Measurement and Fairness

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Abstract

We introduce the language of *measurement modeling* from the quantitative social sciences as a framework for understanding fairness in computational systems. Computational systems often involve *unobservable theoretical constructs*, such as "creditworthiness," "teacher quality," or "risk to society," that cannot be measured directly and must instead be inferred from observable properties thought to be related to them—i.e., *operationalized* via a measurement model. This process introduces the potential for mismatch between the theoretical understanding of the construct purported to be measured and its operationalization. Indeed, we argue that many of the harms discussed in the literature on fairness in computational systems are direct results of such mismatches. Further complicating these discussions is the fact that fairness itself is an unobservable theoretical construct. Moreover, it is an *essentially contested construct*—i.e., it has many different theoretical understandings depending on the context. We argue that this contestedness underlies recent debates about fairness definitions: disagreements that appear to be about contradictory operationalizations are, in fact, disagreements about different theoretical understandings of the construct itself. By introducing the language of measurement modeling, we provide the computer science community with a process for making explicit and testing assumptions about unobservable theoretical constructs, thereby making it easier to identify, characterize, and even mitigate fairness-related harms.

1 Introduction

Computational systems have long been touted as having the potential to counter human biases and structural inequalities—yet, they often end up encoding and exacerbating them instead. The literature on fairness in computational systems has identified many ways that fairness-related harms can occur, including problematic training data (e.g., deriving credit scores from data about racist lending practices), questionable modeling choices (e.g., modeling teacher quality as only a function of students' test scores), and lack of due process (e.g., automating consequential decisions about people's lives without due process). We argue that these discussions have overlooked an important subtlety—specifically, that computational systems often involve *unobservable theoretical constructs* that cannot be measured directly and must instead be inferred from observable properties thought to be related to them—i.e., *operationalized* via a measurement model. By introducing the language of measurement modeling, a familiar tool to most quantitative social scientists, we provide the computer science community a framework for understanding fairness in computational systems, thereby making it easier to identify, characterize, and mitigate fairness-related harms.[1]

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[1] Our primary intended audience is the computer science community; however, we anticipate that the language of measurement modeling may also be useful for researchers and practitioners in other disciplines. Readers from the quantitative social sciences will likely be familiar with the language of measurement modeling already. As a result, we encourage them to view this familiarity as a way to support and contribute to discussions about fairness in computational systems.

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Why measurement? When we record data about the world, our measurements are only as good as our measurement tools. Although some properties like "height" might be relatively easy to conceptualize, define, and measure, we are often more interested in *unobservable theoretical constructs*—i.e., abstractions that describe phenomena of theoretical interest—such as "creditworthiness," "teacher quality," or "risk to society." Such constructs cannot be measured directly. Instead, constructs must be *operationalized* by something that can be inferred from observable properties theorized to be relevant—i.e., by defining a measurement model.

Although unfamiliar to computer scientists, the language of *measurement modeling* from the social sciences provides a framework for this process of operationalizing theoretical constructs and evaluating those operationalizations (Figure 1). (For example, we might operationalize the construct of "teacher quality" with a measurement model that infers latent teacher quality from students' test scores.) Precisely, a *measurement model* is a statistical model that links unobservable theoretical constructs, operationalized as latent variables, and data about the world [34]. We return to this in detail in section 2.

We argue that many well-studied harms are direct results of a *mismatch between the constructs purported to be measured and their operationalizations* inferred from observed data. Collapsing the distinction between a construct and its operationalization in a measurement model masks critical assumptions about the world, making it easier to exacerbate historical injustices (Figure 1). This is all the more true because the world is not fair, so data about the world will necessarily reflect that unfairness. (For example, operationalizing "employee quality" directly as "past salary" without accounting for the distinction between them will necessarily reproduce and reinforce structural discrimination.) In section 3, we explain how the language of measurement modeling makes precise the distinctions between constructs and their operationalizations, and introduce the concepts of *construct validity* and *construct reliability* as a way to guide discussions about fairness in computational systems. Then in section 4, we explore validity and reliability in several well-known systems to reveal how this process can illuminate potential harms. With the tools of measurement modeling, construct validity, and construct reliability, we can identify, address, and prevent the harms that emerge from the mismatch between construct and operationalization.

Finally, while many of the well-studied harms emerge from a mismatch between theoretical constructs and their operationalization, many debates in the current fairness literature emerge from the *mismatch between different theoretical understandings* of a construct. We argue that the construct of fairness is itself an *essentially contested construct*, such that there will always be a fundamental disagreement between theoretical understandings inherent to the phenomenon itself (c.f. Mulligan et al. [48])—however, to the extent that people are going to try to measure it, we ought to reason about it as an unobservable theoretical construct. Using the tools of measurement and construct validity, we can then evaluate and interpret our measurements of fairness in the context of this theoretical mismatch. In section 5, we touch on other notions of fairness not well included by existing debates, as well as other essentially contested constructs that are fundamental to this literature.

By emphasizing the role of measurement modeling in computational systems, we provide the community with established language and processes from the social sciences. Articulating the distinction between constructs and their operationalizations allows us to make assumptions explicit, identify the source of existing fairness-related harms, and characterize and even remedy potential harms. The language of measurement allows us to negotiate and evaluate our constructs and operationalizations thereof, providing a common framework to unite and clarify existing conflicts in the fairness, accountability, and transparency in machine learning community. To quote Carter [10], "language is power."
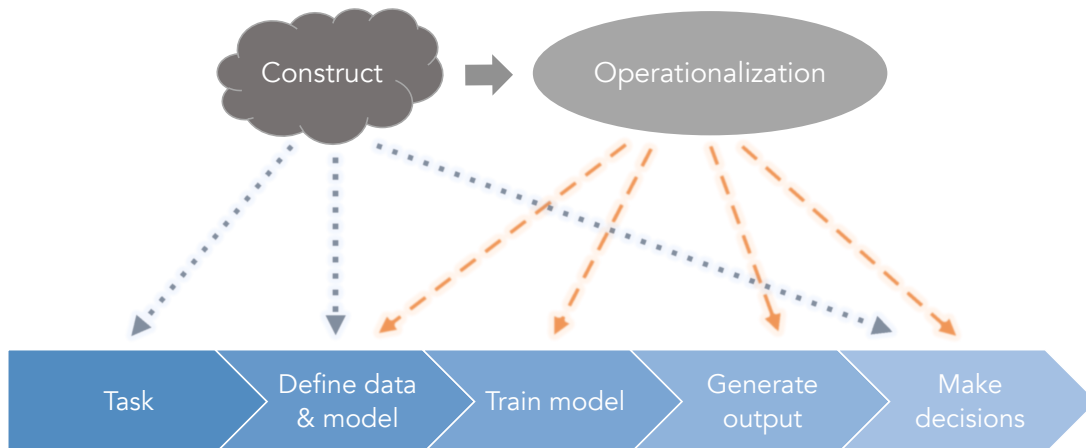
Figure 1: The social sciences emphasize *theorizing* and then *operationalizing* constructs in order to understand the world. In contrast, in computer science, understandings of constructs—and their operationalizations—are implicitly assumed across multiple stages of typical model development. We argue that many well-studied harms emerge from mismatches between theoretical understandings of a construct and between the construct and its operationalization. The typical stages of development in computer science *collapse the distinction* between construct and operationalization. Thus we need the language of measurement to make these assumptions explicit—enabling us to identify, address, and prevent such harms.

2 Measurement Modeling

Measurement modeling plays a central role in the social sciences, where many theories and hypotheses involve *unobservable theoretical constructs*—i.e., phenomena of theoretical interest that cannot be measured directly. For example, researchers in psychology and education have long been interested in studying "intelligence," while political scientists and sociologists are often concerned with theories involving "political ideology" and "socioeconomic status," respectively. These unobservable theoretical constructs are abstractions—i.e., they do not manifest themselves directly in the world—yet they are fundamental to society, influencing a wide range of observable properties. A measurement model is a statistical model that links unobservable theoretical constructs, operationalized as latent variables, and data about the world [34]. In this section, we introduce the language of measurement modeling, starting with a familiar example and getting progressively more sophisticated.

2.1 Measuring Height of a Person

We start by formalizing the process of measuring "height"—a property that we typically think of as being observable and hence easily measured. Although height of a person is not an unobservable theoretical construct, for the purpose of exposition we refer to the abstraction of height as a construct $\mathcal{H}$ and so we operationalize $\mathcal{H}$ directly as a variable h. Having operationalized height,[2]

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[2]Even this seemingly simple example has complications. Consider some understanding of the construct "height of a person" to be "the length from the top of one's head to the bottom of their feet." *Operationalizing* this construct requires articulating the implicit assumptions made about "height of a person." For example: does hair count towards height? Does slouching matter? What about mobility aids (e.g., a wheelchair), or do we use standing

we have many standard tools for measuring h, such as rulers, tape measures, or height rods. Measurements of constructs like height are sometimes called *representational* measurements, which are derived by "representing physical objects and their relationships by numbers" [30]—for example, using a ruler to represent a unit of height.

Despite the widespread availability of standard tools for measuring height, it is not possible to obtain noise-free measurements. For instance, when using a ruler to measure someone's height, the angle of the ruler, the granularity of the marks, or human error may all result in inexact measurements. However, if we take N measurements $\{\hat{h}_n\}_{n=1}^N$, then provided the ruler is not statistically biased, the measurements will in expectation equal the person's true height h as $N \to \infty$. Specifically and pedantically, the person's true height—the latent variable h—influences the measurements $\{\hat{h}_n\}_{n=1}^N$—a set of N observed variables. We can represent this measurement process using a graphical model, as shown below. Observed variables are shaded, while latent variables are unshaded; annotated "plates" denote replication.
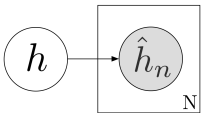
Alternatively, we can explicitly represent the error with which we measure the person's height via the following equation:

$$\hat{h}_n = h + \epsilon_n \tag{1}$$

where ϵ_n is the error associated with the nth measurement. In many settings, it is reasonable to assume that the errors are well-behaved—i.e., normally distributed, statistically unbiased, and possessing small variance σ^2. Under this assumption, $\epsilon_n \sim \mathcal{N}(0, \sigma^2)$ and $\frac{1}{N}\sum_{n=1}^N h_n \to h$ as $N \to \infty$. Equation 1 is equivalent to the graphical model representation shown in the figure above, provided that $h_n \sim \mathcal{N}(h, \sigma^2)$ for $n = 1, \ldots, N$. Borrowing from the economics literature, we refer to this kind of model as a *measurement error model*.

In practice, measurement errors may not be not well-behaved and may even be correlated with sensitive attributes, such as race or gender. For example, suppose our measurements of height come not from a ruler but instead from self-reports on dating websites. It might initially seem reasonable to assume that the errors are well-behaved in this in this setting. Instead, Toma et al. [62] found that while both men and women over-report their height on online dating websites, men exaggerate more and are more likely to over-report their height. Toma et al. suggest this is strategic, representing intentional deception; though, regardless of the source of the errors, self-reported height systematically differs from true height both in general and by gender. In other words, when measuring height via self-reports on dating websites, the errors are a function of gender.

2.2 Measuring Socioeconomic Status

Now suppose we are interested in measuring someone's "socioeconomic status" (SES). SES is understood to comprise someones social and economic position in relation to others: this construct can be understood as a function of unobservable phenomena such as social and cultural capital, access to opportunity, occupational status, as well as more concrete phenomena such as income, wealth, or education. Measuring *any* construct requires operationalizing it in such a way that measurements can be inferred from observable properties; however, unlike height, SES is an unobservable theoretical construct—i.e., it is an abstraction that does not manifest itself directly in

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height? Bodies vary, and so not every operationalization will be inclusive to all. Assumptions made to operationalize this construct may have systematic consequences for different groups.

the world. For inherently unobservable constructs such as SES, Hand [30] calls these *pragmatic measurements*, which are designed for an intended purpose to capture underlying phenomena.

Representing SES as a construct $\mathcal{S}$, we must operationalize $\mathcal{S}$ as a variable s that can be inferred from observable properties thought to be influenced by it. One way to operationalize s is with a very simple understanding of SES: for example, using an observable property—in this case, income—to represent SES. That is, here we directly substitute an observable property (income) for a theoretical construct (SES), i.e., we treat income as a *proxy* for SES.[3]

We can now characterize the measurement of SES using income as a proxy. For the purpose of exposition, we refer to the abstraction of income as another construct $\mathcal{I}$, operationalized as a variable i. Using income as a proxy for SES corresponds to specifying a *measurement model* that links s and i—for example, via the identity function

$$i = f(s) = s. \tag{2}$$

If we can obtain noise-free measurements of income—i.e., if our measurement error model is $\hat{i} = i + \epsilon$ where $\epsilon = 0$—then inferring SES corresponds to substituting our measurement model into our measurement error model and rearranging to yield $s = \hat{i}$ as desired. That is, *by specifying a measurement model and a measurement error model, we are making our assumptions about the relationships between the unobservable theoretical constructs of interest and the observed data explicit.* The measurement model represented by equation 2 links s and i via the identity function; our simple measurement error model assumes noise-free measurements of income.

There are many other measurement models that use income as a proxy for SES but make different assumptions about the way in which income is influenced by SES. For example,

- a different deterministic model, $i = f(s) = 4 \times s^2$;

- a random model where income is normally distributed around SES with variance σ^2, $i \sim N(s, \sigma^2)$.

Similarly, we could also include more complex measurement error models, incorporating noise or relationships to other attributes.

Beyond income, there are arbitrarily many ways to operationalize SES. For example, we could extend our operationalization to include years of education, location of residence, wealth, or occupation. We could also use other indicators drawn from observed properties, such as online purchasing behavior or group affiliations. In section 3, we will return to our simplest model: assuming that we observe income without measurement error ($\hat{i} = i + \epsilon$, $\epsilon = 0$), we operationalize SES using income i as a proxy ($i = s$).

2.3 Measuring Topics

Finally, we briefly consider another unobservable theoretical construct to illustrate the diversity of measurement models. Many social scientists are interested in theories involving "topics" in documents, such as representations of democracy in legal documents or the evolution of identity politics in online communities. However, topics are unobservable theoretical constructs that are indirectly evidenced. As a result, we must infer topics from observed data—i.e., words. Typically, this is done via a particular type of measurement model known as a topic model.[4] A topic model

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[3]We can also use one observable property as a proxy for another. If we had access to, say, shoes but not a ruler, e.g., we could use shoe size as a proxy for height.

[4]Topic models were originally developed in computer science, where they are typically thought of as models for exploring document collections, not as measurement models. We note that even the name conflates the construct and operationalization.

collectively operationalizes the topics represented in a corpus of D documents as a set of categorical distributions over words $\phi_1, \ldots, \phi_K$—one for each topic. The extent to which the dth document is "about" each of these topics is operationalized as a categorical distribution θ_d over the K topics. These latent variables are then linked to observed data—i.e., the words used in the documents, operationalized as D integer-valued vectors $\hat{w}_1, \ldots, \hat{w}_D$—via the following model:

$$\prod_{k=1}^{K} P(\phi_k) \prod_{d=1}^{D} P(\theta_d) \, P(\hat{w}_d \,|\, z_d, \phi_1, \ldots, \phi_K) \, P(z_d \,|\, \theta_d), \tag{3}$$

where z_d is a set of "topic assignments"—i.e., latent variables that assign each of the words in the dth document to one of the topics. Implicit in this model is the assumption that there is no measurement error—i.e., the measurement error model is $\hat{w}_d = w_d$. Inferring the topics then corresponds to forming the posterior distribution over the topics given the observed data—i.e., $P(\phi_1, \ldots, \phi_K \,|\, \hat{w}_1, \ldots, \hat{w}_D)$.

3   Evaluating Measurement Models

Specifying a measurement model and a measurement error model means making explicit our assumptions about the relationships between unobservable theoretical constructs of interest, their operationalizations, and the observed data. However, before relying on the resulting measurements, these assumptions must be thoroughly evaluated. This is where measurement modeling in the social sciences differs the most from general statistical modeling in computer science. Rather than relying primarily on out-of-sample prediction, social scientists typically evaluate their assumptions by focusing on two concepts: *construct validity* and *construct reliability*. Quinn et al. describe these concepts succinctly: "The evaluation of any measurement is generally based on its reliability (can it be repeated?) and validity (is it right?). Embedded within the complex notion of validity are interpretation (what does it mean?) and application (does it 'work?')" [56]. These concepts are both rooted in the psychology and education literature, where unobservable theoretical constructs, such as "personality" and "intelligence," play a central role [34].

It is here—the tools of construct validity and reliability—that we think that measurement modeling brings the biggest value to fairness. In practice, evaluation of computational systems can fail to characterize potential harms which are otherwise captured by failures of construct validity [27, 53, 59]. The language of measurement, with the tools of construct validity and reliability, provide a concrete framework to assess whether, and how, operationalizations are useful matches for the construct they try to measure. Moreover, assessing construct validity and reliability—or lack thereof—gives us a concrete path forward to assess the social, political, and organizational *values* designed into computational systems and the potential *consequences* of such systems.

We present a novel categorization of measurement and construct validity issues, drawing on decades of measurement research from statistics, psychometrics, education, political science, and beyond to inform this framework. Among others, we draw on the work of Samuel Messick.[5] This work shows that this critical evaluation is generative for revealing the space of potential harms applied to computational systems more broadly. Messick [44] argues, emphasis ours:

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[5]Messick united several traditions of construct validity while working for the Educational Testing Service (ETS)—the organization that today administers the Test of English as a Foreign Language (TOEFL), the Graduate Record Examinations (GRE), and other tests with nontrivial impact on individuals' livelihoods. Much of this research drew from education and psychology; Messick himself was strongly influenced by the psychologist Jane Loevinger (c.f. [42, 44]). Beyond educational testing, we argue that his ideas about testing apply to computational systems more broadly.

"The value of the testing must depend on the total set of effects it achieves, whether intended or not (Cook & Shadish, 1986). However, enumerating the potential consequences of test use to evaluate their social import is likely to be [interminable] . . . and there is no guarantee that at any point in time we will identify all of the critical possibilities, especially those unintended side effects that are remote from the expressed testing aims . . . the construct theory, by articulating links between processes and outcomes, provides clues to possible effects. *Thus, evidence of construct meaning is not only essential for evaluating the import of testing consequences, it also helps determine where to look for testing consequences.*"

Drawing from this rich field, we introduce this categorization to unite understandings of essentially contested constructs, practices from the social sciences, and values in design of computational systems; clarify and unite existing conflicts in the fairness, accountability, and transparency in machine learning community; and provide a common foundation for our emerging interdisciplinary field.

3.1   Construct Validity

Establishing construct validity is the process of showing that an operationalization of an unobservable theoretical construct is meaningful and useful. Broadly speaking, establishing construct validity involves a diversity of ways to interrogate the quality of a measurement. For example, is our measurement model systematically, if approximately, producing measurements centered around the theoretical construct of interest? (Drawing an analogy to statistics, validity is for theoretical constructs "roughly analogous to the notion of unbiasedness in the context of parameter estimation [in statistical modeling]" [34].) Do the measurements capture all relevant facets of the construct? Do the measurements behave as expected—perhaps through correlation with other relevant measurements? Or do they vary in ways that suggest they are capturing unintended properties—or noise? Are the measurements useful for answering substantive questions? What are the societal consequences of relying on these measurements? Construct validity allows us to actively explore the theoretical and practical assumptions—i.e., the framing, values, and potential consequences [59, 44]—built in to computational systems. A feature, not a bug, of validity is that it is not a binary to be achieved, or a box to be checked: it is always a matter of degree, backed by critical reasoning [42].

Different traditions in the social sciences have subtly different characterizations of how to evaluate measurements. Notions of construct validity have a rich history; in some fields, *content validity* and *criterion validity* are historically considered distinct from construct validity, but it is common to group all of these types of validity under the umbrella of *construct validity*, as we do here. We situate our framework largely with the traditions laid out by Quinn et al. [56], Messick [44], and Loevinger [42]. Specifically, we *unite* traditions from political science, education, and psychology to propose a framework useful for the fairness, accountability, and transparency in machine learning literature and computer science more broadly.

Our proposed framework brings together seven components of construct validity which we outline below. We illustrate how to interrogate the quality of a measurement using these seven components with a running example: the measurement model described in section 2.2. That is, we assume that we observe income without measurement error ($\hat{i} = i + \epsilon$, $\epsilon = 0$), and operationalize SES using income i as a proxy ($i = s$). Using this model—which makes many simplifying assumptions about a deeply complex unobservable theoretical construct—we show how this framework allows us to explore and evaluate our assumptions, goals, and potential consequences.

3.1.1 Face Validity

Face validity refers to the extent to which the measurements produced by a measurement model look plausible—a "sniff test" of sorts. Face validity is inherently subjective and often viewed with skepticism if not supplemented with other, less subjective evidence. That said, it is a prerequisite for construct validity—if the measurements produced by a model aren't facially valid, then they are unlikely to possess other types of construct validity.

Measurements of SES produced by income, the model described in section 2.2, would likely possess face validity. That is, SES certainly influences income: indeed, someone at the higher end of the income distribution (e.g., a billionnaire) has a different socioeconomic status than someone at the lower end (e.g., a barista). Face validity is necessary but not sufficient to establish overall validity; we can now move forward with evaluating our measurement model along more dimensions.

3.1.2 Content Validity

Unobservable theoretical constructs are often deeply complex—though we may wish to use relatively simple models to measure them. Content validity refers to the extent to which a measurement model captures captures everything we might want it to (see further discussion by Jackman [34]). That is, content validity comprises two types of agreement: first, some degree of coherent theoretical understanding about the construct, and second, agreement between the operationalization and that understanding. We can explore the first aspect by asking: is there a theoretically coherent understanding of this construct? (If so, what is it?) Prior works consider theoretical agreement a prerequisite to any content validity [34, 30]; however, even in the face of disagreement, we persist in trying to measure constructs of interest. Indeed, theoretical contestedness is common to many constructs of interest. (For example, the construct "fairness" has many conflicting theoretical understandings; we explore this later in the context of essentially contested constructs in section 5.) In practice, we can state our assumptions about what theoretical understanding of a construct we are using, and from there, move on to operationalize this construct in a valid way. Second, having assumed a theoretical understanding of the construct, does the operationalization capture all relevant parts of the construct [44, 56]? Furthermore, our construct has some theorized relationship to the observed world. Does our operationalization capture the *structure* of this relationship [42, 44]? Establishing content validity ensures that there is a substantive match between the observed world being measured and all relevant aspects of the construct.

Returning to our simple model of SES of section 2.2, income does capture socioeconomic status to some degree, but it is hard to argue that income wholly operationalizes the substantive content of SES. There are facets of someone's social and economic position in relation to others that are not captured by their income, such as wealth, occupation, education, and geographical location. For example, an artist of significant wealth but low income would occupy a higher socioeconomic position than suggested by their income alone. A physician with Médecins Sans Frontières (Doctors Without Borders) might have high occupational status, but low income; janitors in Palo Alto and Nebraska have equal occupational status, but potentially very different incomes due to geographic location. As the measurements produced by our model only consider income, our model would have limited content validity. However, we could use this exercise to reveal ways to improve our measurement model: for example, by including zip code in our model of SES in the United States.

3.1.3 Convergent Validity

Do our measurements match other accepted measurements of this construct? Convergent validity refers to the extent to which the measurements produced by a model are closely related to exist-

ing measurements of the same construct for which construct validity has already been established, potentially on a different sample [34, 56, 44]. Typically, this type of validity is explored more quantitatively, but can reveal qualitative differences between operationalizations.

Consider our SES example. We could compare our measurements (i.e., income as SES) to other accepted measures of SES, for example, following the recommendation of the National Committee on Vital and Health Statistics of the Department of Health and Human Services. They operationalize SES using education, number of years and degree attainment; income, wealth, and economic pressure, potentially accounting for geographic variation; occupation; and family size [51]. By definition, our operationalization would likely perform fairly well, to the degree that it correlates with income. We could also use any mismatches to *diagnose* which substantive aspects are missing from our operationalization—for instance, geography or wealth—thereby using this quantitative process to reason about content validity. This *quantitative* assessment serves as a diagnostic to highlight assumptions made during the modeling process, thus bringing greater *qualitative* understanding to our model.

3.1.4 Discriminant Validity

Face, content, and convergent validity confirm that our measurements wholly capture the intended construct. However, our measurements may capture other constructs: to the degree to which other constructs are related to the construct of interest, we should expect their measurements to be related. Discriminant validity refers to the extent to which this is the case. For example, measurements of "quality of life" should be related to measurements of "perceived social support"—but only to the extent that the constructs themselves are related. As a special case, if two constructs are totally unrelated, then there should be zero correlation between their measurements [30].

Many constructs are related to each other in theoretically expected ways: for instance, "perceived community ties" might be strongly related to "perceived social support." SES, on the other hand, is related to just about all social and economic constructs. (Consider, for example, how political participation, political ideology, language use, media consumption, online and offline behavior or health might interact with, or reflect, social and economic position. If we were instead trying to measure *these* constructs, we might want to confirm that we were not simply measuring SES instead of the intended construct, using discriminant validity.)

For the sake of argument, consider a *different* measurement of SES using income: instead of perfectly observing income (as in section 2.2), assume instead that we observe income by having individuals report their income received so far this month. Then, among a set of individuals with similar annual income levels, we might find variation in SES that is *not* attributed to either variation in true income or variation in SES. Instead we might find much stronger variation in our measure of SES due to an unrelated construct—timing of pay schedule, for instance. Observations of individuals' incomes could vary depending on whether they are paid biweekly or monthly, on the first or last of the month, or, for example, on freelance or commissioned contracts; in this case, discriminant validity reveals an important source of measurement error.

Other important confounds would also readily appear when we measure SES using income. Persistent wage gaps due to gender and race, for example, would suggest systematic differences in social and economic opportunity due to these attributes under this model. This raises a philosophical question: how much is SES a part of identity (such as gender and race)? SES is a deeply complex construct that reflects the many racial injustices and privileges that people are born into or curate. As a result, any measurement of SES will be correlated with race. But how correlated is too correlated? While the philosophical basis for this argument is beyond the scope of this document, questions like this quickly become practical problems. As soon as measurements are

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incorporated into computational systems that make decisions about people's lives, the answers to these questions determine the extent to which these systems will reinforce or remedy historical injustices. We return to this idea in the context of fairness and justice in section 5.3.

3.1.5 Predictive validity

Establishing predictive validity is often performed as a sanity check: are our measurements related to other external properties we expect to be influenced by that construct? This can be done quantitatively (do our measurements correlated with related properties?) or qualitatively (do our measurements vary with properties we expect them to?). In contrast to convergent validity—where we compared our measurements to other validated measurements of the *same* construct—predictive validity lets us look more broadly to *properties we expect to be coarsely related to the construct.* Showing that our measurements are related to these external properties serves as evidence that we are capturing the intended construct [34, 44].[6] This task is not necessarily about making the most accurate predictions *per se*, but about showing that our constructs follow expected relationships with properties that were not explicitly included in the model.

In the case of SES, we could look at variation with respect to an observed property that we expect to be related to SES. For example, we could consider data representing properties such as buying a Tesla, being mentioned in the *New York Times*, or applying for a government assistance program. We would need to determine the extent to which the measurements are predictive of any of these external properties; because income is generally predictive of these properties, the measurements would likely suggest predictive validity, at least in the upper and lower ends of the income distribution.

3.1.6 Hypothesis validity

Hypothesis validity establishes whether or not we have operationalized our construct in a way that is theoretically meaningful and useful. Here we take advantage of the framework of measurement to operationalize *other* constructs, to show that *our* operationalization is useful to test hypotheses and ask new questions. We can establish hypothesis validity by replicating past ideas: that is, if we can establish that (measurements of) our construct is related to (measurements of) others in expected ways.

Returning to our simple SES example, our model would have strong hypothesis validity for some hypotheses, but not for others. (As with all types of validity—and preventing harms in computational systems—context matters.) For example, standard hypotheses in social sciences have centered around lower SES leading to worse health outcomes, which we could likely replicate. However in the case of, e.g., wealthy college students, students may have low reported incomes, but be young and have great access to health resources, and so have good health outcomes. This task may ultimately look similar to predictive validity: for example, we could operationalize "cultural capital" with "being mentioned in the New York Times," and assuming validity for the moment, ask if our measurements of SES are related to these measurements of cultural capital. The motivation for such a task, however, would be arrived at by testing a theoretically grounded, substantive hypothesis, thereby establishing our ability to test new ideas.

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[6]Despite the name, predictive validity is not the same as out-of-sample prediction [29, 47]. When out-of-sample prediction is done using data assumed to be drawn from the same distribution as the training set—e.g., a withheld test set—this establishes *reliability*, which we define in section 3.2. For out-of-sample prediction on data from some unknown distribution, prediction performance might tell us how generalizable our model is (per Messick [44]); however, we also ought to consider the *consequences* of applying a computational system with potentially unknown behavior (section 3.1.7).

3.1.7 Consequential Validity

The previous types of validity establish that there is agreement between construct and operationalization, theoretically and practically. In contrast, consequential validity asks if that operationalization should *ever* be used, regardless of how well the construct is operationalized—that is, consequential validity considers the potential downstream societal impacts. Analogous to considering values in design [24], Messick argued that the *use* and *consequences* of a 'test'—i.e., a measurement model embedded in a computational system—is necessary to understand its validity. Downstream consequences are not only a normative concern, but fundamentally an aspect of validity: how these measurements are *used* may affect how they are interpreted and used in the future [44, 45].

Fairness-related harms can emerge from a number of directions, including directly from how a measurement performs (e.g., lack of model validity across groups leads to different health treatment outcomes by race [49]); from feedback loops that exacerbate existing biases (e.g., a predictive policing algorithm sends more police to an already over-policed neighborhood [43]); or shifting incentives (sometimes expressed as Goodhart's Law: "when a measure becomes a target, it ceases to be a good measure" [61, 31]). Messick argued that "the values served in the intended and unintended outcomes of test interpretation and test use both derive from and contribute to the meaning of the test scores" [44]. Indeed, interacting with measurements can create room for more individual judgments, automation bias, and (lack of) intuition and interpretability [6, 16, 28, 38, 55, 60]. That is, as measurements themselves may change the world in possibly unintended ways, consequential validity must be a necessary aspect of construct validity. Fortunately, the process of establishing construct validity can reveal potential shortcomings, consequences, and harms—not only revealing existing problems, but by providing a framework to imagine potential harms.

Returning to our running example of SES and income, income might be a valid measure of SES in many settings, but context matters. For instance, consider a specific setting, returning to our example of college students: wealthy students typically will have the resources to take unpaid internships, from which they gain no income but do gain professional experience, status, and connections. Other students may have to take positions with greater income but potentially with lower status and fewer professional connections. Here, a student's summer income would be a misleading measure of SES. Distribution of aid based on recent income could then favor wealthy, no-income students over working students, potentially leading to harms and skewed individual incentives. By exploring the different aspects of construct validity of this measure in this context, we would uncover a lack of validity along certain aspects—failure to represent wealth and social capital—which would help us explore potential downstream harms.

3.2 Reliability

Validity, while desirable, only matters insofar as our measure is reliable. Measures that are governed primarily by noise—due to inference, stability of the quantity measured, or imprecise measurement tools or meaningless scales—are of limited use. If we were to rerun our model right now, or again tomorrow, or on a similar test set, would we recover similar results? Would the same input to our operationalization reliably yield the same output? Reliability—or rather, lack thereof—can emerge across several stages of development, and is commonly discussed in the context of data collection.[7] In the context of designing computational systems, a lack of reliability could emerge from numerical instability; a failure of the model to converge; strong dependence on particular physical processes,

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[7] *Inter-rater reliability* is a well known type of reliability: commonly used when developing human-labeled data and in qualitative research. Inter-rater reliability estimates the agreement between multiple experts, observers, or coders (i.e., raters) evaluating the same system. While inter-rater reliability matters for reliability of our input data, this may not be available in the empirical settings we consider here.

random seeds, or implementation. Sensitivity of a model to small amounts of noise, outliers in training data, and to these types of implementation variants are not often clearly reported. This type of reliability is analogous to test–re-test reliability, which, paraphrasing Jackman [34], assumes that when the latent variable does not change, two measurements made at different time points should not vary meaningfully. Failure to consider reliability hinders the development of meaningful computational systems [21], and failure to report reliability can mask potentially meaningless variation in measurements used in practice. Assignment of effectively meaningless scores, or distribution of resources across meaningless guidelines, may be fair under some definitions, but may not be equitable or just.

4   Measurement and Bias/Harms

Unfairness in computational systems can emerge from statistical biases in data and societal biases in data, which encode the legacy of past inequities [6, 50]. Failure to articulate the assumptions made while designing computational systems masks the sources of potential harms. Furthermore, many of the fairness-related harms that arise from computational systems emerge from the mismatch between unobservable theoretical constructs and their operationalizations. (This can be all the more difficult when an operationalization is understood *as* the construct itself, colloquially or epistemically [27]: for example, understanding credit scores as equivalent to "creditworthiness," or fixed racial categories as "race" [7].) Failure to make the distinction between constructs and their operationalizations obscures the process of measurement, making it difficult to prevent future harms or diagnose sources of existing harms. We present several well known examples through the lens of measurement, each selected to highlight how different failures of construct validity and reliability are connected to harms emerging from them.

4.1   Recidivism Risk

We first turn to a prominent example: recidivism risk scores in the criminal justice system. Northpointe's COMPAS tools—now developed under equivant—produce scores operationalizing criminal risk, and these tools are widely used in sentencing, bail, probation, and parole decisions. We focus here on general recidivism risk, which operationalizes the likelihood a defendant commits a crime in the future. After ProPublica published results asserting racial bias in the COMPAS tool[8], equivant released detailed documentation showing that their model is "reliable and has good predictive and construct validity" [20]. Critically, the COMPAS documentation specifically claims to have construct validity, yet fails to fully account for the process of measurement. In particular, the documentation [20] explains, emphasis ours, that: "the COMPAS risk scales are actuarial risk assessment instruments. Actuarial risk assessment is an *objective method* of estimating the likelihood of reoffending. An individual's level of risk is estimated based on known recidivism rates of offenders with similar characteristics."

Using the tools of construct validity, we can challenge the claims of the COMPAS report. First, being caught offending is different than committing a criminal act, so we have already altered the substantive meaning of recidivism—a challenge to content validity. Scond, policing, police interactions, police records and arrest rates are currently and historically racist and unequally distributed; this directly relates to different observed frequencies of being caught. This threat to consequential validity matters not only for our interpretation of historical data, but also would be exacerbated

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[8]Angwin et al. published "Machine Bias" in ProPublica [4] (see also [14]). Much of this public and academic conflict is about mismatched theoretical understandings of fairness [13, 33]; we discuss this in greater depth in section 5.

in the future. That is, this racial bias would be built in to any model that is built from this unfair system: we know, for example, that historical and geographical patterns of (racist) policing are exacerbated by predictive policing systems trained on historical data [43]. Third, the claimed predictive validity was challenged by Angwin: "the formula was particularly likely to falsely flag black defendants as future criminals, wrongly labeling them this way at almost twice the rate as white defendants. White defendants were mislabeled as low risk more often than black defendants" [4]. This represents a different type of prediction task than used by Northpointe (see section 5.1), but uncovers poor predictive performance for both black and white defendants, with even more threats to consequential validity (black defendants denied bail at disproportionately high rates).

Finally, the claim that this is an "objective" method fundamentally misrepresents the process of measurement. The American criminal justice system is deeply and historically racist, and so any model trained on this history will necessarily encode and perpetuate these inequities. Northpointe's method is only objective *conditional on* the strong assumptions made to construct their model; the values of Northpointe and the criminal justice system are baked in to the training data, model, and evaluation of the COMPAS system. By labeling this system objective, they obscure the organizational, political, social, and cultural values they have implemented in this system, masking inequality with a label of objectiveness. Computational decision-making tools have the potential of being trusted as fair or unbiased, and so the quality of these measurements have to be assessed with that use case in mind. It remains a promising pursuit to mitigate human biases in high-stakes settings such as criminal sentencing. The design of any decision-making system—human, bureaucratic, or machine-aided—needs to explicitly consider how to minimize or compensate for historical injustices [11]. This nontrivial measurement task is deeply complex and requires significant debate about justice, policy, and fairness [8, 13, 15, 37].

4.2 Value-Added Modeling in Education

We now look to the well-known example of value-added modeling for teacher evaluation. In her book [52], O'Neil describes the case of Tim Clifford, a New York City middle school teacher with over 25 years of experience. Clifford received a score of 6 from a value-added model one year, followed by a score of 96 from the same model the next year. This model, the Education Value-Added Assessment System (EVAAS), is a popular teacher evaluation tool, claiming to provide measurements of several different constructs using two types of models. In this example, we focus specifically on teacher quality, measured using students' scores on tests administered in consecutive grades, such as literacy and mathematics state tests for grades three through eight. At a high level, EVAAS [57] assumes that a teacher's quality score for a particular subject, grade, and year is the state or district average score for that subject, grade, and year, accounting for their students' past teacher effects, plus some teacher-specific "evidence-based" offset (which can be negative) based on their students' test scores. Teacher quality is inferred as a function of their students' performance, their students' past teachers and past performance, and their own own expected performance [57] (see appendix for more details). School districts made decisions using these scores, without due process with respect to their score, the model, or employment decision.

The use of this score has drawn widespread negative attention, all focused on harms arising from this mismatch between construct and its operationalization. Most notably, this score drew attention for its dramatic lack of reliability, as illustrated by Tim Clifford's case [52]. EVAAS in particular assumes that the only quality of teachers is measurable through their students' deviation in test performance from expected; this is a strong substantive and structural assumption about how teachers add value. Due to EVAAS's lack of reliability, we would necessarily expect that we would struggle to establish any kind of convergent, discriminant, predictive, or hypothesis valid-

ity. These noisy measurements would be sensitive to changes in test design and school districting, which would further challenge discriminant validity. O'Neil also highlights other attributes of Tim Clifford—his 25-year teaching history and status in the community. If these attributes are relevant to our understanding of teacher quality, then this model lacks content validity as well. Furthermore, Amrein-Beardsley [3] demonstrates the score's lack of construct validity—particularly the lack of convergent validity and content validity (she classifies this as "criterion validity" and "construct-related validity," respectively) in great detail.

Consequential validity highlights the realized and potential consequences of reliance on EVAAS [3]. Teachers lost their jobs and careers due to this score, which was also used to distribute resources. This led to schools manipulating their scores [52]; in addition, setting such objectives leads educators and schools to "teach to the test," i.e., the curriculum tested on, rather than a more diverse and substantive curriculum [52, 31]. The use of EVAAS also led to a successful lawsuit in Texas, focusing primarily on the lack of due process (see section 5.3). This lawsuit led to the involvement of teachers in the future development of value-added models, in line with ideal practices for using measurement models in high stakes settings. Amrein-Beardsley [3] points to paths forward for the appropriate use of tests using guidelines from the American Educational Research Association. She argues that tests must be thoroughly validated, consistently evaluated, reliable, with clearly articulated potential negative side effects [3]. We argue that we can and should move forward with these guidelines, but to do so requires the language of measurement and the tools of construct validity and reliability.

4.3   Quality and Similarity

We now draw an example that comes from the literature on fair machine learning—within the literature of solutions, not problems—designed with purpose of achieving fairness in settings such as as hiring, college admissions, and lending. In one line of work, Joseph et al. [36, 35] focus on the setting where individuals are selected based on their *quality*. Here, the goal is to hire, admit, or lend to the most qualified individuals while guaranteeing "meritocratic fairness," capturing the general, stylized problem where we would like to ensure that a more qualified individual is at least as likely to be selected as a less qualified individual. Critically, it is assumed that quality is both directly *observable* and *perfectly observed*: "our definition of fairness... assumes the existence of an accurate mapping from features to true quality for the task at hand" [35].[9] This not only assumes that such a mapping exists, but that it is also an unbiased, reliable measurement of this unobservable construct. In related work, Dwork et al. [18] analyze the setting where individuals are selected based on their *similarity* of their traits relevant to hiring, admissions, or lending, where the goal is that similar individuals are treated similarly. However, this still requires measuring similarity: that is, measuring differences in quality. Dwork et al. acknowledge that this construct may not be directly observable: in this case, "the metric may reflect the 'best' available approximation as agreed upon by society." This assumes that the construct and operationalization are well-defined, can be explicitly externally agreed upon, and potentially that the public can be engaged meaningfully (unlike, e.g., the case of EVAAS). While this more strongly foregrounds the role of measurement, it carries strong assumptions about validity and reliability.

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[9]One approach by Friedler et al. [22] is to characterize the mappings between constructs theoretically. They operationalize constructs with their notion of a "construct space." Their model assumes that each construct that exists, is well-defined, and is a metric space; operationalizations are valid, lack contestedness, and are related in well-defined ways. These are nontrivial assumptions for characterizing unobservable constructs about which there may be theoretical disagreement. We strongly agree with the authors that fairness researchers need shared language that disentangles constructs and their operationalizations; translating and paraphrasing their core insight to the language of measurement, to study algorithmic fairness is to study measurement modeling.

Validity and reliability can be subtle and difficult to characterize in general. However, assuming them away downplays the role of measurement in systems for policy and decision-making; in practice, systems are implemented, and the challenge of measurement sneaks in regardless. Worse yet, a label of 'fair machine learning' may raise the stakes of such a system being adopted without critical assessment, where fairness is assumed to be guaranteed. These systems provide beautiful and rigorous machinery for creating fairness, but these systems still rest on the assumption of the *existence* of perfect measurements of similarity or quality, which have been as of yet largely out of reach. (This problem is not just theoretical pedantry; empirically, we can directly observe how these fairness-preserving algorithms fail to be reliable across variations of operationalizations and observed data [23].) Ultimately, any such system will only be as fair as its measurements.

5   Measurement and Fairness

In the previous section, we focused on the measurement of constructs that can be used to inform decision-making; this literature emphasizes, implicitly or explicitly, some notion of 'achieving fairness.' Fairness might feel instinctively different to the type of constructs already discussed, but it is still a construct—and one about which there has been millennia of theoretical disagreement. This disagreement marks fairness as as an *essentially contested construct*, i.e., a construct for which the space of theoretical understandings are inherently conflicting and context-specific [25, 48]. Without theoretical agreement, there ought to be no way to assess how well any operationalization captures the construct of fairness; yet to the extent that we continue to try to measure fairness, we ought to use the tools of construct validity and reliability. The language of measurement allows us to negotiate and evaluate our constructs and operationalizations thereof, providing a common framework to unite and clarify existing conflicts. That is, the language of measurement gives us a way to talk about the contested nature of fairness and how that comes to light under different operationalizations.

We focus on three examples of conflicts in the recent fairness literature to illustrate—far from exhaustively—how the language of measurement can contribute to these discussions. First, we consider how different operationalizations of fairness have been the focus of disagreements about the COMPAS risk scores in the criminal justice system. Second, we look to disagreement between two classes of operationalizations of fairness: individual fairness vs. group-level fairness. At the surface level, these two disagreements are about operationalizations; however, these disagreements reflect a deeper *mismatch between different theoretical understandings* of fairness. While these operationalizations of fairness are precise (and well-catalogued and discussed in a rich literature of their own, e.g., [5, 8, 13, 33]), all use very stylized models of fairness from which the language of measurement is largely, and crucially, missing. Disagreement among these operationalizations reveals underlying *theoretical* disagreement about the construct of fairness, but failing to recognize the process and importance of measurement modeling obscures the conflict at hand. Finally, we turn to the content and consequential validity of common operationalizations of fairness. Stylized operationalizations of fairness (and other meaningful constructs) will necessarily fall short without pathways to due process, justice, and broader social, political and philosophical understandings. Assuming simple operationalizations and failing to consider validity stands in the way of meaningfully engaging with these constructs, and so we can and should use the language of measurement. Failure to engage with constructs prevents us from confronting our values.

5.1 Parity- and Calibration-based Fairness

We return to the Northpointe COMPAS risk assessment tools. While we previously focused on their operationalization of recidivism risk, disagreements about fairness itself have been at the heart of the COMPAS controversies. In 2016, Angwin and colleagues published their landmark article in *ProPublica* on bias in risk assessment tools. They found that COMPAS systematically falsely labeled black defendants as risky at a higher rate than for white defendants [4], i.e., the algorithm lacked parity. Northpointe, who designed the algorithm, countered with the fact that their algorithm *was* fair under their operationalization, i.e., calibration. The fairness in machine learning community responded, largely reflecting the incompatibilities and shortcomings of different fairness operationalizations (e.g., [8, 11, 15, 13, 39, 54]). Meanwhile, Chouldechova [11] and Kleinberg et al. [39] proved that the two prominent and desirable classes of operationalizations of fairness at the heart of the COMPAS debate—*parity* and *calibration*—were fundamentally in conflict. Corbett-Davies et al., among others, quickly drew attention to the core issue: "at the heart of their disagreement is a subtle ethical question: What does it mean for an algorithm to be fair?" [14]—and a very public debate about measurement was born.

Now explicitly reframing this past debate in terms of measurement, the disagreement between these two operationalizations yields challenges to convergent validity (measures are misaligned) and content validity (each capturing different theoretical understandings of fairness); this lack of validity can be used to uncover theoretical disagreement. While superficially a conflict between (precise) operationalizations, this is a distraction: fundamentally, parity and calibration represent two different *theoretical* understandings of what it means to be fair. Calibration suggests equitable treatment: for the same risk score, outcomes should be the same across groups. But parity means that rates of error and potential consequences must be the same across groups; in the case of COMPAS, black defendants were significantly more likely to face harsher punishment [14, 13]. We thus need the language of measurement to disentangle and meaningfully move forward in these debates. The *values* inherent to these different theoretical understandings of fairness—and thus to different operationalizations of fairness—represent different ideas of equity, justice, and fairness. Negotiating the consequences we desire for our society requires confronting these values.

5.2 Individual Fairness and Group Fairness

Fairness, as we have already suggested, is complex and essentially contested: different central meanings underlie our understanding of this construct [25]. Dwork et al. [18] tease apart a subtle dimension of this construct. *Individual fairness*, which requires that similar individuals are treated—or rather, classified—similarly. *Group fairness* requires that groups are classified similarly—that is, on average, those in one group are treated similarly (e.g., with similar false positive rates) to another group. Statistically, there is necessarily incompatibility between optimizing for individual outcomes vs. group-level outcomes [13, 12]. Dwork et al. [18] argue that harms emerge for the individual using traditional group-based operationalizations of fairness. Approaching this from the language of measurement, they would argue that measurements of group fairness lack *content validity* by failing to account for individual experiences of fairness and justice, and thus also suffer from threats to *consequential validity*, by failing to provide equality of opportunity for individuals. Again, while this argument is largely held at the operationalization level [13, 18, 36, 12], this disagreement lives at the construct level. While this line of work precisely specifies *operationalizations*, corresponding to specific definitions of fairness, the meaningful debate lies outside. The reasons to pursue individual-based definitions of fairness are based on *values* inherent to different theoretical understandings of fairness. Moving this argument to the construct level allows us to interrogate

our theoretical assumptions and our values—of our past and of our ideal future.

5.3   Beyond Parity: Justice, Due Process

Thus far, we have only made brief reference to *content validity* and *consequential validity* in our operationalizations of fairness. Measurements of fairness that do not account for many of the different philosophical, legal, economic and practical notions of the theoretical construct of "fairness" necessarily lack content validity. Operationalizations of fairness that fail to account for due process and concepts of justice, distributive or otherwise, represent deep threats to consequential validity. Despite this inherently irreconcilable tension, as practitioners or researchers, we will continue to operationalize fairness, and yet measurement must in practice "accommodate both evidential and consequential determinants. Under such circumstances, it is likely that these 'judgments embody trade-offs, not truths' (Cronbach, 1980, p. 102)" [44]. In light of these tradeoffs, evaluating the validity of these operationalizations helps us understand the choices we are making and their consequences.

Recalling our discussion of individual fairness, the construct of "equal opportunity" is nontrivial to operationalize [18, 22]. In fact, the complexity of the theoretical understandings of this construct is nontrivial: Arneson [5] captures four sources of theoretical disagreement about the construct of equal opportunity—at best, only one or two could be captured by parity-based definitions. Then content validity is difficult to establish, both in substance (what is necessary to encompass equal opportunity) and in structure (how constructs must relate to each other). But, as we continue to operationalize equal opportunity in practice, we can and ought to use the language of measurement to assess our systems. Again, this matters because the design of "fair" systems—or rather, purely theoretical or real-world systems that optimize for a specific operationalization of fairness—is only as good as our operationalization of fairness. (Even this is a high bar: as soon as a measurement model of fairness is set, it becomes something that can be gamed [31, 52].) Fundamentally, if we conflate operationalization and its construct, it becomes more difficult to diagnose the harms emerging from our lack of validity.

Resource allocation with distributive justice, for example, compensates for current or historical inequities (which, of course, must be themselves measured). This requires a different set of tools and assumptions than may be captured by parity-based operationalizations of fairness. More complete conceptions of the construct of fairness will help us expand the space of possible operationalizations; guides to exploring the construct validity of fairness in prediction systems (e.g., [46])—will help assess these systems in practice. Through due process or better governance around the operationalization of constructs of significant social impact, there may also be more opportunities for collaborative evaluation of measurements—for example, through programs for restorative justice.

5.4   Sensitive Attributes

We have thus far frequently mentioned complex and often sensitive attributes, such as race and gender. These constructs are often fundamental to understanding fairness, or lack thereof. And yet, race and gender (among other related constructs) are themselves essentially contested. Each carry different theoretical understandings across cultures, geography, and time. There are entire fields are devoted to confronting—defining and rejecting—these constructs, and we defer to those. As with "fairness," critically engaging with our theoretical understandings of these constructs is necessary to understand what values and assumptions we are building in to our measurements.

Much of the work in the space of fairness also relies on metrics and other approaches that assume access to attributes, such as race or gender (for instance, structured transparency documents [26]). This assumption can be problematic: often such attributes are not available for individual-

level data, and it can be tempting to infer these attributes—even for the intended task of assessing fairness. However, it is common to then operationalize these constructs without the language of measurement and interrogation of validity that we argue are necessary here. The task of 'inferring' race or gender—common in industry and academia—not only implies agreed upon understandings of these categories, but also the (problematic) possibility of inferring these attributes from observed features, such as facial analysis or language use. (Of course, inferring these attributes may lead to other types of harms, and are often inferred for reasons other than assessing fairness. These types of harms are central to the literature on fairness for this reason. For recent general discussion about measurement and fairness in computer vision, natural language processing, and platforms, see, e.g., [27, 41, 50].) Inequality can become further entrenched by failing to consider the role of measurement in these categories. Assuming these attributes are fixed, observable, valid across contexts, and valid across individuals can mask this inequality. The language of measurement can help confront the values built into our assumptions and our models.

6 Discussion

Almost all interesting theoretical constructs—from "financial stability" and "risk to society" to "quality of life" and "fairness"—are unobservable. These constructs cannot be measured directly and must instead be inferred from observable properties thought to be influenced by them—i.e., observed data about the world. However, the world is deeply unfair, and we necessarily embed our political, organizational, social, and cultural values in our systems. Historical injustices in our social, legal, political, and economic systems are therefore necessarily encoded in observed data. In turn, these injustices affect our measurements of unobservable theoretical constructs. By collapsing the distinctions between constructs and their operationalizations in measurement models, we are denying ourselves opportunities to identify, characterize, and even remedy potential harms resulting from these injustices. In contrast, by articulating these distinctions, we are better able to highlight sources of harm, interrogate our values, and question our assumptions. For example, by recognizing that risk scores are inferred from arrest data, which reflects policing practices, not crimes committed [6, 43], we are better able to assess their consequential validity, potentially allowing us to conclude that the harms outweigh any benefits.

Further compounding this issue is the fact that measurements of theoretical constructs become more deeply embedded in and normalized by society as if they were obtained directly and without noise. They are incorporated into computational systems that make decisions about people's lives, standing in for the constructs purported to be measured, reinforcing historical injustices. We generalize Bowker and Star's consequences of classification [9]: measurement models are active creators of categories and stratifications in the world. Broadly, "measures are more than a creation of society, they *create* society" [1].[10] As a result, articulating the distinctions between constructs

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[10]Bowker and Star capture the notion that measurements create society through their discussion of classification in computational systems [9]. To see how classification in computational systems might subtly but fundamentally creates categories and stratifications in the world, consider a user creating an account on a website. The website might require the user to select either "Male" or "Female" as their gender, refusing to create the user's account if one of these options is not selected. Bowker and Star argue that these kinds of design choices are fundamentally political: "Seemingly purely technical issues like how to name things and how to store data in fact constitute much of human interaction and much of what we come to know as natural." They are not alone in this viewpoint; indeed, Hand echoes a similar sentiment, arguing that "measurements both reflect structure in the natural world, and impose structure upon it" [31]. This reflection and imposition is far from hypothetical. Obermeyer and Mullainathan, for example, show how a computational system that guides healthcare decisions for over 70 million Americans further entrenches racial differences in access and treatment in healthcare [49]. Underlying categorizations being treated as an unseen "truth" without critical examination lends credibility to harmful practices.

and their operationalizations is not a purely pedantic matter. Measurements of constructs that play a central role in society, such as "financial stability," "mental health status," and "violent risk to society," become encoded in policy. Fundamentally, race as a category itself further entrenches structural racism [7, 27].

In computer science, it is particularly rare to articulate the distinctions between constructs and their operationalizations. This is especially problematic because computer scientists are largely responsible for designing the measurements used in computational systems. However, it is not surprising. Unobservable theoretical constructs, such as "risk to society," are not easy to define, let alone measure. The same is true for historical injustices, such as racial disparities in sentencing. Moreover, both can be abstracted away from the creation and evaluation of computational systems by focusing on observed data and out-of-sample prediction. In practice, measurement in data science—what Passi and Barocas call "problem formulation" in their ethnography of a data science company—captures organizational decisions, masking normative choices and downstream societal impacts [53]. The disconnect between the goals of an organization, constructs of interest, and their operationalization become apparent when data scientists diagnose known sources of fairness-related harms [32]. Furthermore, a focus on "fairness" in systems that lack validity and reliability generally will be misdirected. Eckhouse et al. [19] speak to "layers of bias" in risk assessment models: "we show that each layer depends on the layers below it: Without assurances about the foundational layers, the fairness of the top layers is irrelevant." The language of measurement and construct validity can and should be used to illuminate the space of potential harms.

Collapsing the distinctions between unobservable theoretical constructs and their operationalizations makes society less fair, less transparent, and less accountable [40, 58]. The language of measurement provides a framework to make our assumptions explicit, and construct validity and reliability provide a process to question these assumptions and potentially reveal unintended consequences. Yet, the language of measurement modeling has been largely missing from computer science and from the literature on fairness in computational systems; to (again) quote Carter [10], "language is power." By embracing this language, progress awaits.

7 Conclusion

The language of measurement and construct validity can and should be used to illuminate the space of potential fairness-related harms, and has thus far been largely missing from the study of fairness in computational systems. We argue that many well-studied harms are direct results of an unarticulated mismatch between the construct purported to be measured and the properties actually measured—i.e., observed data. By emphasizing the role of measurement in computational systems, we provide the community with established language, tools, and processes from the social sciences for making assumptions explicit and identifying, characterizing, and even remedying potential harms. We argue that fairness is an essentially contested construct, and theoretical disagreement about the construct itself is at the root of current debates about fairness definitions. To those ends, we introduce a novel framework within the measurement literature, providing a common framework to unite and clarify existing conflicts in the fairness, accountability, and transparency in machine learning community. By articulating the distinctions between constructs and their operationalizations, we are better able to question our assumptions about the world, interrogate our values, and develop more fair (and just) computational systems.

Acknowledgments

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Appendix

Supplementary material on the EVAAS measurement model

In section 4.2, we discuss the popular teacher evaluation tool, the Education Value-Added Assessment System (EVAAS), focusing on their measurement of teacher quality. EVAAS measures teacher quality using students' scores on tests administered in consecutive grades for grades three through eight. At a high level, EVAAS [57] assumes that a teacher's quality score for a particular subject, grade, and year is the state or district average score for that subject, grade, and year, accounting for their students' past teacher effects, plus some teacher-specific "evidence-based" offset (which can be negative) based on their students' test scores.

Mathematically, EVAAS [57] operationalizes quality of teacher t for subject j, grade k, and year l as q_{tjkl} using the following measurement model:

$$y_{ijkl} = \mu_{jkl} + \left(\sum_{k^* <= k} \sum_{t=1}^{T_{ijk^*l^*}} w_{ijk^*l^*t} \tau_{ijk^*l^*t} \right) \tag{4}$$

$$q_{tjkl} = \mu_{jkl} + \sum_{i} \tau_{ijklt}, \tag{5}$$

where y_{ijkl} is the test score for student i in subject j in grade k in year l; l is effectively determined by (i, j, k). The weight $w_{ijk^*l^*t}$ is the fraction of student i's instructional time claimed by teacher t in subject j in grade k in year l, and $\tau_{ijk^*l^*t}$ is the effect of teacher t on student i in in subject j in grade k^* in year l^*. The subject-grade-year term μ_{jkl} captures yearly population-level changes in student performance for that subject and grade; teacher performance q_{tjkl} is a function of this population-level change μ_{jkl} and their own "teacher effect"—a function of their students' performance with respect to their own expected performance $\{\tau_{ijkl}\}$ [57]. (Following the documentation, year l is for accounting purposes, and is largely redundant conditional on (i, j, k).) The measurement error for student performance ϵ_{ijkl} is assumed to have mean zero, reflecting random deviation from the subject-grade-year mean; for teacher effects, by subject, error is assumed to be $\mathcal{N}(0, \sigma^2_{jkl})$ with no covariance across subjects.

This model has been widely challenged. O'Neil focused on the test's lack of reliability and due process, which was later used in court cases against the use of EVAAS [52]. In Texas, one court case moved to ban EVAAS unless there could be due process, with scores contested [17]. The American Federation of Teachers issued a press release supporting this decision, calling the above model "inexplicable" [2]. For a more thorough discussion of the validity EVAAS, Amrein-Beardsley [3] demonstrates the score's lack of construct validity—particularly the lack of convergent validity and content validity (she classifies this as "criterion validity" and "construct-related validity," respectively) in great detail.