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EXECUTIVE SUMMARY

# The Stories Algorithms Tell: Bias and Financial Inclusion at the Data Margins

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# Executive Summary

## New Visibilities, New Stories

Algorithms—mathematical recipes ranging from the simple to the complex—have a long history in the field of banking.<sup>1</sup> But in recent years, several trends have converged to supercharge their application, especially in emerging markets. The growth in mobile phone ownership and internet use continues to march ahead. Average internet use, as measured from any type of device, is staggering: 9 hours and 45 minutes per day in the Philippines, 9 hours and 17 minutes in Brazil, and 6 hours and 30 minutes in India, with more than a third of that time on social media.<sup>1</sup> Digitalization in the wake of the COVID-19 pandemic, in part encouraged by governments through temporary reductions in mobile money fees, has further pushed consumers into using their mobile devices as financial tools. In Rwanda, for instance, this resulted in a doubling, *within two weeks*, of unique mobile money subscribers sending a P2P transfer, from 600,000 to 1.2 million.<sup>2</sup>

The “data fumes” generated from the seismic increases in digital activity have found a home in ever-increasing computational power as well as advanced algorithms and machine learning techniques. These practical superpowers are being applied by financial service providers and regulators alike with the intention of lowering costs, expanding economic opportunity, and improving how markets function.<sup>3</sup> The applications are seemingly boundless, from customer segmentation, product design, marketing, and portfolio monitoring to underwriting, ID verification, fraud detection, and collection.<sup>4</sup> The opportunities have ushered in highly skilled technologists, data scientists, and engineers who build internal data infrastructure as well as test, prototype, monitor, and tweak models.

Across all industries, predictive, data-driven algorithms are being used to tell stories about individuals and, depending on how they are wielded, can drive high-stakes decisions: who receives a loan, what sentencing a judge will recommend, what therapeutics a doctor will provide. The exploding data ecosystem has created billions of new stories for financial service providers; at the Center for Financial Inclusion (CFI) we are most interested in the ones they try to tell (or don't tell) about low-income consumers.

This research explores the stories algorithms can tell about who is creditworthy in emerging markets, the risks of that narrative for those it leaves out, and what it all might mean for inclusive finance. As data ethicist Professor David Robinson writes, “There's often a gap between how much of a person's story an algorithm can tell, and how much we want it to tell.”<sup>5</sup> We have two main objectives: a) to ground some of the universal challenges on the use of algorithms, automated decisions, alternative data, and bias in the context of inclusive financial services; and b) to present the current state of play among inclusive finance actors from desk research and interviews with a sample of fintechs, regulators, and other experts. It is aimed at the stakeholders that can influence the trajectory of the inclusive finance industry, with specific recommendations for regulators, investors, and donors. Our broader goal is to break down silos between data science teams and those that view themselves in non-technical positions while playing a crucial role in shaping investments, business processes, partnerships, staff composition, project scope, and legal frameworks.

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<sup>i</sup> For example, international credit cards have long used scores to immediately recommend what type of credit card to offer customers. (“[From Catalogs to Clicks: The Fair Lending Implications of Targeted, Internet Marketing](#)”)

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## Exploring Algorithms and Bias in Inclusive Finance

When designed and used to maximize benefits, algorithm-driven decisions can counter human biases and increase the speed and accuracy of disbursing appropriate loans to people who need them but were previously denied access to credit. Algorithms have the potential to overcome some of the entrenched implicit and explicit biases of face-to-face interactions. In India, mystery shopping audits showed that individual bank staff can strongly influence financial access, even when regulation and eligibility rules should not give such discretion.<sup>6</sup> A U.S.-based study conducted by the Haas School of Business found that fintech algorithms discriminated 40 percent less on average than loan officers in loan prices, and the algorithms did not discriminate at all in accepting and rejecting loans.<sup>7</sup> At CFI, we share in the inclusive finance community's optimism for the power of increased digitalization, data processing capabilities, and troves of data trails to increase financial inclusion.

However, the pace of change and the opacity of the technology has outstripped the ability of most in the sector to understand potential risks and issues. Underwriting, and many other operational functions within financial services, are being digitized and increasingly automated. Whether it's a decision-supporting algorithm or a decision-making algorithm, humans are less in control than ever before.

Issues have cropped up with real-world consequences and harms, across all sectors. The now-infamous AppleCard (a partnership between Goldman Sachs and Apple) came under investigation by financial regulators for discrimination against women when complaints surfaced that for couples with comparable credit scores, husbands had received 10 to 20 times the credit limit of their wives.<sup>8</sup> The U.S. Department of Housing and Urban Development (HUD) filed a lawsuit against Facebook in 2019 for violations of the Fair Housing Act by limiting a person's housing choices based on protected characteristics. The suit alleged that Facebook allowed its advertising algorithms to exclude

housing ads for people classified as parents, non-Christian, or interested in Hispanic culture; it also alleged that through its massive collection of online and offline data and machine learning techniques, Facebook recreated groups defined by their protected class.<sup>9</sup> An algorithm used by commercial healthcare providers to identify individuals for "high-risk care management" programs recommended that white patients receive more comprehensive care than equally sick black patients.<sup>10</sup> Carnegie Mellon researchers uncovered that, despite treating gender as a sensitive attribute, Google's ad listings for high-earning positions were shared with men at almost six times the rate they were presented to women.<sup>11</sup>

The scale of harm or exclusion that could be wrought by a discriminatory algorithm dwarfs that of a biased individual; in economics literature this distinction is known as statistical vs. taste-based discrimination, respectively.<sup>12</sup> For instance, in the healthcare example, the flawed algorithm was applied commercially to over 200 million people annually.<sup>13</sup> How do these misfires happen? We categorize the issues into three interrelated buckets: inputs, code, and context.

### Inputs, Code, and Context

Evidence has demonstrated how, despite good intentions, bias can seep into algorithms from a variety of entry points. Most foundationally, data leveraged for a predictive algorithm can unintentionally reflect existing societal biases and historical discrimination. A country's legacy of inequality, such as mandatory migration, entrenched gender norms, racial segregation, or other types of discrimination in education and employment, for example, will inevitably reflect itself in the data trails crunched by algorithms. In the healthcare example cited above, the algorithm relied on past healthcare expenditures to predict what care a patient would require going forward. But Black Americans have had to deal with decades of institutional and cultural barriers in healthcare access, resulting in lower past expenditures. The story the algorithm was telling, then, was not the patients' actual medical need but rather

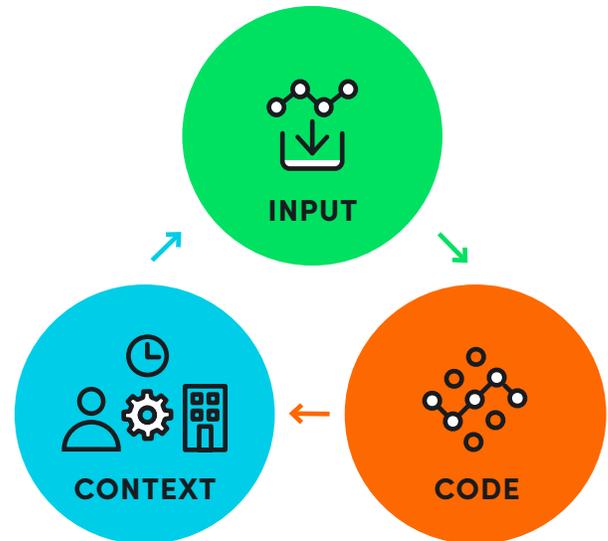
the history of disparate access to healthcare between white and Black America.<sup>14</sup> Beyond challenges of representativeness, data inputs face issues in stability, quality, and control, which is particularly relevant in a fast-moving world of digital finance where small tweaks in mobile money platforms or apps lead to big changes in consumer behavior and the stability of data trails.

Even if developers take pains to avoid using data on protected categories, particular variables could easily proxy for such sensitive data in the code—for instance, using geolocation in a country that has clear geographic divisions by race or religion, or the educational level of the applicant in a country that has traditionally limited access to education for certain groups, or mobility data as a sign of stability in a country where internal migration is common. Additionally, the opacity of many models can make it even harder to detect, with machine learning techniques undecipherable sometimes even for the developers themselves, creating challenges to auditing.

Organizational diversity and grounding in local context are important dynamics that, when absent, can lead to oversights, incorrect assumptions, and exclusion. Additionally, increasing reliance on automated algorithms to make decisions, such as credit approval, may distance organizational leaders from decisions that could harm consumers. Numerous financial service providers interviewed report that data science solutions are created by short-term consultants, purchased through off-the-shelf packages, or developed by teams that are relatively siloed off from senior management. In one case in East Asia, an investor seconded an entire data science team to a financial service provider, but the team had little interaction with the rest of the organization and did not know the context or client base well. Senior management had only a superficial idea how the data science solutions were being designed or deployed, which is problematic both for monitoring for harms and for accountability, should things go amiss.

While the framework of inputs, code, and context help explain algorithm development and facilitate the categorization of risks and tools, in practice they overlap and addressing one area without the others is limiting.

#### FRAMEWORK TO UNDERSTAND ALGORITHMIC BIAS



Long-term solutions for organizations should aim to be holistic and address all three areas through an iterative process. For instance, context will determine what kind of data is available and the methods necessary to evaluate your model. Data science skills will come into play, but fear of the “black box” should not stop sector and country specialists from getting involved, as they have critical knowledge that will help guide choices about algorithm development and deployment.

#### Why it Matters for Inclusive Finance and What We Want to Know

[In credit scoring, inaccurate and incomplete data presents risks of incorrectly categorizing individuals’ creditworthiness. This risk is heightened for vulnerable groups since the data trails of vulnerable individuals can encode realities of their environment and the types of experimental or predatory products they’ve been exposed to, making their individual profile appear riskier due to the conditions under which they are accessing credit.<sup>15</sup> This has been documented in traditional credit scoring mechanisms in the U.S., where communities of color are exposed to more payday and “fringe” lenders, a parallel of which in the inclusive

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finance space has existed in Kenya, where a digital lending laboratory exposed low-income consumers to credit bureau blacklisting which may have barred them from loans or negatively marked their digital footprints.<sup>16</sup>

Taken to scale in emerging markets, this could run counter to the goals for inclusive financial services and result in the denial of economic opportunities to consumers at the data margins. Recent research conducted by MSC shows that digital credit customers tend to be younger, male, and living in urban areas, generally fitting into categories of those who tend to be more financially included and digitally savvy.<sup>17</sup> A 2018 study of digital credit transaction data in Tanzania also revealed striking gender and rural/urban gaps in digital credit users.<sup>18</sup> This challenges the story that alternative, mobile phone data will inevitably solve the thin file problem of many rural or female consumers.

For CFI, the proliferation of these tools raises a host of fundamental questions that deserve further inquiry:

- Are algorithm-driven tools helping providers and markets achieve inclusive finance goals or further cementing the digital divide? How can inclusive finance algorithms become biased and exclusionary?
- What are providers and other stakeholders doing today to identify and mitigate against bias? What are the incentives and challenges for providers to do anything about it? Can advances in other fields be applied in inclusive financial services?
- How can marketplaces be effectively supervised as these complex tools are being deployed? Does increased use of algorithms change market competition or influence competitive dynamics?
- How do the new universal approaches to data protection intersect with algorithms, bias, and inclusive financial services?
- How do consumers think about the decisions made about them using algorithms, the data they share, and their nascent data rights?

## State of Practice in Inclusive Finance: Early Days

While fintechs show an awareness of the importance of bias and exclusion, most are only at an early stage of mitigating against these risks. This reality is also reflected in larger cross-sectoral surveys of AI developers who have called for domain-specific tools as well as voiced concern around internal capacity, such as time or staff dedicated to understanding fairness.<sup>19</sup> Many fintechs are also operating amid regulatory uncertainty, as new data frameworks are being passed but the capacity for enforcement is limited and unclear.

Additionally, the tradeoffs for regulators between risk and opportunity currently seem tilted towards the latter. One data protection law professor described the attitude as an approach that sees that “the benefits [of algorithms] are immediate and real; the potential harm is gradual and distributed.”<sup>20</sup> Another regulator from East Africa noted that until an algorithm has been proven to be risky, “Let’s have an algorithm before we think about risks related to algorithms. The risks are something that come afterward...to be frank, it’s something we haven’t started to think so much about.”<sup>21</sup>

Technological developments will always keep regulators searching for the best ways to approach the challenge of protecting consumers while fostering growth and business opportunities. And while new data protection regulation ostensibly gives consumers new rights, they place the onus of action on the individual. Realistically, how likely are low-income consumers to take advantage of these rights and understand their responsibilities? Additionally, as regulatory-based rights and recourse are currently framed around harm at the individual level and the exclusionary impacts of algorithms might be occurring at the group level, this deserves more attention and concern.<sup>22</sup>

## A Learning Agenda for the Path Forward

Given the swirl of unknowns around the deployment of algorithms in inclusive finance, we recommend a learning agenda to support responsible and inclusive lending; many of the topics can also be applied to a wider set

of products and business models. These are a broad set of questions and topics, and their breadth signals the large unmet need for useful, focused, feasible, and inclusive evidence to guide the field forward.<sup>23</sup> It's critical that we begin the search for answers now given the rapidly transforming global data ecosystem as well as

the gaps in agency between those designing the algorithms and those impacted by them. We would emphasize that the perspective of other actors beyond technical teams, both provider staff and outside stakeholders, bring crucial insights on the contexts in which, and the consumers for which, algorithms are being deployed.

**LEARNING AGENDA (continued on next page)**

**STAKEHOLDER**

**RECOMMENDATIONS**

**DONORS**

**Support Inclusivity Frameworks for Fintechs:** Help develop frameworks that leverage fintech-level data to understand impact, while supporting fintechs to invest in systems to identify and onboard previously unbanked customers.

**Test and Adapt Tools to Improve Fairness of Algorithms:** Test existing methods to mitigate AI bias with inclusive fintechs to understand gaps and limitations that may be sector-specific, as well as to identify the cost of compliance.

**Prioritize Consumer Research:** Support demand-side work with customers on data protection, perceptions of algorithms, and emerging data rights in developing markets.

**Support the Evolution of Financial Infrastructure:** Support infrastructure development and capacity building for data reporting, integration of data new sources, and trend analysis to meet the scale and speed of fintech.

**Develop Frameworks to Conduct Market Mappings:** Support market-level research to map existing data sources leveraged for inclusive finance and how they intersect with marginalized groups, access to technology, historic deprivations, social norms, and other data idiosyncrasies particular to the context.

**Support Efforts to Improve Consumer Digital Capability and Consumer Rights Agendas:** Build digital and financial capability for low-income customers and capacity of local consumer organizations around data harms.

**STAKEHOLDER**

**RECOMMENDATIONS**

**INVESTORS**

**Document and Screen for Responsible Algorithms Practices:**

Engage investees in discussions on design and decision-making process for data inputs, model development and testing, and understanding of market context.

**Require Audits:** Use relationships to incentive and test audit approaches to discover which tools work best in for the inclusive finance sector.

**Align KPIs to Incentivize Inclusive Lending:** Leverage existing reporting mechanisms to incorporate metrics and learning agendas around algorithms and exclusion.

**REGULATORS,  
POLICYMAKERS,  
SUPERVISORS**

**Market Monitoring:** Create incentives for companies to monitor and test their systems while investing in building internal supervisory capacity.

**Provide Space to Test and Learn:** Create or establish relationships with learning partners through spaces such as fintech associations and incubators, regulatory sandboxes, innovation hubs, or hotlines for governments to collect, test, and acquire evidence on emerging and innovative technology.



## Notes

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The Center for Financial Inclusion (CFI) works to advance inclusive financial services for the billions of people who currently lack the financial tools needed to improve their lives and prosper. We leverage partnerships to conduct rigorous research and test promising solutions, and then advocate for evidence-based change. CFI was founded by Accion in 2008 to serve as an independent think tank on inclusive finance.

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