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Fairness in algorithmic decision systems: a microfinance perspective

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Preface

The EIF supports Europe's SMEs by improving their access to finance through a wide range of selected financial intermediaries. To this end, the EIF primarily designs, promotes and implements equity and debt financial instruments which specifically target SMEs. In this role, the EIF fosters EU objectives in support of entrepreneurship, growth, innovation, research and development, and employment.

The EIF has been involved in the European inclusive finance - including microfinance - sector since 2000, providing funding (equity and loans), guarantees and technical assistance to a broad range of financial intermediaries, from small non-bank financial institutions to well established microfinance banks to make inclusive finance a fully-fledged segment of the European financial sector. The EIF has become an important pillar of this segment, by managing specific initiatives mandated by the European Commission, the EIB, and other third parties, as well as by setting up operations using own resources.

This working paper results from a research project on "Strengthening Financial Inclusion through Digitalisation" (SFIDE), initiated by EIF's Research & Market Analysis division. The project is funded by the EIB Institute under the EIB-University Sponsorship Programme (EIBURS). EIBURS supports university research centres working on research topics and themes of major interest to the EIB Group. Digitalisation and financial innovations in the European SME finance sector is strategically relevant to the EIF and to the EIB Group. The EIF believes that supporting financial innovations can disrupt funding instruments, including inclusive finance, and improve its ability to contribute to the achievement of social policy targets.

The aim of the SFIDE project is to investigate the potential of technological and financial innovation to increase the efficiency of the inclusive finance sector, through the identification and promotion of best practices. Artificial intelligence (AI), among other technologies, is becoming an important tool for achieving operational efficiency. However, using AI may raise risks associated with fairness which is particularly important to ensure when operating in socially driven environments like microfinance. The paper discusses fairness in AI-enabled credit-scoring systems. By means of a case study, focusing on a European non-profit microfinance organisation, it unveils the typical challenges associated with implementing fairness principles in practice. This working paper is expected to be followed by other papers conducted by researchers involved in the SFIDE project.

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Abstract

Fairness is a crucial concept in the context of artificial intelligence (AI) ethics and policy. It is an incremental component in existing ethical principle frameworks, especially for algorithm-enabled decision systems. Yet, unwanted biases in algorithms persist due to the failure of practitioners to consider the social context in which algorithms operate. Recent initiatives have led to the development of ethical principles, guidelines and codes to guide organisations through the development, implementation and use of fair AI. However, practitioners still struggle with the various interpretations of abstract fairness principles, making it necessary to ask context-specific questions to create organisational awareness of fairness-related risks and how AI affects them. This paper argues that there is a gap between the potential and actual realised value of AI. We propose a framework that analyses the challenges throughout a typical AI product life cycle while focusing on the critical question of how rather broadly defined fairness principles may be translated into day-to-day practical solutions at the organisational level. We report on an exploratory case study of a social impact microfinance organisation that is using AI-enabled credit scoring to support the screening process of particularly financially marginalised entrepreneurs. This paper highlights the importance of considering the strategic role of the organisation when developing and evaluating fair algorithm-enabled decision systems. The paper concludes that the framework, introduced in this paper, provides a set of questions that can guide thinking processes inside organisations when aiming to implement fair AI systems.

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1 | Introduction

The use of artificial intelligence has rapidly gained momentum in various industries. Decision-makers have been immensely empowered with enhanced information processing capabilities and understanding of the business environment by leveraging big data to interpret economic and environmental contexts (Moustakas, 1994; Namvar and Intezari, 2021). This, in turn, holds the potential for creating economic and social value for both organisations and society. However, the challenge of unwanted biases in algorithms persists (Edwards and Veale, 2017; Katell et al., 2020; Selbst et al., 2019; Tsamados et al., 2012), often caused by the failure of practitioners to consider the social context in which algorithms operate. At the same time, the issue of 'abstraction traps' makes achieving fair AI in day-to-day organisational practices more complex (Selbst et al., 2019). Practitioners may be left with generic and abstract guidelines on the development, implementation and use of AI systems in organisations without technical explanations (Peters and Calvo, 2019). A survey revealed that 79% of tech workers require more practical resources and guidance to help them navigate ethical considerations[1] (Floridi, 2021; Miller and Coldicott, 2019; Morley et al., 2021).

Recent public initiatives have led to the development of ethical principles, guidelines and codes to guide organisations through the development, implementation and use of fair AI (Floridi, 2021). This has resulted in the emergence of a large pool of AI principles that are gradually converging, fostering coherence and compatibility of existing principles. This development is particularly helpful for organisational actors who face challenges due to the lack of a unified AI terminology and fairness definition required to implement fair AI (Floridi and Cowls, 2021; Peters and Calvo, 2019). However, researchers have warned against 'algorithmic formalism' that could result in prescribed definitions and abstractions ignoring the social complexity of the real world (Green and Viljoen, 2020; Katell et al., 2020; Xivuri and Twinomurinzi, 2021).

Without practical guidance, practitioners struggle with the various interpretations of abstract fairness principles (Alshammari and Simpson, 2017). Additionally, organisations risk to become exposed to phenomena such as 'ethics blue washing' and 'ethics shirking' (Floridi, 2021). To mitigate the organisational risks associated with the implementation of fair AI, research emphasises the importance of involving the firm as a strategic player (Fu et al., 2022). Rather than redefining fairness frameworks, industry professionals should ask context specific questions which create organisational awareness of fairness-related risks and how AI affects them (Lee et al., 2021). Therefore, the debate should shift from what ethics are needed to how ethics can be successfully applied and implemented in context-specific environments (Taddeo and Floridi, 2021). By doing so, organisations can reduce the risks associated with fairness-related AI and implement AI systems that provide the intended added value.

This research uses a case study of a non-profit microfinance institution in the Netherlands to explore the implementation challenges and implications of adopting AI technology in the financial sector. As AI becomes increasingly important for achieving operational efficiency and

[1] The survey was undertaken by Doteveryone, a UK based independent think tank who champion responsible technology for a fairer future. 1,000 people working in technology roles across all parts of the UK economy were surveyed.

gaining competitive advantage, organisations must consider the potential risks and fairness implications of this adoption, particularly in socially driven environments like microfinance. Microfinance delivers services that are life-altering for marginalised clients and hence necessary to consider practices that ensure fair treatment and outcomes.

In addition, fair AI research focuses on the financial sector despite its relevance for financial organisations and society. Bias in the financial sector, such as gender and race, could result in punishment by courts and fines (Xivuri and Twinomurinzi, 2021).

The paper follows an AI product life cycle, from initial design to final implementation and operations, to explore the implementation challenges that organisations may encounter with AI technology. The authors present a framework that can assist practitioners in designing and deploying AI practices effectively while also achieving fair outcomes. The framework elaborates on crucial aspects that should be considered to overcome major development and implementation challenges by elaborating on important aspects. We focus in specific on AI-enabled decision systems given that this technology has recently been introduced to support the decision processing during loan applicant screening in our chosen case study. The authors hope that the taken approach in this paper will inspire and help practitioners to ask more context-specific questions and avoid organisational risks associated with AI adoption.

The paper aims to contribute to current research discourse on fair AI in the social finance literature by applying a context-specific case. Moreover, we also attempt to raise the Fair AI debate to a different level. We take a holistic view that guides the entire AI life cycle from the initial steps to the final outcome and its operation. In addition, we contribute to literature on decision support systems in particular.

In the remainder of this paper, we first define the relevant concepts of artificial intelligence, AI-enabled decision systems and AI fairness before putting them in the context of financial services in the microfinance industry. After describing our research method, we present our framework and case study findings. Finally, we discuss the implications of our findings and conclude.

2 | Theoretical background

2.1 | Artificial Intelligence and AI-enabled decision systems

The term Artificial Intelligence refers to the intelligence of machines, as opposed to human intelligence that resides in the brain. In most publications, artificial intelligence is used synonymously with the study of intelligent actors, which are defined as "any system that perceives its environment and takes actions that maximise its chance of achieving its goals" (Poole et al., 1998). The most recent definition of AI on a European level was established by the European Parliament, defining AI as "[...] systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals" (European Commission, 2018).

From a technical perspective, AI systems can generally be divided into two categories: supervised systems and unsupervised, depending on how the system is trained. In supervised systems, both input data and corresponding output data are fed into the system, and the system tries to find statistical transformations for the input data to match the output data as closely as possible (Braga-Neto, 2020). In unsupervised learning, only input data is fed into the system, and the system tries to identify patterns that can be used for clustering, dimensional reduction, or anomaly detection (Braga-Neto, 2020). This paper focuses on 'weak' AI, which aims to solve a specific problem set by performing operational tasks through the use of machine learning, as opposed to 'strong' AI which theoretically solves any problem but does not exist at the moment (Braga et al., 2017).

2.2 | Fairness and AI

The field of fair AI is concerned with the design, development, and implementation of an AI system as it ensures biases are removed. One of the main principles of AI ethics is fairness, which requires that AI is built in a manner that promotes democratic values and principles such as freedom and equality (Ienca, 2019). Algorithmic biases that produce discriminatory outcomes for certain groups of people may not only reproduce societal inequality but also cause reputation damage to the organisation (Fu et al., 2022; Xivuri and Twinomurinzi, 2021).

In general, the concept of fairness is applicable to the behaviour of human beings, and sees a situation as fair, if all free, reasonable and equal persons agree to that (Chapman, 1975). This statement, however, is not undisputed and there are many critics that see the concept of fairness from a different point of view. Another definition that is closely linked to the "performance equity"-concept is that a situation is fair if every person gets what they deserve. Some researchers also see a situation as fair, if no person looks for and exploits loopholes (Dimitriou and Schweiger, 2015).

Merely establishing fairness principles in organisations with good intentions may not be sufficient. Additionally, despite the ongoing debate on the meaning of fairness, certain well-meaning fairness definitions may not necessarily benefit the group that is experiencing discrimination. For example, the concept of equal treatment implies that individuals who are equal should be treated equally, regardless of their demographic classification (Corbett-Davies and Goel, 2018; Fu et al., 2020). This notion addresses procedural discrimination, indicating that organisations should avoid incorporating sensitive attributes into algorithmic input for their decision-making systems. However, this approach of equal treatment through algorithms frequently results in an unequal impact on different demographic groups when systematic differences between the groups exist (Chouldechova et al., 2018; Green and Viljoen, 2020; O'neil, 2016; Taddeo and Floridi, 2021). To achieve equal impact, algorithmic systems require different rather than equal treatment of groups. Hence, recent research has come up with different notions focusing on equal impact in algorithmic decision-making, such as equal opportunity, demographic parity, equalised odds, and conditional statistical parity which focus on achieving equal impact (Fu et al., 2022; Skeem and Lowenkamp, 2016; Corbett-Davies and Goel, 2018; Fu et al., 2020; Hardt et al., 2016).

The discussion has developed into a critical policy debate as to whether algorithms should be handled with equal treatment or equal impact notions (Barocas et al, 2016; Corbett-Davies and Goel, 2018; Fu et al., 2020; Hardt et al., 2016; Skeem and Lowenkamp, 2016). The authors Hardt et al. (2016), for example, argue that the notion of equal opportunity "incentives the decision maker to invest additional resources toward building a better model" (Fu et al., 2022; Hardt et al., 2016). Nevertheless, this argument ignores the importance of the learning effort that decision-makers exert upon which the accuracy of the algorithm depends (Fu et al., 2022). To ensure an outcome is fair, the strategic role of the organisation needs to be accounted for, in particular the costs of learning. This includes building a fitting organisational infrastructure as well as an experimental organisational environment (Fu et al., 2022).

2.3 | Artificial Intelligence and Fairness in the Context of Financial Services in the Microfinance Industry

Microfinance institutions are financial intermediaries that pursue a lending strategy that serves disadvantaged borrowers. These disadvantages translate into information asymmetries, lack of credit history and disproportionate transaction costs when accessing small loans to start up a new business venture. Mostly vulnerable members of society, such as unemployed persons, young and elderly people, migrants, women and minorities are affected by these disadvantages (Canales and Greenberg, 2016).

Advances in AI-enabled decision systems are consistently transforming the landscape in the previously relationship-oriented microfinance industry. In particular, credit scoring systems have expanded rapidly and are argued to increase the availability of credit to opaque and marginalised entrepreneurs as they improve the accuracy of risk-based pricing of loans. Credit scoring refers to the calculation of a single metric that expresses the creditworthiness of an individual (Finlay, 2012). Most credit scoring systems make use of machine learning, a subcategory of artificial intelligence, in which the system creates the rules itself. The development team only prepares the data as well as the function to evaluate the accuracy and precision of the model (Gunnarsson et al., 2021).

Research has shown that the inclusion of increasingly comprehensive databases as well as new methods of analysis help financial product developers (FinTechs) to deploy complex algorithms to predict the likelihood of repayment and profitability (Johnson, 2019). Nevertheless, integrating algorithmic systems in decision-making processes and existing business structures is raising concerns. Research particularly investigates the social welfare effects of permitting FinTech firms to operate in credit markets (Johnson, 2019).

While the recently published "European Code of Good Conduct for Microcredit Provision" brings attention to ethical considerations when utilising algorithms in the underwriting process, it is worth noting that the code's comments on algorithmic use in decision-making are somewhat limited. Although the code calls for providers to have a non-discrimination policy that specifies that discriminatory variables in algorithms should be excluded, even if they correlate with repayment likelihood, it may not go far enough in addressing the complexities of the notion of fairness (see Chapter 2.2 |), (European Commission, 2022).

2.4 | Existing frameworks for ethical principles

In this section, three prominent ethical frameworks are discussed. One framework was published by UNESCO. It was chosen, amongst others[2], because of its focus on fairness and the fundamental recommendations it gives. Subsequently, the AI-Blindspot framework by the Massachusetts Institute of Technology (MIT) is discussed. The AI-Blindspot framework is being discussed due to its relevant life cycle model. It offers general guidelines to avoid unintended outcomes of the use of AI. The framework provided the key inspiration for the fairness-centred life cycle proposed in this paper. Next, the Policy Guidance on AI for children (UNICEF) was chosen given the focus on a specific vulnerable group. Hence, it informs our understanding of AI fairness policies when dealing with marginalised as well as particularly vulnerable population

[2] Other examples, such as the High-Level Expert Group on AI set up by the European Commission have a similar definition of the principle of fairness (Ethics guidelines for trustworthy AI (Apr 2019); Assessment list for trustworthy AI (ALTAI) (Jul 2020)).

groups. Other examples, such as the High-Level Expert Group on AI set up by the European Commission have a similar definition of the principles of fairness.

The UNESCO Recommendation on the Ethics of Artificial Intelligence (UNESCO, 2021) has a dedicated section on fairness and non-discrimination in which three recommendations are written out: (i) AI needs to be accessible to everyone that wants to use it. This not only means finding a way for giving people access to the system, but also respecting specific needs based on "different age groups, cultural systems, different language groups, persons with disabilities, girls and women, and disadvantages, marginalised and vulnerable people or people in vulnerable situations"(UNESCO, 2021). (ii) Creators of AI systems need to make "reasonable efforts to minimise and avoid reinforcing or perpetuating discriminatory or biased applications". Additionally, there needs to be an easy and effective way to remedy discrimination and biased algorithmic determination. (iii) Knowledge divides between countries and local communities have to be addressed in accordance with legal and regional frameworks, so that every person is treated equitably.

AI-Blindspot[3] is a tool developed by the MIT Media Lab, which provides a process for finding unintended outcomes of AI systems with a focus on machine learning as the most common technology in this field. It is stated that the consequences of such blind spots are difficult to foresee, but in nearly all cases marginalised communities are affected. To avoid blind spots a series of steps are proposed for the development and use of AI systems. The process is subdivided into 4 phases: Planning, building, deploying and monitoring. In the planning phase, the creator of the AI system needs to think about the purpose of the system, how representative the data is, if and how it can be abused and how privacy can be secured. In the building phase, the optimisation criterion has to be set. This is very important for an AI system as the system tries to improve every indicator that is part of the optimisation criterion and ignores all others. In the same step the explainability of the AI system has to be clarified. In the deploying phase, the creators have to set up a system to monitor the AI and react to any changes that may come over time, as well as offer individuals the right to contest (Wachter, 2017). The last phase is about monitoring the AI and frequently discussing with experts to ensure the AI system still fulfilling the same purpose it started with (Namvar, 2016).

The Policy Guidance on AI for Children (UNICEF) was published to develop requirements for AI systems that are specifically designed for, or mainly used by children (Dignum et al., 2021). The guidance explicates 9 requirements for ethical AI for children. This paragraph focuses on the need to "Prioritise fairness and non-discrimination for children". The specific challenges to fairness for children lie mainly in two things: first, AI systems should actively support the most marginalised children to provide equal access to all of them. Second, datasets should include diverse data from all children, especially in healthcare. Children's treatment should be based on representative data from their age group. Limits in representativeness should always be explicitly stated.[4]

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[3] MIT Media Lab: AI blindspot: *AI Blindspot: A Discovery Process for preventing, detecting, and mitigating bias in AI systems*

[4] The risk of unfair outcomes in the implementation of an AI system is larger with children, since they are often not in the position to contest unfair outcomes, demand equal opportunity, and defend their own rights. The case study in section concerns a microfinance institution that does not work with children on any level. The risk of unfairness regarding children in this case study follows from unfairness towards their parents/caregivers. Hence, the Policy Guidance on AI for Children is not mentioned in the case study.

3 | Framework Development

Fairness has many different levels and is often connected to, and sometimes seen as a synonym of, non-discrimination. However, Malgieri (2020) shows that even within the limited context of GDPR (European Parliament, 2016) the principle of fairness is far more complex. It is being translated in different contexts as correctness, loyalty and equitability.

With this complexity in mind, it would be easy to think that fairness by design is impossible to reach, but any reasonable effort to approach it, should, in the authors' opinion, be taken. Following the principles of the *UNESCO Recommendation on the Ethics of Artificial Intelligence* (UNESCO, 2021) we promote an inclusive approach that tries to minimise unfair and discriminatory outcomes and ensures effective remedies against unintended effects. Moreover, the large variety of available tools and frameworks to manage AI risks are often employed in isolation. A structured process that identifies when ethical failures (may) occur is necessary. This is why we take a holistic view by applying a life cycle framework.

3.1 | The Life Cycle of AI Systems

Throughout the life cycle of an AI system, we identify the following five stages: problem statement, development, deployment, review & monitoring, and discontinuation. These stages lean on the four stages of MIT Media Lab's AI Blindspot tool (planning, building, deploying and monitoring) (Morley et al., 2021) but are modified to use a more inclusive definition of AI and focus on fairness specifically. Furthermore, it is usable not only by actors that develop AI systems themselves, but also by those who acquire (existing) technologies from external suppliers.

The stages are structured along natural decision moments (the decision to invest in developing a technology, the decision to deploy a system to the public, etc.) We have identified several relevant sub-stages in Table 1 that should be taken into account to ensure fairness on as many levels as possible. For every stage a more detailed explanation is given in the sections below.

The Problem Statement Stage often starts naturally when organisations encounter a problem. In this stage it is important to create a clear definition of the problem. The definition is elemental to the choice of technology. It is important to identify individuals and groups that are at risk of suffering real damage from negative outcomes when using the intended system. The questions should be raised whether there are known risks of unfairness in the chosen technology, explicate the fairness trade-offs and how risks can be mitigated or compensated for. Once the potential pitfalls are identified, the organisation can explicitly answer whether a technology delivers the expected benefits and whether these outweigh the expected costs for all stakeholders.

Table 1: The five stages of the life cycle of a fair AI system.

Stage	Description
Problem statement	- Definition of the problem - Technology selection - Unfairness risk identification - Definition of steps to minimise risk of unfairness and ensure effective remedy - Continuation decision based on the positive and negative effects identified above
Development	- Implementation of the selected technology - Organisational process evaluation - Development of strategies for the "right to contest" and remedy - Equal opportunity strategy development - Explainability assessment - Unfairness risk and impact assessment
Deployment	- Evaluation of changes in the context of the system - Deployment of the system - Implementation of equal opportunity strategy - Implementation of the right to contest and remedy strategy
Review & Monitoring	- Introduction of a formal oversight body - Regular stakeholder consultation - Continuous unfairness risk assessment - Continuous improvement identification - Definition of reasons for discontinuation
Discontinuation	- Suspension of the deployed system - Identification of persisting risks - Long-term remedy implementation

The Development Stage surpasses the mere programming of the selected solution. We argue that it should incorporate the evaluation of current organisational processes and the development of new ones. This not only ensures a clearly identified path for any stakeholder to contest the automated decision advice produced by the AI system but also a remedy in case negative outcomes do lead to actual damage among individuals or groups of stakeholders. Furthermore, the explainability of the system should be assessed. If on any level the system is not explainable, the right to contest and implementation of remedies for unintended negative outcomes needs to be clear within an organisational structure. Appropriate organisational processes to ensure the above should be seen as the basis for an extensive unfairness impact assessment. It is possible to conduct these evaluations publicly, but if circumstances do not allow for it, an impartial review may be considered based on the potential level of impact that may result from the assessment.

The Deployment Stage consists not only of the actual deployment of the system, but also of the steps that should be taken before and alongside this process. An important step before deploying a system is to evaluate whether the context has changed in ways that impact its performance or the fairness of the outcome. Such changes can be small and context-specific, but also on a worldwide scale, like in the case of a pandemic. Next, the deployment should not begin without the implementation of strategies for equal opportunity, the right to contest and remedies. To support equal opportunity, it may be necessary to actively reach out to the most marginalised people so that they may benefit from your system.

The Review and Monitoring Stage consists of regularly organised reviews and continuous monitoring of all relevant changes in the context of the system. This stage requests a formal oversight body with sufficient authority.[5] This body should organise regular consultations with all stakeholders given that fairness related problems may escalate over time and go unnoticed. Fairness risk assessments can focus on incrementally changing external and internal organisational processes. In addition, potential improvements to the system itself can be identified. Finally, thresholds should be defined that may result in the discontinuation of the AI-decision system, for example, when the risk of unfairness becomes so high that an effective remedy can no longer be guaranteed.

The Discontinuation Stage can be instantiated by "natural" processes, such as replacement by another system, but also by active interference by the oversight body, on the basis of unintended negative or unfair impact. It is always important to assess the risks that persist after discontinuation. These could be unfair situations that might escalate in the future, but also risks that come from reusage of parts of the system. For these and other previously unnoticed unfair outcomes, a long-term remedy should be put into place in such a way that the negatively affected stakeholders have access to it.

3.2 | Framework Implementation

Since our framework uses an inclusive approach, it is recommended to combine it with toolkits and frameworks that are more specific to the situation and technology in use.[6] It is important to keep in mind that due to the variety of definitions of fairness, achieving fairness on one level, does not guarantee fairness on all levels. There are various examples of literature review studies that can be used to find guidance in the field of AI ethics (Floridi and Cowls, 2021; Morley et al., 2021; Tsamados, 2021) and toolkits (AI blindspot[7], Ethics and algorithms toolkit[8], Algorithmic accountability policy toolkit[9], Consequence scanning[10], AdaLovelace Institute, 2020; PwC, 2022) meant to tackle common ethical problems in AI. For any framework (including this one) to

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[5] The oversight body is meant to prevent the opaqueness of AI systems and should provide regulation to prevent the common traps mentioned in O'neil (2016). I can be placed independently within the organisation without interests that conflict with its role.

[6] Such as the seven dimensions framework for machine learning systems provided by Greene (2019) and further analyzed by Le Piano (2020).

[7] MIT Media Lab: AI blindspot: A discovery process for preventing, detecting, and mitigating bias in AI systems. *https://aiblindspot.media.mit.edu/* (2019), accessed: 2022-1-13

[8] Ethics & algorithms toolkit. *https://ethicstoolkit.ai/*, accessed: 2022-1-15.

[9] Algorithmic accountability policy toolkit. Tech. rep., AI Now Institute at New York University (Oct 2018).

[10] Consequence scanning: An agile event for responsible innovators. *https://doteveryone.org.uk/project/consequence-scanning/* (Apr 2019), accessed: 2022-1-15.

be effective, it should be adapted in such a way that it fits into the organisational environment (Madaio et al., 2020).

4 | Case Study

A case study is a suitable research method for exploring complex new phenomena holistically and with a focus on "how" questions. Our exploratory case study uses documents and open publications retrieved from a non-profit microfinance institution. In addition, a pilot interview with two data analysts was used to identify personal experiences in the use of AI-supported credit scoring systems in the screening processes of credit applications. We used semi-structured questionnaires during the interview to encourage a free-flowing discussion (Moustakas, 1994), and encouraged the participants to provide examples of business situations where they observed challenges[11]. Since the objective of microfinance is the delivery of services that can be life-altering for marginalised clients, the chosen industry has special reasons to maintain consistent standards of eligibility to ensure fairness.

This section will give a short overview of the organisation case study. The information has been collected from internal documentation at Qredits as well as publicly available reports, such as "Qredits: A Data-driven High-Tech Approach to European Microfinance. A Ten-Year Perspective" (Groenevelt, 2019).

4.1 | Qredits - A data-driven Microfinance Institution with a social mission

Launched in January 2009, Qredits is a non-profit microfinance institution with a vision to build a strong and independent entrepreneurship culture in the Netherlands. Qredits achieves this by providing appropriate loan products, mentoring as well as educational tools for micro-entrepreneurs who wish to successfully start or invest in their business. The average loan size is 20,000 Euro, as support to small enterprises in the Netherlands. The organisation understands the lack of small loan sizes (between 5,000-50,000 Euro) in the Dutch market as a failure of the market and has since then focused on fair financing of financially excluded start-up entrepreneurs in this market. For instance, a recent social impact report shows that 12.1% of entrepreneurs they serve have migration background, 16% are unemployed, and 19% above the age of 50 have received support to help them create a career in the Netherlands.

Qredits' business case could have not been possible without the use of technology. Foremost due to cost- and time-efficiency reasons, one of the most important technologies introduced are those that improve insights that can be gathered about the entrepreneur and/or his/her

[11] The interviews conducted for this study were conducted in January 2022 and represent the opinions and views of the participants at that time, based on the information available to them. It is important to note that since the time of the interviews, changes in the organisation as well as shifts in policy and regulation may have occurred that could affect the current views and opinions of the participants.

business. The non-profit feeds its predictive algorithm from external data sources, including Chamber of Commerce and PSD2-enabled bank data (since 2020) and back-tested the output on historical data from approved and rejected applications. This enables risk-assessing loan advisors to have a more informed input before making decisions on the creditworthiness of a loan request.

The institution introduced its own machine-based risk score in 2017 to predict early signs of risk during the assessment of new applications. The machine-based risk score is useful in analysing collected data and increasing efficiencies of the decision-making process. Before the deployment of the algorithmic scorecard risk assessments would take more time and effort given the overwhelming availability of variables that could indicate potential risks; sometimes up to 1,200 variables. Given that typically 70% of Qredit clients are start-up companies, company financials and collateral are usually limited. Hence, the score also needs to include insights on the entrepreneur, such as experience or personal finance.

Scores range from 0 to 10 and are provided as a complementary information source for the loan officer. While applicants will never be rejected based on the initial risk score, a score between 0 and 6 may indicate a higher probability of loan risks. A benchmark of 7 or higher may trigger access to the Fast Track screening process. This means that client visits are not necessary to speed up the screening process. Nevertheless, it is up to the discretion of the loan officer to deviate from the initial score recommendation and request a follow-up meeting (Groenevelt, 2019).

4.2 | Preliminary Findings

This section elaborates on the preliminary findings in each stage of the life cycle of AI systems on fair decisions.

The Problem Statement Stage: The preliminary investigation into the problem statement stage resulted in some practical questions:

First, the interviewees have pointed out that while microfinance as an industry itself is not known for highly autonomous processes, AI-supported workflows are becoming more common. The industry has been changing throughout the last decade, thanks to the growing competition in the financial technology (FinTech) industry. Due to new technologies, the operational costs of many financial service providers have decreased and the time to process an application has shortened. In 2017 Qredits implemented the credit score to strategically support the application process.

Second, the choice of technology was guided by a clear definition of how the technology should be used and what it should aim to achieve: decisions on the creditworthiness of an applicant should not solely be based on the credit score output as the company still envisions a close relationship with its customers throughout the screening and monitoring phase. However, the relationship between technology and loan professional is envisioned in such a way that it will speed up the application process without disadvantaging marginalised client groups. When asked whether the expected benefits outweighed the expected costs when implementing the tool, the interviewees were aware of the likelihood that marginalised groups may not benefit from the implementation of the tool directly.

Third, fairness towards marginalised communities can be attained by enabling loan professionals to allocate more time for high-risk borrowers (e.g., additional in-person meetings), while low-risk borrowers can be processed swiftly based on their risk score indication.

Below are the questions that an organisation can ask to assist them in identifying strategies that reduce the risk of implementing unfair AI:

- Does the development of the technology undermine the company's mission?
- To what extent is the tool solving issues for our stakeholders, including, data analysts, marginalised borrowers, and loan advisors?

The Development Stage: The interviewees recognised that there was no clearly identified path for stakeholders to contest the results of the credit score. Nevertheless, given the size of the institution it seemed as though an unofficial process was in place that gave loan professionals and risk managers the right to contest the results. An example was given during the interview. At the time that the score was implemented, there was a lot of confusion about either too high or too low scores that did not add up with the opinion of the professionals. Hence, a communication process between data analysts, loan professionals and risk managers was established via email or in-person to evaluate, explain and adjust the outcome of the score.

In addition, it should be mentioned that Qredits is working with a product supplier who has been supporting the development of the statistical model. Throughout the interview, they recognised the lack of checks in place that would ensure the quality of data, such as robustness and reliability.

Nevertheless, the company believes that since the model only uses objective variables, rather than demographic data, such as gender and country of origin, the model should not lead to a negative/unfair outcome. Therefore, it seems non-discrimination is taken into account.

Below are the questions that an organisation can ask to assist them in identifying strategies that reduce the risk of implementing unfair AI:

- Does the supplier of the technology offer quantitative data to support the statement that the technology offers a fair outcome?
- Whilst stakeholders should have the right to contest the results, have there been independent checks in place to check unintended negative outcomes?

The Deployment Stage: The score's fairness performance has been significantly influenced by external shocks due to the statistical model not taking into account the altered circumstances caused by the corona crisis on entrepreneurs. Even though the data analysts recognise that the statistical model requires recalibration, the score is still being used as a risk indicator. There are plans to modify the statistical model in 2022.

During the deployment and monitoring stage, the company faced problems that were mainly linked to the absence of techniques to assist them in determining if the score's results would be impartial. On one side the feedback from professional loan officers regarding the score output supports the process but is mostly subjective. On the other side, it has been an issue for Qredits to measure the impact of the AI-enabled score output. This is due to the fact that Type 1 and Type 2 errors can only be measured over several years. For example, the company can check whether the score output of 8 (Low Risk) was true once the customer has repaid, or his/her company achieved his/her targets. Besides relying on subjective feedback of the loan professionals, Qredits will be able to take more data into account in the coming year that will allow them to check reliably for biases, discrimination or unfair treatment.

Below are the questions that an organisation can ask to assist them in identifying strategies that reduce the risk of implementing unfair AI:

- Have we considered changing circumstances, such as external shocks into our statistical model and has it created unfair outcomes?
- Are there industry-specific difficulties in testing and measuring whether the score outcome is robust, correct and fair?

The Review and Monitoring Stage: According to the interviewees there is no oversight body in place that would review AI Fairness as risk within a separate agenda point, in addition to the other risks that need to be assessed, i.e., default risks, operational risks, equity risks, etc. Moreover, there seems to be a purpose behind the lack of transparency of the algorithm for most stakeholders. Although data analysts possess knowledge of the factors that affect an assessment's score, it has been a conscious decision to withhold this information from organisational stakeholders and maintain it as a "black box." Reasons are not entirely clear. Moreover, the competitive market at the time when the score was introduced also led to the decision to not bother stakeholders with the details of the algorithms. Nevertheless, the interviewees noted that since the score only uses objective variables there should be no reason to keep the information in a black box and the issue has already been discussed on the executive level.

Below are the questions that an organisation can ask to assist them in identifying strategies that reduce the risk of implementing unfair AI:

- Are there context-specific reasons why transparency as well as explainability of our AI tool should be minimised?
- If so, how can we find workarounds of this deficit that still mitigates risks of unfair AI due to a lack of transparency and explainability of the statistical model?

The Discontinuation Stage: The risk score was implemented in 2017 only, hence the product has not reached its discontinuation stage yet. Nevertheless, the investigation has raised many questions that require further research by the company to clarify and identify what kind of tools and practices they could deploy to ensure that the risk of unfair outcomes is mitigated.

5 | Discussion and Conclusion

The framework introduced in this paper is intended to provide a set of questions that can guide thinking processes inside organisations when aiming to implement fair AI systems. The case study, which focuses on a non-profit microfinance institution, provides good insights into the existing practices as well as challenges when implementing fairness principles in practice. While some principles, such as the right to contest, were already implemented, albeit informally, others were not. However, the value of these principles was acknowledged by the interviewees and further recommendations could be made to the company based on the framework introduced in this paper. There are three major findings the authors wish to raise.

Firstly, within our framework we identified a large risk of unfair AI when problems go unnoticed (i.e. in a black box system) and may escalate over time. Only through existing feedback loops which momentarily exist between the loan professionals and data analysts in our case study, the credit score output is continuously being questioned and adjusted. The second finding highlights the significance of comprehending the strategic position of the company in influencing the utilisation of AI-powered decision systems, as indicated by Fu et al. (2021). In our case study, for example, the organisation aims to preserve the involvement of loan experts in the assessment process to maintain customer relationships, which aligns with the company's values and vision. The organisational values are likely to continue shaping the practices that determine how AI is utilised in decision systems. Additionally, being cognizant of its potential shortcomings in addressing marginalised groups may constrain the extent to which unfair outcomes occur. Thirdly and importantly, it becomes apparent that the company perceives the notion of fairness as equal treatment of applications. This becomes evident in their belief that the score output cannot be discriminatory as it only uses objective variables as model input. However, as pointed out by previous research, further investigations should ensure that AI-enabled decision systems take into account existing systematic inequality between groups, which means treating customers up to the same standards may lead to unfair outcomes, and reproduce existing inequalities (Chouldechova et al.,2018; Fuster et al., 2022, O'neil, 2016; Taddeo and Floridi, 2021).

The preliminary findings show no concrete obstacles to implementing the framework in practice, at least in the case of our case study. However, the results have to be seen with caution. As our collected data is only provided by one company active in the space, it is not representative of the entire sector. Further research may apply the framework to a larger group of organisations and therefore give a more representative view. Additionally, further research can apply our framework to different domains to get a wider overview of the practical application. Lastly, the framework proposed in our paper is technology-agnostic and does not imply the use of a specific AI technology. Therefore, it is very important to not solely rely on it, but instead combine it with frameworks that correspond to a specific context to prevent technology-specific risks like biased data collection for machine learning systems. Furthermore, this approach is focused on fairness, but other elements of ethical AI should be taken into account.[12]

To conclude, the preliminary findings provide insights into the application of the proposed framework for fairness in AI and AI-enabled systems. Its holistic approach will hopefully inspire further research to investigate how ethical principles can be implemented in context-specific environments, such as microfinance to realise the value an AI technology has set out to achieve.

[12] There is no clear consensus on the priorities and subdivisions in the ethics of AI, but several overarching frameworks are mentioned in section 2.4 |

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