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ORIGINAL PAPER

Do the Ends Justify the Means? Variation in the Distributive and Procedural Fairness of Machine Learning Algorithms

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Abstract

Recent advances in machine learning methods have created opportunities to eliminate unfairness from algorithmic decision making. Multiple computational techniques (i.e., algorithmic fairness criteria) have arisen out of this work. Yet, urgent questions remain about the perceived fairness of these criteria and in which situations organizations should use them. In this paper, we seek to gain insight into these questions by exploring fairness perceptions of five algorithmic criteria. We focus on two key dimensions of fairness evaluations: distributive fairness and procedural fairness. We shed light on variation in the potential for different algorithmic criteria to facilitate distributive fairness. Subsequently, we discuss procedural fairness and provide a framework for understanding how algorithmic criteria relate to essential aspects of this construct, which helps to identify when a specific criterion is suitable. From a practical standpoint, we encourage organizations to recognize that managing fairness in machine learning systems is complex, and that adopting a blind or one-size-fits-all mentality toward algorithmic criteria will surely damage people's attitudes and trust in automated technology. Instead, firms should carefully consider the subtle yet significant differences between these technical solutions.

Keywords Fairness · Machine learning · Distributive fairness · Procedural fairness · Algorithm design

Introduction

Machine learning (ML) is appealing for organizations because it reduces tedious tasks and can enhance decision performance in situations where human bias and errors are likely (Miller, 2018; Pezzo & Beckstead, 2020; Silverman & Waller, 2015). As such, managers increasingly rely on ML algorithms to make decisions. Yet, the rise of artificial intelligence tools has also sparked new ethical challenges for business and society (Greenwood et al., 2020; Kim & Scheller-Wolf, 2019; Leicht-Deobald et al., 2019; Martin, 2019a; North-Samardzic, 2019).

One crucial challenge involves ensuring that ML models make decisions that are fair and inclusive. This area of research is active in computer science. It has led to the development of many statistical techniques, known collectively as fairness criteria, that embed notions of fairness into the design of algorithms. However, researchers have primarily conducted this work without considering people's perceptions of these criteria. Consequently, we lack an understanding of whether individuals believe they are fair—an important predictor of people's willingness to trust and support algorithmic decisions as well as organizations that implement them (McFarlin & Sweeney, 1992; Newman et al., 2020). It is further unclear whether relevant differences exist in how people perceive these metrics. If found, such variation can be used to inform when managers and developers should apply a particular criterion, if at all, as they are often mutually incompatible.

To address these questions, we explore the perceived fairness of five algorithmic criteria proposed in the computer

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science literature. Using an organizational justice theory lens, we focus on two key elements that shape individuals' fairness perceptions—distributive fairness (i.e., the fairness of decision outcomes) and procedural fairness (i.e., the fairness of decision processes). Our analysis leads to several insights. First, we shed light on variation in the potential for different algorithmic criteria to facilitate distributive fairness. More broadly, we discern that statistical solutions for fairness tend to emphasize distributive concerns. Subsequently, we discuss procedural fairness and propose a framework for understanding how algorithmic criteria relate to essential aspects of this construct, which helps to identify when a specific criterion is suitable. From a practical standpoint, our research might motivate changes to the way managers and developers oversee ML systems. Rather than adopting a blind or one-size-fits-all mentality toward fairness criteria, which will surely damage people's attitudes and willingness to accept algorithmic decisions, we advise practitioners to carefully consider the subtle yet significant differences between these technical solutions.

Background of Fairness in ML

ML is the field of computer science referring to *algorithms*—a set of machine-computable instructions that solve a problem in a finite number of steps—which derive patterns from prior data. ML is at the intersection of computer science, statistics, linguistics, and mathematics as a research field. The key objective of ML is to enable predictions that improve as additional data becomes available to the algorithm. While ML tools are promising in providing substantial increases in organizational efficiency and cheaper implementation of specific tasks, significant shortcomings should not be overlooked, including those that may negatively impact fairness. Only recently did fairness and ethics issues begin to take a more prominent role in ML scholarship by emphasizing that developers should expect an approach of "awareness" to the problem of fairness as part of the development process (Dwork et al., 2012). This view has given rise to the subfield of fairness in ML. However, it is essential first to understand how ML models operate in practice.

ML involves the use of computer algorithms to create models from data automatically. These algorithms learn from existing labeled datasets where developers label the observed outcomes for every predictor variable, otherwise known as a *feature* (James et al., 2013). For example, a bank may have data profiles of applicants who filed for a mortgage application and the bank's decision for each applicant. The developer then splits this labeled dataset into a *training set* and a *test set*. This process allows the ML model to train or tune its parameters to fit the data but leaves out part of the known (labeled) data to verify whether the algorithm produces correct predictions (Teodorescu, 2017). For a binary criterion variable, such as hiring a job candidate or not, the developer can categorize the outcome as follows: true positive (the organization hires the candidate), true negative (the organization rejects the candidate), false positive (the algorithm predicts the organization will hire the candidate, but it rejects the candidate), and false negative (the algorithm predicts the organization will reject the candidate, but it hires the candidate). The developer then uses these four values to determine the accuracy of the algorithm.

Accuracy represents the ratio of correct predictions (actual hires, actual rejections) versus the total number of prediction attempts. Although accuracy is the primary and often default measure used by programers to determine the performance of an algorithm, it does not capture any of the nuances in Type I or Type II errors (for an overview of types of classification errors and costs of such errors in different fields, see Martin, 2019b). More broadly, accuracy is conceptualized solely in terms of predicted outcomes based on a test set—comparing the correct responses to predicted responses and counting the correctly predicted against total attempts.[1]

It is noteworthy that designing and managing algorithms from a perspective of accuracy says virtually nothing about notions of *fairness*, defined in computer science as lack of "any prejudice or favoritism toward an individual or group based on their inherent or acquired characteristics" (Mehrabi et al., 2019, p. 1). Algorithms that maximize the model's prediction accuracy may behave differently toward different subgroups within the data, leading to misclassification errors and unfair bias. For instance, a teacher may be unfairly deemed a poor worker by an ML model due to age, leading to their wrongful dismissal (O'Neil, 2016). A more well-known example is the recidivism prediction system COMPAS which discriminated against defendants based upon their race and gender (Brennan et al., 2009).

In response to these prediction pitfalls, the subfield of fairness in ML has focused on engineering algorithms that mathematically incorporate fairness ideals while maintaining a level of accurate performance. Many fairness criteria have arisen from this work (Hardt et al., 2016; Teodorescu & Yao, 2021). Each criterion provides a narrow definition of fairness, as it must for the sake of formalism, which are not all satisfiable concurrently. In other words, there is no one universally accepted conceptualization of fairness in ML (Verma & Rubin, 2018). The present article discusses five of the most popular fairness criteria in computer science: fairness through unawareness, demographic parity, accuracy

[1] Actual human operators label the outcomes in the case of supervised learning. This paper assumes that the developers train the ML model on a training set created using human input.

parity, equality of opportunity, and equalized odds. Unlike more inscrutable ML, researchers operationalize these definitions in terms of their tradeoffs between fairness and performance accuracy (Martin, 2019b).

The most straightforward criterion is fairness through unawareness, where variables deemed sensitive to unfairness, such as gender, age, ethnicity, and disability status, are dropped from the prediction model. In theory, this approach would make the ML model unaware and unable to discriminate based upon sensitive characteristics. However, as some of these variables tend to highly correlate with other features in the data that do end up in the model or deduced from other variables (the issue of "redundant encoding"; Bird et al., 2019), this approach simply does not work well. It may end up perpetuating discrimination while its overseers are unaware of it (Hardt et al., 2016).

Moving beyond this criterion, which is the same as not checking for discrimination by the algorithm, there are 'fairness-aware' approaches, four of which we focus on here: demographic parity, accuracy parity, equalized odds, and equality of opportunity. While each of these criteria presents unique tradeoffs in fairness versus accuracy, they all broadly seek to ensure fairer outcomes across different subgroups.

A Note on Protected Attributes

It is important to note that in addition to utilizing fairness criteria, a separate critical step in developing fairer ML systems involves determining which features in a training dataset constitute *protected attributes.* Protected attributes represent demographic features such as race, gender, age, sexual orientation, disability status, marital status, ethnicity, national origin, and socioeconomic status. If a feature in the dataset represents a protected attribute, developers should never use it as a predictor in the ML model.

The computer science literature has historically relied upon legally protected characteristics when determining what qualifies as a protected attribute. In the United States, these protected characteristics are codified into law through equal opportunity in hiring (FEEO), credit lending (ECOA), non-discrimination based on gender or race (Civil Rights Act Title VII 1964), and non-discrimination based on disability (ADA 1990, Rehabilitation Act 1973). Though legal safeguards and laws may only capture a small strand of characteristics that people believe merit protection in a given situation, this is a sensible starting point as fairness scholarship in computer science is relatively new. Indeed, the legal field had implemented the concept of a protected class long before ML existed, representing different categories within a given protected attribute. The idea has expanded over time through acts of Congress in the United States (as were the laws mentioned above) and through legal scholarship debate (e.g., Clarke, 2017; Schwartz, 2009). As such, it was perhaps the most convenient method to use an already-defined set of protected categories from the legal literature to begin testing for fairness in a newer field such as ML.

Questions remain regarding whether this is an ethical or socially desirable approach to fairness. For example, laws usually take longer to negotiate or litigate than creating new technology; hence there is often a lag between what companies may do in practice or what is considered fair by society versus what is deemed lawful. Who should decide whether someone is part of a protected class is important and has real consequences for individuals' livelihood. Currently, the court system mainly settles this issue (Clarke, 2017). In the field of ML, however, there is no universally accepted solution for determining whether certain features or ambiguous cases in the data should be protected beyond existing protected attributes. Furthermore, current lawmaking and litigation systems for selecting protected attributes lack input from ethicists on what should qualify as a protected class. We discern that this is an opportunity to change the status quo and that business ethics is integral.

Algorithmic Fairness Criteria: Insights from Organizational Justice Theory

Business ethicists sit at the crossroads between business, technology, and society (Martin & Freeman, 2004). We integrate theory from organizational justice scholarship to provide a deeper understanding of algorithmic fairness criteria with this consideration in mind. This knowledge is critical for theoretical reasons as well as practical ones. The central theoretical problem is that organizations and developers must choose between the algorithmic criteria, as they are mutually incompatible. Yet, we do not know how to people will react to the use of a particular criterion. The central practical problem is that the advice we can offer to organizations who wish to implement algorithmic criteria is lacking, potentially creating friction with employees, customers, partners, and broader communities (Lee, 2018; Newman et al., 2020).

Organizational Justice Theory

Organizational justice theory is broadly concerned with people's perceptions of fairness in the workplace, which includes distributive and procedural components (c.f. Colquitt, 2012; Colquitt & Rodell, 2015; Goldman &

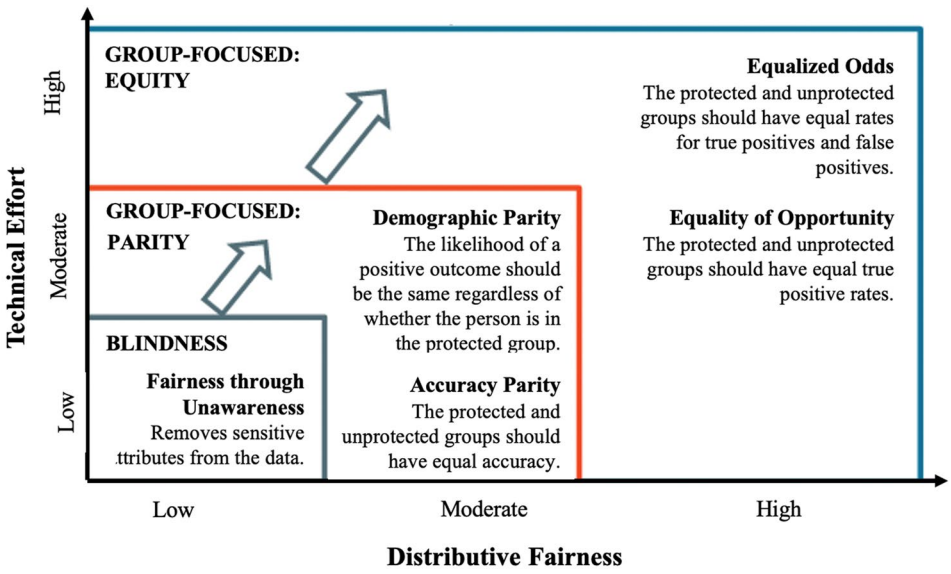

Fig. 1 Distributive fairness of algorithmic criteria and their technical effort

Cropanzano, 2015; Greenberg, 2011; Khan et al., 2015).[2, 3] Distributive fairness refers to the perceived fairness of outcomes and is judged according to how fair a decision is in its effect on the distribution of rewards and resources (Adams, 1965; Colquitt et al., 2001). Procedural fairness reflects the perceived fairness of decision processes, such as how decisions are made (e.g., Are procedures consistent? Are decisions based on accurate and bias-free information?) It also reflects how much control individuals have over the decision process (e.g., Are there opportunities for correcting flawed decisions?) (Leventhal, 1980; Thibaut & Walker, 1975).

In the sections that follow, we describe the distributive and procedural fairness of five popular computational solutions for resolving bias in ML. In doing so, we identify a central theme across this research: algorithmic criteria tend to emphasize distributive concerns. Informed by insights from organizational justice theory, we subsequently explore whether procedural fairness can be enhanced and consider the role of contextual influences in shaping justice experiences. We specify some situations in which developers and managers might increase perceptions of procedural fairness for each criterion, which provides a foundation for understanding when a given fairness metric may be suitable.

[2] Organizational justice researchers have also studied fairness as a single dimension (e.g., Ambrose & Schminke, 2009) and as a multidimensional construct comprising distributive, procedural, and interactional fairness components (Colquitt et al., 2013; Karriker & Williams, 2009).

[3] In line with organizational justice scholarship, we use the terms fairness and justice interchangeably. Although differences exist among the concepts, both are geared toward promoting equity and avoiding bias.

Algorithmic Criteria Emphasize Distributive Fairness

Although our understanding of organizational justice research in the ML landscape is nascent, computer science scholars are beginning to recognize that they have designed fairness metrics to focus almost exclusively on distributive fairness (Saxena et al., 2019; Selbst et al., 2019). Indeed, a recent review by Robert et al. (2020) noted that researchers operationalize technical definitions of algorithmic fairness based on the equity of the outcomes received, which involves comparing one's inputs to obtained outputs relative to others. Figure 1 describes five fairness criteria that are among the most popular in computer science and the extent to which they achieve distributive fairness ideals. These metrics represent two broad approaches to fairness that have received substantial attention in the literature: a blindness approach (i.e., fairness through unawareness) and a group-focused approach (i.e., ensuring equality across one or several measures for all categories of a protected attribute).

Within the group-focused approach we further discern that researchers design some metrics to achieve parity ideals (i.e., an equal distribution of outcomes among subgroups despite differences, such as demographic parity and accuracy parity). At the same time, they develop other metrics to achieve equity ideals (i.e., an equal distribution of opportunities based on the circumstances of each subgroup, such as equality of opportunity and equalized odds). For simplicity, we focus on two metrics for each subtype in this paper. We expect that our critical analysis generalizes to other criteria that fall within these subtypes as they are considered the same from a distributive fairness perspective.

Importantly, we observe that some computational solutions, such as fairness through unawareness, likely achieve relatively low levels of distributive fairness. In contrast,

others adopt more proactive techniques for mitigating bias and thus achieve increasingly fairer outcomes. Yet, as indicated by the y-axis in the figure, each deeper intervention requires more significant technical effort and comes with a greater risk of over-correcting and forcing equality where it is not expected (Dwork et al., 2012).

Blindness Approach: Fairness Through Unawareness

The most commonly applied approach in organizations is fairness through unawareness. Developers consider this metric "unaware" such that it will simply ignore fairness information by leaving out protected attributes from the data such as age, sex, and race/ethnicity. It is not surprising that developers and managers have favored this technique seeing that organizations have historically adopted similar approaches for managing diversity and equality. For instance, the colorblind diversity strategy, defined by a belief that organizations should treat people equally no matter their cultural background, is still used in many occupational settings and involves denying or not "seeing" race or other sensitive attributes (Apfelbaum et al., 2010; Podsiadlowski et al., 2013). Although colorblind ideologies may appear to function successfully on the surface, thereby promoting an illusion of fairness in the short-term, research indicates they are ineffective in rooting out perceived bias and instead perpetuate social inequities over time (Ely & Thomas, 2001). Indeed, ignoring the plausibility of discrimination often results in stronger perceptions of unfairness and worse outcomes for members of minority groups (Purdie-Vaughns & Eibach, 2008).

Fairness through unawareness likewise fails to reduce discrimination and prejudicial outcomes in practice. A critical flaw of this criterion is that ignoring protected attributes does not change the fact that other variables in an ML model may strongly correlate with these attributes. These correlations effectively serve as proxies for the removed variables, making a mockery of the claim to be unaware.

For example, the algorithm used to determine credit lines for an Apple credit card did not include gender as an input yet learned to rely on inputs highly correlated with gender, such as historical salary data that contained hidden prejudices against women. Public responses to the algorithm's credit lending decisions were numerous and hostile, as evidenced by Twitter profiles of affected applicants. Even Apple's co-founder Steve Wosniak raised fairness concerns, questioning "whether the card might harbor some misogynistic tendencies" (Knight, 2019, para. 9). Taken together, we contend that fairness through unawareness does little to ensure that individuals will perceive a fair distribution of rewards and resources in algorithmic decisions. This criterion, therefore, achieves an unacceptably low level of distributive fairness.

Group-Focused Parity Approach: Demographic Parity and Accuracy Parity

Demographic parity is a well-known fairness intervention in which the algorithm reaches a positive outcome at the same rate irrespective of the categories of a protected attribute. For example, if a firm's hiring rate for one gender is 20%, then the hiring rate for all other values of gender should also be 20% irrespective of other constraints. This approach is more accountable than fairness through unawareness because the developer makes a conscious decision to tune the algorithm. In the hiring scenario, the developer ensures that the positive outcome (a recommended hire) is independent of gender. Thus, the sensitive variable is not discarded but rather a part of the process of ensuring equitable outcomes (Kusner et al., 2017). From an organizational justice standpoint, demographic parity promotes greater distributive fairness than does fairness through unawareness. Particular challenges remain, however, that restricts this approach's promise in real-world settings.

Demographic parity is concerned with preventing adverse or disparate impacts for disadvantaged groups, yet a significant downside is that it often fails to reach fair outcomes in practice. In particular, demographic parity cannot deal with differences between subgroups other than to assume that success rates are equal. In other words, it neglects individual unfairness, sacrificing in some cases qualified individuals to obtain equality at the group level. Consider a hiring scenario in which an organization wishes to achieve equal hiring success rates across two groups, group A and group B. Candidates from group A tend to be less qualified than the least-qualified candidate in group B. If demographic parity is applied, the organization would hire from the two groups at the same rate; however, this would likely create perceptions of unfairness for the qualified but rejected candidates in group B. In this example, demographic parity might initially lead management to form impressions that hiring outcomes are fairer due to the parity created across the two groups. Yet, these judgments may soon fade as people begin to realize that the algorithm overlooks qualified applicants from one particular group.

This outcome can also engender negative attitudes toward candidates who would not otherwise have qualified but were hired to meet the parity requirement, potentially leading to a self-fulfilling prophecy. Imagine a company that rigorously hires male job applicants at a rate of 35% and indiscriminately hires female applicants at the same rate (Ghassami, 2018). Although the acceptance rate in both gender groups is the same, the low effort to ensure that the algorithm chooses the best female candidates under demographic parity will likely cause female hires look like poor performers. The result may establish a negative track record for the female group.

Like any simple solution to bias in ML, demographic parity is by design a blunt instrument and tends to fix one distributive fairness problem at the cost of exacerbating others. Notably, demographic parity can compound outcome-based bias against those who are members of multiple sensitive categories. For instance, while developers can enforce equality across genders, as can equality across races, there is no protection against the possibility that such methods will exacerbate bias against specific gender-race pairings or other combinations of sensitive attributes (Teodorescu et al., 2021). Such errors in fairness intensify as the data become more imbalanced across sensitive groups, including multiple-protected groups. Thus, we propose that demographic parity may obtain, at best, perceptions of moderately fairer outcomes (i.e., a moderate level of distributive fairness) in practice depending on the data and parameters under which the algorithm must optimize.

A closely related cousin to demographic parity is accuracy parity. As previously discussed, the default algorithm performance measure in ML is accuracy, operationalized as the ratio between the count of correctly predicted outcomes to the overall count of prediction attempts. While this measure does not distinguish between Type I and Type II errors, optimizing an algorithm is intuitive and straightforward. An extension of this measure to fairness would involve subsetting the data by the protected attribute and calculating the accuracy per subgroup (Zhao et al., 2019). In this case, the algorithm is considered fair in computer science if the subgroups' accuracy is equal (or close). Accuracy parity is well-liked by computer scientists because accuracy is often the default measure in standard ML packages. Researchers calculate accuracy by running the trained model onto the test set to infer the expected behavior of the model out of the sample.

However, like demographic parity, several constraints are associated with accuracy parity that inhibit the ability to achieve fairer outcomes, prompting more moderate perceptions of distributive fairness in occupational settings. First, we may be trading off the false positives of one group for another group's false negatives and not know about it. Second, accuracy parity works poorly for datasets where the classes are imbalanced (i.e., there is no even division across subgroups). As an extreme example, let us assume we have a dataset where the model rejects 95% of job applicants, irrespective of other attributes. A classifier that simply returns "reject" for all applicants would have an accuracy of 95% and pass accuracy parity. This outcome, of course, would not be perceived as fair to the applicant pool. Thus, we turn to more sophisticated techniques that rely on more than just accuracy.

Group-Focused Equity Approach: Equality of Opportunity and Equalized Odds

Equality of opportunity measures whether individuals who should qualify for an opportunity have the same likelihood of being deemed qualified by the ML model regardless of the value of a protected attribute. Like demographic and accuracy parity, this fairness metric focuses on equalizing positive outcomes. Specifically, it ensures that, whatever the value of the protected attribute, the model equalizes the rate of a predicted positive result for a qualified individual (Hardt et al., 2016; Kusner et al., 2017). Thus equality of opportunity is a more targeted metric that allows for demographic differences but levels the playing field by requiring that unfair/erroneous judgments, or false-positive rates, be equitably distributed. In an organizational hiring example, while strong male and female candidates may be of comparable quality, the algorithm could detect a significant difference among the weak candidates across gender. In this case, *weak* corresponds to job performance for the firm's position, such as females in the weak job performance category being more qualified candidates than males.

The equalized odds fairness metric is a stricter version of equality of opportunity. It adds to the requirements that the true positive rate and the false positive rate are equal across categories of the same protected attribute (Hardt et al., 2016). If false positive rates significantly differ between two categories, individuals who belong to the one with lower false positives may feel that decision outcomes are biased and thus feel demeaned. Essentially, instead of having one equality condition, such as a true positive rate that is equal across sample subgroups by a protected attribute, we must now satisfy a system of two equations. It involves strict equality (in the pure mathematical definition) across both true positive and false positive rates across all population subgroups by protected attributes. The requirement of a system of equations and strict equality makes this criterion more challenging to fulfill.

Because equality of opportunity and equalized odds take a more nuanced and narrow approach to ensuring equitable outcomes across different subgroups, we suggest they potentially produce higher perceived levels of distributive fairness. By the same token, they tend to address very targeted forms of outcome-based unfairness, which results in a scenario where plugging one leak could result in the emergence or worsening of other leaks.

Overall, reflecting on these five criteria, we broadly conclude that computer scientists have made rapid progress in engineering algorithms that incorporate distributive fairness concerns. However, there is still no known roadmap for applying these metrics so that people will perceive algorithmic decisions as fairer. This leads to the question of where to go from here. How can managers and organizations

determine whether a particular criterion is the "right" one? To answer this question, we draw attention to the role of procedural fairness, which we argue can provide a more robust understanding of when individuals will perceive a specific criterion as suitable.

Procedural Fairness and Algorithmic Criteria

Procedural fairness, defined as the perceived fairness of the methods used to make decisions (Colquitt et al., 2001), plays a vital role in shaping how people react to decisions. Six components underlie procedural fairness: consistency, accuracy, ethicality, representativeness, bias suppression, and correctability (Leventhal, 1980). Consistency reflects in the uniformity of decision procedures across people and time. Accuracy represents the extent to which methods utilize valid, high-quality information. Ethicality captures whether practices uphold moral standards and values. Representativeness demands that procedures duly consider the needs and concerns of the entire group. Bias suppression requires that decision procedures are impartial and prevent favoritism by the decision maker. Lastly, correctability captures techniques that provide opportunities to challenge or correct flawed decisions.

Procedural fairness is essential because "just processes signal that [individuals] are valued and esteemed by their referent social groups" (Cropanzano & Stein, 2009, p. 200). Procedures also signal the decision maker's goals, such as intentions to maximize societal welfare, which provides vital information about why the decision maker made a particular choice (Tyler, 2003). While distributive and procedural fairness mutually influence justice evaluations, procedural fairness has been considered the more robust predictor of the two (Thibaut & Walker, 1975; van den Bos et al., 2001). Indeed, people are more willing to support an unfair outcome when they feel the process is fair. They especially rely on procedural fairness when information about a decision maker's trustworthiness is uncertain (van den Bos et al., 1998), which is often the case for artificial intelligence systems (Glikson & Woolley, 2020).

Conversations about procedural fairness in ML are beginning to emerge across the fields of computer science and management; however, this work has almost entirely focused on comparing the procedural fairness of algorithms to humans (e.g., Bigman et al., 2020; Lee, 2018; Newman et al., 2020). To date, we still know very little about the procedural fairness of different algorithmic criteria and whether relevant differences exist in how people perceive them (for exceptions, see Grgić-Hlača et al., 2018 and Lee et al., 2019). We encourage scholars and practitioners to develop a deeper understanding of procedural fairness in this domain.

Procedural Fairness and the Role of Contextuality

While there may be multiple ways to promote procedural fairness in ML, we examine the situational context's power to shape justice perceptions. We chose to focus on situations because managers do not always know an algorithm's design and data structure. Still, they may more readily take responsibility for learning the contexts in which algorithmic criteria are likely to be viewed as procedurally fair.

We reason that if organizations or developers apply a fairness metric in the right setting, people will perceive it as procedurally fairer. Our discussion primarily draws from prior organizational justice research indicating that people react more positively to decisions when the situational context heightens the salience of procedural fairness components (Farrar et al., 2020; Mathur & Sarin Jain, 2020). For example, fairness evaluations are higher when contextual conditions signal a decision maker's normatively ethical goals to others (as opposed to productivity goals, which often violate societal moral standards). This condition satisfies the ethicality component of procedural fairness (Barrett-Howard & Tyler, 1986). Presumably, situations that signal multiple components will lead to stronger perceptions of procedural fairness.

Our assessment of the capacity for different algorithmic criteria to signal procedural fairness components is depicted in Table 1. These insights translate to specific contextual applications for each metric. For simplicity, we focus on diversity and inclusion scenarios to illustrate the value of our analysis. We intend to demonstrate proof of concept, not develop a comprehensive solution. Further, the situational examples we discuss may change according to the prevailing notions of fairness in a particular society at a given time. It is also important to note that our distinctions among these criteria derive from their general approach toward fairness (i.e., blindness, group-focused with emphasis on parity vs. equity). We expect that other metrics that fall within these categories are viewed similarly from a procedural fairness perspective.

Blindness Approach: Fairness through Unawareness

We begin with fairness through unawareness, which enforces willful blindness to protected attributes linked to unfairness. Currently, this method is the default approach for organizations and developers when implementing ML models. However, the prevalence of fairness through unawareness stems more from its technical practicality and capacity to make decision processes remarkably *consistent* compared to human decision making, yet it severely neglects the remaining procedural fairness components. Because this metric does little to satisfy multiple procedural concerns, it

Table 1 Framework of algorithmic criteria and their relation to procedural fairness components

Fairness metrics	Ability to signal procedural fairness components						Contextual applications: diversity and inclusion
	Consistency	Accuracy	Ethicality	Representativeness	Bias suppression	Correctability	
Fairness through unawareness	High	Low	Low	Low	Low	Low	Rarely suitable
Demographic Parity, Accuracy Parity	High	Moderate	High	High	Moderate	Low	May be applied to improve representation of minority groups, such as hiring decisions
Equality of Opportunity, Equalized Odds	High	Moderate	High	Moderate	High	Low	May be applied to remove barriers to entry, such as in interview and college admissions processes

is doubtful whether individuals would view it favorably in any diversity and inclusion context.

Consider the case of Amazon's now-disbanded recruitment model that reviewed job candidates' resumes (Dastin, 2018). Originally intended to filter through hundreds of resumes to select qualified candidates (using consistent procedures), Amazon's model took an unexpected turn when developers discovered it to have developed a bias against women. The bias emerged from the data used to train the algorithm, which consisted of actual resumes submitted to Amazon over ten years. Because most job applicants in the data pool were male, the program determined that men were more qualified than women. Specifically, the model learned to downgrade candidates who belonged to all-female extracurricular groups or had graduated from all-women's colleges—predictors highly correlated with gender.

In the Amazon incident, the use of fairness through unawareness made it challenging to determine which characteristics the ML model was optimizing on, including whether protected attributes were imputed using proxy information. It called into question whether the algorithm achieved *accuracy*, *representativeness*, and *bias suppression*. Likewise, the design of fairness through unawareness did not provide interpretable signals to the public about the ML model's *ethicality*, such as moral motives to hire more diverse talent. It also lacked mechanisms for rectifying flawed choices (*correctability*). A likely result is that people struggled to assess whether the algorithm's decisions were procedurally fair. By maintaining willful blindness, there is no practical way to counter indirect discrimination and bias when it arises. Together, we believe these shortcomings led to negative perceptions of fairness, which intensified as unfair outcomes inevitably emerged.

Accordingly, we argue that fairness through unawareness is rarely, if ever, suitable for practical use in diversity and inclusion contexts. Even if there is strong evidence that the algorithm's features do not correlate with the protected attributes—which is seldom, if ever, true—this approach cannot make procedural fairness components salient beyond consistency. Thus, people will likely perceive it as procedurally unfair. As long as algorithms are deployed in real-world settings and can influence individuals' fairness experiences, we caution against the use of fairness through unawareness.

That said, we acknowledge a possible exception to its preclusion. Namely, fairness through unawareness may be appropriate when organizations use ML models for purely mechanical, simple tasks. These tasks would not involve protected attributes in the data or directly impact human beings. Examples include character recognition, object classification, and spam classification. Research has shown that people regard fairness through unawareness favorably in such situations (Lee, 2018), likely because the model's decisions to not personally affect individuals (otherwise known as low outcome dependence in the field of social psychology; van der Toorn et al., 2011).

Group-Focused Parity Approach: Demographic Parity and Accuracy Parity

Next, we explore the procedural fairness of demographic parity and accuracy parity. Given the technical constraints associated with these metrics in achieving fairer outcomes, it is important that organizations implement them in the right setting so that the procedural gains can outweigh potential distributive losses.

Like fairness through unawareness, demographic parity and accuracy parity can provide high *consistency* in decision procedures across persons and over time. Indeed, algorithms almost always surpass consistency levels achieved by human decision makers (Lee et al., 2019). In contrast to fairness through unawareness, however, demographic parity and accuracy parity ensure that decisions are independent of protected attributes, yielding higher *accuracy*.

These criteria are also designed with moral principles in mind, taking active steps to prevent disparate treatment and impact for disadvantaged groups. Thus, we argue they

have higher potential to *suppress bias* as it arises in the decision process and deliver more interpretable signals to others about an ML model's *ethicality*. Ethicality may be especially easy to make salient in practice as managers and developers might only need to provide a basic understanding of these metrics to users to convey their moral intentions. On the other hand, the technical limitations of these criteria may make it tricky for practitioners to demonstrate that bias suppression has been achieved, and so we expect more moderate effects on fairness judgments. Not to be overlooked, these criteria do little to fix poor or flawed decisions when they arise. Thus, they are likely interpreted as providing low *correctability*.

Perhaps most significantly, we contend that demographic parity and accuracy parity are unique in their powerful potential to address concerns related to *representativeness*.[4] As part of their underlying structure, demographic parity and accuracy parity explicitly represent all affected subgroups and ensure equal rates of success between them. Accordingly, we encourage organizations to apply these two criteria in situations where concerns for representativeness are serious. Doing so is likely to enhance the perceived fairness of these algorithms.

For example, managers who wish to hire more diverse talent may implement demographic parity as part of the automated stages of the job interview process. Managers should also explain their use of this criterion to job candidates. Because the design of demographic parity can signal that members of underrepresented groups are valued and accepted, it may strengthen minority candidates' sense of belongingness and increase their trust in the ML model (Valcke et al., 2020). In some cases, there is intriguing evidence that deploying demographic parity (or accuracy parity) can attract more minority candidates to an organization and boost a minority group's social standing. For instance, Hu and Chen (2018) showed that applying demographic parity to hiring decisions combatted racial inequality in labor markets by temporarily increasing the number of minorities hired for entry-level positions. This subsequently improved the societal reputation of the minority group and contributed to their downstream career success. Demographic parity and accuracy parity, then, may strongly enhance perceived fairness when properly applied.

[4] Closely related to representativeness is the concept of voice, which allows individuals from different subgroups to express their concerns, opinions, and values to decision makers as part of the decision process (Thibaut & Walker, 1975). While we believe that voice is an influential factor to consider when examining perceived fairness, it falls outside Leventhal's (1980) theory of procedural fairness criteria—our current focus—and is thus beyond the scope of this paper.

Group-Focused Equity Approach: Equality of Opportunity and Equalized Odds

Finally, we turn to equality of opportunity and equalized odds, which we have argued can obtain fairer outcomes than the previous metrics. Given their distributive strengths, firms might initially conclude that these metrics are the frontrunners for improving perceived fairness. Yet, they are also more challenging than others to implement in real-world settings due to their strict constraints. With these tradeoffs in mind, we examine the procedural fairness of these two criteria.

Similar to the other metrics discussed, we observe that equality of opportunity and equalized odds deliver highly *consistent* decision making procedures due to their automated nature. They also do not take *correctability* into account in the event of bad outcomes or errors, at least not without human intervention. We further observe that equality of opportunity and equalized odds match the parity-focused metrics in their capacity to signal *accuracy* and *ethicality*. First, these metrics ensure that decisions are not based on protected attributes, which likely improves accuracy perceptions of the ML model. Second, they are designed to uphold standards of ethics and morality. For instance, equality of opportunity promotes equity ideals by ensuring that qualified individuals from different subgroups receive positive opportunities at the same rate. Equalized odds establishes similar equity between subgroups across both positive and negative outcomes.

Importantly, we argue that equality of opportunity and equalized odds outshine demographic parity and accuracy parity in their capacity to signal *bias suppression*. For one, these metrics apply more targeted rules to promote fair decision making (e.g., requiring that false-positive rates be equitably distributed) and thus better prevent preferential treatment from arising in the decision process. In the case of equalized odds, impressions of neutrality—a key aspect of bias suppression—may also increase because the decision rules influence everyone (Solomon et al., 2021). That is, all cases in the dataset are affected across both positive and negative outcomes. These procedural advances carry some costs with respect to *representativeness*, as different subgroups can be treated unequally when equity principles are emphasized; therefore subgroups may not be represented in the same way.

Based on this analysis, we suggest that managers and developers might benefit most by deploying equality of opportunity and equalized odds in situations where bias and special treatment are serious concerns. We believe that procedural fairness judgments of these algorithms may be enhanced in such contexts. In diversity and inclusion scenarios, this may translate to removing barriers to entry. As an illustration, consider the American National Football League (NFL), which created the Rooney Rule in 2002 to reduce racial discrimination

when hiring head coaches. The Rooney Rule requires football teams to interview at least two external minority candidates for head coaching positions and at least one minority candidate for other positions, including senior football operations, general managers, coordinators, and club presidents (Patra, 2020). Three years after the NFL implemented this policy, the percentage of Black coaches increased from 6% to 22% (Cook, 2021). We argue that applying equality of opportunity may similarly help to level the playing field among job candidates in automated phases of the interview process. Organizations should explain their use of this criterion to both recruiters and job candidates, emphasizing its ability to reduce favoritism and close the societal gap between different subgroups.

We expect that equalized odds is more appropriate when people care about preventing bias for both positive and negative outcomes. Generally speaking, this concern arises less frequently in real-world settings. People tend to focus more on whether positive opportunities are awarded across subgroups and pay less attention to whether adverse opportunities are equal. This criterion also has stricter technical constraints that lead us to question its utility in practice. Yet, there are some institutions that may stand to benefit by applying equalized odds, at least at certain times and in certain situations. For instance, universities and colleges may wish to implement equalized odds in the automated stages of the college admission process. Doing so may help to signal to the public that applicants from different backgrounds are equally likely to be considered if they are qualified (or denied if they are unqualified), thereby improving perceived fairness.

Discussion

This research has examined essential questions regarding the perceived fairness of five algorithmic criteria in ML, which has seen little integration with management and ethics research to date. Our main objective was to provide a more comprehensive understanding of how people may view the different criteria through the lens of distributive and procedural fairness, which provides a navigation aid for determining when a particular metric may be suitable. We shed light on variation in the ability for different algorithmic metrics to facilitate distributive fairness, noting that obtaining fairer outcomes comes at the cost of more technical effort. We also examine differences in the extent to which these criteria satisfy conditions of procedural fairness, which informs their contextual applications. In the spirit of interdisciplinary scholarship, we sought to provide a robust discussion of fairness that offers sufficient breadth and depth. Our analysis considers the complex interplay between human and machine, technology and organizations, processes and outcomes, and inherent tensions between fairness and accuracy across the different disciplines.

Theoretical Implications

Several theoretical implications arise from our discussion, which suggest future directions. First, the present work illuminates the potential for behavioral ethics research to enrich our theoretical understanding of ML tools. Looking forward, we encourage organizational behavior and ethics scholars to further explore the relevance of distributive and procedural fairness for algorithmic criteria as we still have much to learn. One direction for future work is to examine the extent to which our theorizing generalizes to categories of algorithmic criteria not covered in our conceptual analysis. For instance, computer scientists have developed metrics that emphasize individual fairness and causal reasoning, such as fairness through awareness, counterfactual fairness, and fairness in relational domains (Lazo, 2020). Thoughtful consideration of the ways in which these criteria may connect to distributive and procedural fairness is needed.

In particular, we expect that certain metrics might have unique relationships with procedural fairness that extend beyond our discussion in this paper. Fairness in relational domains, for example, may have pronounced effects on both perceived *accuracy* and *bias suppression.* This criterion takes a socially rich set of information (individual, relational, organizational, and ecological data) into account when making decisions (Farnadi et al., 2018). In a performance review scenario, fairness in relational domains can collectively evaluate managerial opinions of an employee based on prior performance reviews while simultaneously preventing bias from a particular manager from emerging.

As we did not perform empirical studies in this paper, we also encourage future research to test the arguments we have put forward in occupational settings. Further, scholars might productively build upon on our work by exploring other situational contexts that might enhance the perceived fairness of algorithmic criteria.

Practical Implications

In addition to theoretical implications for scholars, we also offer recommendations for organizations that deploy ML systems. As evidenced by corporate mission statements and company ethics codes, many, if not most, organizations state that they value integrity and ethical conduct. Managers and developers may also personally care about fairness, such as those who display high levels of moral character (Cohen & Morse, 2014; Cohen et al., 2014). For such individuals, an obvious implication is to avoid adopting a blindness or a one-size-fits-all approach toward algorithmic criteria. Instead, we advise practitioners to carefully consider

the conceptual differences among these choices and select a metric that best aligns with the situation at hand when developing an ML model.

We also strongly recommend that practitioners broaden their understanding of the variables that may be sensitive to unfairness within a particular dataset. While the current standard in computer science is to focus on legally protected attributes, there are many more factors that can shape people's worldviews of fairness. For example, management research has linked organizational tenure (Hambrick et al., 1996), functional background and values (Jehn et al., 1999), politics (Chao & Moon, 2005), physical appearance (Rafaeli & Pratt, 1993), attitudes and personality (Harrison et al., 1998), network ties (Beckman & Haunschild, 2002), and pay (Pfeffer & Langton, 1988) to fairness evaluations, though these are not legally protected. We acknowledge that these characteristics are fluid and likely fluctuate across situations, time, and societies. Still, it is incumbent on organizations to make concerted and frequent efforts to discern which features should be protected when applying a fairness criterion.

Lastly, it is essential to note that while it would be tempting to simply deploy a fairness metric in a particular situation and, after the organization achieves some performance data, fail to oversee or maintain it, doing so would violate the *correctability* element of procedural fairness. Because correctability is noticeably absent from the algorithmic criteria we have assessed, organizations must offset this weakness by tasking humans with monitoring the ML model's decisions and stepping in when errors and bad outcomes arise (Teodorescu et al., 2021). Indeed, humans and machines must work together to alleviate unfairness in this new digital age of work. Mastering a suite of algorithmic criteria and building cross-functional talent in management teams with ML and business ethics backgrounds would do much to resolve the challenges exemplified in our paper.

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