Alternative credit scoring and financial inclusion: a structural data justice perspective

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Thesis submitted for assessment with a view to obtaining the degree of Master of Arts in Transnational Governance of the European University Institute

Florence, 15/05/2023

European University Institute
School of Transnational Governance

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Student declaration to accompany the submission of written work School of Transnational Governance

I, Gonzalo Grau, certify that I am the author of the work Alternative Credit Scoring have presented for examination for the Master of Arts in Transnational Governance. at the European University Institute. I also certify that this is solely my own original work, other than where I have clearly indicated, in this declaration and in the thesis, that it is the work of others.

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I confirm that some of the ideas in this thesis were discussed in the final paper submitted for the course in Artificial Intelligence and Democracy at the School of Transnational Governance. This course was taught by Professor Daniel Innerarity, who has also supervised this work.

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ABSTRACT

This paper explores questions of justice surrounding the use of alternative credit scoring techniques for promoting financial inclusion in emerging economies. It adopts a structural data justice framework to move beyond mainstream political analyses of datafication and understand the structural determinants of how data systems behind phenomena like alternative credit scoring are designed. The analysis focuses on three structural components of alternative credit scoring processes, namely the institutional framework, relational dynamics, and epistemic issues. By applying a structural data justice critique to alternative credit scoring, the paper offers new insights into where injustice may lie within the use of this technology for development. It finds the relative opacity of the institutional actors that wield these technologies, the power imbalance that underlies the scoring process, and the epistemic constraints on consumers' ability to contest the truthfulness of their credit score to constitute forms of injustice. This study underscores the importance of addressing the structural elements behind datafication processes for an evaluation of their justness.

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1. INTRODUCTION

Mainstream public discourse on technological progress is characterized by either naïve enthusiasm – technophilia – or fervent warnings against its potential dystopian consequences – technophobia. This is true of the global north, where some regulatory protections have been introduced in response to dedicated efforts from academia and civil society to map out the ethical concerns associated with the unbridled datafication of society and the technosolutionist discourse that has, at times, accompanied it.[1] Conversely, the same datafication and deployment of predictive technologies in emerging economies is lacking in critical perspectives. Institutional discourse around the quantification of development and the use of 'Big Data' technologies is broadly enthusiastic – both academia and large development-oriented institutions echo calls of a "data revolution" (UNDP, 2014) as key to speeding up the march towards the Sustainable Development Goals (SDGs) (Heeks & Shekhar, 2019).

The use of algorithmic decision-making in financial services and elsewhere has been heavily monitored in the global north, especially in the United States (Hurley & Adebayo, 2016) and the UK. The importance of fairness in financial service provision has meant that existing concerns regarding the transparency, privacy, and biases of artificial intelligence systems and the data they are trained on have become extremely salient in this particular sector. However, when investigating the use of these technologies in emerging economies, the practical usefulness of these technologies in increasing the efficiency of development initiatives as well as the markedly more complex information value chain[2] has made raising these same concerns more difficult. Artificial intelligence and its use in credit scoring is no different. The benefits it brings in enhancing accuracy and lowering costs are tangible and should be recognized. Similarly, the limitations of said technology mean that its application in such a socially delicate context must be carefully monitored. This work seeks to broaden the scope through which the justness of this form of datified development is scrutinized.

This research project will examine questions of justice regarding the use of alternative credit scoring in promoting 'financial inclusion' in emerging economies. The research question is then the following: is the use of alternative credit scoring in promoting financial inclusion unjust? If so, in what ways? Said investigation will be divided across 4 chapters. Chapter 2 presents an outline of the research's design and the methodology with which the research question is to be addressed. Chapter 3 conducts a systematic literature review to present the

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[1] (Zuboff, 2019) (Crawford, 2022) (Hurley & Adebayo, 2016), among others.

[2] The information value chain for development – as opposed to more developed contexts in which information flows can be more easily tracked – includes a myriad of transnational institutions and stakeholders (data brokers, tech corporations, financial institutions) (Taylor, 2017).

reader with a chronological account of alternative credit scoring and its development. Here, the mechanisms that underlie alternative credit scoring are explained, and an overview of the debate surrounding its use in financial risk assessment is laid out. Chapter 4 moves to provide a map of the existing literature on data justice, arguing that structural data justice is best positioned as a framework with which to assess the justness of alternative credit scoring in developing contexts. Finally, an analysis is carried out according to three structural components of datafication – institutional context, structural relations, and epistemic injustice – in which two FinTechs are used as case studies. The analysis finds that widening the scope of the inquiry reveals potential injustices across all three components. What is at first glance a rigorous data protection policy is weakened by structural constraints that undermine the consumer's agency on multiple levels.

2. RESEARCH DESIGN AND METHODOLOGY

This section outlines the research design and methodology used to answer the research question. It provides an overview of the qualitative nature of the methods used, as well as justification for the cases selected for the analysis. The limitations of the research are also addressed.

2.1. Systematic literature review and conceptual framework

In framing the context for subsequent analysis, the research conducts a systematic literature review of secondary literature produced across various fields. The aim of this section is to use existing literature to provide the reader with an intelligible mapping of the evolution of credit scoring from its initial, qualitative methodology to the version which is to be the object of study – alternative credit scoring. In so doing, it will draw from multiple perspectives in the aforementioned fields to frame the debate to which this work seeks to contribute. The secondary literature consulted will also serve to delineate the arguments supporting the use of this technology in promoting financial inclusion as well as the concerns that have been raised around it. This will provide context for the selection of data justice as a broad conceptual framework with which to analyze the use of alternative credit scoring for financial inclusion.

Similarly, the conceptual framework used for analysis will be selected by conducting a systematic literature review. A consultation of debates in data justice will serve to outline existing conceptions, putting different streams of the literature in dialogue with one another and contrasting its different conceptions so as to shed light on their respective limitations. The literature review therefore serves to justify the use of structural data justice as the most optimal conceptual framework from which to address the use of alternative credit scoring technologies in developing contexts.

2.2. Case selection and primary sources

Part of the analysis will incorporate two case studies. The case studies consist of two FinTech firms, *CredoLab* and *CreditInfo Group*. Both of these were selected for being firms that specialize in providing financial institutions and businesses with alternative scoring tools. Both have stated their commitment to driving financial inclusion in emerging economies and operate across multiple countries in the African continent.[3] The reason two cases have been selected as opposed to one is that having two cases allowed for comparative analysis, which would be useful in illuminating differences in practices regarding data collection and processing as well as dispute policy. The case studies will be conducted via an analysis of primary literature that these firms make publicly available, including privacy and data usage policies, press releases, and website material.

2.3. Limitations and scope

The limitations of the above methodology are several. First, the qualitative nature of the research means that the more technical aspects of the debate cannot be engaged with in sufficient depth. The literature review limits itself to navigating the results of quantitative research on the predictive power of different algorithmic scoring techniques but cannot give the reader an in-depth overview of the technical facets of the debate. Perhaps this limitation is somewhat circumvented in that the research focuses more on the political and social implications of such technology, reducing the need for a thorough technical frame. Second, the analysis – specifically the case studies – could have benefitted from additional methods. Interviews with staff members could have been conducted so as to better inform this work's understanding of these firms' data collection, processing, and privacy policies. Considering the relative opacity of CreditInfo in terms of primary sources, this would have enriched the analysis substantially. In terms of scope, spatial constraints mean that this work does not analyze all of the structural components behind algorithmic credit scoring, but rather the three most relevant. This is a limitation insofar as the forgone components of the analysis could have offered useful insights.

3. LITERATURE REVIEW: ARTIFICIAL INTELLIGENCE IN CREDIT SCORING

3.1. From 'traditional' to algorithmic credit scoring

Modelling credit risk involves assessing a loanee's probability of default (Machado & Karray, 2022). Credit scoring performs a crucial role in financial services, counteracting the informational asymmetries that exist between the borrower and the lender that may lead to problems of moral hazard or adverse selection (Ahmed, 2020). As such, the efficiency with which

[3] CredoLab's recent expansion into South Africa in 2019 was announced as a mission to "drive financial inclusion in emerging economies" (CredoLab, 2019). CreditInfo has a regional subsidiary in West Africa, spanning multiple locations (CreditInfo, 2023)

such risk or probability of default is measured is the primary concern behind the design of these models. Though early iterations of credit risk assessment were unmediated by technology and more evaluative[4] in character (McClanahan, 2014), the earliest versions of *automated* credit scoring models were statistical in nature.[5] Examples of statistical credit scoring include the Fair and Isaac Corporation's model – the FICO score – in the United States, whereby creditworthiness (ranked on a scale between 300 and 850 points) is a function of a limited set of data points such as payment history, debt amount, and previous credit uses (Hurley & Adebayo, 2016). These models' use of limited data points with direct relevance to a loanee's ability to service debt (exclusively financial data) also meant that they often had difficulty assessing the creditworthiness of consumers whose financial data was scarce. As of 2016, roughly 64 million US consumers are considered 'unscorable' in FICO terms due to the limited amount of financial data they produce (Hurley & Adebayo, 2016). Justified concerns about statistical credit scoring's discrimination against 'thin file' consumers coupled with the financial incentive[6] of providing more loans at lower default risk led to the development of more advanced credit-scoring models.[7] Also contributing to the uptake of algorithmic models were the vast increase in consumer data following the rise of the internet and a post-2008 contraction in bank lending (Aggarwal, 2021).

Algorithmic credit scoring models surpass statistical ones both in complexity of analysis and amount of data points considered. As part of the Big Data phenomenon, the algorithms used to predict consumer behaviour in credit markets require an enormous amount of data which often departs from what is directly relevant to financial responsibility (Hurley & Adebayo, 2016). Because creditworthiness is an 'unstructured'[8] data problem, the rapid analysis of large amounts of data to discover patterns which may have gone unnoticed is, from a risk analysis point of view, a more efficient way to solve the under-inclusivity problem. In other words, moving beyond the sole use of structured data (credit history, payment information, assets, etc.) to consider data from social media use, emails, text message traffic, and more intangible activities is considered a step in the right direction in terms of making credit markets more inclusive and efficient (Ahmed, 2020). Indeed, the adoption of scoring algorithms is heralded by many as the most fitting solution to tackle the 'complexity' of credit markets in the developed world and beyond.[9]

[4] Based upon subjective judgement by human creditors, using questionnaires and techniques like the 5 C's: character, capacity, capital, collateral, and conditions. (Marqués, García, & Sánchez, 2013)

[5] Discriminant analysis, linear and logistic regression, multivariate adaptive regression splines, among others. (Marqués, García, & Sánchez, 2013)

[6] For creditors, a small increase in predictive power can lead to a substantial increase in profitability (Machado & Karray, 2022).

[8] Unstructured refers to data that cannot be quantified and measured according to a given metric (IBM, 2021).

[9] In the United Kingdom, great hopes are being placed on algorithmic scoring and other AI techniques to reduce risk, streamline, and cut red tape in mortgage markets (Basu, Sirelkhatim, & Chakraborty, 2022) (Wainwright, 2011).

3.2. Algorithmic credit-scoring and 'alternative' credit scoring

Many scholars have participated in the development and assessment of various algorithmic models for evaluating credit default risk. Machado & Karray (2022) introduce the possibility of using hybrid models to evaluate the creditworthiness of commercial customers. The hybrid model in question consists of a combination of supervised – where a desired output guides the analysis of the data points – and unsupervised – where relationships between data are discovered without a specific end value in mind – algorithms. They find that the use of unsupervised techniques to cluster loan applicants around common characteristics before applying supervised prediction techniques outperforms individual models that exclusively rely on supervised or unsupervised techniques. Weng & Huang (2021) also investigate the effectiveness of hybrid models for algorithmic credit scoring, again highlighting the usefulness of clustering techniques in improving predictive accuracy.

Beyond the use of supervised, unsupervised, and hybrid algorithmic models for measuring creditworthiness, scholars have explored the usefulness of 'alternative' data sources for measuring default risk. As outlined above, 'alternative' data sources are often unstructured in nature, consisting of behavioural data that algorithms may detect as a valuable proxy for risk (Hurley & Adebayo, 2016). Ots et al. (2020) find that mobile phone usage data can help circumvent the problem of small datasets when measuring creditworthiness. Advanced data collection methods that capture categories such as "average call duration", "average number of images made in distinct places per month" and the like mean that personality and other psychosocial variables can be "extracted" without the manual collection of structured financial data. Óskarsdottir et al. (2019) find that analysing phone call and social media data to infer default risk from prior defaulters in a consumer's 'network' improves predictive performance. Djeundje et al. (2021) explore email usage and "psychometric variables" as proxy indicators of creditworthiness.[10] By incorporating these variables into the algorithm, they find that predictive power is higher than when creditworthiness is modeled exclusively on demographic data. Such combined use of structured demographic data and unstructured psychometric data obtained from digital sources constitutes *alternative credit scoring* (Njuguna & Sowon, 2021).

To obtain such data, creditors can rely on *embedded machine learning* techniques that FinTechs such as *CredoLab* provide. These techniques consist of algorithmic tools that are installed into a fixed device (usually a mobile phone) or webpage to "collect metadata"[11]

[10] Demographic data points considered were age, years of work experience, gender, income, number of dependents and the amount of time (in years) the subject had owned a phone. The psychometric category included the applicant's "time taken to answer simple questions such as date of birth" or whether he/she identified as an individualist (Djeundje, Crook, Calabrese, & Hamid, 2021).

[11] Metadata can be described as "data about data". More elaborately, it can be imagined as "the sum of what one can say at a given moment about an *information object* (…)" (Gilliland, 2016). In analysing a consumer's mobile phone, *use metadata* would include all data that results from its use. This metadata varies in granularity – a data

(CredoLab, 2023). The resource constrained environment of a fixed device or website can also mean that embedded techniques carry a certain trade-off with respect to more traditional predictive techniques. Ajani et al. (2021) outline how some machine learning methods' need for high computational power can limit their predictive efficiency so as to offset any gain in prediction speed with respect to cloud-based methods. It should be noted that given the vague nature of a category like creditworthiness, different models consider different variables. The selection of these very much depends on the subjective ideas of the development team or, in the case of unsupervised learning, the patterns detected by the machine (Hurley & Adebayo, 2016). Other sources of alternative data can be found in public records or transnational data brokers – unemployment, evictions, petty crime data, ZIP codes – among a myriad of other sources.

3.3. Alternative credit scoring for financial inclusion

With approximately 1.7 billion people having no access to financial services, the advent of alternative credit scoring techniques has raised hopes for its potential use in capturing thin-file, 'unscorable' consumers (Njuguna & Sowon, 2021). By leveraging alternative data sources, consumers whose limited financial data previously excluded them from financial services can now access credit. As such, alternative credit-scoring has been deemed by many to be the path towards *financial inclusion.*[12] Financial incentives are also sizeable, to say the least. The global banking sector could, at relatively low risk, gain approximately USD 380 billion in annual revenues by tapping into underbanked consumers like agriculturalists or gig workers (Madasu, 2022, p.4). Beyond its existing use in developed contexts such as the United States, the application of these technologies in more developing contexts is seen as having enormous potential (Mhlanga, 2021) (Kshetri, 2021).

Kshetri (2021) discusses more potential pathways for alternative credit scoring to help secure financial inclusion. Outside the use of alternative datasets to overcome large information asymmetry problems, algorithmic models for risk can assess businesses' risk exposure to catastrophe, such as natural disasters or pandemics. The use of AI in developing credit markets further fosters financial inclusion through the reduction of operational and other costs as well as increasing transactional efficiency. For small, consumer-oriented loans, high transaction costs are often a significant obstacle (Kshetri, 2021).

There is little to dispute regarding alternative credit-scoring's ability to expand access to financial services. By harnessing non-traditional data points, the impasse at which creditors typically find themselves with regards to unscorable consumers is circumvented. It can therefore be said that from a strictly quantified, utilitarian lens, alternative credit-scoring is financially

point can be as standard as CDR (Call Detail Records) or the proportion of selfies in one's camera roll (Jacques, 2018).

[12] Broadly defined as being a matter of *appropriate access* to 'necessary' financial services (Mhlanga, 2021).

inclusive – people traditionally marginalized from financial services and their associated benefits (consumption smoothing, protection from shocks, etc.) no longer fall outside the market. That being said, other streams in the debate that point towards the importance of *dignified access* as a parameter of "full" financial inclusion[13] offer some critical perspectives on the application of this technology. Indeed, moving away from a strictly aggregational notion of financial inclusion towards one that focuses more on conditions of access may provide a more balanced assessment of this technology's use for achieving financial inclusion.

3.4. Limitations of alternative credit-scoring and potential justice concerns

Alternative credit scoring is the latest development in a broader trend of automation within the financial sector. Scholars have observed this paradigmatic shift brought about by information technologies as altering the balance between judgement and rules-based management – there is now a stronger psychological and economic rationale behind the use of "judgement-free" decision-making (Bhidé, 2010). Though the replacement of evaluative, case-by-case judgement in areas like credit scoring may have brought about greater accuracy at lower cost in predicting default rates, some argue that this has come at the expense of adaptability and resilience of these terms to external shocks. Due diligence and relationship-based credit judgement's replacement by centralized, assumption-ridden algorithmic modelling will struggle to account for the complexity and ubiquity of change in a contemporary economic system (Bhidé, 2010). This does not imply that pre-statistical credit scoring techniques were not flawed systems and, to a large extent, a reflection of the biases of the human agents behind it. Rather, an exploration of the literature assessing the application of algorithmic credit scoring in contemporary contexts serves to shed light on why an uncritical adoption of these systems has potentially serious implications from a justice perspective.

Hurley & Adebayo (2016) find that the use of algorithmic credit scoring in the United States raises numerous justice concerns. The unstructured nature of creditworthiness means that an "outcome of interest" must be expressed in formal terms for the algorithm's understanding. Said target variable is typically based on a sample population of inputs that tends to be unrepresentative of consumers outside of registered databases. Increasing the granularity of the data on which the algorithm is trained may prove counterproductive – despite a potential increase in accuracy, the incidence of spurious correlations that are found is also likely to rise. Here, discriminatory results and arbitrary decisions on which customers are branded creditworthy are not a question of biased or unclean data – they are *constitutive* of the algorithmic construction of creditworthiness as a category. Indeed, the opacity of creditors regarding the parameters that inform their notion of a "creditworthy" consumer reflects its inherently vague

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[13] For example, *full* financial inclusion should require a "culturally appropriate" design of financial products for unbanked indigenous communities. Consumer education and awareness about the nature of the financial products they are using is also considered key in contributing to a consensual and sustainable integration of unbanked individuals into the financial system (Arun & Kamath, 2015).

and subjective character.[14] The importance and permeability of creditworthiness as an "all-purpose reputational metric" means that arbitrary and inaccurate score calculations are certain to severely hamper discriminated consumers' ability to access key goods and services on fair terms (Pasquale, 2015, p.25) (Bhidé, 2010).

Though it is true that some feature selection[15] processes can be manipulated by a human agent so as to mitigate the appearance of spurious correlations, the sheer volume of data being handled means that arbitrary inferences are likely to remain. Neumann et al. (2022) offer some valuable pushback on the notion that increased data granularity is necessarily conducive to more accurate predictions. Their study of 21 data brokers finds that many of the demographic features used to inform contemporary creditworthiness are more accurately predicted for consumers of higher socio-economic status. Affluent households' tendency to enjoy higher levels of consumption translates to a much larger and better-quality data footprint. More generally, much of the demographic data these footprints carry risk of acting as proxies for more sensitive demographic categories (race, gender, etc.) (Ahmed, 2020) (Hurley & Adebayo, 2016). The positive association between data-quality and socio-economic status means that these proxy associations disproportionately affect underprivileged consumers.

More concerning is the unsuitability of contemporary regulatory frameworks in addressing these issues. Ahmed (2020) is quick to point out that Indian regulators are struggling to apply existing anti-discrimination legislation to alternative credit scoring practices due to the sheer volume of data involved as well as the opacity surrounding it. Scholars like Guégan & Hassani (2018), Chopra (2021), and Remolina (2022) coincide in their analysis – contemporary legislation is underequipped for the complexity of this technology.[16] Moreover, clear prohibition on discriminatory practices in lending does not entail an obstacle-free path in seeking redress – the complexity of the algorithms at hand entails major difficulties for providing clear evidence in case of discrimination. Although recent developments in the regulatory landscape – the EU's Payment Services Directive 2, the landmark General Data Protection Regulation, and the recent

[14] The credit-score of an individual consumer can vary greatly depending on the bureau that is responsible for the rating process, with up to 29% of US consumers having had scores that varied by at least 50 points between bureaus (Pasquale, 2015, p.24)

[15] Feature selection refers to the selection of features in data which are thought to be most relevant in the prediction process. It can also refer to the manual removal of features that are considered to have no predictive power (Gupta, 2023).

[16] Whilst Guégan and Hassani (2018) speak of regulatory shortcomings in a general sense, Chopra (2021) focuses on US legislation, namely the Fair Credit Reporting Act and the Equal Credit Opportunity Act.

Artificial Intelligence Act[17] – are indicative of a regulatory concern for these issues, these are generally limited to the global north.[18]

Though the above is merely a brief overview of some ethical concerns surrounding the deployment of artificial intelligence in credit scoring, it is evident that they are as ubiquitous as they are serious. Indeed, it is clear that beyond questions of inclusivity and increased measurability of progress in development, the *datafication* of developmental projects carries with it injustices relating to the extraction, analysis, and commoditization of private data (Qureshi, 2020). Similarly, potential injustices in alternative credit scoring have to do with the way data is collected, processed, and utilized, as well as the structures that inform these processes. As a technology, alternative credit scoring is fundamentally concerned with and embedded in datafication. In assessing the justness of this technology's deployment in developmental projects, the blossoming literature around *data justice* is best positioned as an analytical framework. As Braun & Hummel (2022) put it, data justice is the "first virtue of social institutions in a datified and data-driven society". Different streams of the data justice debate will be explored in the following section.

4. CONCEPTUAL FRAMEWORK: PERSPECTIVES ON DATA JUSTICE FOR DEVELOPMENT

4.1. Datafication and development

Datafication, or the phenomenon whereby social phenomena are increasingly quantifiable and stored as 'data', has become crucial to projects in international development (Cieslik & Margócsy, 2022). Much of the discourse within developmental institutions credits data collection and processing with fostering efficiency, transparency, and accountability in developmental projects.[19] The excitement around alternative credit scoring for financial inclusion is an example of this – previously out-of-reach data is seen to have enabled a more efficient and inclusive credit market in developing contexts. Despite this, multiple concerns have arisen surrounding datafication's creation of new forms of inequality and injustice.[20] Beyond the

[17] Under the AI act's third annex categorizing high-risk applications of AI, private actors using algorithmic credit scoring techniques are required to carry out extensive conformity assessments. (European Commission, 2021).

[18] On the African continent, for example, there exists a large divide in data protection legislation – some countries offer extensive provisions whilst others' have much more limited, "patchwork" legislation (Daigle, 2021).

[19] New areas for research and practice such as Big Data for Development (BD4D) advocate for big data's ability to capture the wellbeing of populations in unprecedently precise and pluralistic ways (Qureshi, 2020) (Mann, 2017).

[20] The 'data divide' refers to the domination of big-data methodologies and how this fuels a more extreme marginalization of those outside the scope of data extraction and analysis (approximately 3 billion people) (Qureshi, 2020). Data is granted an "ontological power" to represent reality, despite its only partial and often biased explanatory power (Cinnamon, 2019).

data divide, scholars have recognized that datafication has brought about multiple new dimensions of inequality that span problems of access, representation, and control (Cinnamon, 2019). Research and praxis on the beneficial uses of datafication for citizenship are marginal in comparison to the ability of transnational corporations and state bodies to influence the ends it serves (Taylor, 2017). As such, it is necessary to articulate a comprehensive framework of data justice that incorporates the multiple dimensions at which injustice can occur in datafication.

4.2. Data justice: mainstream perspectives

As outlined above, datafication and the exponential rise in the importance of data technologies in in society have implications for justice. Developments in data cannot be separated from social justice concerns and agendas – they are deeply intertwined (Dencik & Sanchez-Monedero, 2022). Here, data justice has emerged as a polyvalent framework for grappling with issues that contemporary developments in digital technologies have brought about, finding expression in movements around the environment, labour rights, and media (Dencik & Sanchez-Monedero, 2022). As a path towards understanding the data-related developments in ongoing social justice struggles, scholars have come to agree that data justice is best used as a form of critique (Dencik, Hintz, Redden, & Treré, 2019). Branching out from Johnson (2014)'s conception of "information justice", where datafication's potential to exacerbate existing inequalities was first laid out, several perspectives on data justice have begun to take shape.

Heeks & Renken (2016) provide a good outline of three major streams in the data justice debate, each linked to a particular conception of justice: *instrumental* data justice, *procedural* data justice, and *distributive/rights-based* data justice. These perspectives are mainstream insofar as they consider the data in its immediate context within the information value chain – how it is collected, handled, and used (Heeks & Renken, 2016). Instrumental data justice is concerned with the outcomes of datified processes – whether the use of data in this process results in a fair outcome, for example. Procedural data justice, concerned with the fair handling or processing of data, is slightly more complex. The first dimension of procedural justice touches on the scope of the data-handling process – a narrow interpretation would incorporate only *upstream* handling of data (capture/collection, cleaning, and storage), whilst a broad one would include *downstream* components that are more to do with the application of the data in decision-making. The second dimension of procedural data justice has to do with fairness in the data-handling process. Here, a narrow interpretation would consider only questions of control over the data handling-process – fairness would be proportional to the degree of control that individuals can exercise over it.

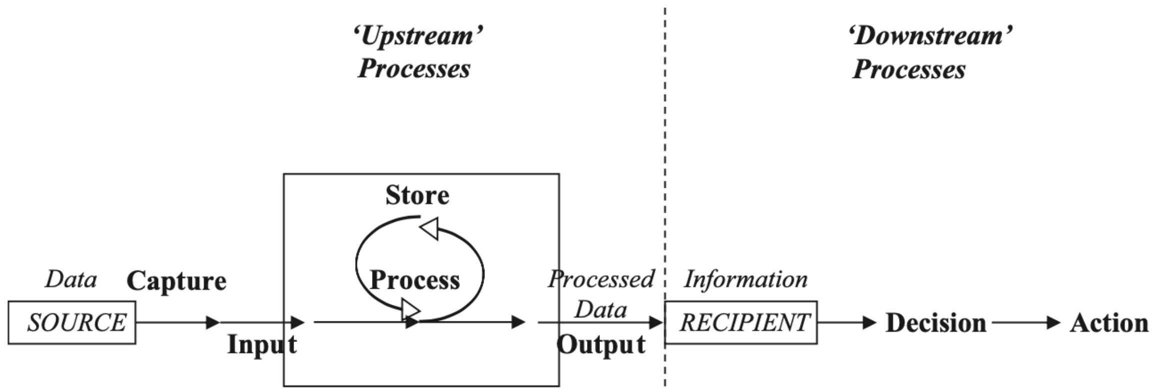

Figure 1: The information value chain, from (Heeks & Renken, 2016)

The distributive/rights-based perspective of data justice is concerned with the distribution of data. By treating data as a resource, distributive data justice understands fairness as a matter of possession, scrutinizing the implications of distributional asymmetries in data ownership. The language of rights has proven useful here, as rights like data privacy and the "right to be forgotten"[21] play an important role in delimiting data distributions. Distributive data justice has in this sense played an important role in shaping the current legal framework around datafication. Other relevant rights shaping data distribution include the right of data access, the right of data ownership, and the right of data representation/inclusion.[22] It should be noted that these rights have been actualized to varying degrees, some of which face significant barriers.

Despite the popularity and usefulness of these mainstream dimensions of data justice, critics are right to point out that their usefulness as distinct categories is somewhat redundant in that they are all at least partly intertwined (Taylor, 2017). Indeed, it is not difficult to see how a broad procedural perspective on data justice can be concerned with more instrumental components, such as the outputs of algorithmic decision making. In this sense, it is unrealistic to look at data justice from a purely outcome-based perspective when these outcomes are influenced, if not determined by how data is processed and collected. Broadly, it can be said that a more complete conception of data justice should account for the structural components that underpin the information value chain (Heeks & Renken, 2016). In exploring critiques and alternative articulations of data justice, many scholars can be observed echoing this concern.

[21] Though attempts to assert it can be observed as early as 2006, the 'right to be forgotten' was first articulated in a ruling by the ECJ in May 2014, requiring big data giants like Google to delete search engine results containing personal information (Liddicoat, 2015). This is a powerful example of rights language's potential in actualizing ownership of personal data.

[22] The right of data access delimits which parties can obtain certain data. The right of data ownership can be interpreted so as to include "exhaust data", produced unknowingly by a given user/subject. The right to data representation articulates a right for an individual to be included in a dataset, as a provision against the aforementioned data divide (Heeks & Renken, 2016).

4.3. Towards data justice for development: limitations of mainstream conceptions

When discussing data justice for development, authors like Taylor (2017) have emphasized the need for a more 'global' perspective that incorporates the rapid globalization of data analytics and their increased use in developing countries to map, sort and guide large scale interventions in development projects. She identifies the overlaps that exist between mainstream conceptions of data justice, as well as how these are only successfully applied in relatively insular and institutionally robust contexts like the EU. Rights-based articulations of data justice like the GDPR require abuses that are clear and visible and are underpinned by the assumption that redress is to be sought at the individual level (Taylor, 2017). Developing contexts in other areas of the globe differ in many respects. The language of individual rights may not be understood by certain collective identities, nor is it always suitable in contexts where violations occur at a group/collective level. Moreover, the transnationality of data systems would require an equally transnational set of redress mechanisms, which mainstream, rights-based conceptions of data justice do not offer. A more complete conception of data justice, she argues, should be articulated in a culturally permeable language. It should also acknowledge the role data systems play in actualising power asymmetries, and vice versa.

Braun & Hummel (2022) argue that mainstream conceptions of data justice are overly concerned with fairness as a guiding principle. Though fairness in a substantive – meaning equal distribution of costs and benefits as well as freedom from discrimination and bias – as well as procedural – to do with contestation and redress capacity – sense is an important component of justice, the authors point out that it is insufficient as the central parameter. Indeed, an excessive preoccupation with fairness may come at the cost of insights gained from other useful dimensions of justice. A given distribution or procedure can appear to satisfy conceptions of fairness whilst simultaneously excluding groups and individuals as well as being unduly disciplining and oppressive.[23] When narrowing this critique to the field of artificial intelligence, Bui & Noble (2020) seem to coincide in their analysis, stating that an ethics of fairness falls short of the need to "interrogate the power structures and issues that undergird these critical narratives about AI's harms and risks." (Bui & Noble, 2020, p.178). Hoffman (2019) is similarly critical of mainstream data justice conceptions. She contends that anti-discrimination discourse is, in its narrow concern for "liberal goods" (rights, opportunities, resources), lack of intersectionality, and its discrete emphasis on "bad actors",[24] unable to actualize justice in any meaningful way. With specific reference to alternative credit scoring, Hiller (2021) points out that attempting to

[23] Aadhar, India's biometric population database good example of this. In its inability to read worn out fingerprints from manual labour or malnutrition, it fails to account for many materially significant struggles. There is no alternative path back to administrative legibility in these cases, making it difficult to assert a right to representation (Taylor, 2017).

[24] The 'bad actor frame' situates injustice as the result of the outlier behaviour, stripping it of its broader cultural or social context. Hoffman argues that this is very much the norm in discourse around issues like algorithmic discrimination – the fault is assumed to lie in the biases and "blind spots" of the engineers that design the algorithms (see Hooker, 2021). Similarly, de-emphasizing intentionality by framing it as an issue of "biased data" is equally problematic – it situates bias as external instead of something that is internally cultivated (Hoffmann, 2019).

understand data justice in terms of fairness is insufficient insofar as the disciplines of data science and law have fundamentally different understandings of it.[25] By ignoring the broader structures that inform distributional and procedural elements of datified decision-making, mainstream perspectives are not fully equipped to deal with the more complex questions in data justice.

Scholars working in the field have also pointed out the absence of structural-epistemic considerations in data justice literature. In their exploration of datified development in India's Public Distribution System (PDS), a food security scheme, Masiero & Das (2019) notice the need to address the epistemic/discursive implications of datafication. Through their interview-based fieldwork, they identify a significant asymmetry between the technosolutionist discourse that surrounds the datafication of the programme (less illicit inclusion of non-entitled users, or exclusion of entitled ones) and the "socially embedded" perspective. The socially embedded perspective is drawn from users, who are, to put it lightly, uninvolved in what is considered an insular, top-down datafication process.[26] Indeed, contrasting both epistemologies revealed a significant design-reality gap with regards to the datified PDS. For one, the contingency of access to the PDS on registration within Aadhar *(see footnote 23)* subordinated users' right to food to their enrolment in a severely discriminatory biometric database. The system was also found to be significantly less effective at preventing wrongful exclusion as opposed to removing illicit recipients. The gap between the lived reality of users participating in datified anti-poverty programmes and the technosolutionist discourse surrounding it points to a need for data justice to address how knowledge systems and epistemic control can contribute to injustices.

An overview of data justice literature has showcased the shortcomings of its more mainstream conceptions. For one, it seems these mainstream conceptions are too limited in scope, concerned only with allocative or procedural problems within the information value chain. Second, their tendency to use the language of rights reveals an excessive focus on questions of fairness that, while an important notion to consider, does not go far enough in its consideration of the power asymmetries that underpin data systems and their design. The literature points to the need for data justice theory to consider the broader, more structural components that influence the distributional issues with which it has hitherto been concerned. When speaking of data justice for development, the transnationality and complexity of the data systems that underpin datified development necessitates a consideration of these structural components (Heeks & Renken, 2016). Regardless of the view of political economy and power that is adopted, a theory of data justice for development should address the inequalities that govern international capitalist development. Some streams of the literature have begun to

[25] In analytic science, there are at least 25 different applicable definitions of fairness, and it is mathematically impossible to apply multiple of these to the same problem simultaneously (Hiller, 2021, p.921).

[26] The PDS system's updated design goes far beyond streamlining to include two more tools (known as the JAM Trinity) – a financial inclusion programme and mobile phones. Users were unaware of this connection (Masiero & Das, 2019).

articulate models that attempt to encompass these elements. Structural data justice is one such model.

4.4. Structural data justice

Introduced by Heeks (2017), structural data justice is concerned with "the degree to which society contains and supports the data-related institutions, relations and knowledge systems necessary for the realisation of the values comprised in a good life." (Heeks, 2017, p.1). The model incorporates all types of data justice, paying special attention to the question of how "power over" and "power" are exercised in data-intensive development. For structural data justice, structures are, as vehicles for actors to shape aspects of data justice, crucial determinants of how data systems are designed and the outcomes of their use. Heeks identifies power as originating in control over resources and practices, as well as three other elements that determine control over resources and practices – institutional framework, position within structural relations, and epistemic control over knowledge systems (Heeks, 2017). After developing a theoretical framework of the model, Heeks refined it through its application to various case studies, the most relevant of which was carried out in 2019.

Heeks & Shekhar (2019) use a structural data justice framework to analyse the datafication process behind some community mappping initiatives in India, Indonesia, and Kenya. They find evidence of structural determinisms within each of the cases. On the institutional level, they found that the use of data produced by such initiatives was determined by the institutional framework surrounding them. In Chennai (India), the lack of accountability mechanisms – no elected representatives, no public hearings, no open reporting policy – present in institutions[27] meant that there were no incentives for changes in practice despite the availability of new data streams. In terms of structural relations, they found the initiative in Kenya and the use of its produced data to have been shaped by the state's monopoly on violence – 'provocative' uses of the data (exposing underfunding, neglect, and systematic sidelining of the community from public budgets) were avoided so as to not 'antagonize' state actors and stir civil unrest (Heeks & Shekhar, 2019). From a resource perspective, it was known that all initiatives had been funded by international donors, meaning these were shaped by an agenda that demanded highly-visible short term results. This disconnect was manifest in the donor's financially guided interest for tangible data artifacts (maps, demographic data) and simultaneous disregard for more long-term, invisible support such as funding the use of said data by the communties themselves. Similarly, the lack of resources among the mapped communities determined their engagement with these initiatives – their need to work for a living meant that community members would often not participate in the projects due to their being at work. The data did not include these community members. On the epistemic level, the power of "smart city discourse" – characterized by a firm belief that adding technology to urban processes is enough to deliver urban development – blocked out the engagement of funds for more downstream

[27] Specifically, the Slum Clearance Board and the Water Corporation (Heeks & Shekhar, 2019, p.1004).

processes (using the data as a means rather than an end in itself) (Heeks & Shekhar, 2019, p.1004).

The cases investigated above reveal the extent to which structural mechanisms determine datafication processes and their outcomes. When discussing the datafication process that underlies alternative credit scoring as a vehicle for financial inclusion, many of the structures identified by Heeks (2017) come into play.

5. A STRUCTURAL DATA JUSTICE PERSPECTIVE OF ALTERNATIVE CREDIT SCORING FOR FINANCIAL INCLUSION

5.1. Structural components of alternative credit scoring

When applying a structural data justice framework to alternative credit scoring, three of Heeks' proposed components are particularly relevant. These are – in no partiuclar order – institutional context, structural relations, and epistemic concerns. This section will address the use of alternative credit scoring from the analytical lens that these three components of structural data justice provide. When looking at the institutional context, it will focus on the case of two alternative credit scoring FinTechs that operate in the African continent, *CredoLab* and *CreditInfo Group*, scrutinizing their policies on data harvesting, privacy and usage. The analysis of structural relations will attempt focus on the conditions under which consumers access the loans that alternative credit scores allow them, investigating the potentially coercive dynamics that underlie informed consent in developing contexts. Lastly, the epistemic dimension will look at whether the interaction between credit scoring and algorithmic decision making's respective epistemologies constitutes a form of epistemic injustice as articulated by Fricker (1998).

5.2. Institutional context: the case of CredoLab and CreditInfo

(i) Background information

Established in 2016, Singapore-based CredoLab is a FinTech developing "bank-grade digital scorecards built on mobile devices and online web behavioural metadata." (CredoLab, 2023). Operating in 5 continents, it has powered over $1 billion in consumer loans by partnering with financial institutions. Its "data modelling pipeline" uses Machine Learning algorithms to anlayze "over 70,000 privacy-consented data points from a smartphone device"[28] (CredoLab, 2023). CredoLab's alternative scoring method boasts of reducing the cost of risk by 21.9%, increasing predictive accuracy by 50% and raising the approval rates of its clients' loan applications by 32% (CredoLab, 2023). It takes less than a second for a credit score to be

[28] Other publications from CredoLab claim that its credit scores are synthesized from "over 10 million behavioural features" (CredoLab, 2023).

generated. These metrics underpin CredoLab's broader identity as a champion of financial inclusion. London-based CreditInfo Group, despite operating in the same industry, has been providing software solutions for credit risk management since 1997 (CreditInfo, 2023). Though it offers a myriad of other services, its main proposal for driving financial inclusion is its alternative scoring tool, analyzing data points from mobile phone usage, social media, mobile and internet waller behaviour, and financial transaction details (CreditInfo, 2023).

(ii) Policies on data collection, usage and privacy

Examining both FinTechs' policy on data usage and model training, a first glance reveals a commitment to protecting data and the anonymity of the consumer. CredoLab states that it does not "collect, process, or share users' personal information" (CredoLab, 2023). Its embedded scoring models do not collect data in the background and are deleted from clients' device after the scoring process is over. Its scoring model only collects "permissioned" information and transforms it into "anonymous metadata", a process that was successfully (and last) independently audited in 2019 by eShard, a software security testing firm (CredoLab, 2023). Because CredoLab only uses metadata that is inherently anonymous (*see footnote 11*), no personal information is retrieved or analyzed at any point of the scoring process. The firm's models do not access social media accounts nor track the activity of other applications (CredoLab, 2023). CredoLab states that all data points are encrypted and that user data is not sold to any third parties (CredoLab, 2021).

A closer look reveals a few gaps in transparency, however. Despite having clear policy on data collection, usage and protection for the EU (in line with GDPR), Indonesia, Singapore and California, CredoLab does not disclose its policy for operations in Latin America or Africa. This is concerning considering Africa's incomplete regulatory landscape with regards to consumer data privacy. Similarly, an examination of CreditInfo's privacy policy does not reveal any details as to how data is sourced or used for its alternative scoring process – policy seems to revolve around data collected about the user when visiting the website alone.[29] In this sense, it is unclear to what extent consumers' anonmity is protected, nor is it understood how said data is stored. Unlike CredoLab, CreditInfo does not specify if the data that they use for their scorecards is anonymized metadata. Other alternative credit scoring FinTechs, such as Kenya's *Tala,* have been found using highly personal datapoints such as the content of SMS messages, GPS location data, and social media data for analyzing the consumer profiles of users' friends as a parameter for creditworthiness (Koo, Zhou, & Li, 2019, p.8).[30] Additionally, CreditInfo does not specify how long consumer data is held. Neither of the two disclose how their predicitve models are constructed, nor how they define "creditworthiness". Despite CredoLab's apparent commitment to privacy protection, it seems that CreditInfo's lack of transparency on data collection, use and storage is indicative of a systemic issue within the credit scoring business as a whole – alternative

[29] For more details, consult: https://uemoa.creditinfo.com/en/privacy-policy/

scoring models are treated as a trade secret and are a key driver of market competition (Koo, Zhou, & Li, 2019, p.10).

(iii) Contestation and the explainability problem

The partial lack of transparency of alternative scoring FinTechs regarding data usage illuminates existing questions on the issue of *explainability* and *contestastion.* An examination of CredoLab's Online User Agreement and their GDPR privacy policy reveals no explicit possibility for consumers to dispute their scores, aside from a "right to rectification" under the GDPR, which is limited to correcting "incomplete information" (CredoLab, 2021). Similarly, CreditInfo offers consumers the possibility of dispute if their reports contain "innaccuracies" (CreditInfo, 2023). These disputes are free of charge, but are only limited to standard personal and financial information (account balance, address, spelling). Unbanked consumers are therefore denied any possibility of redress, as they are not scored using this data. Regarding consumers that are alternatively scored, CreditInfo explicitly states that a consumers' "credit score cannot be the subject of dispute because it is the output of a scoring model and cannot be changed as such." (CreditInfo, 2023). This rationale is potentially due to the explainability problem, or the accruacy-explainability tradeoff.

The accuracy-explainability tradeoff is one that is well understood in artificial intellgence circles – the more powerful an algorthim's predictive power is, the less understandable its process becomes. Incredibly complex models that process millions of metadata are so much so that not even the engineers who design the algorithm understand how a given decision is reached (Gryz & Rojszczak, 2021). Both CredoLab and CreditInfo acknowledge this.[31] The technical difficulty of reconstructing the criteria used by an algorithm in formulating an output is so high that, if not impossible, the error margins would be too high for such a reconstruction to be reliable (Gryz & Rojszczak, 2021, p.12). As such, the explainability problem represents a significant barrier to redress should a consumer request to challenge the credit score given to them. Scholars on artificial intellgence ethics have pointed out that even if a 'right to explanation' were to exist with regards to automated decision making, it could not realistically be exercised in practice (Gryz & Rojszczak, 2021, p.5).

5.3. Structural relations: informed consent in developing credit markets

An examination of the insitutional context in which these alternative scoring practices take place (CredoLab and CreditInfo) has revealed that there exists a degree of opacity regarding data protection, usage and model construction. Additionally, we have seen that the explainability problem – which is more pronounced in alternative scoring models due to the quantity and nature of the data being processed – is a significant obstacle to any contestation of

[31] CreditInfo specifies that its alternative scoring models have "higher predictive power and a lower degree of interpretability" (CreditInfo, 2023).

a consumer's score. In this context, it is crucial that a cosnumer be able to give informed consent so as to safeguard their agency and retain some form of control over the process. Informed consent is underpinned by three elements: clear communication of purpose of product or transaction, comprehension of these on the consumer's part, and ability to voluntarily engage in a transaction (Chadwick, Marshall, & Royal, 2020, p.12). Whilst the cases investigated above do to some extent meet a few of these requirements, informed consent is known to be defined by structural inequalities (Schuck, 1994), especially in developing contexts (O'Connell, 2016, p.77).

In the case of alternative credit scoring for financial inclusion, the context in which the transaction is taking place is one of *skewed incentives*. The unbanked consumer is cut off from financial services, and alternative scoring is presented as the only alternative. As such, there is an overwhelming incentive for the consumer to accept any conditions he is presented with. Unbanked consumers in developing countries – areas with already lagging data literacy rates[32] (Global Voice Group, 2020) – are also more likely to have difficulties in comprehending privacy policies, data usage policies and are therfore unlikely to adequately grasp the extent to which they are relinquishing control over their data.[33] Research by Mandava et al. (2012) shows that participants from developing countries have more trouble understanding conditions for voluntary withdrawal from clinical research trials due to having more sources of pressure to participate. In the context of alternative credit scoring, the monopoly that this risk assessment tool has over underbanked consumers' access to financial services can determine the extent to which they are willing to ignore their lack of understanding around how their data is to be processed or the implicaitons of the agreement for their privacy. The informational asymmetry of traditional credit markets is here reversed rather than eliminated – creditors now possess more information about consumers' behaviour than they may be aware of.

Such an asymmetry, together with the unavailability of substitutes for access to financial services and the significant economic incentive for utilizing alternative scoring tools, is crucial in how it shapes the dynamics behind informed consent. It reflects a significant power imbalance which limits the effectiveness of mechanisms of informed consent (Schuck, 1994, p.928).

5.4. Epistemic injustice in datafied credit markets

(i) Epistemic injustice

The kind of epistemic injustice Miranda Fricker sought to articulate in her work was fundamentally concerned with the exercise of one's capacities as a knower, an agent of knowledge

[32] Data literacy, or the extent to which an individual comprehends and can make use of data, is often given as much importance as standard literacy as a determinant of "constructive social change" (Frank, Walker, Attard, & Tygel, 2016, p.7)

(Fricker, 2007). In a break from what she labels 'traditionalist' epistemology, Fricker seeks to explore the relation between knowledge production and power. Indeed, a concern for truth and rationality cannot be disconnected from power and the social identities of those who take part in epistemic practices, or knowledge production (Fricker, 1998, p.160).

In contemporary society, the concept of knowledge is embodied by the "good informant" (Fricker, 1998, p.163). Two key requirements of the good informant are *credibility* – the posession of properties that indicate the likelihood of being right about *x* – and *rational authority* – when an agent is competent and trustworthy in relation to *x*. However, exercising the power that comes with being perceived as a good informant requires only *credibility* (Fricker, 1998, p.167). Indeed, there is a strong possibility for a mismatch between these two requirements. To the extent that having mere credibility is enough to wield the social power attached to the position of the good informant, there is a structural and political *incentive for corruption* embedded in epistemic practice (Fricker, 1998, p.168). Insofar as credibility depends on socio-culturally contigent indicators, credibility is attributed to those who are able to wield these indicators. The attribution of social power in relation to knowledge therefore mirrors existing structures of power in society.

The incentive for the norm of credibility to imitate the structures of social power brings about a mismatch between rational authority and credibility. In this sense, the powerful tend to be given mere credibility and those at the margins are denied it. This would, in Fricker's terms, constitute *epistemic injusitce* (Fricker, 1998, p.170). When inspecting the blossoming relationship between credit scoring and data science more closely, one can observe these mechanisms at play.

(ii) Big Data and credit-scoring: complementary epistemologies

As the concept of creditworthiness has evolved from binary categories of the "good" or "bad" consumer to more statistical, risk-based notions of it, the logic behind the credit score has progressively been defended as one that is grounded in objectivity (Marron, 2007). This is problematic in the sense that such a chartacterization of credit scoring does not account for the large extent to which the development of these scorecards is inherently shaped by subjective practices (Wainwright, 2011, p.650). Scholars that have conducted genealogical analyses of credit scoring practices have shown how the state-sanctioned institutionalization of these techniques helped legitimize them as objective metrics for risk. Indeed, the forced uptake of statistical models after the enacment of the Equal Opportunity Act of 1974 in the United States codified statistical scoring techniques as an objective measure of risk – the "scientific-statistical-empirical" framework of statistical scoring techniques allowed creditors to claim that all decisions were not subject to bias, discrimination or subjective reasoning, but rather the result of some scientific process whereby "real" creditworthiness was determined (Marron, 2007, pp.110 – 111). The institutionalization of statistical credit scoring techniques also served to shield it from legal threats by making them "rigorously documented and amenable to audit", thus granting them a "defensible procedural rationality" (Marron, 2007, p.111). This served to "blackbox" the subjective judgements that underpin decisions about which individual attributes constitute default risk, rendering credit scores ontologically uncontestable to a large degree. Wainwright (2010) posits that the uptake of more methodologically rigorous scoring techniques (statistical and beyond) should be understood not in terms of a desire for objectivity, but for lower uncertainty and a better forecast of expected losses. In other words, the framing of statistical credit-scoring's motivation as being one of truth-seeking and increased efficiency hides the fact that these metrics are actually subordinate to financial incentives.[34]

Although statistical credit scoring models have proved to predict default risk to a better degree than its previous, more evaluative counterparts, the subjective component of their design is regularly dismissed. This is the result of epistemic devices – framing, institutionalization, and expertise – that have been mobilized by the "epistemic elites" that create them (Wainwright, 2011, p.654). The increased datafication of credit-scoring practices and the gradual adoption of algorithmic scoring techniques by creditors is another step in this direction. The epistemological clout of Big Data as a methodology for truth-seeking has bolstered credit scoring's credibility as a rational, objective, and scientific metric of consumer behaviour.

The fact that the advent of Big Data has significant epistemic implications is undisputed. Epistemologically, data are literally a "collection of facts" (Floridi, 2008). The Internet of Things (IoT) is, also quite literally, a network of objects constantly producing data about the world in a granular, exhaustive, flexible, and scalable way (Kitchin, 2014). In this sense, the data revolution is leading a paradigm shift in the way research and knowledge-seeking is conducted. It reflects an onltological shift towards inductive reasoning in knowledge seeking – patterns in data are the guiding framework for social inquiry as opposed to a theoretical proposition (Paganoni, 2019, p.6). By eliminating the need for theoretical frameworks in model construction and research, it ushers in a new era of empiricism in which the world has never been more 'knowable' (Kitchin, 2014, p.3). Contrary to statistics, "big data (...) claims to process individual elements of the population with all their idiosyncrasies" (Esposito, 2022, p.95). In a commercial society whith an unforeseeably complex market, technologies which *promise* to forecast consumer behaviour are given epistemic and commercial value (Rieder, 2020, p.43).

Indeed, datafication has been framed as an unprecedntly accurate way to capture previously intangible components of human experience, such as friendship, emotional state, and so on (Paganoni, 2019). This epistemic posture is ubiquitous in Big Data discourse, claiming to be the optimal way to capture the complexity of the social world.[35] The power of such a posture is evident in how pushback about the efficacy of big data techniques such as algorithmic decision making is mostly framed in terms of issues within their technical design (Shin & Choi, 2015).

[34] Risk analysts often forgo opporunities for increasing their models' predictive power due to the costs these may carry, such as purchasing datasets (Wainwright, 2011, p.658).

[35] One key idea behind data science is that in the case of "irreducible complexity", models with "theoretical background assumptions" are inadequate, as opposed to inductivist approaches that make inferences from patterns in data (Pietsch, 2022, p.6).

Though scandals like that of Cambridge Analytica have forced such discourse to shift away from overt technological determinism, there is still significant resistance within Big Data's inner circles to acknowledge the subjectivity embedded in these technologies.[36] Some of these framings do well to point out their weighty assumptions, one being that bias can fully be addressed within the data pipeline (Hooker, 2021, p.3).

Big Data's epistemological claim to be the ideal method for truth-seeking is commanding. This position is well reflected within the general discourse around algorithmic decision making and datafication. Credit scoring's reliance on such claims to sustain the concept of creditworthiness as one grounded in objectivity means that it epistemically benefits from Big Data's credibility as a tool for capturing complex social phenomena. Algorithmic credit scoring carries, insofar as it the result of fusing Big Data techniques and credit scoring practices, epistemic authority. The injustice of this authority becomes more apparent when examining the limitations of Big Data and algorithmic prediction in capturing complexity. This is not to say that knowledge seeking should be exclusively guided by overly abstract, assumption-based models. Rather, Big Data epistemology and discourse profess a level of objectivity that is not entirely honest; they hide the extent to which subjective components inform its technologies.

(iii) Epistemic injustice: the shortcomings of algorithmic credit scoring as a truth-seeking technology

Despite claims to being an objective measuring tool, algorithms and Big Data technologies are in reality deeply influenced by a myriad of subjective forces – the design of Big Data techniques is mediated by cultural, political, economic and managerial constraints. As tools, data models are evaluated by criteria unrelated to correctness or accuracy – cost, speed, training requirements and reusability are among these (Shaw, 2015). As such, their effectiveness as accurate representations of the social world is subordinate to market forces. In the case of algorithmic information-ordering, the goal is not only to make information more intelligible, but more "navigable, actionable, and economically exploitable" (Rieder, 2020, p.41). As a result, models and algorithms are often designed to be as broadly usable as possible, making them less useful as scientific instruments in specific inquiries (Shaw, 2015). As Rieder (2020) puts it: "when the task is to make distinctions in a seemingly amorphous mass of customers (...) the epistemic objective is not disinterested, conceptually rich knowledge (...) it is to make (quick) decisions that are more accurate than a coin toss" (p.44).

Algorithms, to the extent that they are increasingly crucial "epistemic operators" – organizing information in public administration, markets, and public forums (social media) – have penetrated, and are *embedded* in the very reality they seek to measure (Rieder, 2020, p.33). In this sense, the vast majority of data generated by the IoT originates in quasi-experimental

[36] Publications from Google Brain employees such as Hooker (2021) attempt to reframe the biased algorithm problem. Despite conceding that the problem is more complicated than a simple matter of biased data, she contends that algorithmic bias is more dependent on decisions about *model design*.

contexts that can be modified by manipulating user interface design and algorithmic processing, rather than an observation of actual sociality (Rieder, 2020, p.45). To a certain extent, algorithms "manufacture" the future they intend to predict (Esposito, 2022, p.98). The predictive accuracy of algorithms is also limited in the sense that all they can detect are correlations in data that has already been produced. As such, their ability to discover anomalies or unprecedented behaviour is non-existant (Innerarity, p.10). Regarding algorithmic credit scoring, this would mean that a consumer's agency is constrained by his past behaviour: there is no tolerance for sudden changes in one's attitude towards financial responsibility.

Algorithmic prediction also suffers from a data source selection problem. Okidegbe (2022) argues that the problem of algorithmic discrimination cannot be solved within the data pipeline (i.e. by cleaning data, technical adjustments, or auditing). Algorithms used in courts, for example, draw almost exclusively from carceral knowledge sources (Okidegbe, 2022). This does not just include quantitative data – arrests, convictions, court appearance records and the like – but qualitatative, discretionary and value-laden decisions about how the algorithm should engage with the legal and policy landscape.[37] This means that other knowledge sources are discounted from decision-making processes. These may be knowledge sources that carry racially, culturally and socioeconomically different conceptions of public safety, and consequently may provide interesting inputs or mititgating factors during the formulation of judicial decisions (Okidegbe, 2022, p.2039). In the case of algorithmic credit scoring, an algorithms' conception of creditworthiness suffers from a similar knowledge sourcing problem – notions of creditworhtiness are informed by socioeconomically charged ideas of trust. The fact that the individual algorithms of different credit scoring FinTechs are unique in the parameters they utilize should be testament to the arbitrariness of the process by which the very idea of "creditworthiness" is constructed.

It seems that insofar as algorithmic prediction suffers from substantial constraints in different areas – subordination to market constraints, endogeneity of predicitons, inability to account for anomalies, and knowledge source discrimination – it fails to to live up to the epistemic claims which Big Data discourse makes about its ability to measure reality. This seems to reflect an asymmetry between its *credibility* as a knowledge source and its *rational authority*, or the extent to which it is as competent as it claims. This would, in the Frickerian sense, constitute epistemic injustice.

6. CONCLUSION

This paper has examined questions of justice surrounding the use of alternative credit socring techniques for the promotion of financial inclusion in emerging economies. By adopting a structural data justice perspective, the paper sought to move beyond mainstream political

[37] Such qualitative data tends to be sourced from actors within elite circles of the judicial sector, such as judges, prosecutors, and the like (Okidegbe, 2022, p.2049)

analyses of datafication, whereby injustice is taken to occur within the information value chain. Indeed, the purpose of the paper was to widen such an analytical lens. Instead of focusing on injustices within the data pipeline, it sought to understand the structural determinants of how the data systems behind phenomena like alternative credit scoring are designed.

The paper began by providing an overview of the use of artificial intelligence in default risk assessment, tracing the development of algorithmic credit scoring models from their inception to the use of alternative scorecards. In doing so, it introduced the benefits of using this technology for development – as a tool for driving financial inclusion – as well as the ethical concerns that surround it. After an overview of the debate around alternative scoring models, it proposed data justice as the best analytical tool with which to evaluate the justness of using this technology to drive financial inclusion. When exploring debates within the existing data justice literature, it found the limitations – an overt concern for liberal definitions of fairness as well as an ignorance of structural determinisms – of its more mainstream conceptions to weaken their analytical power when analyzing datafication processes in developing contexts. Indeed, it found Heeks (2017)'s articulation of structural data justice as an adequate frame for capturing the structural elements that underpin international development and the design of data systems like that behind alternative credit scoring. Indeed, addressing the structural elements that determine datafication processes – data collection, processing, and usage – is key for an evaluation of the justness of said processes.

The analysis focused on three structural components of alternative credit scoring processes. The analysis of the institutional framework consisted of a review of the policies of two alternative scoring FinTechs – CredoLab and CreditInfo Group – and their respective policies on data collection, processing, and storage as well as their privacy policies. It was found that despite CredoLab having relatively robust and transparent policies on consumer protection, privacy and data use, its lack of privacy policy for its African or Latin American consumers as well as CreditInfo's comparative opacity raised questions around the control consumers in developing contexts had over their data. Such questions meant that analysing the structural relations between the FinTechs and the consumer was crucial in assessing the justness of the interaction. An analysis of these found that informed consent was limited in its capacity to limit the power imbalance that underpinned the transaction – consumers' likely lack of data literacy (informational asymmetry) and lack of alternative paths to financial services (skewed incentives) made their decision to consent to release their data a fundamentally coercive exchange. An analysis of the epistemic component of alternative credit scoring found that the fusion of Big Data's epistemic claims of being the best methodology with which to capture reality and credit scoring's need for scientific credibility constituted a case of epistemic injustice. Consumers are epistemically constrained in their ability to contest the truthfulness of their credit score, which holds a degree of social and political credibility that is not reflective of its rigour as a representation of reality.

Applying a structural data justice critique to alternative credit scoring has therefore offered new insights into where injustice may lie within the use of this technology for development. Institutionally, the opacity of the actors that wield these technologies limits the ability of consumers to control and comprehend the extent to which they are relinquishing control of their data. Relationally, the power imbalance that underlies the scoring process reflects a coercive exchange whereby the agency of the consumer is constrained significantly. Epistemically, the consumer can difficultly contest the rigour of his score as metric of default risk.

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