

# Testing for Implicit Bias: Values, Psychometrics, and Science Communication

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**Abstract.** Our understanding of implicit bias and how to measure it has yet to be settled. Various debates *between* cognitive scientists are unresolved. Moreover, the public's understanding of implicit bias tests continues to lag behind cognitive scientists'. These discrepancies pose potential problems. After all, a great deal of implicit bias research has been publicly funded. Further, implicit bias tests continue to feature in discourse about public- and private-sector policies surrounding discrimination, inequality, and even the purpose of science. We aim to do our part by reconstructing some of the recent arguments in ordinary language and then revealing some of the operative norms or values that are often hidden beneath the surface of these arguments. This may help the public learn more about the science of implicit bias. It may also help both laypeople and scientists reflect on the values, interests, and stakeholders involved in establishing, justifying, and communicating scientific research.

**Keywords:** implicit bias, implicit association test, affect misattribution procedure, evaluative priming task, indirect measurement, social psychology, psychometrics, philosophy of science, philosophy of cognitive science, values in science

## Introduction

Myths about indirect measures like the Implicit Association Test continue to abound. Scholars in the field cringe whenever we experience another mandated training suggesting that implicit bias is entirely unconscious, a stable trait in each of us that we can measure with a test on Project Implicit's website, or the primary cause of prejudice in the workplace. However, it is difficult to blame the non-experts who are trying to relay highlights from a massive literature. Some of scholars' most accessible quotes about indirect measures jump to conclusions that do not follow from the evidence (Machery, 2021b).

At another level of discourse, however, scholars debate about the indirect measures that sparked the implicit bias literature. These debaters are aware of the well-known myths about indirect measures: they often list them as they situate their position in the debate (e.g., Brownstein et al., 2019; Machery, 2021b). Nonetheless, some scholarly debates about indirect measures remain unresolved.

In a recent exchange, one party starts by saying that indirect measures “assess *behavior*”

(Brownstein et al., 2019) but a response reframes the debate to be about “measurement of *attitudes*” (Machery, 2021b). In principle, the differences between these frames could lead to different expectations of indirect measures and, therefore, different evaluations of how well indirect measures meet our expectations. In what remains, we will elaborate on how these mismatches can result in debaters talking past one another, consider some of the justifications for the two views that exist so far, and how values play a role in these justifications (e.g., determining which evidence is relevant, appropriately interpreted, and significant). If successful, this could improve not just debates about implicit bias, but debates about psychometrics and science communication as well.

## Stable vs. Variable Constructs

Consider the kinds of information that a doctor may collect during regular checkups. After confirming our identity, a nurse measures our height, weight, blood pressure, etc. They may also draw some blood to run routine tests.

We are not necessarily surprised if our blood pressure changes significantly between health examinations. When it is significantly higher than our last visit, we are probably not suspicious of our doctor's blood pressure measurement instrument. Rather, we recognize that blood pressure varies within a relatively wide but expected range in response to many factors. For example, new responsibilities at work and home can disrupt our exercise and diet regimen in ways that increase our blood pressure (Filippou et al., 2020; Herrod et al., 2018; Xu et al., 2021).

Of course, we *are* surprised if our blood *type* changes between doctor visits. Unlike our blood *pressure*, which is predictably lower while we are sitting in a doctor's office than when we are exercising (Oh et al., 2016), our blood type is—except in very rare circumstances—the same across situations. So if we got a different blood type result every time our doctor measured it, we would rightly become suspicious of our doctor's blood type measurement instrument(s).

This illustrates how assumptions about a measured construct determine how we evaluate its measurement.

- If we assume that something is *stable* across time and contexts, then unreliable measurement of it across time and contexts is an anomaly.
- If we assume that something *varies* systematically across time and contexts, then unreliable measurement of it across time and contexts is to be expected.

### **Implicit Bias: Stable or Variable?**

The stable-variable distinction also applies to psychological constructs like implicit bias. Do we expect implicit bias to be more like blood pressure or blood type?

Our answer to this question has a significant impact on what we think about the legitimacy of the indirect measures that have been said to measure implicit bias (e.g., Greenwald et al., 1998; Payne et al., 2005). After all, there is plenty of evidence that performance on indirect measures of bias can vary between tests and contexts resulting in relatively low test-retest reliability for

one and the same person (e.g.,  $0.45 < r < 0.63$  in Bar-Anan & Nosek, 2014; average  $r = 0.54$  in Gawronski et al., 2017;  $0.24 < r < 0.51$  in Greenwald & Lai, 2020).

Those who expect implicit bias to vary between contexts (like blood *pressure*) are not necessarily concerned about unreliability (e.g., Byrd, 2019, Section 2.3; Gawronski et al., 2022). However, those who expect implicit bias to be stable across contexts (like blood *type*), take unreliability to indicate a problem with tests of implicit bias (e.g., Machery, 2021b).

The upshot is not that analogies with measuring blood pressure and blood type will resolve this debate. As one party to the debate rightly points out,

whether low reliability is an issue depends on what use a measure is put to. [...] if the point is to measure large deviations from a baseline of repeated measurements, low reliability may not be a serious issue. The situation is different when the point is to measure individual differences so as to predict or explain behavior (Machery, 2021b, p. 6).

So the upshot is that psychometric debates may turn on our assumptions about the purpose or goal of our research.

### **Do Tests of Implicit Bias Measure Behavior or Trait-like Mental Constructs?**

When a debate is predicated on different assumptions, then we need to step back and evaluate those assumptions. Otherwise, each side of the debate will probably talk past the other. So consider the reasons that have been offered for each set of assumptions about tests of implicit bias.

### **An Illegitimacy Argument**

Machery's "historical preamble" masterfully reviews the concept of 'attitude' in scientific psychology from the 20<sup>th</sup> and 21<sup>st</sup> century and then points out that tests of implicit bias "are often

presented as measuring individuals' attitudes" (Machery, 2021b, Section 2). Machery proceeds to argue that tests of implicit bias lack many of the psychometric properties we would expect from measurements of psychological traits like attitudes: discriminant validity, reliability, predictive validity, and more. Those who accept the premise that indirect measures should be evaluated according to the psychometric standards for trait-like mental constructs such as attitudes will probably be impressed by the evidence that Machery marshals in his argument that "the use of [indirect measures] is deeply problematic" (Machery, 2021b, p. 13). A simplified version of the illegitimacy argument can be constructed as follows.

1. Legitimate measures of attitudes exhibit certain psychometric properties.
  2. Indirect measures of bias do not exhibit those properties.
- So indirect measures of bias are illegitimate.

### A Reclassification Argument

A careful reader may have noticed that the conclusion of the illegitimacy argument is not guaranteed by the premises. After all, the first proposition is about measures of *attitudes*, but the remaining propositions are about *bias*. So while the premises may provide inductive support of the conclusion, another conclusion is also available:

Indirect measures of bias are not legitimate measures of *attitudes*.

This alternative conclusion transforms the illegitimacy argument into a sort of *reclassification argument*. The reclassification argument admits that indirect measures may not legitimately measure the "individual differences in implicit attitudes" that they were thought to measure (Greenwald et al., 1998, p. 1478). However, it raises the possibility that indirect measures can be legitimate if their goal is to measure another class of psychological constructs.

The reclassification argument may be similar to the response from Gawronski and colleagues: they emphasize that their original stance was that tests of implicit bias measure behavior rather than "trait-like constructs that are highly stable over time" (Gawronski et al., 2022, p. 2). This stance aligns with other discussions about measuring and manipulating "implicitly biased *behavior*" (Byrd, 2019, italics added): "responses on implicit measures are behaviors, and these behaviors should not be equated with their underlying mental constructs" (Gawronski et al., 2022, p. 4). This allows Gawronski and colleagues to accommodate many of Machery's claims without accepting the illegitimacy argument's conclusion.

### An Instrumentalist Shift

Responding to Gawronski and colleagues, Machery acknowledges the possibility that indirect measures track "context-bound individual differences" but also registers uncertainty the utility of such measures (Machery, 2022). How are indirect measures useful *for research*? The answer is a common refrain in philosopher's discourse: "it isn't fully clear" (Machery, 2022).

This move shifts the debate from one about psychometric legitimacy and construct classification to questions about significance. Here the sense of scientific significance is in terms of what epistemic and social benefits result from the research: "what important discovery about human behavior has been made thanks to...indirect measure[s?]" (Machery, 2022). Important discoveries may be those that answer explanatory questions from the scientific community and/or the public, identify predictors of socially relevant behaviors, or aid the adoption of some effective intervention or policy.

Your response to this instrumentalist shift may depend on which side of the debate you prefer. If you find yourself unsatisfied with indirect measures, you may be pleased to shift the burden back onto the friends of indirect measures. However, if you are largely satisfied with indirect measures, you may be thinking that it is not the burden that was shifted, but the goal posts.

### Values and Justification In Psychometric Debates

This debate about indirect measures of bias also reveals how psychometric debates can be value-laden (broadly construed to include epistemic, social, and/or political values). Our evaluation of psychological measures depends in large part on what we want from them (Wijisen et al., 2021).

We seem to want measures to deliver certain psychometric properties. Further, even if a measure fulfills what we want, we may nonetheless step back and reflect on whether we should care. So while psychometrics is largely an empirical enterprise in which data drive decisions about the validation of measures, data cannot determine the standards of validation such as what we *ought* to want from our measures or what *ought* to count as an important contribution to research.

So debates can remain unresolved even after background assumptions have been identified: we can agree about the evidence without agreeing about its relevance, meaning, or significance.

### Relevance

Feminist philosophers of science have long pointed out that there are often disagreements about the relevance of evidence for particular scientific claims (e.g., Longino, 1990). In the case of implicit bias, this disagreement plays out in judgments about which evidence from different indirect measures are relevant to claims about implicit bias. Both sides agree that different indirect measures (such as the Implicit Association Test (IAT), Evaluative Priming Task (EPT), and Affect Misattribution Procedure (AMP) provide evidence about something in our psychology (attitudes or behaviors). However, there is disagreement about whether specific evidence is relevant to claims about implicit bias. Machery (2021b, p. 6) notes that evidence produced by the AMP is unlikely relevant to claims about *implicit* attitudes. Gawronski and colleagues (2022, p. 2) do take evidence about the internal consistency of the AMP to be relevant to claims about the psychometric qualities of indirect measures of implicit bias. Both views recognize

the importance of employing multiple methods to examine the same phenomenon, outcome, or result (a strategy called 'triangulation'), but they come to different conclusions about the extent to which different methods produce evidence that is relevant to claims about implicit attitudes or biases.

Some psychologists and philosophers use a triangulation argument for implicit attitudes in which claims about the existence of a phenomenon are better confirmed by evidence from different methods than a single method alone. This argument is used to transcend debates about the nature of implicit attitudes. Thompson (2022) has raised these issues concerning triangulation arguments using evidence from the IAT and EPT, which are taken to be more related to measurement of implicit attitudes and biases than the AMP (Cummins et al., 2019; Hughes et al., 2021). She argued that triangulation is not necessarily successful in confirming the *existence* of a single construct and instead, researchers should use different methods to develop their *understanding* of a construct.

### Meaning

Another point of agreement is the lack of settled answer on the nature of implicit bias. Yet, there are different interpretations about the extent to which we should expect to have a well-established consensus on the appropriate characterization of the construct. Over 30 years, many proposed features have been ruled out or challenged, such as the claim that implicit biases are unconscious (e.g., Hahn & Goedderz, 2020) or that they are associative (Byrd, 2019). The positive account remains unclear. Some view this underdevelopment of psychological constructs as a part of the normal trajectory of research in psychology and take the elimination of previous characterizations as a positive development in the field (e.g., Feest, 2020; Gawronski et al., 2022; see also Thompson, 2020 on microaggressions). Others interpret underdevelopment of psychological constructs as a serious problem when construct validity has also not been established (e.g., Machery, 2022).

## Significance

Concerning the significance of evidence, both sides acknowledged evidence suggesting that indirect measures can measure population-level phenomena. For example, Payne and Hannay (2021) argue that indirect measures track the “systemic” prejudices that can emerge as people are exposed to disproportionately positive or negative representations of people groups. Gawronski and colleagues refer to this capacity of indirect measures as “extremely important” (2022, p. 1), whereas Machery merely admits the possibility that indirect measures have this capacity to measure “aggregate level” phenomena and then asks why that is “useful for research purposes” (2022, p. 9).

Acknowledging such value mismatches, however, is just the first step. The next step would be to reconstruct the arguments for each set of values, if reasons have been given. If not, then we may need to construct novel arguments about which values ought to drive psychometric decisions, conventions, and debates. This can reveal hitherto unappreciated stakes such as the role of values in validation standards and revealing overlooked risks in public communication.

## Standards

Take one example that arises in Machery’s (2021b) arguments that indirect measures lack many of the psychometric properties associated with good measures. He argues that the validity of indirect measures is still unclear. In particular, Machery focuses on discriminant validity, or the extent to which measures that are theorized to measure distinct constructs do in fact measure distinct constructs. Discriminant validity is often assessed based on correlation coefficients of the scores of these measures. In this argument, Machery describes Schimmack’s (2021) re-analysis of existing data as indicating the scores of direct and indirect measures are highly correlated, thus “providing no evidence for the reality of the two distinct constructs” (Machery, 2021b, p. 5). To make this judgment, Schimmack (and by extension, Machery) are relying on an assessment

that the high correlation on scores from direct and indirect measures is sufficiently high that discriminant validity among the measures is low. We do not wish to claim that this judgment is unjustified, but rather we aim to point out that values are involved in setting psychometric standards for what sort of evidence is sufficient for the judgment that some measure has (or does not have) discriminant validity (Thompson, 2022; Wijsen et al., 2021).

This point should stand even if construct validity is thought to be graded rather than categorical (Feest, 2020). There is a need for more explicit discussion about which standards for discriminant validity—or convergent validity (Thompson, 2022)—ought to be in practice in implicit bias research.

## Science Communication

Further, there are risks of ignoring these different valuations concerning the public’s understanding of the research. We agree with Machery (2022, p. 8), who raises serious concerns about the mismatch between the understanding of the research’s goal that have taken hold in public ideas about implicit bias and the one advocated by Gawronski and colleagues, namely, to provide population-level explanations of behavior. Here is yet another place where values play a role: to the extent that the public takes psychology to be answering questions concerning general, context-independent explanations and predictions of individual behavior, many psychologists have changed the subject in their research to a different construct that fulfills a different goal. Such changes in topic may be warranted, but they require better public justification and communication that cannot be “clearly distinguish[ed]” from scientific research (contra Gawronski et al., 2021, p. 1).

The overlooked risk here is not just that the public might misunderstand the inferences some psychologists make based on their research, but rather that the research may be disconnected from the problems that the public expects it to address. On the *aims approach to values*, appeals to values in science are legitimate when they serve the

democratic aims of research (Intemann, 2015). This departure from the public's understanding of the aims of implicit bias research requires not only better scientific communication about the shift, but public endorsement of it (perhaps via some democratic process). It may also require answering Machery's request to specify the significance of such findings for research purposes and, in our opinion, for social and policy purposes too.

### Conclusion

Sometimes it takes a psychometric dispute like this debate about indirect measures to identify the values and assumptions that may drive our psychometric conventions. There are formal justifications for many of the relevant psychometric standards and best practices. However, sometimes researchers begin to question whether a convention meets our needs (e.g., Benjamin et al., 2018), which provides an opportunity to reflect on whether and how to formally justify our conventions (e.g., Lakens et al., 2018). These kinds of reappraisals can lead to better justification of a research program's standards, goals, and societal impacts.

The current debate seems to have launched this kind of reflection. Perhaps we should capitalize on this opportunity to familiarize ourselves with concerns about measurement (Machery, 2021a) and measurement of implicit bias in particular (Gawronski, 2019; Greenwald et al., 2021). If nothing else, it may serve as a reminder of what we can and cannot infer from implicit bias experiments (Byrd, 2019). However, it may do more. It may reshape the conventions that drive our investigations of phenomena like implicit bias. It may also open space to consider when it is appropriate for a research program to deviate from its public representation and how researchers can better justify these changes in light of social and policy problems.

### Funding

Nick Byrd was supported by an appointment to the Intelligence Community Postdoctoral

Research Fellowship Program at Stevens Institute of Technology, administered by Oak Ridge Institute for Science and Education through an interagency agreement between the U.S. Department of Energy and the Office of the Director of National Intelligence.

Morgan Thompson was funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – Project 254954344/GRK2073/2.

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