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Designing AI Systems that Support Fairness Across Distributive, Procedural, and Interactional Justice Dimensions

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Abstract: The need for the most fair AI systems has been overemphasized as the AI influence keeps growing and critical decisions, among others, states by the healthcare, finance, and human resources sectors, are made.

AI fairness is not only about the fair distribution of results but also it involves fair processes in which decisions are made and the features of the interactions between the AI system and users.

This article uses the concepts of organizational justice as a frame to explain the ways by which the design of an AI system could become a vehicle for: distributive justice (fair distribution of resources and results); procedural justice (decision, making process that is open and impartial); and interactional justice (communication that is respectful and empathetic). The conjunction of the three dimensions that the AI system can facilitate will make it possible for the latter to be more in line with human values and hence receive more trust, legitimacy, and acceptance from the stakeholders (Colquitt et al., 2013; Binns, 2018).

This paper also refers to the various ways which include bias mitigation techniques, algorithmic transparency, and user, centric interfaces that bring fairness into the system.

Further on, the authors explain the present continuous issues (for instance, data bias and ethical tradeoffs) and recommend future research directions for enhancing just AI systems at the end of this paper (Miller, 2017; Selbst et al., 2019).

Keywords: Artificial Intelligence, Fairness, Organizational Justice, Distributive Justice, Procedural Justice, Interactional Justice.

I. Introduction

Artificial intelligence (AI) has had a rapid and deep penetration in most areas of human society, and its usage has been extended to the decision, making processes of companies and organizations in various sectors, such as recruitment, finance, law enforcement, and healthcare (Brynjolfsson & McAfee, 2017). These computational models provide a user with increased efficiency, scalability, and neutrality; on the other hand, they raise severe issues concerning justice and equality (Barocas & Selbst, 2016). AI, supported techniques largely operate on numeric data and instructions. This means that the errors of a close nature to human errors become even more serious, as they can unknowingly perpetuate the existing prejudices and even increase them. As a result, the affected people are becoming even more marginalized. Hence, it becomes imperative to imbue fairness into the very fabric of AI development and application.

Fairness is a difficult concept, as it does not solely concern equal treatment in terms of outcomes. From the perspectives of organizational and social psychology, fairness is a construct of the larger concept of organizational justice, which implies three different, yet interconnected aspects, distributive, procedural, and interactional justice (Greenberg, 1987; Colquitt, 2001). The issue of distributive justice relates to fairness in the allocation of resources while procedural justice is the one dealing with the fairness of the processes through which decisions are made. Interactional justice, however, is the quality of interpersonal conduct during these processes. Thus, these dimensions provide an extensive framework for justice examination with AI (Folger & Cropanzano, 1998).

The use of these principles of justice can create a design of a social and moral problem, solving AI that would address the ethical and social issues related to automated decision, making. The facet of distributive justice ensures that AI results are not, at one extreme, violating, or, at the other, benefiting a certain group unfairly without their knowledge. At the same time, procedural justice is about the issues of visibility, power, and responsibility in the so, called "algorithmic processes". With respect to AI, interactional justice is not thoroughly comprehended and therefore it is considered to be the farthest from the AI systems. On the other hand, it may be illustrated with the AI efficiency that is the manner whereby AI communicates with its users and the way it treats them. Therefore, it has an even greater function as it indicates respect, dignity, and empathy (Binns, 2018).

This piece is a deep and insightful exploration into the judicial framework of how it can be applied in the development and the evaluation of AI systems that are able to integrate the principles of justice in a lasting manner. Much of this paper is dedicated to the analysis of existing theories and challenges of distributive, procedural, and interactional justice in AI, which leads to the offer of guidance as well as the illumination for the creation of AI systems that are socially and ethically responsible besides being technically robust. This approach is necessary for user trust, usability, and acceptance in a world where AI is happening more and more.

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Theoretical Foundations of Organizational Justice

Organizational justice has shifted the way we look at fairness in our work environment and it also provides us with new insights on how AI decision, making systems should be designed so that they are fair. This principle of the fair treatment of individuals in organizations, which comes from social psychology and behavior research, is now expanded to the consideration of fairness of results, procedures, and human treatment received in companies by individuals (Greenberg, 1990). This is a multidimensional justice model which, as has been validated to a large extent and widely applied, is used to measure justice in various situations.

There has been substantial literature on organizational justice along with its main areas such as distributive justice, procedural justice, and interactional justice (Colquitt, 2001). Each of these aspects approaches the issue of fairness from a different perspective and when they are combined, they provide a deeper understanding of the way people feel and judge fairness.

Distributive Justice is a core parameter through which the issues of the equitable distribution of resources, benefits, or outcomes are raised. The notion of distributive justice, grounded on equity theory (Adams, 1965), entails that the individuals should be provided with results corresponding to their inputs, works, or even needs if that is the case. It this aspect was to be reinterpreted in AI, the central issue would be the fair distribution of the advantages as well as the disadvantages caused by the algorithmic decisions that is also the society free of bias or discrimination in the system (Lind & Tyler, 1988).

Procedural Justice exemplifies the fairness of the methods and processes that lead to certain outcomes. In addition to the procedures being equal, transparent, and unbiased, this aspect of fairness also asserts that they provide people who are involved the possibility to have their say and appeal a decision (Leventhal, 1980). Along with that, procedural justice points out that decision, making procedures should be standard in both time and cases. For example, AI systems in this context might have features such as algorithms being transparent, a clear accountability mechanism, and a design process that allows the engagement of stakeholders who hold different views (Thibaut & Walker, 1975; Binns, 2018).

Interactional Justice refers to the fair treatment aspect as well as the good communication of the positive outcomes that resulted from the implementation of a particular procedure. The aspects taken into account are that decision, makers treat the people they deal with in a dignified way, i.e. with respect, and providing them with the necessary help at the time of the decision (Bies & Moag, 1986). AI factors that must be met for human, AI interaction to be just and fair are the ease with which AI, interfaces communicate their decisions to the users, the empathetic attitude that is fostered when user concerns are registered and the manners and clarity in the interaction even though performed by machines (Kim et al., 2019).

However, it is worth noting that the three justice dimensions are, on the one hand, interconnected, and, on the other hand, separate, which reflects individuals' general view of fairness. Different researches had been conducted on the topic and had revealed the linkage between individuals’ perception of fairness across the different justice dimensions and their trust, acceptance, satisfaction, and compliance with decisions (Colquitt et al., 2013). This, in turn, legitimizes such a complete theoretical approach as the basis for judgment not only of the AI fairness issue by simply looking at the results but by going even further into the AI systems.

By adopting the organizational justice model not only the AI but also the human decision, makers can know the detailed manner in which fairness is present in the automated systems, be able to create different strategies which relate not only to the AI decision but also to how that decision is made and communicated. Such an all, encompassing approach to the problem of AI ethics and human rights would be a prerequisite for AI systems that are at once ethical, transparent, and respectful of human dignity.

Distributive Justice in AI Systems

Distributive justice mainly focuses on how fair it is that the results are allocated, or the sharing of resources or rewards among individuals or groups (Adams, 1965). In a traditional organizational setting, the concept of justice is related to the ways people present and perceive if the results they get are fair compared to their inputs, efforts, or needs. In the case of AI, the principle of distributive justice in AI means that credits and results of AI should not be given to the groups that are the easiest while the treatment is fair across the different demographic groups (Barocas & Selbst, 2016).

The issue with distributive justice in AI is the presence of biases in data and algorithms which is the root of the problem. Biases in training datasets that mirror history and society can lead to bias in AI systems resulting in those that are in minorities or other vulnerable groups will be affected more. Biased facial recognition algorithms can be used as an example that are said to have more errors in the recognition of people of color and women, thus these unfair treatments may happen in the areas of law enforcement or employment screening (Buolamwini & Gebru, 2018). These disparities are the key grounds for the creation of AI systems that do not only detect but also solve such issues of justice.

The developers employ a number of measures to facilitate distributive justice, such as taking steps to moderate bias and to ensure fairness in the outcomes. One of the significant methods is the deployment of fairness, aware machine learning tools which change the working of algorithms in the manner as to lessen the Apart effect across groups to a minimum. Some of these Parametric, technological mechanisms comprise re, weighting of training data, model optimization with the inclusion of fairness constraints, and finally post, processing of outputs for achieving more balanced results (Kamiran & Calders, 2012; Hardt et al., 2016). Furthermore, fairness metrics such as demographic parity, equal opportunity, and predictive equality are also considered methods for numerically measuring the fairness of AI decisions (Dwork et al., 2012).

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IX, September 2025

Though, fairness in AI is about decision transparency and goes beyond technical solutions. Along with the question "what" and "how", "when", "who" can also be added to the list of things that are a part of the decision, making process which will help to uncover the ways the system has handled the issue of fairness. In this way, the transparency, feature enhances accountability and also builds support for the AI system, particularly when the distribution is seen as fair by the users (Binns, 2018).

Distributive justice is not only a matter of fairness but also it is closely linked to ethical and legal principles that exist within the realms of these frameworks whereby discrimination is proscribed and equality fostered. It is, however, still very important that AI is compliant to standards so as to prevent problematic impacts and help in the promotion of the societal norms around fairness (Crawford & Paglen, 2019). As an example, regulations such as the European Union's General Data Protection Regulation (GDPR) are setting prerequisites for the transparency and fairness of the leading AI system design and implementation thereby being influenced by them.

In short, AI systems distributive justice entail the uncovering of bias together with the alleviation thereof by the use of metrics and also open communication on results. Therefore, AI will be able to accomplish the mission of serving a diversity of customers without the risk of perpetuating or deepening the history of the biased societies and, thus, becomes an instrument that facilitates the emergence of more just and equitable societies.

Procedural Justice in AI Systems

Procedural justice is about the perceived fairness of the processes and the methods used to make decisions, rather than focusing only on the outcomes themselves (Thibaut & Walker, 1975). It lays down the criteria for everything that is necessary for fairness; openness, equal treatment of everyone and neutrality in ways of making decisions as well as giving those who are affected the chance to present their objections and receive the understanding and sympathy that they deserve (Leventhal, 1980). It is all the same with AI just that procedural justice is a pointer to what goes on in the AI algorithms before a decision is reached, and how the way these results are communicated affects the trust and acceptance of AI by the users (Colquitt et al., 2001).

The transparency of algorithms is the aspect of just procedures in AI that we spoke most about. Users and stakeholders must be given a very straightforward and comprehensible explanation of the AI decision, making process so that they can trust that the processes are fair and unbiased (Burrell, 2016). Many AI models, especially those based on deep learning, are often referred to as "black boxes" because they are so complex, and they are entirely closed off to the outside world, and thus, it is very difficult to find their decision pathways (Lipton, 2016). This opacity could limit procedural justice as users may not have as much freedom to scrutinize or contradict the system's logic. Therefore, explainability techniques such as model interpretability tools and the provision of detailed algorithm documentation are very effective tools for bringing about transparency and the assumption of responsibility (Doshi, Velez & Kim, 2017).

Consistent application of decision, making processes, as well as the treatment of people in the same way, is also one of the other main features of procedural justice (Leventhal, 1980). AI is the right way to go in this direction because it has the capability to implement the rules in a uniform manner without human errors or personal biases. Yet, the final outcome is still heavily dependent on the data quality and algorithms. If the data used is inconsistent or biased, the decisions made by the machine might be even less fair, which, in turn, can lead to fairness being back at the center of attention. (Kleinberg et al., 2018). AI systems will have to be exposed to rigorous fairness testing, be fair in different environments and have not only the rehabilitation mechanisms but also the detection of deviations and correction of unfairness (Holstein et al., 2019).

The other aspects of procedural justice are voice and participation, which signify an individual's opportunity to make the input or challenge the decision by appealing (Thibaut & Walker, 1975). Although mostly autonomous, AI systems' implementation of features that would allow a user to challenge or ask for the rationale of a decision would make the systems seem fairer. They could be models where human control goes hand in hand with the AI output or interactive user interfaces that make AI querying possible (Rahwan et al., 2019). Besides raising the level of procedural fairness, user involvement in the decision, making process can be a source of errors and bias recognition and the correction of AI systems (Kleinberg et al., 2018).

Moreover, accountability remains a major factor that affects procedural justice. The very thing about responsibility for AI is that if the developers, organizations, or regulators, it is then that there will be ways for redress in the case of unfair or incorrect outcomes (Wachter et al., 2017). Accountability frameworks as well as audit trails and regulatory oversight are the principal features that reassure the trust in AI systems by holding those actors accountable for the fairness of AI processes.

Procedural justice in AI, on the whole, demands open, consistent, and inclusive processes with users providing understandable explanations and chances for involvement. Organizations can raise the reliability and the acceptance of AI, propelled decisions, by putting these values into the AI design and governance thereby they can decrease the suspicion of unfair or non, transparent algorithmic systems.

Interactional Justice in AI Systems

Interactional justice involves the ways in which interpersonal treatment and communication meet individuals' needs during the decision, making process (Bies & Moag, 1986). Along with interactional justice respect, dignity, and empathy to the decision, conveyance, and enactment are the main features while distributive and procedural justice focus on outcomes and processes.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IX, September 2025

Moreover, it also asks how well automated systems understand and communicate users' emotions and concerns as being transparent and respectful (Kim et al., 2019).

In contrast to humans who are able to change their communication style and give emotional support, AI systems operate according to pre, established interfaces and programmed responses, which generally lack the subtleness and empathy of human interactions (Brave & Nass, 2003). This would, therefore, lead to situations in which the people affected may see the machines as cold, unfeeling or disrespectful in the case of loan refusals or dismissal of employment which are decisions that have already become personal as examples, (Binns, 2018). As a result, it means that the use of interactional justice in AI design can imply the intentional humanizing the way technology users relate with each other and also the promotion of fairness ones through good communication.

The quality of the explanation is also among the top concerns of interactional justice in AI. As users of AI would say, the reasoning in an understandable language and relevant to the context rather than being too general or too technical makes them understand the AI decision better and thus they are more likely to accept it as fair (Miller, 2017). Justifications largely alleviate users' comprehension of the AI results, thus minimizing their aggravation and increasing their trust. This is actually very necessary in the sphere of health or criminal justice, where decisions have the deepest impact on human lives(Eiband et al., 2018).

That is not all, AI can also be given a program that would allow it to understand the emotions of the person it is interacting with, and then it can respond accordingly using an affective technology. The technology equips machines with the ability to determine the emotional state of a person through sound, facial movements, or text analysis (Picard, 1997). Emotionally intelligent machines, therefore, are the ones who can soften their tone and even motivate, thus making the interactional justice experience better as the person feels that the other party is listening and respects them (Hoffman et al., 2018). Such as it is, the user who has encountered an awful situation can be comforted by a virtual assistant that can alter its tone or provide him with some reassuring words to help him release the stress and to make him feel that he can be treated fairly.

Still another vital aspect of respectful communication is, however, the use of manipulative or deceptive tactics, and if overlooked, it could be a concern in AI interactions. There is a close connection between a situation depicting truthfulness in the interactional environment and the AI showing its capability and limitation as well as being truthful about the decision, making criteria (Zarsky, 2016). Users may be driven to suspect that they are being duped, when AI is allowed to operate in a way that overpromises certain capabilities or conceals its functioning, thus leading to the feeling of fairness and trust being lowered.

Moreover, in the same way, the importance of the design of AI interfaces is not any less than that of the AI Interface. The user, centered design principles which prioritize accessibility, cultural sensitivity, and personalization are very beneficial to the quality of interaction and can even make users happy and their rights respected (Norman, 2013). This might also mean that there are different ways for the users to check for answers, ask for help from a human, or ward off decisions, thus making sure that AI did not completely rule out the possibility of human control especially in situations where empathy is crucial (Rahwan et al., 2019).

Interpersonal Justice in AI is mainly concerned with the distribution of resources among members of society, and the processes by which these decisions are made. Over the last few decades, user experience with AI has been improved as AI deals with the emotional and the interpersonal side of fairness and in addition, trust is built signifying a more extensive recognition of the practice of automated decision, making.

Integrating Justice Dimensions into AI Design

The development of AI systems that are really fair, the entire distributive, procedural, and interactional justice aspects have to be managed simultaneously in a comprehensive manner. Each dimension is characterized in different ways, but it is the most crucial aspect to consider in the creation of fair AI technologies that are considered as mice ethical and trusted by the users as well as other stakeholders (Colquitt, 2001; Binns, 2018). Such multidimensional fairness appears to be even more inclusive than just the aspects of justice represented in human, decision and relationships.

The features attributed to the distributive integration of justice are those that facilitate AI to accomplish results that are fair to all groups despite their diversities. Consequently, developers need to implement fairness metrics in AI designing and training, for instance, demographic parity and equalized odds, which not only maintain the balance but also reduce the effect of the least advantaged groups on the total number of the protected groups (Hardt et al., 2016; Kamiran & Calders, 2012). Apart from this, organizations are expected to supply a variety of bias detection and mitigation tools starting from data processing methods, by the most recent model constraining and finishing with the result correction (Barocas & Selbst, 2016). These technical measures are frequently supported by ongoing impact assessments, that keep track of how the AI's decisions affect different populations over time (Raji et al., 2020).

Procedural justice that goes beyond mere technical fairness asks that AI design incorporate transparency, uniformity, and responsibility. Openness requires the explanation of machine learning models as well as the provision of reasonable decision justifications to users (Doshi, Velez & Kim, 2017; Lipton, 2016). In this way, stakeholders know the process through which the decisions have been made, and this makes their feeling of procedural justice and trust probable (Binns, 2018). Uniformity is realized when methods for data collection, model training, decision, making, and application are standardized, hence the likelihood of random or biased variations is minimized (Leventhal, 1980). Organizations must promote responsibility by defining the characteristics of the firm's governance structures that provide the setting of accountability for AI outcomes and the availability of

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the conditions provided for being able to carry out an audit and to receive redress in the event of mistakes or unfair treatment (Wachter et al., 2017).

Just Interaction integration focuses on the creation of AI systems that are fair and humane in dealing with their users and provide them transparent and sincere communication. These are all examples that could improve the fairness perception in AI interactions (Kim et al., 2019; Picard, 1997): utilizing natural language explanations, simplifying a user, friendly interface, and creating an affect, aware system that can recognize the user's emotions and react to them appropriately. In addition to that, designers should prevent the use of deceptive or manipulative ways of communication by ensuring that AI is honest and clear about functionalities and limitations (Zarsky, 2016). Moreover, users who are allowed to give feedback, file complaints, or be supervised by a person will generate a more participatory and a respectful environment that accords with the principles of interactional justice (Rahwan et al., 2019).

These aspects of justice, first of all, can be implemented only by the joint work of experts from various spheres like AI developers, social scientists, ethicists and the communities that are impacted by the variety of perspectives they take into account for the design of the AI system (Whittaker et al., 2018). The involvement of stakeholders in the co, creation of AI tools, a participatory design approach, may facilitate the timely discovery of potential fairness concerns and modifying the solutions to suit the actual, world context (Eubanks, 2018). This method of collaboration not only achieves the enhancement of fairness outcomes but also the increase of the AI systems' legitimacy and trust.

It is equally important that ongoing monitoring and flexibility are core components that help justice AI systems maintain their level of fairness even in changing situations. Justice is not a one, time event but a continuous process that depends on regular audits, societal change reflections and actuality through user feedback incorporation as well as the provision for the wrongs cases to be corrected (Holstein et al., 2019; Raji et al., 2020).

Incorporating distributive, procedural, and interactional justice in AI design is nonetheless a daunting task but it is a must. The fact is, fair results are not a guarantee that the AI system is operating through fairness and that users are treated with respect. Thus, the last characteristic of ethical, accountable, and socially acceptable AI technologies is what ultimately becomes the winner.

Case Studies and Applications

With the advent of AI systems that are penetrating various settings, the real, world application of the six principles of fairness across the different facets of the justice has been increasingly important. One of the means of comprehending how to implement justice in real, life AI design is by delving into the numerous implementation triumphs and challenges of justice by diverse application, contexts.

AI in Criminal Justice

The main issues that are frequently raised in the context of the use of AI in predictive policing and risk assessment are those related to justice. Tools like COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) are designed to assist judges in making decisions regarding sentencing and parole by estimating the probability that a person will reoffend (Angwin et al., 2016). A number of investigations, however, have uncovered that COMPAS was exhibiting racial bias to a large extent. The system was thereby overestimating the risks for Black defendants and at the same time underestimating those for white ones, leading to serious distributive justice concerns (Larson et al., 2016).

Transparency has been one of the main issues that researchers and lawmakers have raised since then and it is considered a key requirement alongside the procedural justice that can be improved, among other things, through the use of open, source algorithms and the presence of independent auditors who systematically gauge fairness (Chouldechova, 2017). Moreover, introducing interactional justice by giving defendants and lawyers risk scores in simple terms may turn out to be a very effective way as it allows the affected to request clarification and even dispute the decisions (Kim et al., 2019). What this example demonstrates is that fairer and more trustworthy AI applications in such high, stakes areas are possible if all three justice dimensions are resolved.

AI in Hiring and Recruitment

Artificial intelligence, based tools are a great promise to open up the selection process in a simplified way that does not replicate the biases of the past. However, this can only be the case if they are correctly designed. The usage of an AI tool for recruiting, which was at Amazon, has been discontinued when the system was discovered to discriminate against women by embedding biases that favored men from the historical hiring data (Dastin, 2018). Distributive injustice is the only case that can be used to explain this event by demonstrating how the outcomes are unequally allocated.

The companies are currently employing the methods of fairness, based training that assist the decision, makers in choosing the candidates in a way that gender or other demographic factors do not have a dominant role in the scenario (Kleinberg et al., 2018). Additionally, procedural justice might become better if AI discloses the selection criteria and even allows candidates to pose questions and challenge the decisions (Binns, 2018). Interactional justice may also be achieved with those candidate, facing the interfaces, which permit that decisions to be given in a respectful way and offer constructive feedback that, throughout the whole hiring process, makes the experience of dignity possible (Miller, 2017).

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IX, September 2025

AI in Healthcare

Similarly, in the medical field AI is also utilized for forecasting. Algorithms, however, must not be biased while granting functionalities and benefits to the treatment of all patient populations. To illustrate, Obermeyer et al. (2019) discovered that a health care algorithm that was widely employed greatly underestimated the health needs of Black patients, thereby resulting in fewer referrals for specialized care and thus being an instance of distributive injustice.

One time to remedy these inequalities is through conducting the bias audits and retraining using inclusive datasets(Holstein et al., 2019) which fulfill the criteria of distributive justice. Healthcare practitioners can be engaged in the AI decision process to verify the findings and keep the same standard which is an instance of procedural justice(Rajkomar et al., 2018). The latter is further supported when AI, fueled by systems, gives easy, to, understand explanations of the suggestions and implements empathy as the communication strategy that makes the patient feel respected and informed (Binns et al., 2018).

AI in Financial Services

The AI technologies that power credit scoring and loan approval processes in financial Services should adhere very strictly to the fairness principles so as to prevent discriminatory Lending practices. One of the reasons for bias in credit evaluations has been the history of the groups that were marginalized. These groups have, therefore, been facing discrimination, a thing that AI can do just unintentionally (Fuster et al., 2019). The institutions imposing fairness constraints is the way for them to be sure that credit decisions will not exclude certain demographic groups in a disproportionate manner due to which distributive justice will be facilitated (Friedler et al., 2019).

Transparency, and means for users to influence decisions based on procedural justice, are the main features of the field, with the regulator's obligation that agencies responsible for credit scoring should ensure that AI, based decisions, are explained, and that consumers should have avenues to contest decisions, in case they find themselves at a disadvantage. Customer service interfaces with interactional justice are the ones where loan decision is done in a visible and clear way and personalized support is given which, as a result, leads to the reduction of the feeling of being alienated or disrespected (Eiband et al., 2018).

Challenges and Future Directions

Despite the massive evolution of the AI systems that assert themselves to be one of the three facets of justice, distributive, procedural, and interactional, and, along the way, have been substantially improved, quite a few problems remain to be solved in front of them. The main reasons for these problems are the technical, moral, social, and organizational complexities that result from the need to incorporate the concept of justice into AI systems. The potential for AI that is not only fair and reliable but also fully exploited lies in resolving these problems.

Technical Challenges

At the core of the issue is the challenge of how to measure and operationalize fairness. The concept of fairness is a multifaceted one which is dependent on the context and those involved, hence the difficulty in coming up with metrics that are unanimously accepted (Verma & Rubin, 2018). For instance, the effort to achieve one fairness goal (e.g., demographic parity) might unintentionally hinder another (e.g., equalized odds), thus leading to trade, offs that are not easily controlled (Kleinberg et al., 2016). Moreover, distributive justice requires the use of accurate and unbiased data, but nearly every real, world dataset is either biased in history, has missing values, or is not representative of the whole population, and this makes it very difficult to develop fair models (Barocas & Selbst, 2016).

Procedural justice, as for the fairness aspect, brings along tough and technical problems e.g. explainability and transparency issues. Deep learning systems, which are among the most advanced AI models, are leading the technological frontier, and they are "black boxes" since their decision, making processes are not understandable by the users (Lipton, 2016). Even so, in the process of creating more interpretable models, the issue of retaining high performance is still there. In addition to that, one of the issues that the AI field is facing with is the production of the right technical aspects of the explanation and their being available to an immensely diverse group of users. This means that besides experts, non, experts also need to be considered in the making of these explanations, and for this, we need experts in computer science, social science, and communication (Miller, 2017).

Interactional justice, which is the other form of justice, is just as hard and is about empathetic incorporation and respect in machine interaction. AI systems are now quickly able to detect the emotions of people, and to generate the same kinds of responses as humans thanks to the progress in affective computing and natural language processing, but these systems might still be lacking the ability to fully understand the context or the cultural nuances which may cause them to make errors or give a feeling of disrespect (Hoffman et al., 2018). In addition, the AI being imbued with humanlike characteristics may lead to users overestimating the AI's capabilities, thereby, if the AI is not meeting this high standard, it will result in users losing their trust (Nass & Moon, 2000).

Ethical and Social Challenges

In addition to the technical challenges, the topic of AI fairness deals with the environment, the ethical and social aspects of which are in question. The manner of (distributive justice) combining the benefits and the harms is very often at the intersection with greater societal inequalities and power relations, which, however, cannot be completely solved even by technology (Eubanks, 2018).

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For instance, the data and the implementation of AI machines might serve as (social) racism or poverty, while these AIs may be 'neutral' by nature, thus reflecting the already existing types of injustice in their automated decisions (Benjamin, 2019).

The question of who builds AI and what kind of person the voice that is heard/considered represented is another significant factor in making the process fair. A lack of diversity among the developers of AI can result in the continuous existence of some blind spots as well as biased assumptions (West et al., 2019). Besides, the involvement of the target design which concerns the communities that will be impacted is very important but it can be quite expensive and difficult to manage (Whittaker et al., 2018). These issues in the society are about the kind of organization that would be committed and have governing authorities taking inclusiveness, fairness, and accountability as their priorities.

Social justice, on the other hand, deals with the limits of an ethical company in interaction with AI. One example is the question which asks if AI should trick the user into thinking it has empathy or emotion when in reality it doesn't. The issue is about the authenticity of AI, manipulation, and user autonomy (Turkle, 2011). Furthermore, any AI employed in delicate situations like mental health support or provision of legal advice has to strike the most efficient balance between machine use and human supervision to evade causing harm (Shah & Robinson, 2007).

Organizational and Regulatory Challenges

Another point is that the execution of a fairness, based AI system must also reflect the company's values and comply with the laws related to the topic. Normally, organizations find themselves in the position of having to choose between the time of the innovation, saving costs or raising the level of ethics, which as a consequence, results in the barriers of the full fairness integration. The melding of fairness inspections into the process development as well as into the decision, the making practices requires different work procedures, knowledge, and the distribution of resources.

Regulation (or the lack thereof), is a changing case that is still very different from one country to another and they all have different standards and ways of enforcing rules (Wachter et al., 2017). Even though laws like the EU's General Data Protection Regulation (GDPR) do give people new rights, such as the understanding of AI and data protection, it is quite difficult to actually operationalize these rights in AI systems (Goodman & Flaxman, 2017). Lawmakers have to ensure that they provide maximum protection for people and at the same time not hinder the industry which makes it necessary to have co, governing models that comprise different stakeholder groups.

Future Directions

One of the many ways that AI fairness can be improved in the future is through the development of fairness frameworks that can adapt to different contextual situations and dynamically meet the needs of the stakeholders. Conditions of fairness should not be a way to stay forever, but should alter as social norms and data distributions change (Holstein et al., 2019).

Another point to the new justice areas is deepening the interdisciplinary collaboration amongst AI scientists, ethicists, social scientists, legal scholars, and communities adversely affected by AI systems. This is what will enable the discovery of lands of justice (Whittaker et al., 2018). Design approaches that rely on participant and co, creation techniques can raise the bar of AI systems making it possible for them to become a living representation of different values and the day to day experience of people from various social strata (Eubanks, 2018).

Thirdly, it would be to allocate resources for education and training that would promote ethical AI literacy and justice, oriented perspectives among the practitioners of AI. This aspect, which is the most significant, can never be overemphasized as it is the surest way of establishing a culture of responsible AI development (Friedman & Nissenbaum, 1996). Additionally, users' digital literacy programs can condition them to be actively involved with AI systems in a more critical manner.

We can still expect the consequences that will be very positive such as accountability, transparency, and protection of rights among others, if only the process of policy innovation and governance mechanisms will keep on moving as it has been so far. Rahwan et al. (2019) are of the opinion that the good sides of governance mechanisms and regulatory innovations are the clearest, unambiguously accountable agents that operate with full transparency and rights protection while, at the same time, stimulating innovation. Besides that, thorough oversight of AI fairness will become simpler and more efficient with the help of such regulatory and standard, setting bodies, independent auditing frameworks, and public, private, ventures.

II. Conclusion

The increasing spread of AI technologies in the different segments of the society, such as criminal justice, healthcare, hiring, and finance, has finally made it a big criterion to ensure that the AI systems are designed in a way that guarantees fairness along with multiple other justice dimensions. This document has explored the relationships of distributive, procedural, and interactional justice as the main factors governing the development of AI systems, which, besides the efficiency, also have to be of ethical and social legitimacy.

Distributive justice, for instance, ensures fairness in AI outcomes, and that these outcomes do not cause any sort of societal imbalance. AI can easily become biased in certain situations if the distribution dimension is not considered cautiously because of the data and/or the algorithmic processes. There is a risk that historical biases may be perpetuated, thus leading to the unfair

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allocation of resources, opportunities, and risks. Whereas procedural justice aims at demonstrating the ways AI decisions are fair, it highlights the requirements for transparency, consistency, and the existence of accountability and recourse. Finally, interactional justice reconciles with the others through focusing on the quality of interpersonal treatment in AI, the human contacts, and by acknowledging respect, dignity, and sincere communication to those users who are affected by automated decisions.

The combination of these aspects, on the one hand, does not only represent huge challenges, but, on the other hand, it also provides significant opportunities. These issues accompany technology just like the need for defining and measuring fairness or the production of easily comprehensible models coexist with ethical and social problems in regard to inclusivity, cultural sensitiveness, and governance. The real, life examples from such domains like criminal justice, hiring, healthcare, and finance provide a better understanding of justice, aware AI that leaves, at the same time, the implementation gaps and unintended consequences to be resolved.

In the coming days, the promotion of AI fairness is going to require contributions from various disciplines, participatory design, always on learning, and the necessity for rules that are well balanced between innovation and the protection of individual rights. The organizations and policy makers should step up and commit to educating, governing, and practicing transparency that is inclusive of justice at all stages of AI development and deployment. In addition, the realization of AI fairness is not a one, time achievement but a continuous operation that has to be adapted to the changing values and contexts of a society.

Ultimately, the incorporation of AI systems that represent distributive, procedural, and interactional justice is the cornerstone for public trust, social equity advancement, and ensuring that AI technologies are not a threat to human well, being but an aid on the contrary. The adopting of a comprehensive justice, centered approach makes research community, developers, and stakeholders the architects of the future where AI is one of the forces that bring about fairness, dignity, and shared prosperity.

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