stillwell & Thore Graepel, *Private Traits and Attributes are*

mitigate risks to individuals should be respect for human rights, particularly when AI models have the potential to affect marginalized groups within society.¹³⁵

Beyond the legal and regulatory recognition of the need to respect human rights in the context of AI, it is of paramount importance to develop design solutions that ensure models are created with respect for values (“Design for Values”).¹³⁶ Indeed, numerous studies in computer science are dedicated to embedding values and ethical principles within the design infrastructure of technological systems,¹³⁷ as part of the effort to develop Responsible AI.¹³⁸ Various scholars have called for considering the societal context within which the technological system is embedded, and for examining how social and ethical needs can be translated into design requirements.¹³⁹ Value-driven design of algorithmic models can be achieved by a range of methodologies aimed at accounting for the social circumstances surrounding the algorithmic model, with the goal of addressing specific social needs.¹⁴⁰

2. Fairness

Ensuring the fairness of AI-based models is a fundamental ethical principle aimed at mitigating the risk of discrimination. As

Predictable from Digital Records of Human Behavior, 110 PNAS 5802, 5802 (2013), <https://pubmed.ncbi.nlm.nih.gov/23479631> [<https://perma.cc/Z3KH-7LDQ>].

135. EUR. COMM’N HIGH LEVEL EXPERT GRP. ON A.I., ETHICS GUIDELINES FOR TRUSTWORTHY AI (2019), <https://ec.europa.eu/futurium/en/ai-alliance-consultation.1.html> [<https://perma.cc/Q2BU-48BA>].

136. Evgeni Aizenberg & Jeroen van den Hoven, *Designing for Human Rights in AI*, 7 BIG DATA & SOC’Y 1, 2 (2020); see also MJ Van den Hoven, *Design for Values and Values for Design*, 7 INFORMATIONAGE 1, 4–7 (2005).

137. Andrea Aler et al., *Governance by Glass-Box: Implementing Transparent Moral Bounds for AI Behavior*, PROC. OF THE 28TH INT’L JOINT CONFERENCE ON AI FOR IMPROVING HUMAN WELL-BEING (IJCAI) 5787, 5788 (2019), <https://www.ijcai.org/proceedings/2019/0802.pdf> [<https://perma.cc/UX3B-4LTK>]; Iyad Rahwan, *Society-in-the-loop: Programming the Algorithmic Social Contract*, 20 ETHICS & INFO. TECH. 5, 6 (2018).

138. VIRGINIA DIGNUM, RESPONSIBLE ARTIFICIAL INTELLIGENCE: HOW TO DEVELOP AND USE AI IN A RESPONSIBLE WAY (2019).

139. Batya Friedman & Helen Nissenbaum, *Bias in Computer Systems*, 14 ACM TRANSACTIONS IN INFO. SYS. 330, 344 (1996).

140. HUMAN VALUES AND THE DESIGN OF COMPUTER TECHNOLOGY (Batya Friedman ed., 1997); HELEN NISSENBAUM, *Values in Technical Design*, in ENCYCLOPEDIA OF SCIENCE, TECHNOLOGY AND ETHICS (C. Mitcham ed., 2005), <https://nissenbaum.tech.cornell.edu/papers/valuesintechicaldesign.pdf> [<https://perma.cc/79RW-ZC34>].

models become more complex and incorporate more parameters and correlations among diverse data points, identifying discrimination and ensuring fairness becomes increasingly challenging, especially with respect to disparate impact.¹⁴¹ Consequently, various mathematical methods have been developed to detect discrimination, focusing on three stages: pre-processing, which examines the data intended for machine learning; in-processing, which shapes the algorithm's learning process; and post-processing, which updates the model's output to reduce discrimination risks.¹⁴²

In light of these considerations, lenders must be obligated to make their best efforts to neutralize bias, addressing various stages of the model's lifecycle: data collection during model development, the learning and training phases, and the model's actual implementation. Additionally, as part of the explainability requirement discussed below, lenders should be mandated to explain the steps taken in designing and implementing the system to ensure its decisions are unbiased and lead to equitable outcomes.

Moreover, given that these models are dynamic and continuously evolving, a one-time assessment of the model's fairness at the outset is insufficient.¹⁴³ The obligation to prevent discrimination should be a perpetual and ongoing duty, maintained for as long as the model is in use.

3. Transparency

Transparency refers to the openness and accessibility of information about an AI system's design, development, and operation. It involves making the system's functioning and decision-making criteria understandable to stakeholders, including developers, users, affected individuals, and regulators.

141. FINREGLAB, THE USE OF MACHINE LEARNING FOR CREDIT UNDERWRITING: MARKET & DATA SCIENCE CONTEXT 80 (2021), https://finreglab.org/wp-content/uploads/2021/09/The-Use-of-ML-for-Credit-Underwriting-Market-and-Data-Science-Context_09-16-2021.pdf [https://perma.cc/TXC5-K5TY]; Zefar et al., *supra* note 75.

142. Nikita Kozodoi, Johannes Jacob & Stefan Lessmann, *Fairness in Credit Scoring: Assessment Implementation and Profit Implications*, 29 EUR. J. OPERATIONAL RES. 1083, 1085 (2021), <https://arxiv.org/pdf/2103.01907.pdf> [https://perma.cc/5VEV-NGQ6].

143. Harry Surden, *Machine Learning and Law*, 89 WASH. L. REV. 87, 90 (2014); Joshua A. Kroll et al., *Accountable Algorithms*, 165 U. PA. L. REV. 633, 648 (2017).

Transparency can mitigate risks associated with bias, discrimination, and errors, ultimately leading to more reliable and fair AI applications. It is important for ensuring public trust in AI systems. In addition, it fosters accountability among lenders and enables them to provide an account to the public, borrowers, and regulators regarding the underwriting decisions they make.

The requirement for transparency in AI-based models is not straightforward. First, as was explained above, many models are highly complex, making it challenging to articulate the underlying logic.¹⁴⁴ Additionally, these models are the intellectual property of the lenders.¹⁴⁵ Maintaining the confidentiality of these models not only gives lenders a crucial competitive edge but also prevents strategic circumvention of the underwriting models.

Despite these challenges, it is feasible to ensure different levels of transparency for AI-based models. For example, transparency can be achieved by providing clear documentation of how the AI system was developed, including the data used, the algorithms implemented, and the rationale behind its decisions. This can be accomplished through several methods, such as open access to code and data, detailed model documentation, and the implementation of explainability techniques that elucidate how decisions are made. Additionally, regular audits and assessments by independent parties can further ensure transparency.¹⁴⁶

In light of the above, MFIs should be required to maintain transparency towards both regulators (where applicable) and the general public. The level of transparency for regulators should be higher, encompassing both the development process of the model and its operational mechanisms. In contrast, the transparency required for borrowers could be at a lower level, primarily enabling them to identify flaws that could impact their chances of securing a loan.

Transparency remains essential in microfinance, even when borrowers may lack the literacy or technical understanding to grasp complex AI systems. It is critical for ensuring accountability to regulators, institutions, and civil society, who can oversee and challenge unfair or biased outcomes. Designing systems with

144. See *supra* Part III.

145. Di Maggio et al., *supra* note 53.

146. Perel & Elkin-Koren, *supra* note 85; Bathaee, *supra* note 85, at 929; De Mulder, Baeck & Valcke, *supra* note 85.

transparency in mind enhances fairness and supports compliance with ethical and legal standards.

4. Explainability

Explainability deals with the ability to explain how a decision affecting an individual was actually made. It mandates that AI-based systems employed in decision-making processes regarding individuals, be designed in a manner that enables to explain the underlying logic through which the concrete decision was rendered. This requires a clear account of the data considered and identifying the decisive criteria.¹⁴⁷

Explainability can significantly mitigate the risks inherent in AI-based models in several respects.¹⁴⁸ First, it facilitates the identification and correction of errors. Second, it enables the detection of biases, thereby reducing the risk of discrimination.¹⁴⁹ Third, providing borrowers with an explanation of the types of data incorporated into the model and the manner in which the underwriting decision was reached, allows them to better plan their future financial behavior, thereby enhancing their personal autonomy and control over their personal information.¹⁵⁰

However, the explainability requirement introduces a tension between fostering innovation and minimizing risk to human rights. To optimize the efficacy of AI-driven decision-making mechanisms, it is essential to permit underwriting models to utilize advanced machine learning techniques. Conversely, as these systems become more intricate, incorporating multiple data sources and dynamically adjusting their operations, the challenge of

147. Margot E. Kaminski, *The Right to Explanation Explained*, 34 *BERKELEY TECH. L.J.* 189, 191, 211 (2019); Sandra Wachter, Ben Mittelstadt & Chris Russell, *Counterfactual Explanations without Opening the Black Box: Automated Decisions and the GDPR*, 31 *HARV. J.L. & TECH.* 841, 843 (2018); Hofit Wasserman Rozen, Ran Gilad-Bachrach & Niva Elkin-Koren, *Lost in Translation: The Limits of Explainability in AI*, 42 *CARDOZO ARTS & ENT. L.J.* 391, 395 (2024).

148. In addition to influencing customers' trust in both the model and its outputs, see Arun Rai, *Explainable AI: From Black Box to Glass Box*, 48 *J. ACAD. MKTG. SCI.* 137, 140 (2019).

149. Alejandro Barredo Arrieta et al., *Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges Toward Responsible AI*, 58 *INFO. FUSION* 82, 83 (2020).

150. Sandra Wachter, Ben Mittelstadt & Luciano Floridi, *Why a Right to Explanation of Automated Decision-Making Does Not Exist in the General Data Protection Regulation*, 7 *INT'L DATA PRIVACY L.J.* 76, 78 (2017).

elucidating their processes intensifies, particularly with respect to “black box” models.¹⁵¹

Given that credit is a fundamental service crucial to individual economic, social, and personal development, I believe that MFIs should be obligated, upon the borrower’s request, to explicate at least which specific data points were considered in their underwriting decision and the key criteria underpinning that decision.¹⁵²

Even though borrowers may lack the literacy to grasp this information, explainability remains essential in microfinance. Like transparency, explainability is critical for ensuring accountability to regulators and civil society, who can monitor and challenge unfair or biased outcomes. While consumers may not be able to understand detailed explanations, simplified and culturally appropriate communications can still help them grasp the basic reasons for a decision, fostering trust and enabling more informed financial behavior.

The key challenge, therefore, is to identify effective ways of delivering explanations in forms accessible to low-literacy users. This might include using pictograms or visual aids, interactive voice response (IVR) systems in local languages, short explanatory videos via mobile platforms, or in-person community-based financial education facilitated by trusted local agents.

5. Human Involvement

Human judgment plays a crucial role in mitigating the risks associated with AI-based consumer underwriting. Indeed, technical definitions and technological measures designed to ensure fairness often lack sensitivity to the particular circumstances of the individual borrower, and are unable to address issues related to the collection methods of the raw data used to develop the model.¹⁵³ Therefore, it is not without reason

151. Arrieta et al., *supra* note 149.

152. Such an obligation exists, for example, in the United States, with respect to traditional credit. See Equal Credit Opportunity Act, 15 U.S.C. § 1691(d); Fair Credit Reporting Act, 15 U.S.C. § 1681m.

153. See Ben Green & Lily Hu, *The Myth in the Methodology: Towards a Recontextualization of Fairness in Machine Learning*, 35TH INT’L CONF. ON MACH. LEARNING, (2018), <https://scholar.harvard.edu/lilyhu/publications/myth-methodology-towards-recontextualization-fairness-machine-learning> [<https://perma.cc/BQK4-QPRZ>].

that the principle of human involvement (“human in the loop”) is extensively discussed in academic literature in relation to minimizing the risks associated with the use of AI tools for individual decision-making.¹⁵⁴ Human intervention has also been recognized within the framework of the EU AI Act as a crucial measure for mitigating the risks associated with high risk AI systems.¹⁵⁵

Human involvement can be integrated at various stages throughout the lifecycle of the model. For example, the design and testing phases of the system can be transparently documented by humans.¹⁵⁶ Others advocate for human-led risk assessments, both prior to the model’s launch and during its operation, to evaluate the model’s fairness.¹⁵⁷ Another approach is to assign responsibility to different stakeholders involved in the development and use of the model, ensuring its compliance with ethical standards.¹⁵⁸

Similarly, MFIs should be required to incorporate human intervention when using AI-based models for credit underwriting. Human intervention should occur both during the model’s development stages (pre-deployment) and when validating its reliability and fairness (post-deployment). For example, this could involve conducting random sample checks of the model’s decisions and comparing them to those made by humans. Furthermore, customers should have the right to appeal automated underwriting decisions to a human reviewer.

154. See Ben Wagner, *Liable but not in Control? Ensuring Meaningful Human Agency in Automated Decision-Making Systems: Human Agency in Decision-Making Systems*, 11 POL’Y & INTERNET 104 (2019); Alex Endert et al., *The Human in the Loop: New Directions for Visual Analytics*, 43 J. INTELLIGENT INFO. SYS. 411 (2014); Dirk Zetsche et al., *Artificial Intelligence in Finance: Putting the Human in the Loop*, 43 SYD. L. REV. 43 (2021); Koen Smith & Martijn Zoet, *A Governance Framework for (Semi) Automated Decision-Making*, PROC. OF THE 10TH INT’L CONF. ON INFO., PROCESS & KNOWLEDGE (EKNOW) 83 (2018), http://personales.upv.es/thinkmind/dl/conferences/eknow/eknow_2018/eknow_2018_5_10_68006.pdf [<https://perma.cc/CB5H-KZXB>].

155. See The EU AI Act, art. 14.

156. See Timit Gebru et al., *Datasheets for Datasets*, 64(12) COMM’N. OF THE ASS’N. FOR COMPUTING MACH. 86 (2021); Margaret Mitchell et al., *Model Cards for Model Reporting*, PROC. OF THE CONF. ON FAIRNESS, ACCOUNTABILITY, & TRANSPARENCY 220, 220–21 (2019), <https://dl.acm.org/doi/proceedings/10.1145/3287560> [<https://perma.cc/Z5T2-AH7Z>].

157. See Barocas & Selbst, *supra* note 66; see also Yifat Nahmias & Maayan Perel, *The Oversight of Content Moderation by AI: Impact Assessments and Their Limitations*, 58 HARV. J. LEGIS. 145 (2020).

158. See Zetsche et al., *supra* note 154.

6. Protection of Privacy

Privacy protection is a broad concern that extends beyond credit underwriting and applies to the full spectrum of AI applications across various domains. In many countries, it is governed by cross-sectoral legislation that includes the financial sector within its scope. However, in numerous developing regions, data protection laws are either weak or altogether absent, rendering the development of clear guidelines for microfinance especially critical. Given that AI models inherently rely on the extensive collection, analysis, and processing of personal data to function effectively, imposing restrictions on these activities, while necessary to safeguard individual rights, risks undermining the very viability of such systems. Striking an appropriate balance between privacy protection and technological advancement thus emerges as a central regulatory challenge.

In this regard, it is interesting to learn from the experience in India.¹⁵⁹ In September 2022, the Reserve Bank of India (RBI) issued the Guidelines on Digital Lending,¹⁶⁰ which were replaced in 2025 by the Non-Banking Financial Companies – Credit Facilities Directions.¹⁶¹ The Directions impose strict privacy protection obligations on lenders, including on MFIs which are subject to the RBI's supervision.

Before the Guidelines entered into force, lenders exercised complete freedom to utilize customer data in evaluations of their creditworthiness. By gaining access to a potential borrower's mobile device, they could gather data points such as location, phone book and media gallery. India's entire digital lending ecosystem was born from this unfettered use of customer data,

159. See Rishi Wadhwa, *India's Digital Lending Guidelines Attempt to Regulate Data Privacy Concerns*, IAPP (Feb. 2, 2023), <https://iapp.org/news/a/indias-digital-lending-guidelines-attempts-to-regulate-data-privacy-concerns> [<https://perma.cc/G8SX-8C7W>].

160. See Reserve Bank of India, Guidelines on Digital Lending, RBI/2022-23/111, No. DOR.CRE.REC.66/21.07.001/2022-23 (issued on Sept. 2, 2022) (India), <https://www.rbi.org.in/Scripts/NotificationUser.aspx?Id=12848&Mode=0> [<https://perma.cc/9XQQ-Q8FE>] (these guidelines were withdrawn and replaced by a new set of directions dated May 8, 2025).

161. See Reserve Bank of India, (Non-Banking Financial Companies – Credit Facilities) Directions, 2025, RBI/DOR/2025-26/347 DOR.CRE.REC.No.266/07-01-008/2025-26 (issued on November 28, 2025) (India), https://www.rbi.org.in/Scripts/BS_ViewMasDirections.aspx?id=12957 [<https://perma.cc/W9US-23R3>] [hereinafter RBI Directions].

allowing lenders to distribute uncollateralized loans by profiling their borrowers. The lack of regulatory checks promoted privacy-wary practices.

The Directions set out comprehensive privacy protections for borrowers.¹⁶² First, they mandate explicit consent for data collection. Borrowers have the right to refuse, restrict, or revoke consent at any time, and can request deletion of their data. Borrowers must be informed about the purpose and intended use of the data collected. Data can only be shared with third parties after obtaining separate, explicit consent, unless required by law.¹⁶³

Second, the Directions require data minimization: Only data necessary for the lending process may be collected. Notably, lenders are prohibited from collecting or storing biometric data, unless specifically required by law, such as for Anti Money Laundering purposes.¹⁶⁴

Third, all personal data collected must be stored in India. If data is processed outside India, it must be repatriated and deleted from foreign servers within 24 hours.¹⁶⁵

Fourth, lenders must publish comprehensive privacy policies on their websites and apps. These policies must detail what data is collected, how it is used, and with whom it is shared. Borrowers must receive digitally signed copies of loan agreements and privacy policies.¹⁶⁶

Fifth, borrowers must be informed of grievance redressal mechanisms and have access to complaint channels for privacy violations.¹⁶⁷

Finally, lenders must conduct due diligence on lending service providers they contract with, to ensure their compliance with privacy and data security requirements. In any event, lenders

162. See *RBI's Data Privacy and Sharing Mandates in Digital Lending*, CONCUR – CONSENT MANAGER (2025), <https://blog.concur.live/rbis-data-privacy-and-sharing-mandates-in-digital-lending-2025> [<https://perma.cc/L9P6-7DH2>] (last visited July 13, 2025).

163. See RBI Directions, *supra* note 161, § 13.

164. *Id.* §§ 14.

165. *Id.* § 14(4).

166. *Id.* §15.

167. *Id.* § 12.

remain fully responsible for any privacy violations by their providers.¹⁶⁸

Despite the significant constraints the Guidelines and Directions have imposed on lenders, India's microfinance sector has experienced steady growth since their introduction, suggesting that regulation and expansion can coexist when appropriately balanced.¹⁶⁹

7. Accountability

Accountability is a foundational ethical (and legal) principle in AI governance, requiring that all relevant actors (developers, operators, and other stakeholders) are held responsible and answerable for the design, deployment, and outcomes of AI systems.¹⁷⁰ As AI systems increasingly exhibit autonomous decision-making capabilities, complex questions emerge regarding the appropriate allocation of responsibility for errors, misconduct, and regulatory breaches.¹⁷¹

Accountability in our context means that MFIs employing AI tools in credit underwriting may be held liable for harms caused by algorithmic decisions, particularly where safeguards are insufficient or discriminatory outcomes result. Ensuring robust accountability frameworks is thus critical not only for legal

168. *Id.* § 6.

169. In 2022, the gross loan portfolio (GLP) stood at ₹2,85,441 crore (approx. US\$36 billion). See MICROFINANCE INSTITUTIONS NETWORK (MFIN), MICRO MATTERS MACRO VIEW – INDIA MICROFINANCE REVIEW FT 2021-22 11 (2022), https://mfinindia.org/assets/upload_image/publications/Studies/FY%2021-22_MFIN%20India%20Microfinance%20Review.pdf [https://perma.cc/W4DW-MR4D]. While in 2025, the GLP reached ₹3,81,200 crore (approx. US\$46 billion), with about 140 million active borrowers. See BRICKWORK, MICRO FINANCE SECTOR IN INDIA 4–5 (2025), https://www.brickworkratings.com/Research/Microfinance_Sector_In_India_28May2025.pdf [https://perma.cc/28HK-EF37]. Another source cites over ₹3.6 lakh crore in GLP (approx. US\$43.3 billion) and 65 million active borrowers as of March 2025. See Abhijit Roy, *India's Microfinance Sector in 2025 – A Beacon of Empowerment or a Bubble Waiting to Burst?*, GOLDENPI (June 12, 2025), <https://goldenpi.com/blog/bond-news/capital-market/understanding-the-mfi-sector-in-india-operations-lending-processes-and-current-challenges> [https://perma.cc/WCM2-9S8U].

170. See Ngozi Samuel Uzougbo, Chinonso Gladys Ikegwu & Adefolake Olachi Adewusi, *Legal Accountability and Ethical Considerations of AI in Financial Services*, 19 GSC ADVANCED RSCH. & REVS. 130, 132 (2024), <https://gsconlinepress.com/journals/gscarr/sites/default/files/GSCARR-2024-0171.pdf> [https://perma.cc/P8GJ-EMDT].

171. *See id.*

compliance, but also for maintaining public trust and protecting the rights of vulnerable borrowers.

Accountability is particularly critical in microfinance, where borrowers are often vulnerable and may lack the means to understand, question, or challenge automated decisions. This is a structurally disadvantaged population, frequently without the financial resources, legal literacy, or institutional support necessary to initiate legal proceedings against lenders. In contexts where regulatory oversight is limited and power asymmetries are pronounced, it is therefore essential that MFIs proactively assume and acknowledge responsibility for the outcomes of AI-driven decisions. Such accountability is not only a matter of legal compliance, but a necessary safeguard to protect borrower rights and prevent harm.

In order to ensure accountability, MFIs should be required to implement AI governance that ensures the involvement and responsibility of the senior management in the organization; formulate an AI policy in alignment with the fundamental ethic principles outlined above; create appropriate mechanisms for managing AI risks; establish robust internal compliance, monitoring, and enforcement mechanisms; and adopt any relevant measure to ensure ethical and effective use of AI within the organization.¹⁷²

MFIs should also establish contestability and redress mechanisms that allow customers to challenge AI-driven decisions and submit complaints through easily navigable channels. These mechanisms must be tailored to the literacy levels, technological access, and socioeconomic circumstances of microfinance borrowers, ensuring that grievances are resolved promptly and equitably.

VI. CONCLUSION

The integration of AI into credit underwriting in microfinance offers numerous benefits, from increased efficiency, accuracy, and scalability of MFIs, to improved accessibility, customer

172. See BANK OF ENGLAND, ARTIFICIAL INTELLIGENCE PUBLIC-PRIVATE FORUM, FINAL REPORT 29–34 (2022), <https://www.bankofengland.co.uk/-/media/boe/files/fintech/ai-public-private-forum-final-report.pdf?la=en&hash=F432B83794DDF3F580AC5A454F7DFF433D091AA5> [https://perma.cc/AA9B-6XAH].

empowerment, and financial inclusion. However, these benefits come with significant challenges and ethical issues: algorithmic bias and discrimination, the negative impact on privacy, opacity and lack of explainability—all critical areas that MFIs must address to ensure the responsible use of AI.

In order to harness the benefits of AI while simultaneously mitigating the associated risks and ensuring adequate protection for the vulnerable populations served by microfinance, this Article calls for the regulation of AI through a sector-specific and proportionate regulatory framework that takes into account the distinctive characteristics and social mission of microfinance.

This Article calls on microfinance regulators to mandate MFIs to adopt the following ethical principles when conducting AI-based credit underwriting and performing loan processes: respect for human rights, fairness, transparency, explainability, human involvement, and accountability. By designing the AI models in a manner that respects human rights, adopting strategies to mitigate biases, implementing privacy-enhancing mechanisms, increasing transparency and explainability, and providing consumer protection, MFIs can harness the full potential of AI while safeguarding customers' interests. The central challenge lies in operationalizing these principles in a way that is appropriately tailored to the unique characteristics and needs of the microfinance population.

As the microfinance sector continues to evolve, the role of AI will become increasingly important in driving innovation and growth. The transformative impact of AI on microfinance highlights the potential for AI to revolutionize the sector and improve the lives of millions of underserved individuals. By embracing AI responsibly, MFIs can unlock new opportunities, overcome longstanding challenges, and create a more inclusive and equitable financial system.