

# PROMPTS FOR EQUITABLE ARTIFICIAL INTELLIGENCE IN INCLUSIVE FINANCE



## STRENGTHENING THE INDUSTRY CONVERSATION

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This work is the result of USAID's Equitable AI Challenge. Implemented by DAI's Digital Frontiers, the challenge aimed to identify innovative approaches to address artificial intelligence inequitable outcomes. The Equitable AI Challenge asked for proposals that critically consider holistic and creative approaches to identify and address gender biases in AI systems within global development contexts. This brief is the result of CFI's winning proposal and accompanies a guide for impact investors that considers gender inequity issues from the outset when designing algorithms for inclusive finance. Thanks are due to the investment teams at Quona, DFC, FMO, Accion Venture Lab, and their investee Kuunda who generously provided time and feedback throughout the project.

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# Introduction

It took 16 years for mobile phones to reach 100 million users – a benchmark that OpenAI’s ChatGPT met in just over two months.<sup>i</sup> While attention garnered by generative artificial intelligence (AI) tools like ChatGPT and DALL-E have catapulted discussions around AI to the top of global discourse in recent months, use cases for AI have been growing steadily for some time – and the economic development space is no exception. In fact, from detecting illegal rhino horns in airplane luggage to forecasting harmful algae blooms in Guatemala, there are many applications of AI that are serving to advance the Sustainable Development Goals.<sup>ii</sup>

In inclusive finance, fintechs and AI systems are leveraging the growth of digital consumer data – fueled by mobile phones – to create new products, services, and economic opportunities. In a survey conducted by the World Economic Forum of 151 fintechs and incumbents, over 90 percent of fintechs were using AI, with applications running the gamut from predictive analytics and virtual assistants or chatbots to image analysis.<sup>iii</sup> AI supports credit scoring, pricing, underwriting, customer service, fraud detection, and Know Your Customer (KYC) requirements. Generative AI alone is poised to bolster productivity in the banking industry by US \$200 to \$340 billion.<sup>iv</sup>

And from an inclusivity perspective, AI is creating opportunities for better and more meaningful financial services for women and other marginalized groups. Low-income women were traditionally less likely to meet standard measures of “creditworthiness,” often lacking title ownership, credit or payment history, and access to collateral. But less traditional, alternative data such as social media, utility, and property value data mined by AI systems for credit scoring can help facilitate women’s access to financial services.<sup>v</sup>



**While AI tools are making high-stakes decisions for the economic prospects and future of individuals, their businesses, and their communities, these systems are also introducing new risks.**

However, while AI tools are making high-stakes decisions for the economic prospects and future of individuals, their businesses, and their communities, these systems are also introducing new risks, including data privacy vulnerabilities and unfair outcomes for certain consumers. Women have experienced negative effects, such as being unfairly rejected as “false negative” in credit decisions, or receiving higher pricing, lower credit limits, and more limited choices.<sup>vi</sup> AI models have been trained using historical data that does not represent all types of borrowers, and as a result, the predictions regarding default behavior of underserved borrowers often reflect the traditional unfair financial exclusion of those borrowers.<sup>vii</sup> The use of historical datasets, and the resulting harm this can cause, contradict the goals of financial inclusion and have regulatory and business costs.

As with any technology that experiences exponential growth, stakeholders – like investors, donors, and regulators – must play catch-up, and many questions remain. How, amid all these

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changes, can concerned stakeholders understand, let alone contribute to, shaping the future of AI in a way that is responsible and equitable, particularly for achieving the financial inclusion outcomes we care about for the sector? In practice, making ethical and inclusive algorithms can be expensive, and often requires hiring outside experts to verify the algorithm's practices. As fintech increasingly takes more of a leading role in the financial services space, do early-stage companies have the incentives to invest in equitable AI? With AI regulations pending, but likely several years away in emerging markets and developing economies, will fintechs take the time to ensure their algorithms effectively and ethically consider women, low-income people, and other vulnerable populations? This brief and the accompanying guide, *Investing in Equitable AI: A Risk Management Guide for Impact Investors*, explore these questions and offer early suggestions for how to advance responsible practices in the sector.

## **A RISK MANAGEMENT GUIDE FOR IMPACT INVESTORS: HELPING TO SHAPE A MORE EQUITABLE FUTURE FOR AI IN INCLUSIVE FINANCE**

Despite expressing a strong interest in building portfolios that use inclusive algorithms, many impact investors and donors do not have the accountability tools and resources required to comprehensively assess their portfolios. Observing this gap, the Center for Financial Inclusion (CFI) crafted a guide to support impact investors in better understanding and assessing equitable AI among fintech investees. To develop the equitable AI model, CFI combined an investor needs assessment with lessons from an academic literature review and reviewed more than 120 existing responsible AI toolkits and checklists. The resultant risk management guide for impact investors can be viewed [here](#).

In conducting the research and building the guide, the team encountered several challenges that are useful to share with the wider community, aiming to bring more transparency and accountability to artificial intelligence

in inclusive finance. One challenge is that algorithmic harms in inclusive finance are not always evident. While there are dozens of recorded cases of algorithmic harms impacting women from North America and Europe, there are very few from emerging markets. As a result, many investors in emerging markets are unaware of the risks specific to women and other marginalized groups. Another challenge is the lack of a standard definition of AI fairness. Although recent advances in bias testing and auditing focus on fairness, there is no agreement on the best fairness metrics to use in financial services. Finally, despite the proliferation of tools on ethical AI, there are not many that are tailored to non-technical stakeholders like impact investors, making it difficult for investors and donors to hold conversations about equitable AI with their portfolio companies. We discuss each of these challenges in greater detail in this brief and explain how the guide for impact investors surmounts some, but not all, of these obstacles.

Despite the many challenges, there is also a rich opportunity to shape an emerging area that is critical to the future of digital finance. Given that the field is so nascent, impact investors and donors can help to develop this emerging area, particularly as these stakeholders hold the power of the purse. Finally, supporting efforts in equitable AI is not merely a matter of ethics; it is a strategic imperative. Through work in equitable AI, fintechs and their investors can work towards their goals of increased financial inclusion, which can help to unlock increased market access and growth.

Thus, CFI strongly encourages investors and donors to hold the necessary conversations with providers and those designing and deploying AI to build mutual understanding of the outcomes of these tools on different consumers. Our hope is the *Equitable AI Risk Management Guide* serves as a conversational prompt for promoting equitable AI amongst inclusive fintech providers. The remainder of this brief discusses the challenges encountered, how the guide addresses some of them, and where the industry can focus to move forward in supporting responsible AI for inclusive finance.



# Challenges in Building Accountability & Transparency for AI in Inclusive Finance

## AI HARMS ARE NOT EVIDENT

Strong risk management requires being aware of an underlying risk, any potential harms and their impact, and the likelihood of that risk being realized. Despite the growing prevalence of algorithms in inclusive finance, there are not many examples of inequitable outcomes for women or documentation on the scale of their impact. Several online repositories, including the AI Incident Database<sup>xiii</sup> and the Bias in AI: Examples Tracker<sup>xiv</sup> catalogue harmful algorithms, but these are not specific to finance and almost all examples stem from North America or Europe. An infamous episode occurred when Apple's credit card offered women smaller credit lines than men with similar credit scores. Although Apple had used a "gender-blind" approach, the algorithm was biased against women because the data used for calculating loan approvals was correlated with gender.<sup>xv</sup> In another case, researchers found that the algorithmic scoring models used by American fintech lenders were charging Latinx and African American borrowers 7.9 and 3.6 basis points more, respectively, on interest rates for mortgages and refinancing. The study estimated that these groups were paying an extra \$765 million per year in interest.<sup>xvi</sup> Unfortunately, there are not many examples of similar or related harms to subpopulations in emerging and developing economies.

However, the absence of evidence does not constitute evidence of absence. Rather, it underscores how difficult it is for consumers to realize that they have experienced an inequitable outcome through artificial intelligence. Many algorithms present a different experience or outcome to each user, making it difficult for users to compare their experiences. Most women would not know that they had, for instance, been unfairly rejected as "uninsurable" from an



insurtech company or that they are being charged a premium on their credit products because of their gender.

Many consumers believe that AI will always be fairer than humans. Eighty percent of respondents in a 2021 CFI survey in Rwanda said that they would trust a digital lender's credit assessment over a human loan officer, with one respondent explaining, "People can be unfair if they know someone or if given a carrot [bribe], but automated computer programs cannot be induced."<sup>xvii</sup> Juxtapose this with the clear alarm bells that consumers raised when digital lenders in Kenya misused their personal data through harassing collection calls.<sup>xviii</sup>

Because there is a lack of evidence, often stakeholders like impact investors are not aware of how women (and other marginalized groups) can be negatively affected or of the potential risks these tools introduce. And as a result, fintechs might resist potential costly mitigation measures, especially if the harms are unproven.

Furthermore, impact investors or donors often conduct due diligence before the start-up has fully developed or launched a business model. While a founder may clearly explain the business model and how they will use data, their AI model might not be fully created or put into action yet, and they may not have a team of data scientists on board. In these cases, during due diligence, what is being examined is the founding team's commitment to hiring skilled and responsible data scientists. This also means that there is no evidence of the model building or performance at the time of scrutiny.

## NO STANDARD DEFINITION OF FAIRNESS

Many of the recent advances in testing and auditing for bias are framed around the concept of fairness. While the proliferation of fairness measures has provided a useful starting point for

the development of bias mitigation techniques, there is no consensus on which fairness metric(s) to apply, particularly when it comes to financial services provision.

There are many ways to define “fair” and the definition can be highly contextual and cultural. Social norms have long limited women's mobility and access to resources and, alongside the digital divide, have created systemic barriers that impede women's access to financial services. Some countries have an egregious history of excluding women, or other groups, from formal financial services. A universally agreed-upon and applied definition of fairness might help to address past inequities.

The table below shares examples of fairness metrics around gender in the context of digital lending, where each metric requires different bias detection, mitigation, and corrective actions.

TABLE 1: Examples of Fairness Measures	
FAIRNESS APPROACH	EXAMPLE
STATISTICAL PARITY	There is an equal chance of the AI model predicting a good credit score for both men and women applicants.
PREDICTIVE PARITY	The probability that an applicant who the algorithm predicts will have a good credit score actually has good repayment is the same for both men and women applicants.
TREATMENT EQUALITY	Men and women loan applicants classified as creditworthy and not creditworthy have similar accuracy.
FALSE NEGATIVE ERROR RATE BALANCE	The probability that an applicant who actually pays the loan on time and is assigned a bad predicted credit score is the same for men and women applicants.
FAIRNESS THROUGH UNAWARENESS	No gender-related features are included when training the algorithm. This approach has several challenges given the reality of other data inputs that can easily proxy for gender.
FAIRNESS THROUGH AWARENESS	Men and women loan applicants who are similar in all other attributes aside from gender would have an identical outcome — acceptance or rejection.

(Adapted from Kelly and Mirpourian's [February 2021 paper](#) which was an elaboration of classifications by [Verma and Rubin](#).)



There are usually trade-offs when making decisions about fairness metrics. For example, some fairness metrics may result in AI systems that meet certain fairness standards, such as equal treatment for men and women borrowers, but do so at the expense of a less accurate model. Additionally, researchers have demonstrated that some fairness measures can be incompatible with one another when used simultaneously.<sup>xiv</sup>

Finally, while the data science community has made progress in dealing with bias detection and mitigation, most of the work has focused on addressing the unfairness produced by a single sensitive or protected status attribute. But marginalization in the real world often demonstrates intersectionality and occurs across multiple attributes, such as gender and race, and those attributes may interact in ways that lead to unfairness in a dataset or algorithmic model. When multiple sensitive attributes exist, a model that is fair for one sensitive attribute could still be unfair for other sensitive attributes. For example, a process that leads to an algorithm that is “fair” to women may still be unfair for a marginalized subset (e.g., Black women).

## LACK OF TOOLS FOCUSED ON INCLUSIVE FINANCE AND EVEN FEWER FOR IMPACT INVESTORS

As the team prepared to create the Risk Management Guide, we reviewed over 120

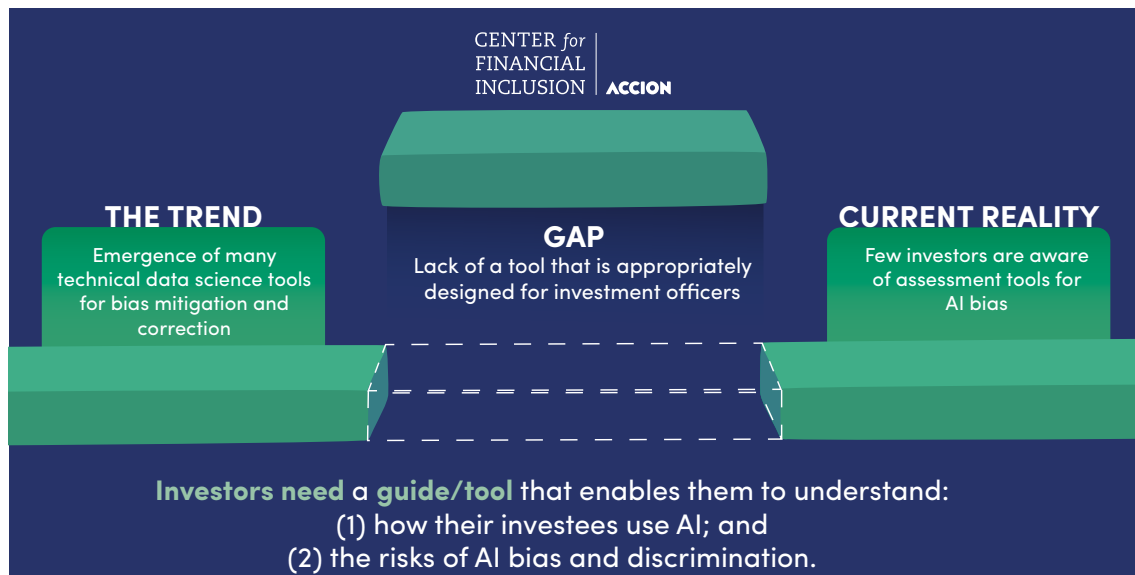
existing tools and checklists on bias mitigation. Tools fell into three groups, differentiated by the level of intervention. The first group includes tools aimed at increasing general awareness about ethical AI practices. The second group consists of tools to improve business processes with an emphasis on properly documented data. The third group involves more specialized data science techniques. Over the years, there have been significant advancements in all three categories.

While the proliferation of tools is a positive development for responsible AI writ large, there are not many that are specifically tailored to the inclusive finance space. There is also no consensus regarding which targeted bias mitigation techniques should be applied for financial services. For example, approaches for bias mitigation coming from the mainstream strategy can be broadly categorized into three types: (a) pre-processing methods focusing on modifying or “repairing” potential biases or imbalances in input data; (b) in-processing methods focusing on incorporating one or more fairness metrics into AI algorithms (e.g., in the model optimization functions); and (c) post-processing methods focusing on editing posteriors (i.e., model output) in a way that satisfies fairness constraints. These broad approaches in turn have a wide range of techniques that fall within them, each with respective advantages and disadvantages. While this proliferation of techniques has created an increasing menu of options for attempting to

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correct bias, it has also led to a lack of clarity on which approaches are most relevant or optimal for a given domain or use cases.

With AI quickly becoming embedded into every facet of inclusive financial services, the lack of standard tools and techniques to identify and mitigate bias is concerning. This is particularly challenging for investment officers, who often need to assess whether a provider has taken appropriate measures to address harmful bias but may not have the technical expertise to do so. Without consensus on the effectiveness of different approaches, how can impact investors enforce or reward their adoption? Additionally, without a tailored set of tools, how can investors enter these critical conversations around AI bias? Today, these conversations simply do not occur, raising concerns for end users, especially women and other marginalized populations who bear the brunt of biased algorithms.

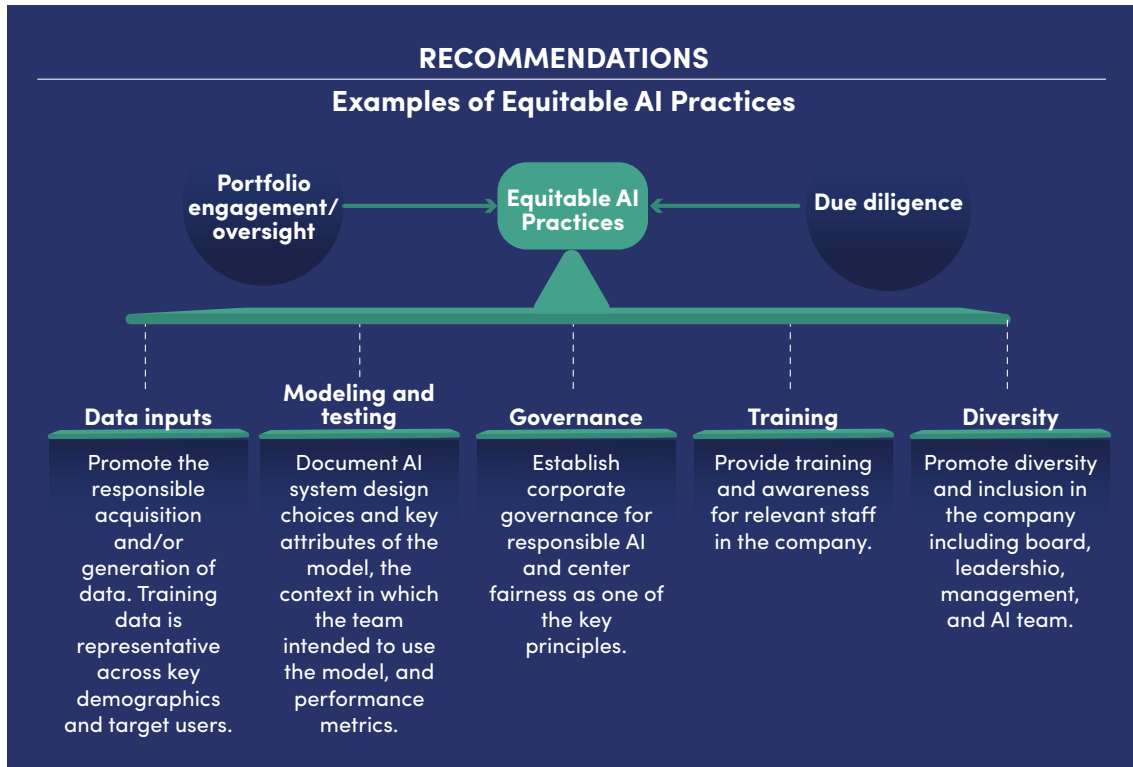






# How CFI's Guide Brings Accountability & Transparency

Despite the aforementioned obstacles, it is critical that impact investors, donors, and other stakeholders working with fintechs initiate conversations about how to build equitable AI and avoid harmful bias. Safeguarding the ground already gained in financial inclusion and responsibly harnessing AI's many benefits calls for proactivity. Addressing the reality of AI's potential unreliability and harmful outcomes cannot be deferred until perfect solutions emerge. CFI's risk management guide aims to address some of the challenges by raising awareness on risks and costs, operationalizing a definition of fairness, and encouraging strong data usage and governance practices.



## RAISE AWARENESS ON RISKS AND COSTS

The guide focuses on the importance of raising awareness among investors on how bias can creep into AI systems and the costs of harmful bias — both to the business and end consumers. If investors understand the business case about why investing in equitable AI is important, they can then take the necessary steps to mitigate, monitor, and correct bias and fund bias mitigation efforts. Because transactions or investments often happen before an AI system is fully deployed, these conversations should happen either during the due diligence processes or should be added to investment covenants and board governance practices.

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## **ARTICULATE AND OPERATIONALIZE FAIRNESS**

While top-level executives may not be directly involved in the technical aspects of implementing fairness standards, there should be agreement between fintech management and data science teams regarding the definition, measurement, and accountability for meeting relevant fairness standards. Investors who prioritize social impact should understand how fintech companies have defined, implemented, and monitored fairness and decide if it aligns with their own investment goals. The guide contains questions that prompt conversations for those discussions and definitions.

## **BUILD STRONG DATA USAGE AND GOVERNANCE PRACTICES**

The questions included in the guide are calibrated for the investor level and designed to fit into existing processes. Because impact investors typically are non-data science stakeholders, the guide does not require strong data science skills to interpret the answers. Additionally, because AI models are constantly changing and evolving,

looking only at the algorithm's outcome will give a limited view of the system. As such, the guide emphasizes that the processes behind the algorithm development, staffing, training, and data documentation are just as important as the model or the results.

While the guide serves as a starting point for conversations to support equitable AI, much more work is needed on equitable and responsible AI practices. We hope that stakeholders use the guide and share feedback and insights on what works, what doesn't, what conversations could be resolved, and what requires more resources and evidence.





# Opportunities to Strengthen the Industry Conversation on Equitable AI

There are tremendous opportunities for artificial intelligence systems to support and build economic empowerment for women and other marginalized groups. And just as AI in inclusive finance cannot be held accountable for long-standing societal gender biases, it cannot fully eliminate these entrenched issues. Below are several recommendations for areas where additional work could enrich and strengthen those conversations between fintechs and investors and, more broadly, with the wider range of industry stakeholders.

## EQUITABLE AI RESEARCH

Although there is a near-endless list of research topics that can help to strengthen the evidence base for the inclusive finance industry's conversations on equitable AI, the following four are critical:

### 1 DATA SCIENCE ADVANCES

#### a. Develop Inclusive Finance Fairness Metrics and Accompanying Bias Mitigation Techniques

There is a need to reach a consensus on which fairness measures should be prioritized in the context of financial inclusion, and which bias mitigation techniques are most relevant, effective, and practical to achieve them. It would be useful to compile and systematize examples from the financial services industry. Additionally, many digital finance providers use “hybrid approaches,” which use AI but have people supporting decision-making. Best practices should address both hybrid and fully digital approaches.

#### a. Fairness When Dealing With Multiple Protected Classes

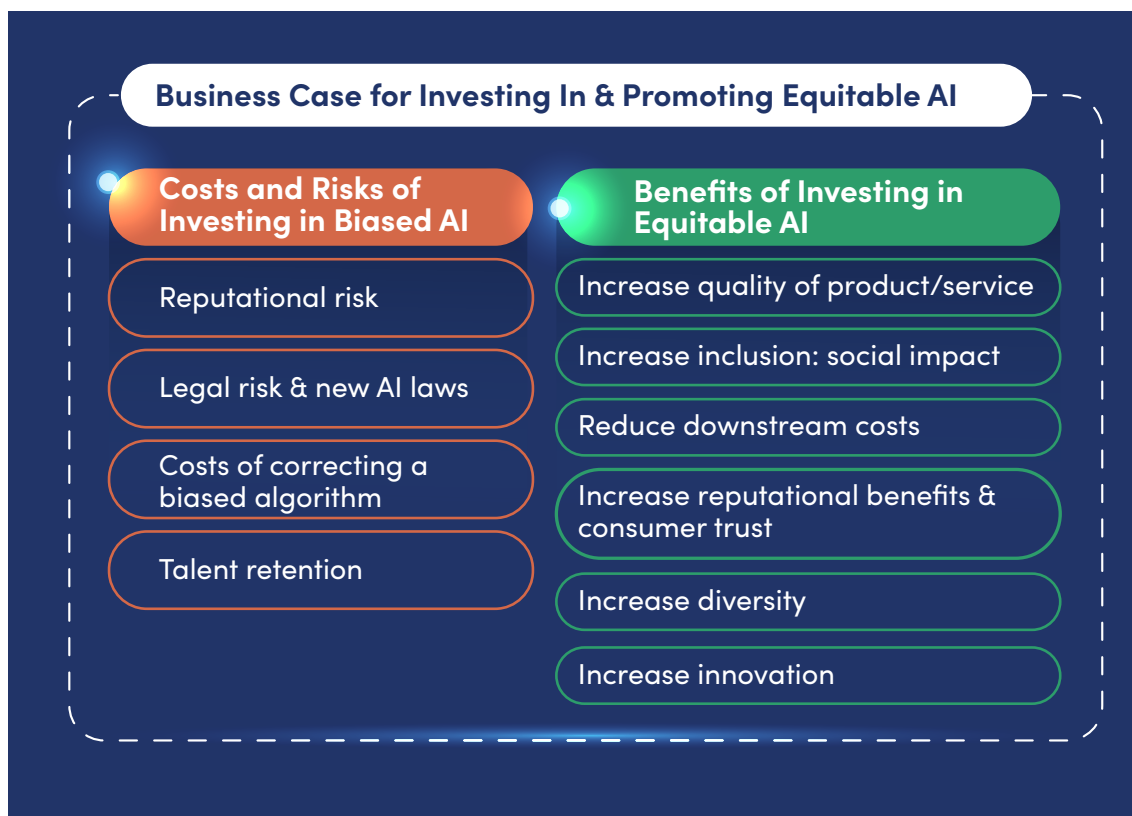
Data science should be applied to help advance fairness among multiple protected status classes. There may be cases in which optimizing a fair algorithm for one protected

status class leads to adverse outcomes for another protected status class or a subgroup. Additional research is needed on how to handle these tensions and to what degree fintechs should be expected to prove a lack of bias for different subgroups.

### 2 BUILD THE BUSINESS CASE AND COST OUT TRADE-OFFS

Implementing equitable AI is an opportunity for a company to build innovative products, a stronger reputation, competitive advantage, and a larger customer base, but it can also be a costly endeavor.<sup>45</sup> The inclusive finance sector would benefit from stronger cost-benefit analyses on the use (or lack) of equitable AI. For instance, while there can be a trade-off between fairness and accuracy, there are few examples of those trade-offs and implications for an institution's bottom line. Additionally, the sector must grapple with how to determine the proportionality of obligations — should large financial institutions have the same responsibility as small start-ups? According to the draft EU AI Act, obligations are proportionate to the level of risk of the AI decision, not the size of the provider.





## SUPPORT JOURNALISM, CIVIL SOCIETY & ACADEMIA TO IDENTIFY RISKS

Consumer advocacy and journalism can play a crucial role in uncovering and highlighting inequitable outcomes. Journalism and citizen research projects — such as YouTube Regrets, the African Digital Rights Network, Northeastern University’s National Internet Observatory, or the University of Toronto’s CitizenLab — could lead to stronger risk detection and catalyze action.<sup>xvi</sup> YouTube Regrets, a project run by Mozilla Foundation, recruited more than 37,000 volunteers to monitor YouTube suggestions and then noted which recommendations they regretted having seen due to their inaccurate, offensive, or violent nature.<sup>xvii</sup> Researchers have also used novel approaches, such as scraping publicly available data from social media, to monitor for consumer protection violations and risks that may not be easily captured elsewhere.<sup>xviii</sup>

## OPERATIONALIZE DATA RIGHTS FOR CONSUMERS

While consumers might at first glance give a blanket approval of data-driven digital financial products, as they receive a more detailed explanation on how these products work, their opinions become more mixed.<sup>xix</sup> This is but one signal of the huge challenge in transparency and explainability to consumers around AI-driven financial decisions. While data rights have accompanied data protection laws, and will likely accompany AI-related legislation, there is a need for more innovation and evidence on how to operationalize those rights, particularly for women and other vulnerable consumers.

## REGULATION

Despite the publication of high-level principles and strategies on ethical artificial intelligence by dozens of countries and multilaterals, including the Organization for Economic Cooperation and Development (OECD), the concrete regulation of AI in financial services remains in early stages



and uncharted territory. The European Union is poised to transform the discussion around regulation and AI with the likely passage of the EU AI Act, a comprehensive omnibus legislation aimed at governing artificial intelligence applications within the European Union.<sup>xx</sup> Other countries are keenly observing the EU's developments, how the AI Act will intersect with GDPR, how it will be operationalized, and how AI systems will be supervised.

In financial services, establishing adaptable regulations that align with the pace of innovation is essential. Providers, regulators, and civil society should collaborate through productive public-private partnerships to experiment, gain knowledge, and identify effective approaches in developing equitable and responsible AI-driven tools. For example, the Monetary Authority of Singapore has developed a consortium with 30 private sector financial service providers to co-create methodologies to achieve fairness, ethics, accountability and transparency (FEAT) in their use of AI.<sup>xxi</sup> And the Financial Conduct Authority in the UK is using its digital sandbox for providers to test and collaborate on new AI use cases.<sup>xxii</sup>

Governments must also look to minimize the “fairness through unawareness” issue, where algorithms’ outputs appear to be fair because the provider did not use gender (or other sensitive characteristics). This doesn’t stand up because systems can inadvertently use proxies for sensitive attribute data in decisions, even if it was unintentional. For instance, the type of apps a person installs on their phone can act as proxies for gender, age, or other characteristics. Overcoming this requires responsibly collecting sensitive demographic data on users and working with regulators on the challenges in existing legal requirements. In the United States, some lenders who are using AI models have begun to allow their fair lending compliance team to use sensitive data to test for bias but forbid their business units access in the model development stage.<sup>xxiii</sup>



## Conclusion

Impact investors, donors, and other stakeholders must have conversations with fintech partners to help advance inclusive finance outcomes. While operationalizing equitable AI remains an ongoing challenge, it should not deter the sector from initiating these crucial conversations that must take place to move the needle towards responsible AI solutions, especially for women and other marginalized groups. Recognizing that a perfect solution does not yet exist should not discourage the sector from taking necessary steps towards progress.

We cannot risk losing the ground we have made in financial inclusion, or risk losing out on the potential benefits AI might offer, because we were blind to its risks. If AI becomes untrustworthy and unaccountable because of its unfair outputs, this risk is very real. By acknowledging the existence of the issue and actively seeking solutions, the inclusive finance sector will create an environment conducive to learning, collaboration, and innovation. Every conversation made around equitable AI brings the sector closer to a more inclusive and fair future for women.





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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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