Twenty-Five Years of Research Using Implicit Measures

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Abstract

The year 2020 marks the 25th anniversary of two seminal publications that have set the foundation for an exponentially growing body of research using implicit measures: Fazio, Jackson, Dunton, and Williams's (1995) work using evaluative priming to measure racial attitudes, and Greenwald and Banaji's (1995) review of implicit social cognition research that served as the basis for the development of the Implicit Association Test. The current article provides an overview of (1) two conceptual roots that continue to shape interpretations of implicit measures, (2) conflicting interpretations of the term *implicit*, (3) different kinds of dissociations between implicit and explicit measures, (4) theoretical developments inspired by these dissociations, and (5) research that used implicit measures to address domain-specific and applied questions. We conclude with a discussion of challenges and open questions that remain to be addressed, offering guidance for the next generation of research using implicit measures.

Keywords: dual-process theory; implicit measures; implicit social cognition; mental representation; science history

The year 2020 marks the 25th anniversary of two seminal publications that have set the foundation for an exponentially growing body of research using implicit measures: Fazio, Jackson, Dunton, and Williams's (1995) validation of the evaluative priming task (EPT; Fazio, Sanbonmatsu, Powell, & Kardes, 1986) for the measurement of racial attitudes, and Greenwald and Banaji's (1995) review of implicit social cognition research that served as the basis for the development of the Implicit Association Test (IAT; Greenwald, McGhee, & Schwartz, 1998). Over the past two decades, known limitations of the two measurement instruments have inspired the development of numerous alternatives, which now allow researchers to choose from at least twenty different tasks (see Table 1). Today, implicit measures have achieved wide visibility and use both inside and outside of the academy. They are used in practical applications and research with implicit measures is frequently cited in the popular media.

However, despite the widespread popularity of implicit measures, controversies remain about broader theoretical, methodological, and empirical questions, and the contribution of implicit measures to solving real-world problems. Given the historical milestone and the continued growth in use in basic and applied research, this Special Issue aims to take stock of the current state of the field and provide an in-depth analysis of what we have learned from implicit measures, what we have not learned, what we still need to learn, where implicit measures have succeeded, where they have failed, and what conclusions we can draw from the available evidence. The goal of this editorial is to provide an integrative context for this endeavor by summarizing key issues in the historical development and current state of the field.

Two Conceptual Roots

Although the EPT and the IAT have been the driving forces behind the surge of research with implicit measures that started 25 years ago, the two instruments have rather distinct conceptual roots (Payne & Gawronski, 2010). The development of the EPT was guided by the idea that attitudes are represented in memory as object-evaluation associations of varying strength (see Fazio, 2007). A central implication of this idea is that encountering an attitude object may automatically activate its associated evaluation via spread of activation to the extent that the associative link between the two is sufficiently strong. Fazio et al. (1986) used evaluative priming to test this hypothesis, setting the groundwork for the use of the EPT as an implicit measure of attitudes (Fazio et al., 1995). In this line of work, the EPT was interpreted as an "unobtrusive" measure of attitudes in the sense that it captures unintended expressions of attitudes that are difficult to control, providing a means to identify attitudes that people are unwilling to share on explicit self-report measures.

Different from the emphasis on unintentional expressions of attitudes that are difficult to control, the development of the IAT was guided by research on implicit memory, suggesting that traces of past experience can influence responses even when they are inaccessible to introspection. This idea is prominently reflected in Greenwald and Banaji's (1995) influential definition of implicit social cognition as "introspectively unidentified (or inaccurately identified) trace of past experience that mediates responses" (p. 4). Although this definition remains ambiguous about whether the qualifier *introspectively unidentified* refers to the past experience, the mental trace of that experience, or the processes by which this trace influences responses (see Gawronski, Hofmann, & Wilbur, 2006), it has contributed to the idea that the IAT captures unconscious attitudes that people are unable to report on explicit self-report measures (because they do not even know that they have these attitudes).

The two conceptual roots continue to shape research using implicit measures until today. In line with the ideas that inspired the development of the EPT, some researchers emphasize the goal-independent activation of representations that presumably shapes responses on implicit measures. Others rely on the idea that inspired the development of the IAT, assuming that implicit measures provide access to unconscious representations that are inaccessible to introspection. However, both of these assumptions face empirical challenges. The first assumption conflicts with evidence suggesting that processing goals can influence responses on implicit measures (e.g., Degner, 2009; Fiedler & Bluemke, 2005; Klauer & Teige-Mocigemba, 2007), raising questions about the extent to which implicit measures capture processes that are unintentional and difficult control. The second assumption conflicts with evidence suggesting that people are able to accurately predict their scores on implicit measures (e.g., Hahn & Gawronski, 2019; Hahn, Judd, Hirsh, & Blair, 2014; Rivers & Hahn, 2019), raising important questions about the extent to which implicit measures capture unconscious representations that are inaccessible to introspection (see Hahn & Goedderz, this issue).

What Is Implicit?

The empirical challenges to the two conceptual roots highlight a broader issue in the literature on implicit measures: the ambiguous meaning of the term *implicit* and its referent (Corneille & Hütter, 2020; Gawronski & Brannon, 2019). Although considerable progress has been made on the empirical side, the field is still fraught by inconsistent use of terminology. Following the theoretical ideas that guided the development of the EPT, some researchers use the term *implicit* to describe a particular class of *measurement instruments* (Fazio & Olson, 2003). According to this view, a measure qualifies as implicit to the extent that it captures information about psychological attributes (e.g., attitudes) without directly asking people for that information (see also Greenwald & Banaji, 2017). Different from this view, other researchers use the term *implicit* to describe the *mental representations* captured by indirect measurement instruments such as the IAT (Greenwald et al., 2002). This view is prominently reflected in the idea that these instruments capture unconscious representations that are inaccessible to introspection (e.g., implicit attitudes). To overcome conceptual problems with either of these ideas, some researchers suggested that the term *implicit* should be used to describe *measurement outcomes* rather than measurement instruments or underlying mental representations (De Houwer, Teige-Mocigemba, Spruyt, & Moors, 2009). According to this view, a measurement outcome qualifies as implicit to the extent that the to-be-measured psychological attribute influences the measurement outcome in an automatic fashion, requiring further specification in which particular sense this influence can be deemed automatic (i.e., unintentional, efficient, unconscious, uncontrollable; see Bargh, 1994; Moors, 2016). Finally, some researchers use the term *implicit* to describe the *behavioral responses* captured by indirect measurement instruments rather than underlying processes or representations (e.g., Gawronski & Bodenhausen, 2011). According to this view, a behavioral response qualifies as implicit if the conceptual meaning of the response is implicit (rather than explicit) in the observed response (e.g., evaluations inferred from differences in response times to different kinds of stimuli in contrast to verbally reported evaluations).

Based on a thorough analysis of how researchers have used the term *implicit*, Corneille and Hütter (2020) identified problems with every single one of these interpretations, concluding that it might be better to abandon the term entirely. It is an open question whether the quest for such radical change is realistic, given the tight connection of the term *implicit* with the use of a particular class of measurement instruments. A more realistic solution might be a change toward a conceptualization that remains agnostic about the processes and representations underlying responses on these instruments (see Rothermund et al., this issue; Van Dessel et al., this issue). A major advantage of such a conceptualization is that statements about the processes and representations underlying observed responses are treated, not as methodological truisms, but as theoretical hypotheses that need to be evaluated based on empirical evidence. Such a shift in the interpretation of terminology has the potential to promote scientific progress by opening the door for innovative ideas that may conflict with dominant assumptions in the field, leading to novel empirical insights in studies designed to test conflicting theoretical ideas (for examples, see Dalege & van der Maas, this issue; Kurdi & Dunham, this issue). In line with this idea, we will use the term *implicit measure* to refer to the measurement instruments listed in Table 1 without committing to particular theoretical views about the processes and representations underlying responses on these instruments. Although we deem an exemplar-based conceptualization the best option for an introduction to a Special Issue that brings together many different views on the nature of implicit measures, it is regrettable that, after 25 years of research using implicit measures, we still need to revert to a conceptualization that is based on whether a measure has been called *implicit* in the past. Several articles in this Special Issue tackle this issue, providing new ideas for furthering conceptual debates about the nature of implicit measures (Dalege & van der Maas, this issue; Rothermund et al, this issue; Van Dessel et al., this issue).

Implicit-Explicit Dissociations

Despite conceptual disagreements regarding the use of terminology, consensus exists in the field that there is an interesting phenomenon that deserves to be examined: dissociations between implicit and explicit measures. Such dissociations have been demonstrated in three forms: (1) correlations between implicit and explicit measures tend to be rather small overall (see Cameron, Brown-Iannuzzi, & Payne, 2012; Hofmann, Gawronski, Gschwendner, Le, & Schmitt, 2005); (2) implicit and explicit measures have been found to predict different kinds of behavior and the same behavior under different conditions (see Friese, Hofmann, & Schmitt, 2008; Greenwald, Phoehlman, Uhlmann, & Banaji, 2009); and (3) implicit and explicit measures have been found to differ in their sensitivity to the same external influence (see Forscher et al., 2019; Gawronski & Bodenhausen, 2006).

Together, these findings have led many researchers to conclude that implicit and explicit measures capture distinct but related constructs (Nosek & Smyth, 2007). Although this assumption is widely shared in the literature, it depends on two underappreciated premises. First, the two kinds of measures have to be comparable in terms of their reliability. Many of the instruments listed in Table 1 have shown low estimates of internal consistency that do not meet the psychometric standards that are commonly applied to explicit measures (see Gawronski & De Houwer, 2014; Greenwald & Lai, 2020). Although such asymmetries do not explain double dissociations in the prediction of distinct behaviors and effects of distinct external factors, they suggest rather trivial interpretations for small correlations between implicit and explicit measures and external effects on explicit but not implicit measures (Cunningham, Preacher, & Banaji, 2001; LeBel & Paunonen, 2011).

Second, the two kinds of measures have to be comparable in terms of the focal stimuli. Although this issue has received considerable attention in some areas (e.g., implicit and explicit measures of personality self-concepts; see Asendorpf, Banse, & Mücke, 2002; Back, Schmukle, & Egloff, 2009; Peters & Gawronski, 2011), it has been largely ignored in other areas, such as research on racial bias (for discussions, see Gawronski, 2019; Payne, Burkley, & Stokes, 2008). For example, whereas most explicit measures of racial bias ask participants to respond to items about social categories (e.g., the categories *African Americans* and *White Americans*), most implicit measures utilize images of exemplars (e.g., faces of Black and White individuals) that are not presented in the explicit measure. Such confounds between type of measure (implicit vs. explicit) and focal object (categories vs. exemplars) lead to theoretical ambiguities about whether observed dissociations reflect genuine differences between implicit and explicit measures (as typically argued) or differences in responses to different focal objects that have nothing to do with the nature of the measurement instrument.

To the extent that alternative interpretations in terms of psychometric properties and focal constructs can be ruled out, dissociations between implicit and explicit measures impose valuable empirical constraints on theories about the processes by which mental representations are formed, the processes by which these representations influence judgments and behavior, and the specific nature of the underlying representations (e.g., single vs. dual; associative vs. propositional). Research on these questions has served as the basis for numerous theories that offer competing explanations of dissociations between implicit and explicit measures (e.g., Fazio, 2007; De Houwer, Van Dessel, & Moran, 2020; Gawronski & Bodenhausen, 2006; Strack & Deutsch, 2004; see also Dalege & van der Maas, this issue; Kurdi & Dunham, this issue). Although these theories differ in terms of the constructs proposed to explain such dissociations, there is consensus that the processing conditions during the completion of implicit and explicit measures play a central role for their relation with each other and their relations with other behaviors. A general hypothesis that is consistent with any of these theories is that relations between measures of any kind should increase as a function of their similarity in terms of (1) the contextual conditions during the measurement process (e.g., time pressure) and (2) the mental processes involved in the production of the measured responses (see Gawronski & De Houwer, 2014).

Theoretical Developments

Research on dissociations between implicit and explicit measures has been strongly shaped by dual-process theories, assuming that implicit and explicit measures reflect the outcomes of two qualitatively distinct processes. Examples include the motivation-and-opportunity-as-determinants (MODE) model (Fazio, 2007), the reflective-impulsive model (RIM; Strack & Deutsch, 2004), the associative-propositional evaluation (APE) model (Gawronski & Bodenhausen, 2006), and the systems-of-evaluation model (SEM; Rydell & McConnell, 2006). Although these theories differ in terms of various details, they are often linked to the generic idea that responses on implicit measures reflect the outcome of automatic associative processes, whereas responses on explicit measures reflect the outcome of controlled reasoning processes that have been described as deliberate (Fazio, 2007), reflective (Strack & Deutsch, 2004), propositional (Gawronski & Bodenhausen, 2006), or rule-based (Rydell & McConnell, 2006).

Over the past decade, dual-process interpretations have been increasingly challenged by single-process theories that explain responses on implicit and explicit measures as the product of a unitary propositional process whose outcomes can vary as a function of the processing conditions under which responses are shown (De Houwer, 2014; De Houwer et al. 2020; see also Kurdi & Dunham, this issue). A common argument by proponents of single-process theories is that evidence for external influences on implicit measures that involve propositional reasoning conflict with the predictions of dual-process theories. Such interpretations are based on the premise that, according to dual-process theories, implicit measures should be uniquely influenced by factors that incrementally strengthen mental associations (e.g., repeated co-occurrences between stimuli) and remain unaffected by factors that involve propositional reasoning (e.g., verbal statements).

However, some dual-process theories explicitly address potential "top-down" effects of propositional or rule-based inferences on associative processes (e.g., Gawronski & Bodenhausen, 2006; Strack & Deutsch, 2004). According to these theories, the critical question is not *whether* higher-order inferences can influence responses on implicit measures, but *when* such effects can be expected to occur. A shared prediction of these theories is that implicit measures should show unique effects of factors that incrementally strengthen mental associations (e.g., repeated co-occurrences between stimuli), whereas explicit measures should show unique effects of factors that involve propositional reasoning (e.g., information about the relation between co-occurring stimuli) when the two kinds of factors have conflicting implications (e.g., when a stimulus stops a co-occurring unpleasant stimulus). Although there is some evidence for such double-dissociations (e.g., Moran & Bar-Anan, 2013; Hu, Gawronski, & Balas, 2017), dual-process theories are difficult to reconcile with the growing body of evidence that implicit and explicit measures are both shaped by factors that involve propositional reasoning when competing associative factors should lead to a different outcome on implicit measures (see Kurdi & Dunham, this issue). Thus, although some dual-process theories explicitly address effects of propositional reasoning on implicit measures (e.g., Gawronski & Bodenhausen, 2006), their validity has been challenged by findings suggesting that propositional inferences determine responses on implicit measures even when antagonistic associative processes would suggest a different outcome.

In addition to providing a theoretical alternative to extant dual-process theories, single-process propositional theories have inspired the development of a new class of implicit measures that aim to capture mental representations of complex relations between objects (e.g., Cummins & De Houwer, 2019; De Houwer, Heider, Roets, & Hughes, 2015; see also Barnes-Holmes, Barnes-Holmes, Stewart, & Boles, 2010). The significance of this endeavor can be illustrated with the inability of traditional implicit measures to distinguish between representations of actual and ideal self in the measurement of self-esteem. For example, in a standard IAT to measure to self-esteem (Greenwald & Farnham, 2000), someone with a representation of their actual self as *I am good* may respond faster when responses to self-related words are mapped onto the same key as responses to positive words than when responses to self-related words are mapped onto the same key as responses to negative words. However, the same response time difference may be observed for someone with a representation of their ideal self as *I want to be good*. Traditional implicit measures are insensitive to such differences, but they can be captured with implicit measures designed to assess patterns of relational responding (e.g., Cummins & De Houwer, 2019; Barnes-Holmes et al., 2010; De Houwer et al., 2015).

Different from the relatively broad focus of single-process and dual-process theories, the bias-of-crowds model has been designed to reconcile three sets of paradoxical findings in research on prejudice and stereotyping (Payne, Vuletich, & Lundberg, 2017). First, how can biases on implicit measures be widespread and robust on average (Nosek et al., 2007), yet highly unstable over just a few weeks at the individual level (Gawronski, Morrison, Phills, & Galdi, 2017)? Second, if biases on implicit measures are highly unstable over just a few weeks (Gawronski et al., 2017), how can they be stable over decades, as suggested by research showing that young children show bias levels on implicit measures that are indistinguishable from those shown by adults (Degner & Calanchini, this issue)? Third, how can aggregate scores of bias on implicit measures at the regional level show strong associations with aggregate levels of societal disparities (Hehman, Calanchini, Flake, & Leitner, 2019), given that meta-analytic associations between implicit measures of bias and discriminatory behavior at the individual are relatively weak overall (Cameron et al., 2012; Greenwald et al., 2009; Kurdi et al., 2019; Oswald, Mitchell, Blanton, Jaccard, & Tetlock, 2013)?

The bias-of-crowds model reconciles these paradoxical findings by assuming that implicit measures of bias reflect situational (rather than chronic) accessibility of bias-related concepts. From this perspective, the biases on implicit measures provide information, not about the person who is completing the measure, but the broader context in which the measure is completed. Thus, whereas robust average levels of bias over time and across age groups reflect the relative stability of bias at the societal level, short-term fluctuations at the individual level reflect variations in concept accessibility driven by incidental features of a person’s context. Moreover, whereas strong associations between aggregate scores of bias on implicit measures at the regional level and aggregate levels of social disparities reflect a causal effect of situational factors on the accessibility of bias-related concepts, the extent to which these concepts have a causal influence on behavior at the individual level remains unclear, at least from the perspective of the bias-of-crowds model.

Another debated issue is that most implicit measures of evaluation assess responses along the valence dimension (positive vs. negative) without further distinguishing between different kinds of evaluative responses. For example, an implicit measure may reveal an overall negative reaction to African American faces, but most implicit measures are insensitive to the emotional quality of this reaction (e.g., fear vs. guilt; see Andreychik & Gill, 2012; Lee, Lindquist, & Payne, 2018; March, Gaertner, & Olson, 2018; Rohr, Degner, & Wentura, 2015). Focusing especially on the role of threat responses, March et al. (2018) have argued that this limitation is relevant not only for interpretations of responses on implicit measures. It also has important implications for extant dual-process theories, given that most of them focus exclusively on valence without considering the significance of early threat-related processes (see March, Olson, & Gaertner, this issue). Although there is disagreement among emotion researchers about the processes underlying the elicitation of qualitatively distinct emotions (Moors, 2009), these considerations suggest that research using implicit measures might benefit from more cross-talk with research on emotion (see Jones, Kirkland, & Cunningham, 2014; Lee et al., 2018).

A valuable development in research using implicit measures is the ongoing trend toward formal models. Whereas early models were designed to disentangle the contribution of multiple distinct processes to responses on particular instruments (e.g., Conrey, Sherman, Gawronski, Hugenberg, & Groom, 2005; Klauer, Voss, Schmitz, & Teige-Mocigemba, 2017; Meissner & Rothermund, 2013; Payne, Hall, Cameron, & Bishara, 2010; for a review, see Sherman, Klauer, & Allen, 2010), the network theory of attitudes provides a broader model of attitudinal processes and representations that goes beyond responses on particular instruments (Dalege et al., 2016; Dalege, Borsboom, van Harreveld, & van der Maas, 2018). Inspired by the notion of entropy in thermodynamics, a key concept of the theory is *entropy reduction*, in that activation of attitudinal representations is assumed to transition from high entropy states (i.e., unstable, inconsistent) to low entropy states (i.e., stable, consistent). According to Dalege and van der Maas (this issue), implicit measures differ from explicit measures in terms of the processing constraints that permit entropy reduction, in that responses on implicit measures reflect attitudes in high entropy states, whereas responses on explicit measures reflect attitudes in low entropy states. From the perspective of the network theory of attitudes, this interpretation leads to the interesting paradox that "implicit measures can provide a more accurate assessment of conflicting evaluative reactions to an attitude object (e.g., evaluative reactions not in line with the dominant evaluative reactions) than explicit measures, *because* they assess these properties in a noisier and less reliable manner" (p. xx). Although the impact of any novel theory may depend on whether it is able to generate novel predictions that can be empirically confirmed (Gawronski & Bodenhausen, 2015), formal modeling approaches that integrate assumptions about attitudinal processes and representations with insights on the elicitation of evaluative reactions with distinct emotional qualities might be an interesting direction for future research with implicit measures.

Applications

In addition to providing valuable insights into the general mechanics of the human mind, implicit measures have been utilized in a wide range of areas to address domain-specific questions. Most of these applications have used implicit measures for the prediction of domain-specific outcomes or to investigate effects of interventions (or both). The most well-known example is research on prejudice and stereotyping, where implicit measures (especially the IAT) helped to increase public awareness of implicit biases and promote the integration of implicit biases into diversity training and other bias interventions. For example, in the domain of legal decision-making, implicit measures have been used to understand biases in jury selection, jury decision-making, and sentencing decisions (Kang et al., 2012; Levinson & Smith, 2012); and in the domain of medical decision-making, implicit measures have been utilized to understand disparities in healthcare, including biases in the communication behavior of healthcare providers, patients' reactions to these behaviors, and treatment recommendations (Hagiwara, Dovidio, Stone, & Penner, this issue).

Beyond applications to understand disparities in healthcare, theoretical frameworks that link implicit measures with impulsive responses (Hofmann, Friese, & Strack, 2009; Strack &

Deutsch, 2004) have played a major role in establishing the significance of implicit measures in health psychology more broadly, including applications to dieting, alcohol consumption, and sexual health behavior (Hofmann, Friese, & Wiers, 2008; Wiers et al., 2010). Relatedly, applications in clinical psychology utilized implicit measures to gain deeper insights into the underpinnings of various psychopathologies and their treatment (Roefs et al., 2011; Teachman, Cody, & Clerkin, 2010). A similar focus has guided applications in forensic psychology, where implicit measures have been used to study characteristics of criminal offenders and the likelihood of recidivism (Schmidt, Banse, & Imhoff, 2015; Snowden & Gray, 2010). A concern with health outcomes also plays a major role in applications that have used implicit measures to study the antecedents and consequences of interpersonal dynamics in close relationships, given that relationship quality is a major determinant of psychological and physical health (Faure, McNulty, Hicks, & Righetti, this issue).

In the areas of marketing and consumer behavior, implicit measures have attracted considerable attention for their presumed potential in overcoming limitations of explicit self-report measures in understanding product preferences, purchasing decisions, and effects of commercial advertisements (Fried & Johnson, 2015; Perkins & Forehand, 2010). A similar focus has guided applications in political psychology, where implicit measures have been used to predict future decisions of undecided voters and to investigate effects of political campaigns (Gawronski, Galdi, & Arcuri, 2015; Nosek, Graham, & Hawkins, 2010).

Although the list of diverse applications may suggest that implicit measures have proven their practical utility outside of the academy, it is worth noting that virtually all of these applications involve applied research, not applications by practitioners. A notable exception is the use of implicit measures by practitioners in marketing (e.g., https://emotiveanalytics.com), although the actual utility of these applications remains unknown (i.e., does it actually help clients achieve their aims?). Thus, the extent to which implicit measures could be helpful in helping practitioners solve real-world problems is still unclear. Whether practical value should be used as criterion to evaluate implicit measures is a matter of debate, and even the authors of this article disagree on this point. For those who emphasize the importance of practical value, it is certainly disappointing that, after 25 years of extensive research, implicit measures have made barely any contribution to resolving real-world problems outside of the academy, and that it is time to provide practitioners with simple ways of using implicit measures to do that. Yet, in light of unresolved challenges and open questions (see below), this state of affairs should not be used to justify premature use of implicit measures to tackle real-world problems, which may cause more damage than good when such endeavors are based on empirically unfounded assumptions. Despite our conflicting views on the importance of practical utility, we agree that implicit measures have made a tremendous contribution to research in both basic and applied psychology.

Challenges and Open Questions

Despite the breathtaking amount of basic and applied research using implicit measures, the field is still facing a number of unresolved challenges and open questions. These issues include the role of methodological factors in the interpretation of results obtained with implicit measures, the meaning and implications of their low temporal stability, their presumed value in predicting behavior and other psychological outcomes, and questions pertaining to the updating and change of underlying mental representations.

Methodological Issues

Although concerns about construct-unrelated effects on the outcomes obtained with implicit measures have been expressed for more than two decades, their significance is still underappreciated in many areas. Using Unkelbach and Fiedler's (this issue) conceptualization of this issue, construct-unrelated effects lead to a higher conditional probability of a measured attribute given the causal influence of an existing attribute *p*(MA+|EA+) compared to the conditional probability of an existing attribute in light of a measured attribute *p*(EA+|MA+). This asymmetry poses a challenge to diagnostic inferences of to-be-measured attributes from observed measurement scores (e.g., inference that a person has an attitude of the value X based on a measurement score of X). A potential solution to this problem is the use of formal modeling approaches that quantify the contributions of construct-related and construct-unrelated effects on the outcomes obtained with implicit measures (e.g., Conrey et al., 2005; Calanchini & Sherman, 2013; Calanchini, Sherman, Klauer, & Lai, 2014; Klauer et al., 2017; Meissner & Rothermund, 2013; Payne et al., 2010; Sherman et al., 2008; for a review, see Sherman et al., 2010). Formal modeling approaches can help to address not only some of the known challenges to diagnostic inferences (see Unkelbach & Fiedler, this issue); they have also demonstrated their value in providing more nuanced insights into the mechanisms underlying various phenomena and resolving paradoxical and seemingly nonsensical findings in the literature (Calanchini, this issue). However, a potential obstacle in the use of formal modeling approaches is the existence of multiple models that could be used to analyze the same data set, and the resulting need to decide which model is the most appropriate for a given task and data set. Calanchini (this issue) provides some valuable guidelines in this regard that may help researchers identify the most appropriate model for their study.

Another challenge is that implicit measures do not constitute a uniform category. In our discussion of single-process propositional theories, we have already mentioned the difference between traditional implicit measures that have been designed to measure mere associations between concepts and a new class of implicit measures that aim to capture specific relations between concepts (e.g., *I am good* vs. *I want to be good*). However, even the category of traditional implicit measures is not homogenous, in that correlations between measures of the same construct can be surprisingly low (e.g., Cunningham et al., 2001; Bar-Anan & Vianello, 2018; Olson & Fazio, 2003) and show different (and sometimes even opposite) effects of the same external factor (e.g., Degner & Wentura, 2010; Deutsch & Gawronski, 2009; Gawronski & Bodenhausen, 2005).

To address the interpretational challenges associated with these measurement-related issues, greater attention to three points may help to move the field forward (for a discussion of additional challenges, see O'Shea & Wiers, this issue). First, implicit measures vary considerably in terms of their internal consistency (Gawronski & De Houwer, 2014), which can reduce their correlations with each other (Cunningham et al., 2001) and their relative sensitivity to the same factor (LeBel & Paunonen, 2011; but see De Schryver, Hughes, Rosseel, & De Houwer, 2016). Second, implicit measures differ in terms of whether they measure responses to abstract categories or individual exemplars of a given category (Fazio & Olson, 2003), which can similarly influence their correlations with each other (Olson & Fazio, 2003) and their relative sensitivity to the same factor (Degner & Wentura, 2010). Finally, implicit measures differ in terms of their underlying mechanisms (Gawronski & De Houwer, 2014), which can lead to different effects of a given factor when this factor influences outcomes via measurement-related processes instead of effects on the to-be-measured construct (Gawronski, Cunningham, LeBel, & Deutsch, 2010). Greater attention to these issues is important not only for the sake of methodological rigor; it is also essential to prevent flawed theoretical conclusions about underlying processes and representations.

Temporal Stability

A related issue is the finding that implicit measures show a lower temporal stability of individual differences in measurement scores compared to explicit measures (Greenwald & Lai, 2020). For implicit measures that suffer from low internal consistencies, this finding may not be surprising, given that low internal consistency suppresses correlations with any measure, including measurements with the same instrument at a different time. However, the fact that even implicit measures with high internal consistencies have shown low stability of individual differences over time (e.g., Gawronski et al., 2017) raises the question of whether temporal fluctuations in measurement scores reflect properties of the measurement instruments or properties of the measured constructs. Based on the dominant view that implicit measures are supposed to capture trait-like characteristics, low temporal stability suggests a major deficit of the measurement instruments in capturing these characteristics. Yet, in contrast to this conclusion, some theories suggest that low temporal stability is a genuine feature of the measured constructs rather than a bug of the measurement instruments. For example, according to the bias-of-crowds model, responses on implicit measures of bias reflect the current accessibility of bias-related concepts, which can vary considerable over time and across contexts (Payne et al., 2017). Similarly, the network model of attitudes suggests that responses on implicit measures reflect attitudes in high entropy states, which tend to be inconsistent and highly unstable (Dalege & van der Maas, this issue).

At a broader level, the conflicting interpretations raise the question of whether responses on implicit measures reflect traits or states. Although this question is often framed in an either-or fashion, research using latent state-trait analyses suggests that such a framing is misguided, in that responses on implicit measures have been found to reflect both temporally stable traits and transient states (e.g., Dentale, Veccione, Ghezzi, & Barbaranelli, 2019; Koch, Ortner, Eid, Caspers, & Schmitt, 2014; Lemmer, Gollwitzer, & Banse, 2015; Schmukle & Egloff, 2005). However, even inclusive conceptualizations that consider the roles of both person-related and situational-related factors could be criticized for ignoring the role of person-by-situation interactions in determining responses on implicit measures (Gawronski & Bodenhausen, 2017). The significance of such interactions can be illustrated with the finding that the temporal stability of implicit measures is considerably higher when the task includes contextual stimuli that are meaningfully related to the target stimuli (Gschwendner, Hofmann, & Schmitt, 2008). These results suggest that the low temporal stability obtained in previous studies might be due to changes in incidental contexts that vary across individuals, and that individual differences within the same context are indeed relatively stable over time. A major challenge for future research using implicit measures is to move beyond one-sided frameworks that emphasize either person-related or situation-related factors to embracing alternative frameworks that explicate their complex interactions (e.g., Fleeson & Jayawickreme, in press).

Predictive Relations

Several meta-analyses suggest that average correlations between implicit measures and behavioral criterion measures are relatively small overall (Cameron et al., 2012; Greenwald et al., 2019; Kurdi et al., 2019; Oswald et al., 2013). Depending on meta-analytic inclusion criteria, type of measure, and statistical techniques, average correlations range from .14 (Oswald et al., 2013) to .28 (Cameron et al., 2012). Although it is common to administer implicit measures and behavioral assessments in the same session, low temporal stability might be an important factor in the use of implicit measures as predictive tools (for reviews, see Friese et al., 2008; Perugini, Richetin, & Zogmaister, 2010). To the extent that their measurement outcomes are inherently unstable, implicit measures may be of limited value for the prediction of behavior and other outcomes over time. Some researchers suggested that this limitation could be overcome by aggregating data from multiple administrations of the same implicit measure at different time points (Greenwald et al., 2020). A similar suggestion has been made more than 30 years ago to increase the predictive value of self-report measures of attitudes and personality traits (Ajzen, 1987), but its impact on research practices remained negligible, presumably because of its low practicality. A more practical solution might be to administer the implicit measure in the same context in which the to-be-predicted behavior will be observed, given that implicit measures may show higher temporal stability within the same context (Gschwendner et al., 2008).

Another historical lesson is that predictive relations between measures of attitudes and behavioral criteria increase as a function of their correspondence (Ajzen & Fishbein, 1977). For example, recycling behavior might show stronger relations to a measure of attitudes toward recycling compared to a measure of attitudes toward the environment in general. Although the correspondence principle has received considerable attention in attitude research using explicit self-report measures, it has received relative little attention in research using implicit measures. Yet, recent evidence suggests that greater correspondence might also increase predictive relations between implicit measures and to-be-predicted behavior (Irving & Smith, 2020; Kurdi et al., 2019).

The above considerations may at least partly account for the small average correlations between implicit measures and behavioral criterion measures obtained in meta-analyses (Cameron et al., 2012; Greenwald et al., 2009; Kurdi et al., 2019; Oswald et al., 2013). Extant dual-process theories similarly suggest that it might be mistaken to interpret these findings as evidence for the limited value of implicit measures for the prediction of behavior (e.g., Fazio, 2007; Strack & Deutsch, 2004). Instead, these theories suggest that predictive relations between implicit measures and behavior depend on whether the processing conditions imposed by the implicit measure correspond to the processing conditions of the to-be-predicted behavior (e.g., unintentional behavior resulting from low deliberation). The same is assumed to be true for the prediction of behavior with explicit measures. Together, these considerations suggest that predictive relations of either type of measure should be moderated by characteristics of the to-be-predicted behavior (what?), the conditions under which the behavior is performed (when?), and the person who is performing the behavior (who?).

Although numerous individual studies designed to test dual-process hypotheses about the moderators of predictive relations found considerable support for these assumptions (for a review, see Friese et al., 2008), meta-analytic evidence for the moderating role of the nature of the to-be-predicted behavior (e.g., spontaneous vs. deliberate) is rather mixed. In general, the available evidence suggests that, whereas different types of behavioral criteria measured within the same study showed the hypothesized moderation of predictive relations (Cameron et al., 2012), meta-analytic codings of different types of behavioral criteria across studies revealed evidence for the hypothesized moderation effects only for explicit, but not implicit, measures (Greenwald et al., 2019; Kurdi et al., 2019).

One potential conclusion from these findings is that the assumptions of extant dual-process theories are at least partly incorrect (Greenwald et al., 2009). Another possibility is that method-related factors contributed to the asymmetries obtained in comparisons of predictive relations across studies (Gawronski, 2019). For example, it is possible that measures of deliberate behavior tend to be more reliable compared to measures of spontaneous behavior (the latter of which are often assessed with a single item).[1] In conjunction with the hypotheses of dual-process theories, such an asymmetry would lead to strong relations between explicit measures and deliberate behavior (because of matching processing conditions with a reliable behavioral criterion) and weak relations between explicit measures and spontaneous behavior (because of mismatching processing conditions with an unreliable behavioral criterion). In contrast, implicit measures should show relatively weak relations to both spontaneous behavior (because of low reliability of the behavioral measure) and deliberate behavior (because of mismatching processing conditions). To the extent that studies on the moderators of predictive relations are more likely to control for differences in the reliability of behavioral criterion measures compared to meta-analytic codings of different types of behavioral criteria across studies, asymmetries in the reliability of behavioral criterion measures may explain the mixed evidence obtained in meta-analyses (Gawronski, 2019). These considerations suggest that the psychometric properties of behavioral criterion measures are essential not only for applied research on the prediction of domain-specific outcomes, but also for basic research on the mechanisms involved in the production of behavior.

An emerging theme in research using implicit measures is the prediction of aggregate outcomes at the regional level (in contrast to the prediction of people's behavior at the individual level). Although there is no meta-analytic summary of this novel line of work at this time, the available evidence suggests that relations between aggregate scores of bias on implicit measures at the regional level show relatively strong associations with aggregate levels of societal disparities, and these associations tend to be much stronger compared to the relatively weak

[1] A notable exception is the prediction of provider-to-patient communication and treatment recommendations in healthcare settings via implicit and explicit measures of racial bias (see Hagiwara et al., 2020). Whereas provider-to-patient communication qualifies as spontaneous and involves aggregate observations of multiple behaviors, treatment recommendations qualify as deliberate and typically involve only one behavioral observation.

associations between implicit measures of bias and discriminatory behavior at the individual level (Payne et al., 2017). Although this discrepancy is consistent with the assumption that implicit measures of bias provide information, not about the person who is completing the measure, but the broader context in which the measure is completed, a number of open questions would need to be addressed to permit stronger and more general conclusions about the meaning of these findings. First, virtually all research on predictive relations at the regional level have used the IAT, which has been criticized for measuring environmental (Karpinski & Hilton, 2001) or extrapersonal (Olson & Fazio, 2004) associations rather personal attitudes. These concerns raise the question of whether the observed relations at the regional level are limited to the IAT or if similar relations can be observed with other implicit measures. Second, although the theoretical meaning of predictive relations at the regional level are relatively clear for implicit measures of bias, it remains unclear whether an explanatory framework that focuses exclusively on contextual factors can be applied to other domains in which implicit measures have proven their predictive utility (e.g., romantic relationships; see Faure et al., this issue). Future research using implicit measures other than the IAT in content domains other than prejudice and stereotyping would be helpful to address these questions.

Updating and Change

A central question in research using implicit measures concerns the factors that lead to changes in their measurement outcomes, guided by the assumption that such changes reflect corresponding changes in underlying mental constructs. Early research on this question has focused heavily on differential effects on implicit and explicit measures, assuming that dissociations in terms of their antecedents provides information about the role of distinct learning mechanisms associated with responses on implicit and explicit measures (e.g., Gawronski &

Bodenhausen, 2006; Rydell & McConnell, 2006). However, due to inherent differences in the processing conditions imposed by the two kinds of measures, it is possible to explain every such dissociation in terms of either (1) learning-related mechanisms operating during the acquisition of new information, or (2) retrieval-related mechanisms operating during the expression of behavioral response (De Houwer et al., 2020; Heycke & Gawronski, 2020; see also Kurdi & Dunham, this issue). Indeed, the available evidence poses a challenge to the idea that responses on implicit measures can be used as a proxy for effects of a unique learning mechanism (e.g., automatic association formation) that is distinct from the learning mechanism underlying responses on explicit measures (Corneille & Mertens, in press).

Another central question in this area is how rapidly the representations underlying responses on implicit measures can be updated and changed. Whereas some studies suggest that responses on implicit measures are rather difficult to change (Lai et al., 2014), other research suggests that responses on implicit measures can change rapidly in response to minimal information (Cone, Mann, & Ferguson, 2017). Given that the former line of work has focused predominantly on pre-existing representations of well-known social categories (i.e., African Americans) and the latter on updating and change of newly created representations of previously unknown individuals, a potential explanation for the discrepant findings is that they are driven by the extent to which the underlying representations have become crystallized in response to multiple experiences over time. However, such an explanation is unable to account for the rapid updating of deep-rooted evaluations of well-known targets (Van Dessel, Ye, & De Houwer, 2019). Future research is still needed to clarify the factors that determine the (in)sensitivity of responses on implicit measures to new information, and why some factors are more effective in producing change than others.

Another important question in this area is whether changes on implicit measures are stable over time. While some studies obtained changes that remained stable over several days (e.g., Dasgupta & Greenwald, 2001; Kawakami, Dovidio, Moll, Hermsen, & Russin, 2000; Mann, Kurdi, & Banaji, 2020; Olson & Fazio, 2006), others studies found only short-lived changes that dissipated over time (e.g., Lai et al., 2016). Yet, reanalyses of the latter findings suggest that the observed mean-level effects conceal considerable variation at the individual level, in that participants' responses did not return to their preexisting levels (Vuletich & Payne, 2019). Instead, aggregate responses returned to regional averages with substantial variation at the individual level, consistent with the idea that implicit measures provide information about the broader context in which a person is completing the measure rather than the person who is completing it (Payne et al., 2017).

Complementing research on the stability of changes over time, some studies have investigated the generalization of change across contexts (see Gawronski & Cesario, 2013; Gawronski et al., 2018). A central finding of these studies is that, although counterattitudinal information about a target object may effectively change responses on implicit measures in the context in which this information has been learned, initial attitudes may continue to influence responses in other contexts, including the context in which the initial attitude was formed and novel contexts in which the target object had not been encountered before. These results raise the possibility that unstable changes over time may not necessarily reflect a temporal effect, but a change in the context during delayed follow-up measurements. Future research investigating the temporal stability of change in different contexts may help to disentangle unique effects of time and context.

Many studies on updating and change of responses on implicit measures are guided by the tacit assumption that, to the extent that responses on implicit measures change, behaviors that have been found to be related to responses on implicit measures will change accordingly. This assumption is based on the idea that (1) implicit measures provide access to specific mental representations and (2) these representations are causally involved in the production of behavior that is predicted by implicit measures. However, counter to this idea, a recent meta-analysis found no evidence for the hypothesis that changes on implicit measures would mediate corresponding changes in behavior (Forscher et al., 2019). One potential interpretation of this finding is that the representations underlying responses on implicit measures are not causally involved in the production of behavior that has been found to be correlated with implicit measures. However, an important caveat to such a conclusion is that external factors can influence the outcomes of implicit measures via measurement-related processes that are independent of the to-be-measured construct (Calanchini & Sherman, 2013; Calanchini et al., 2014; Gawronski, 2019; see also Calanchini, this issue). To the extent that these processes are irrelevant for the production of a focal behavior, a given factor may influence the outcomes of implicit measures without leading to corresponding changes in behavior. Consistent with this interpretation, the above-cited meta-analysis (Forscher et al., 2019) obtained the largest effect for experimental manipulations of executive control processes, which are more likely to influence responses via effects on measurement-processes rather than via changes in underlying mental representations.

Finally, one may question whether the idea of statistical mediation is conceptually appropriate for studying the relation between changes on implicit measures and changes in behavior. In a strict sense, implicit measures assess responses to stimuli, and such responses are behaviors, not mental representations (De Houwer, Gawronski, & Barnes-Holmes, 2013). From this perspective, it seems conceptually problematic to treat one type of behavior as a mediator of a different type of behavior, as it is done in statistical mediation analyses that treat change on implicit measures as a mediator of change in behavior. Nevertheless, the reviewed findings suggest that research on updating and change would benefit from making its tacit assumptions about behavior change explicit, so that they can become the subject of direct empirical tests. Such tests are important not only for basic research on the mechanisms underlying the production of behavior; they are also essential for applied research investigating the effectiveness of interventions in changing behavior.

Conclusion

Implicit measures have inspired an incredible amount of research since their “birth” 25 years ago. Although this work has produced invaluable insights for basic and applied psychology, some important questions remain to be addressed. Yet, regardless of what the final answers to these questions will be, it seems difficult to imagine a future of the field that does not entail a major role for implicit measures. A concerted effort to address unresolved issues may help to move the field forward, and the articles in this Special Issue may provide some helpful directions in this regard.

Following this introduction, the Special Issue starts with a focus on theory (Dalege & van der Maas, this issue; Kurdi & Dunham, this issue) and applications (Hagiwara et al., this issue; Faure et al., this issue). The subsequent contributions address central questions about the meaning of responses on implicit measures (Degner & Calanchini, this issue; Hahn & Goedderz, this issue; March et al., this issues) and fundamental measurement issues (Calanchini, this issue; O'Shea & Wiers, this issue; Unkelbach & Fiedler, this issue). The Special Issue concludes with two contributions offering outlooks and conceptual recommendations for future research (Rothermund et al., this issue; Van Dessel et al., this issue).

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Table 1. *Overview of currently available implicit measures.*

Measurement Instrument	Reference
Action Interference Paradigm	Banse et al. (2010)
Affect Misattribution Procedure	Payne et al. (2005)
Approach-Avoidance Task	Chen & Bargh (1999)
Brief Implicit Association Test	Sriram & Greenwald (2009)
Evaluative Movement Assessment	Brendl et al. (2005)
Evaluative Priming Task	Fazio et al. (1995)
Extrinsic Affective Simon Task	De Houwer (2003)
Go/No-go Association Task	Nosek & Banaji (2001)
Identification Extrinsic Affective Simon Task	De Houwer & De Bruycker (2007)
Implicit Association Procedure	Schnabel et al. (2006)
Implicit Association Test	Greenwald et al. (1998)
Implicit Relational Assessment Procedure	Barnes-Holmes et al. (2010)
Recoding Free Implicit Association Test	Rothermund et al. (2009)
Relational Responding Task	De Houwer et al. (2015)
Semantic Priming (Lexical Decision Task)	Wittenbrink et al. (1997)
Semantic Priming (Semantic Decision Task)	Banaji & Hardin (1996)
Single Attribute Implicit Association Test	Penke et al. (2006)
Single Block Implicit Association Test	Teige-Mocigemba et al. (2008)
Single Category Implicit Association Test	Karpinski & Steinman (2006)
Sorting Paired Features Task	Bar-Anan et al. (2009)
Truth Misattribution Procedure	Cummins & De Houwer (2019)