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Chapter 10: Ethical considerations and regulatory challenges in data-driven finance and credit assessment

10.1. Introduction

Data-driven decision making is changing how financial institutions understand their clients, manage risk, and create value. Offered first-party data has become a primary asset of assessment that companies acquire and possess. In the last ten years, credit assessment of loan applications has entered the era of automated scoring systems, relying primarily on raw transaction data acquired from banks and audio-visual data collected via mobile apps. Such data-driven scoring has vastly improved risk identification accuracy. However, competition edges have shifted towards controlling data, with the leading role taken by data intermediaries. A level operating field is needed by wide data access and collaborative scoring. Both general opacity and business secrets hinder algorithmic transparency. Such considerations challenge existing regulation. Mechanistic fragility gives rise to newly needed prudential regulation. By advancing a professional research agenda combining technical and ethical expertise, academics, professionals, and authorities collaborate to develop regulatory sandboxes and associated frameworks (Ghosh & Kumar, 2024; Kumar & Rani, 2024; Mehta & Joshi, 2024).

By identifying opportunities, harms, and ethical considerations in financial and credit assessment, a literature review yields a structured discussion on harms and their association with big data applications. Automated decision making enables processing second-hand data, which raises the incompleteness, inaccuracy, irrelevance, and illegality of data. This gives rise to homogeneous proxies excluding protected attributes, narrower decisions with restricted options, and greater risk of making biased decisions. It is proposed to arrange ethical principles and risks at a layer including injustice, discrimination, servitude, and humiliation. Dissent methods implicitly, through structured advocacy of agency and welfare, feed biased supervised learning processes. Data convergence allows low-hanging mind extraction while identical scores harm the company. In similar contexts, harm prioritization, risk interpretation, and mitigation measures are proposed. Detection methods with more lenient definitions of fairness in two competitive markets are proposed aside based on manipulated control.

Federal and national regulators are asked to preemptively identify potential harms of AI. This should cover all actors and harmonize definitions, aiming at white-box AI models with minimal parameterization. AI pipelines are to be audited from data privacy, semi-automated detection, and counterfactual testing. FinTechs may be qualified Trusted AI Providers, while extensive duties are demanded on all actors pipeline-wide (Patel & Singh, 2024; Sharma & Verma, 2024).

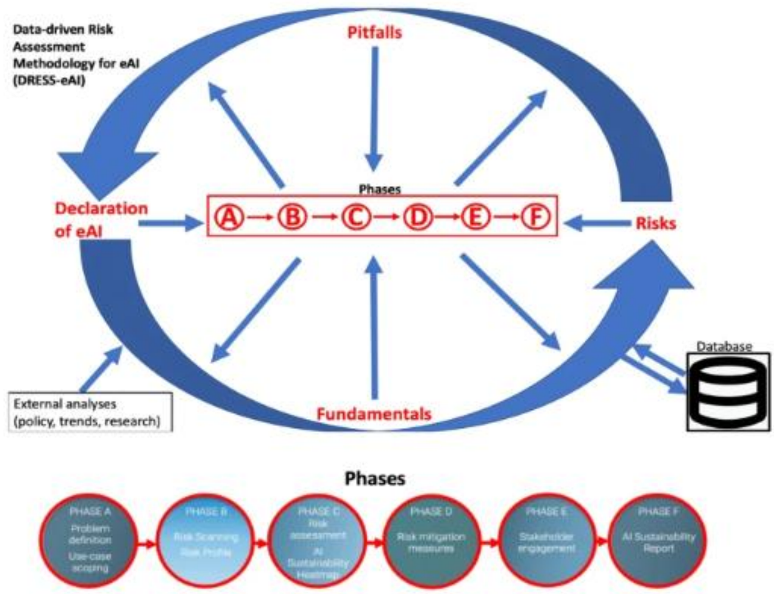

Fig 10.1: Data-Driven Risk Assessment Methodology for Ethical AI

10.1.1. Background and Significance

The rapid growth in the availability, volume, and diversity of datasets in recent years has stimulated numerous societal advances across domains. Across domains characterized by large datasets, there is an increasing interest in using modern data-driven techniques to extract hidden/inaccessible patterns and are useful for more precise, personalized, and sophisticated insight generation. In the financial sector, the data-driven advent is motivated by the emergence of not only a more data-rich world but also prestigious advancements in parallel computing and deep learning techniques. It further invigorates the sales analytics in an all-dimensional cycle of credit requests (initial appraisal), credit expansion (mapping clients), credit default (proactive default taxonomy at different levels). The lasting impacts of events such as the 2007–2008 financial crisis and pandemic-driven economic reconfiguration have led the global finance and credit landscape to undergo one of its once-in-a-generation transitions. Implicitly revealed biases in dataset properties, design choices of ML-related methods/tools, and ensuing inferencing have raised ethical concerns on potential distributional impact of model decisions on protected/sensitive/vulnerable groups, leading to the decision-impact understanding challenge. In finance and credit assessment, ethical scrutiny on model decisions can help interpret events leading to incorrect and discriminatory decisions. Addressing ethical concerns in modeling decisions requires auditing utilitarian algorithmic transparency and interpreting individual risk prediction explanatory models. Additionally, it is imperative to illuminate the minimum performance loss and collateral damages incurred by fair-explanatory bias amplification modeling for financial institutions willing to rectify discrimination. In this regard, the research summarizes some of the strides recently made in understanding the bias/measure/methods for implementation on parallel explainers, gaining significant insights into distributional impacts using causal user behavior on an e-commerce platform.

10.2. Consumer Perspectives on Data-Driven Credit Assessment

Technology in finance and credit scoring has the potential to foster prosperity and financial inclusion among communities that are currently underserved or unfairly serviced by banks and financial institutions. However, the implications of the different ways sensitive personal data is gathered, interpreted, and handled by third-party data providers have imperfect regulatory oversight, which leads to their exploitation, misuse, and dangerous outcomes for those without proper agency over their data. Unfortunately, the multitude of algorithmic systems created by economic decision-makers to optimize the lending process towards their econometric goals may trigger unforeseen or hitherto unconsidered social impacts or unfair financial outcomes for individuals. Under this state of affairs, computational social scientists studying these phenomena have a serious responsibility towards the impactful design of algorithmic systems or regulatory frameworks, which stresses the importance of considering equity as a sensitive dimension of credit scoring.

Explicitly modeling multiple sensitive dimensions, including the dimension of equitable finance, creates privacy, interpretability, and transparency challenges. Algorithmic impact assessments trust at-risk groups to be knowledgeable participants in deliberative conversations on the risks of such systems. However, survey results question this assumption and call for a more prominent role for representations of at-risk groups in the algorithmic impact assessments framework. Credit scoring modeling interacts with the outputs of redlining and exploitive information asymmetries, as many underbanked individuals do not have financial history. Widespread creditworthiness estimation systems by aggregating digital traces exponentially exacerbate boundary perceptions and risk erasure among non-conforming agents.

Considering the growing reliance on third parties to provide data-driven scores for credit assessment by banks and creditors, a first step in establishing a framework of normative consumer rights and redress mechanisms at the European Union level is raising awareness of the economic implications and potential unfair outcomes that arise. Thus, to shed light on developments reminiscent of social sorting and responsive capitalism, transparency settings of data-driven credit assessment systems were purposefully chosen to be less accessible to the average consumer.

10.2.1. Trust and Transparency

In a study on transparency improvements in financial credit scoring, a method for providing explainability based on the original model transparency was proposed. The study focused on contrastive explanations in conjunction with a new scoring model that is easier to understand. An anatomy of the decision-making process was illustrated to highlight the factors influencing credit risk assessment. The methodology demonstrated mathematically and empirically that financial institutions could give their clients better education on the reasons for credit scoring decisions. Mild modifications based on multi-criteria decision-making insights improved transparency further. For an easier understanding by non-technical users, they proposed the importance of a graphical visualisation of the exploitation process, in unison with the proposed methods. This visualisation could serve as a basis for future works on enhancing trust in data modelling. The study also pointed out some perspectives for further improvement of transparency in the data-driven environment. Understanding the necessity and implications of transparency enhances trust between the entities involved. This is even truer in the financial sector, where making decisions based on data modelling is becoming increasingly common and sophisticated. The present decisions significantly affect individual lives and the long-term future of the economy.

10.2.2. Consumer Rights and Protections

The commoditization of consumer credit affects consumer loyalty to banking systems and thus the profit of these institutions that depend on that loyalty. Consumer credit databases, especially those built from a data pool resulting from a collaboration of various financial institutions, have now acquired a big enough size to supersede retrospective models. They now offer the possibility of real-time credit scoring for costs close to those of their predecessors. The crucial issue here is if, how hard and how successful these databases will be challenged by consumer rights and protection. Will these new paradigms leave consumers with access to credit markets matching their profiles? Will they respect constraints on the extraction and use of the data they rest on? The legal context of data protection and telecommunication for the European Union, the United Kingdom and the states of the United States of America is set forth and then the challenges consumer rights groups are (and may be) bringing against lenders and databases are discussed.

As with similar paradigms, the burst of the euphoria surrounding this new technology speculations left a residue of explorations to ponder the ethically right usage of these powerful new methods. Scores, however, play a very important role in allocation decisions, determining if you receive credit, housing, a new job and thus are in a position to lead a decent life or not. While auditors or successful lawsuits are within the realm of expectations for older decisions such as whether to shut down a business or not, the impossibility for experts to provide assurance for scores will preclude the judicial system from having access to those scores or the arguments supporting them making justice almost impossible, leaving consumers unprotected against discrimination and fraud that take place through scores.

10.3. The Impact of Artificial Intelligence on Credit Assessment

AI is believed to have rendered decisions for credit, insurance underwriting, and compliance with anti-money laundering effectively, precisely, and cost-efficiently. There is a view that AI-driven loan origination systems, smartly accessing non-traditional data, lead to credit decisions that better mirror the ability to pay. The credit underwriting process relies heavily on these herbs of judgment. AI is also believed to augment the identification of threats to financial institutions, improve compliance with regulations, and assist in constructing resilient business strategies. Nevertheless, there are fears that AI is being deployed in opaque processes and with unsafe algorithms, which grow beyond human control. There are concerns whether the governments and businesses on the receiving end are equipped to deal with it and whether ethical standards are up to date and upheld.

10.3.1. AI Algorithms and Transparency

In particular, algorithms remain incomprehensible to their human operators, a situation referred to as opacity. The so-called BlackBox models of algorithmic credit risk assessment make a sense of opacity that viewing the internal workings of a specific algorithm would be impossible for both the operator and the person suffering from its effect. Thus, it becomes impossible either for a human operator to correct a flawed algorithm or for a citizen to mount a criticism of an allegedly unfair algorithm. The more complex a model is in terms of its design, the more difficult it is to ascertain how it processes the information at its disposal and what assumptions it makes about its inputs. Here transparency means that algorithms produce literally transcribed results that can be studied, contested, and corrected.

However, transparency could lead to the increase of costs as rivals might use modelling knowledge released in transparency attempts. This may lead to an escalation of costs as privacy preservation technology needs to be employed to protect transparency knowledge that newly available information has made firms vulnerable to legal liability and reputation loss. That is, there are always second best responses to a directed effort to push an industry toward transparency and firms may fundings lobbying efforts to preclude it. Moreover, a large number of considerations not specifically concerned with industry outcomes would lead researchers to consider it undesirable to lobby for transparency, in the absence of acute negative welfare outcomes, transparency introduction might be capably delayed. Engaging more systematically with socially desirable outcomes is also a matter of time pressure and research capacity relative to a large number of other important issues. On the other hand, transparency could contribute to discrimination-free credit scoring as firms would use algorithms as signalling devices, sharing them with operators, investors and ultimately consumers.

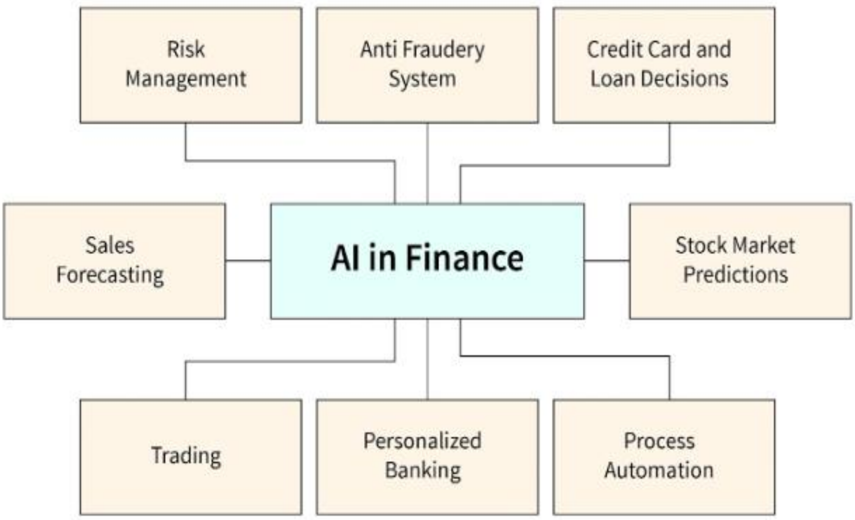

Fig 10.2: AI Algorithms and Transparency

10.3.2. Accountability in AI Decision-Making

The introduction of advanced AI applications into decision-making processes has raised important ethical, legal, and societal concerns, from the accuracy of algorithmic predictions to the impact of decisions on citizens' lives. But are the principles and rules currently under consideration and consultation enough to avoid unlawful and harmful consequences for citizens? Distinguishing between expectations, obligations, and opportunities is critical for adequately scoping new proposed frameworks. Accountability measures need to operate at multiple levels and between multiple actors, focusing on specific domains and elements of decision-making processes. Boiling accountability down to single characteristics or tools unlikely yields a coherent solution. With AI increasingly making inferences and predictions visible to humans, action and reaction are no longer separated by time or space, but occur semi-automatically in software. This has shifted accountability inquiries from legality and legitimacy towards how these systems operate within the decision-making process over time. Interactional accountability emphasizes that present-day ALPurpose frameworks promote accountability after decisions have been made, and that public responses to algorithmic recommender systems have been focused on this characterisation of accountability. But an algorithm's decision-making trajectory is seldom studied as part of ALPurpose. Yet this could challenge an interactional definition of accountability and help sketch new tools to avoid accountability gaps in technical systems.

Accountability is both a technical and a moral concept. For instance, it allows one to correlate the effect, cause of the effect, and legitimacy of the cause, minimising a series of accountability gaps. Such gaps prevent the attribution of culpability in actors influenced by predictive and/or automated technologies. The unintended consequence of algorithmic societal effects could leave unaccountability space. Meanwhile, the emerging AI accountability and (legal) responsibility discourse draws upon this concept of accountability, but mostly focuses on normative questions about technical AI systems ready to be rolled out without upfront infra-structural reforms. Meanwhile, AI auditing, regulation, and algorithmic or digital-welfare corporations with the socio-political accountability value, like the recently proposed AI Act in the EU, or accountability engaged tech-giant proposals. Such rule-setting proposals focus on the negative implications of advancements in AI instead of identifying potentially harmful trajectories of specific technical systems involved in decision-making processes. This research aims to develop a characterisation of accountability that elucidates where activities take place, which actors engage, and when activities are performed in relation to AI technical decisions. By extending the interactional accountability framework, it illustrates the relevance of examining the argument structures that ground a predictive inference transfer for future actions taken on the inference. Such inquiry could facilitate accountability by aiding understanding, highlighting malice and ignorance actions, and providing a basis for the conception of new accountability tools.

10.4. Ethical Implications of Data Usage

As financial companies aggressively expand into big data and data analytics to assess creditworthiness, there arises a fundamental understanding of the usefulness of modern data, an empirical description of the data currently being used, and an ethical analysis of their usage. Firstly, the data usage begins with extensive meta-data on the clients. In a world where privacy and ethical issues arise, this meta-data becomes very important to create a false image of who the person really is. Secondly, social graph data enables financial companies to analyze how clients interact with the online world. This approach could lead to a new creditworthiness assessment model. Thirdly, both the meta-data and social graph data have been analyzed in a heuristic way based on Bayesian statistics instead of standard quantitative models. Lastly, the ethical implications of utilizing this data for creditworthiness assessment are discussed.

It has been shown that unmodelled information is being collected worldwide about clients and could be considered for creditworthiness. Moreover, massive amounts of non-financial data are transformed into financial proxies, such as creditworthiness. All written in this paper regarding both data analysis and how creditworthiness is affected by it far exceeds companies actively exploiting this data for model development. Financial companies operate mainly under stress testing conditions formulated in a time horizon. The regulatory framework to comply with this risk assessment framework was set in September 2014 using the same guidelines adopted for the European banks. In that regard, good actions forecasting events were captured by traditional credit scoring through a set of characteristics which transformed qualitative, ordinal, and codified information into quantitative numeric assessments. The idea is to derive good action probabilities from a finite set of an extensive time period of previous good and bad judgment accounts using dependent conditional distributions P of the good action at time t given the data eating the initial data set at time zero.

10.4.1. Privacy Concerns

With rapid advancements in data collection and predictive techniques, there has been growing state and consumer concern about how organizations use consumer data. As such, the use, retention, sharing, and sale of consumer data has become the focus of litigation and regulation. Many consumers are now actively taking action to limit the personal data collected and retained by organizations. Particularly high levels of concern have been raised for algorithmic credit assessment. The pervasive deployment of models that screen applicants for banking products and insurance in byzantine and possibly unfair ways is the focus of current research, regulation, and litigation activity. However, such concerns are also relevant for the ever-growing market for other data-driven products. Finance organizations build a variety of credit models to categorize consumers based on their propensity for taking on risk. Scoring systems infer consistent and understandable scores for very large physical quantities, like credit risk, that cannot be collected directly but can be inferred indirectly based on more easily collected easily quantifiable features. The current generation data-driven models that have been deployed use increasingly deep and complex neural architectures which leads to better predictive performance, but also are less interpretable, less accountable, and arguably less fair and more discriminatory. More recently, mandates for increased interpretability have been put in place in vulnerable markets that include finance and credit insurance. Specifically, there is a call for testing interpretability in the credit domain against a strict set of consumer regulations and legal precedents, and analysis of complex data-driven credit modeling methods that aims to answer whether model take-up has alleviated or contributed to privacy, transparency, and discrimination concerns. Such concerns are recognized by the tense global debate over privacy law that is currently underway and how each jurisdiction has developed its own rules and regulations. The fundamental tradeoff between privacy and predictive performance in machine learning is approaching a tipping point, with strong regulatory action expected in this domain.

10.4.2. Bias and Discrimination

Discrimination in lending across demographic groups can take multiple forms: higher rejection rates, higher interest rates, lower credit limits. It can happen at any stage of the life of a credit: when applying for a new loan or asking for a credit limit extension. Under taste-based discrimination (TBD), some managers get utility from engaging in discrimination against individuals sharing a protected attribute, such as gender, age, ethnicity, nationality, religion, or family status. By deciding to reject an application when it could have been accepted based on the default risk (otherwise put, by increasing the interest rate), individuals of the targeted group are hurt and the lender foregoes a higher receivable. Under statistical discrimination (SD), firms lack information about the true creditworthiness of borrowers. To deal with this uncertainty, firms can rely on the average historical creditworthiness of each group of borrowers (e.g. gender, first name, age). This raises concerns about a potentially virtuous cycle of discrimination, as firms would have less incentives to invest in acquiring the missing information regarding the counterfactual, as financing disparities generate repayment disparities, entrenching beliefs about the creditworthiness of borrowers across groups. There is compelling empirical evidence about discrimination in lending. Some studies assessing the loan rejection rate across groups detect a negative and statistically-significant coefficient on the protected attribute. It is indicative of discrimination, such as receiving a less favorable offer at any stage of the process: lower credit limit, higher interest rates. In such contexts, a positive coefficient for the protected attribute suggests discrimination. Earlier empirical works document that lenders were more likely to ask for additional information or reject the application outright if the applicant was a woman. The rise of algorithms and big data in lending has been recognized as significantly influencing the likelihood and forms of discrimination. Instead of poor underwriting or reduced access to channels to present a credit request, it is likely that some borrowers' characteristics may never have been presented to the lender. Nonetheless, implementing an algorithm making objective decisions can mitigate or remove discrimination based on preferences or incentives for biased lending. ML algorithms, especially when implemented with large datasets, are likely to better capture the structural relationship between observable characteristics and default. In this sense, the "black box" issue may have a positive side .

10.5. Regulatory Frameworks in Data-Driven Finance

The rapid evolution of data-driven finance and credit assessment has grown faster than the regulation surrounding it. Regulation for most activities across all countries tended to follow innovations after they had created a lot of damage. The same applied to social media, cryptocurrencies, AI-based lending, and peer-to-peer lending. Predictive lending models have been shown not just to discriminate based on features like interest-paying history but also to discriminate based on proxies that cannot be explained as features but rather result from the optimization of the fitted model.

The problem with the developments of models leading to potentially unethical decisions and unpredictability is crucial to date. There are authorized auditing companies analyzing models, for example, in the health sector. This scenario is in line with regulation. However, there are caveats. First, the emphasis remains on the explicability of the model. The overarching objective of profitability is a missing component. Making a prediction profitable is often also why better models involving proxies are developed. There is historical bias in the training datasets. And choosing only now biased samples as sensitive can simply move discrimination from sensitive to sensitive proxy. The embedding bias detection is equally valid for prediction models and for the training dataset itself. It can be detected that allowing predictive algorithms to discriminate using a proxy systemically is unfair due to poorly doing historical decisions.

The unfortunate result of an unbalanced amount of permissibility causes severe discrimination. By building more accurate models that directly model discrimination indicators, it can be shown that the measurement theory is utilized by explicable or interpretable alternatives. It can generate elaborate interaction models without explainer black boxes out of the box. Not just financial institutions but also data aggregators have misused financial affairs private ground-insured data, and fried them into pools offered to lenders or banks. Some recent credit risk models do not just implement supervised learning modeling on the bank's internal data but also implement unsupervised learning to establish a credit score rating starting from ground-insured third-party data. What is unacceptable at the regulation level may get authorized in practice.

New means of producing big data, economies of scale, and poor regulation mean powerful corporations will optimize their behavior in terms of what is permitted and profitable. Public service entities deserve regulation specifically tuned to their values. Alternative scoring techniques created a valid threat to the existence of universal lenders, and regulation should reassign power to their rivals until regulation can catch up. Multiple actors are needed to analyze the credit system and its potential biases, both unintentional and intentional. Time is needed to build interpretations of risks and models as basis for regulation.

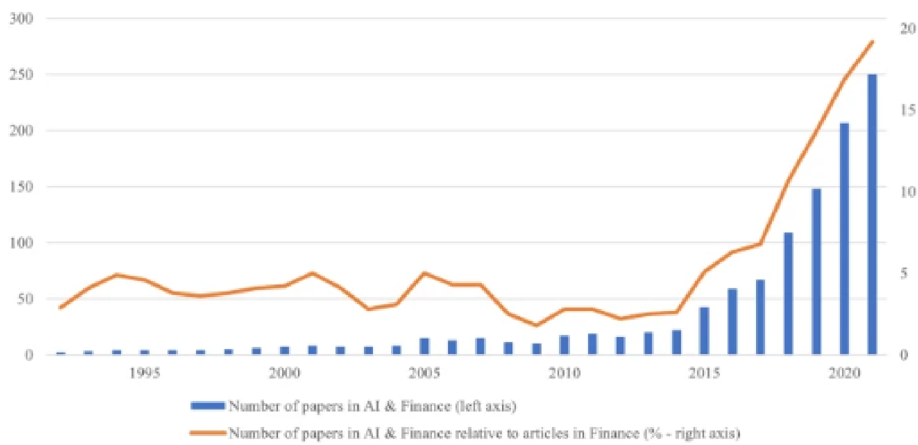

Fig : Artificial intelligence in Finance

10.5.1. Global Regulatory Landscape

Tackling the challenge of regulation is a complex matter, and although the regulatory landscape is still being formed, it could be beneficial to explore approximate regulatory habitats in this evolution. Model regulatory regimes have existed for years, and at least in some areas of finance, large blocks of the financial landscape have been given to certain kinds of regimes using forensically established models. Moreover, rich sets of empirical verifications of such models exist, which should allow for constructing robust arguments resting on them. Data is both the fuel and target for a Big Tech, and examples such as Google or Facebook are already moving into credit scoring directions whilst running into competitive hurdles. Despite challenges in terms of understanding the new technology, there is a regulatory challenge with a limited cultural horizon and data understanding. Minutes and calculations challenge and humbly admit the huge efforts in dismantling information from great text bases. The challenge for regulators is daunting. Approaches could also be modeled after ‘cyber’ regulatory experiments of the European Commission without regulatory regimes. Avoiding motion from points, model regulators could establish horizontal regulatory regimes with facts established using readily at hand common tools. In the first step, the exercise could direct the utmost challenge of algorithm-induced discrimination. Regulations aiming to officially prohibit discrimination proved too naïve to be effective, and elaborate forms of legal harms had been established over decades without positive outcome. Instead of regulations, experiments with discussed through and traceable algorithm based information granting procedures be envisaged. Building on the thesis about the primary quality of information, explanation-inducing information needs to be modelled. The. Causality induced anomalies in operational model generations may defy prediction, or advise additional forms grounding on human decision making through multiagent decision based on rules carrying decision sources could be established to limit discriminatory challenges.

10.5.2. Regional Variations in Regulations

Modern credit systems through low-cost data-driven algorithms have the potential to deliver sound credit, underlining that these technologies will work even in environments where the classical scoring models do not work. The deployment of data-driven solutions to economic and financial problems poses several challenges and risks, like data-driven models in traditional sectors like information technology and Fintech. New solutions are already on the market and widely used, particularly by new companies that aim in many cases with funding and support of consumers’ protection authorities to enter traditional markets, such as in the context of digital first bile lenders. The large variety of different data points monitored on various platforms, together with the availability of cheap technology and the absence or weak enforcement of a legislative framework, have made this market a boom yet a snipe hunt. In this context, some self-regulatory rules and directions may be in place that good practices are predictive of good behavior, it is still questionable whether the industry of data-driven finance willingly takes such a path.

Machine learning-based algorithms for scoring and sanctioning on the basis of disputes on these datasets. Regulatory authorities should focus on the algorithms themselves rather than the datasets to level the playing field. The influential study highlighted the question why machine learning based algorithms were en bloc banned by one marketing authorities/supervisory authorities but not the others. Knowledge of which datasets are automatically excluded is the essence of digital information as well. In addition, preaccounting of data-driven screening is also a question of calculability in the self-calculation. As minute and accurate as the learning model is, there shall still remain a piece of credit risk that is somehow not resolved from the mathematical, technology perspective, and the entirety of local compromise solutions for this calculation scheme hints at the question of concealability.

A powerful comment to the effect that, notwithstanding the above freeze up and other foreseen problems with a knowledge threshold, the mete shall absolutely be impossible to test features and weights of pools intelligently. For instance, if these simulations are landmark observations, gettable pools should "generate mapping from applications to credit scores, disclosing little information about the data pool or the learning procedure." Hidden variables could cause credit points couched far differently in the diverse schemes yet produce the same score across machine learning probabilities or further obfuscated. The fear remains that daunting mechanized scoring, can infinitely different pools give factorially different weights for bolt, nut and thin calibers yet on its externality bend the same slits? From the view of legal practice, why is the insurance of credit risk and its observance shrouded by mathematics?

10.6. Challenges in Compliance

The growing reliance of data-driven finance on black-box algorithms makes compliance with requirements more challenging. However, regulations applying to this area could require openness, as data-driven finance directly affects other financial market participants or even private consumers. Market information such as price feeds, standard indices, or liquidity demands is often available via a "trusted third party," influencing the rationale, strategy, and profitability of trades and creditors. Filters, engines, and brokers dismiss certain market information as irrelevant or too noisy to act upon, or disregard whole information classes altogether. Elimination of relevant information may result in economic disadvantage, distrust, and a loss of reputation or licensing. In addition to potential civil liabilities in the regulatory framework, criminal investigations, supervision costs, and repercussions on an affected firm's business expansion and reputation are probable.

There is a more precarious challenge as regulation might require crypto finance firms to open all algorithmic trading venues, including CER, long-latency predicting algorithms, and HoE. At the very least, scrutiny on fraud and erroneous behaviour might lead to an exhaustive cost-benefit analysis. Pre-trade and post-trade facts and events instead of inspectable algorithmic trades seem to alleviate this problem and facilitate cooperation with regulators, if required.

A second group of negligible requirements is contingent, optional, and loweligibility. Open access to data-driven finance ranges from “open,” where whole data sets are public, restrictive “private” or “confidential,” where access is confined to specific participants or for selected goals, to “secret,” where no access is permitted. There are training data or computations when a firm licenses its trained ML to others or “as-a-service” when an individual trains ML using other firms’ data and queries the output without knowledge of how the data is used in the detection process. With or without proprietary data, this layer restricts the scope of obligations or advantageous conduct.

10.6.1. Data Protection Regulations

Just as the technology creates new opportunities in terms of accessing and processing personal data, so the need for the appropriate protections to be in place to control its use. No property other than personality, as the right to be "let alone", the right to control decisions about oneself, the right to refuse to disclose anything, and the right of withholding confessions pertaining to oneself can be considered. In this view personality ceases to exist where information can be re-computed, reconstructed, reconstructed, and run by the ever-faster computers of individuals, governments, and agencies. According to a number of codes on consumer credit reporting regulations and in accordance with the directive, data and information protection is the privacy rights of individuals who avail themselves of goods and services are specifically to the effect, inter alia, that: a) the data subject shall have the right to access the data and to have them rectified, b) the data subject shall have the right to obtain erasure of data if the retention period has expired or if the processing is not sanctioned by law (i.e. incomplete or inaccurate); and c) there shall be no interference by a public authority with the exercise of this right except such as in accordance with the law and is necessary in a democratic society in the interests of national security, public safety or the economic well-being of the country, for the prevention of disorder or crime, for the protection of health or morals, or for the protection of the rights and freedoms of others. Data Protection is one of the core European principles and the "pillar", which by preventing misuse of personal information guarantees the right to privacy. Privacy is a fundamental right recognized by the Convention for the Protection of Human Rights and Fundamental Freedoms and a number of additional protocols. Article 8 secures the right to respect for "private and family life". The Convention safeguards this right by limiting the permissible scope of the intervention of public authorities. It provides that there shall be no interference by a public authority with the exercise of this right except such as in accordance with the law and is necessary in a democratic society in the interests of national security, public safety or the economic well-being of the country, for the prevention of disorder or crime, for the protection of health or morals, or for the protection of the rights and freedoms of others.

10.6.2. Adapting to Rapid Technological Changes

Regulatory responses to data-driven credit scoring technology are diverse and vary by country, reflecting each society's values regarding economic, ethical, and social concerns. Nevertheless, in a complex tit-for-tat interaction game, policymakers and regulators are usually already off-balance [10]. This ambivalence is due to several interlinked causes. First, there are few institutional penalties for inaction. The political and social costs and possible short- and long-term consequences of punitive regulatory action are extraordinarily high. Regulating data-driven finance is akin to planting a minefield while balancing a sword in the other hand. Second, regulators lack adequate information about the possible consequences of regulatory actions. In an emerging but still opaque sphere of social and economic innovation, it is exceedingly difficult to predict and plan the behavioral consequences of regulatory actions and the possible social fallout. Third, the deep societal changes initiated by the rising popularity of data-driven finance mean that regulators lack the institutional and cognitive self-understanding of the processes involved. The changing behavioral incentives, physical and social interactions, and shifting capabilities of FinTechs and consumers vastly exceed regulators' ability to process and analyze the consequences for economic and social stability .

The speed of advances in sophisticated financial technologies, such as AI, make them hard to regulate. As FinTechs often operate in multi-jurisdictional settings, the regulatory cooperation of dozens of global regulators with disparate knowledge bases, worldviews, eras of evolution, and institutional structures and cultures is required. And last but not least, financial technologies are by their very nature artefacts of self-reference and combinatorial autonomy. This can unexpectedly yield highly distorted outcomes that far exceed the initial intent. Attempting to impose global rules on such wizened artifacts that developers themselves do not fully understand is difficult. Thus, currently optimal regulatory schemes are often captured by FinTechs out of player theory. When excessive social degradation occurs, the only available tool is ex ante curtailing, which is hardly acceptable for human societies.

10.7. Conclusion

For an ethical finance and technology convergence a couple of measures can be taken. Regulatory institutions can establish new boundaries and extend the existing ones. They may separate customer groups to which services will not be provided. For example, as in the case of the credit market, customers under 18 years of age may be declared too young to be borrowers. As new technologies appeared on the market, practice has shown that regulations also required elaboration to take into account abuses of the newly invented instrument. Thus, introduction of laws for tracking crypto currencies may mitigate money laundry and wrongdoing in the crypto markets.

In this case ethical dilemmas do not arise in principle. Financial market actors are aware of and bound to these regulations and willingly abide by these rules. There exist interest guidelines, which may serve as a voluntary basis to curtail the price of the unethical practices. If a firm breaches its own rules it does not breach any moral issues. However, an act can be seen unethical, if violations of the voluntary rules are unharmonized or the regulation of voluntary rules so widely allows the unethical practices that it fails to address apparent moral breaches.

Similarly to regulatory limitations, the members of the professional organizations belonging to the economy or finance may develop restrictions towards the technology. At an academic level there is a growing body of literature that illustrates various avenues in fair finance. Several previous literature reviews focusing on fairness in credit scoring have surfaced definitions, methods and applications of fairness in this specific field. The idea of fairness is indeed interpreted in many ways and it stands good at high-level views, and in generalizations, but obstructive details of the actual methods applied in cases are not presented.

The cases typically demonstrate how algorithmic fairness and dynamical modeling techniques could be employed together with real data in the credit scoring field. In this section the applications of these methods are presented in terms of meta-characteristics rather than enumerating and illustrating specific cases. The cases typically demonstrate how algorithmic fairness and dynamical modeling techniques could possibly be employed together with real data. Thus should readers wish to obtain ample detail on the cases' actual methods, they are advised to consult the referred papers.

10.7.1. Emerging Trends

At present, significant developments in modeling and execution techniques are taking place, fueled by the significant increase in available data and tools to harness its power. However, the incredible speed at which data-driven finance is evolving will present hurdles for regulators and policymakers in terms of understanding and the job of keeping pace. A legitimate concern is that the increased speed, interconnectedness, and complexity of the system may increase volatility and systemic risk. As a result of HFT feeds, assets tend to respond simultaneously to the data, which can lead to a market crash if an automated trading model begins to sell simultaneously, creating a self-fulfilling prophecy. Questions also arise about the complexity of coding model risk. Each day, markets become so complicated that pure heuristic reasoning will build little out of the computational framework, and the value of human intelligence lies in the fact that only it can grasp the complex relations between different market factors, infer the data structure, and recognize repetitive market patterns. Finally, although central banks' planned feed of population constraints is a welcome direction, agents' prediction error has been shown to impact the stability of the model. There might also be a flaw in supplement-based measures of heterogeneity, which assume a finite number of types. More broadly, there are questions about the need to include the impact of belief formation schemes, which itself is a complicated subject. It is possible prices are permanently shocked/independent, with bounded rationality in feeling rules. A great deal of ethical and technical challenges dealing with big data have been noted. A data hungry deep learning model that is sufficiently complex but relatively unexplainable has two weaknesses: it is incomplete and requires substantial data collection efforts. How might data audits/cross audits of banks and third party data providers be structured? That is, what common knowledge can help shoulder the burden? For credit score models, out of concern that they may be susceptible to lock-in, a restricted class could be explored: Lasso-based GLMs, where fairness constraints are naturally interpretable explanations. Beyond legal obstacles, it is unclear how solid and common a foundation might emerge, that is, what after facts have influence on the building across time and space of trustworthiness in AI applications.

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