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What's Outside the Black Box?: The Status of Behavioral Outcomes in Neuroscience Research

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Over the last several decades there have been multiple shifts in the relative emphasis of mental processes versus behavior in psychological science, particularly in social psychology. Studies on one side of this *behavior-mental process* pendulum take behavioral measures (e.g., whether the participant will deliver shocks to another individual) as the primary outcome and view mental processes as occurring in an unobservable black box; studies on the other side adopt mental processes (e.g., attitudes) as the primary outcome and often do not assess relevant behaviors. From a broad perspective, this behavior-mental process pendulum has moved from the *behavior* side during the height of behaviorism in the 1960s, toward the *mental process* side in the 1980s and 1990s during the cognitive revolution (Miller, 2003). Despite the first years of the 21st century being heralded as the "Decade of Behavior" by the American Psychological Association, social psychology has maintained its focus on mental and neural processes with little evidence of a return to direct observation of behavior (Baumeister, Vohs, & Funder, 2007). The rise of social cognition and social cognitive neuroscience (Ochsner & Lieberman, 2001) has further emphasized a shift away from behavior and toward the empirical study of mental processes.

The target article by Kievit and colleagues (this issue) represents a considerable refinement of theoretical and statistical models that can be used to link neural with mental processes. Combining insights from philosophy with methods from psychometrics has great potential to advance the theoretical sophistication of the field. Although we applaud these innovations, we also believe one potential impact of their article is to push the social psychological pendulum even further in the direction of studies on mental processes. In this commentary, we explore the conceptual status of behavior in the models proposed in the target article with the goal of offering several ways to integrate behavior into these models. We also review recent studies by our group that provide the methodological tools to do so (one series on the relationship between response inhibition and smoking cessation, and another on how persuasion relates to health behavior change) and discuss theoretical and methodological considerations relevant to behavior in light of psychometric modeling.

Three Types of Data

Kievit et al. describe two classes of data: indicators of psychological or mental (P) processes, including paper-and-pencil assessments of stable individual differences and performance on tasks thought to assess mental processes, and indicators of neurological (N) processes such as task-related functional activation or brain morphology. Traditional social psychological approaches have also considered *behavior* (B) as a third type of data, and, critically, that the other types of data exist in order to support behavior. According to James (1890/1983), "my thinking is first and last and always for the sake of my doing" (p. 960; see also Fiske, 1992; Gollwitzer & Bargh, 1996). In contrast to a "black box" perspective, mental and neural processes in this pragmatic view of psychology are rendered observable and worthy of investigation insofar as they facilitate behavior.

We argue that behavior (i.e., action) deserves status as its own variable in the current conceptual framework aside from being an indicator of mental process. Aside from being a core phenomenon that social psychology aims to understand, behavior must be considered separate from P and N processes because (a) self-reports of behavior obtained using P-indicators often don't relate strongly to actual behavior and (b) any given behavior likely arises from an array of N processes that may be different across different contexts, and those processes likely simultaneously contribute to the behavior in different ways. First, even sensitive self-report measures cannot circumvent the fact that people are commonly unaware of how their behavior is impacted by situational factors. For example, in a classic study, West and Brown (1975) examined differences between one group of participants who viewed a (staged) accident and were given an opportunity to help by donating money to the victim (real behavior) and another group who merely read about the scenario and reported how much they thought they would give (a self-report of predicted behavior). Not only did the self-report group considerably overestimate how much they would help relative to the real behavior group, but they also were unaware that actual helping would be influenced by a situational factor—the attractiveness of the victim.

Another reason that behavior must be considered as a separate (third) type of data is that even simple actions involve a number of neural processes that cannot always be differentiated from one another. Poldrack and colleagues (Poldrack, 2010; Poldrack, Halchenko, & Hanson, 2009) have begun to develop the notion of a "cognitive ontology" that maps cognitive processes (i.e., P-indicators) into neural regions and networks (i.e., N-indicators) using neuroinformatics. They recently used this approach to classify psychological and neural subcomponents of "cognitive control" based on the results of a large number of neuroimaging studies indexed in the BrainMap database (Lenartowicz, Kalar, Congdon, & Poldrack, 2010). A cross-classification analysis revealed that "response selection" could be differentiated from "cognitive control," "response inhibition," or "working memory," but distinctions between the last three were difficult due to extensive neural commonality among the latter processes. The authors suggest that their results call into question the "ontological reality" of several proposed subcomponents of cognitive control. For our purposes here, the important point is that it is difficult to separate neural components of basic behaviors (e.g., response inhibition vs. working memory encoding), even in tasks that have been developed and refined to isolate these behaviors. If N-indicators are not sufficient to capture the distinctions between these tasks, they seem unlikely to be useful in explaining differences among more complex real-world behaviors (e.g., helping vs. not helping an accident victim). In other words, the mapping between behaviors and either neural or psychological processes is not one-to-one, so behavior must be measured separately from those other types of data.

Finally, we note that some of the behaviors that are most interesting to social psychologists are difficult or impossible to obtain along with N-indicators because the behaviors themselves (e.g., group-on-group aggression) or important situational factors relevant to the behaviors (e.g., social influence) simply cannot be reproduced realistically in the experimental settings where N-indicators are typically collected. This issue can be addressed in at least two ways. First, methodological and statistical advances will allow researchers to better integrate the disparate tools used to assess each of the three types of data. If some behaviors can only be captured faithfully as they occur during ongoing daily experience, then linking those behaviors to N-indicators will require methods to integrate longitudinal data with neuroimaging data. Just as Kievit et al. used structural equation modeling (SEM) to address conceptual issues with N- and P-indicators, others have begun to use hierarchical linear modeling to integrate daily B with P-indicators. Several studies that use this approach are reviewed next. Second, new methods for assessing brain function such as functional near-infrared spectroscopy are now available, and allow researchers to investigate N-indicators during ongoing behavior such as realistic face-to-face conversation (e.g., Suda et al., 2010). We anticipate that in the coming years these measures will be helpful in clarifying some of the issues addressed in the target article and in this commentary.

Integrating Behavior With N and P Variables

The target article provides two contrasting theoretical frameworks, *identity* and *supervenience* (each with a corresponding statistical model), that can be adapted to include behavioral measures. In this section we describe how behavior might be integrated using each of the frameworks and discuss open questions that remain to be resolved with each.

Behavior and the Identity Model

Under the identity model, B, N, and P variables are all considered indictors of the same underlying latent construct (see target article, Figure 1). The identity model posits that the intercorrelations among N,

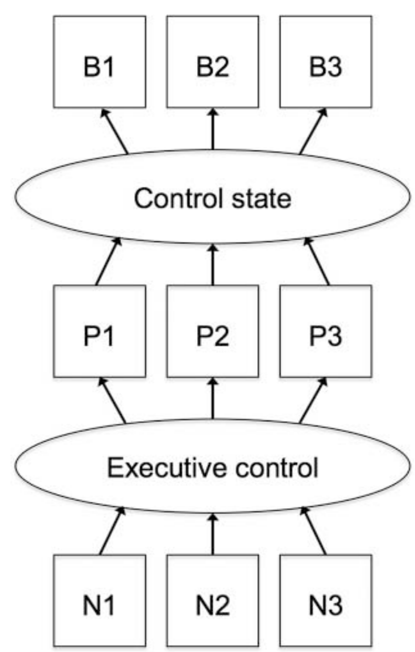

Figure 1. A multiple-indicator multiple-causes model of executive control including neurological (N) indicators of a psychological construct ("executive control"), which in turn alter psychological (P) indicators of a behavioral construct ("control state"), which in turn alter behavioral (B) indicators.

P, and B indicators are explained by their common dependence on the latent construct and are thus expected to be high. For example, suppose a researcher defines the latent construct "executive control ability" as indicated by a questionnaire measure of self-control (a P-indicator), neural activation in dorsolateral prefrontal activation during the task (an N-indicator), and a demonstrated ability to resist immediate temptations in exchange for larger long-term rewards (a B-indicator). Implications of the identity model include that all three of these variables have the equal ontological status as indicators of "executive control ability" and that the construct itself should be robust to changes in the indicators (i.e., "indicator indifference").

Although we do not present new data here, we can make some general conclusions about this model based on existing research. First, allowing P- and N-indicators equal status with behavior as indicators of some latent construct is a theoretical stance favored by some social psychologists whose primary aim is to understand mental processes but is not appropriate for those adopting a traditional pragmatic perspective. In this view, the purpose of psychological investigations is first to identify and explain a behavioral phenomenon (e.g., bystander nonintervention in emergencies) and then identify the hypothesized mediating internal mental processes (Baumeister et al., 2007). But the underlying theoretical orientation of identity models seems to be that the purpose of empirical measurement of any variables (by they behavioral, psychological, or neural) is to better characterize some latent construct (that explains the relations among those variables). The pragmatic approach to social psychology is less concerned with explaining why behavior and mental processes or neural indicators are highly correlated than it is in identifying the conditions under which behaviors of interest do and do not occur. For instance, in the "executive control ability" example just cited, the implied perspective of the identity model is that the ability to resist immediate temptations is highly correlated with self-report scores of self-control because they are both measurements of the same construct, but the pragmatic perspective seeks to understand when self-report measures would *diverge* from behavior and according to which moderating factors.

Second, the infamous disconnect between behavior and psychological processes presents a considerable problem for this class of models, which assumes indicators to be highly correlated. There are two main reasons why behavior doesn't always match up with mental states—one situational and one methodological. The situational reason is that behavior is determined by more than just the obviously corresponding mental processes alone; contextual variables have an enormous impact on behavior. Of course, these situations exert their influence via *other* mental processes, but ones that are easily overlooked or ignored because they are associated with unexpected situational factors. Health psychologists in particular have been concerned with this question, as intentions to change health behaviors explain only about a one fourth of the actual variability in health behavior (Webb & Sheeran, 2006). Factors such as the social context, implicit cues (e.g., primes), and mood are each important factors that can moderate the association between mental processes (e.g., the capacity to engage in executive control) and the actual implementation of that control (Aarts & Dijksterhuis, 2000; Fishbach, Eyal, & Finkelstein, 2010; Gollwitzer, Sheeran, Michalski, & Seifert, 2009). The methodological reason why behaviors don't always correspond to mental processes is because a common tool for assessing mental processes—self-reports of introspection—is prone to biases such as post hoc confabulation in certain circumstances. For example, forced-choice decisions made between similar options can be determined by trivial factors such as the left-to-right arrangement of the items, but the lay theories on which people base explanations of their own behavior do not account for these kinds of situational factors (Nisbett & Wilson, 1977).

The discordance between behavior and mental processes highlights another important issue—that the temporal dynamics of the measurements matter. Specifically, the reliability of the behavior–mental process link is decreased as time between measurements increases (Ajzen & Fishbein, 1977; Davidson & Jaccard, 1979). This is important when considering whether to measure behavior in the laboratory or in situ. On one hand, measuring behavior as it occurs in the real world is likely to increase the temporal gap between the behavior and the corresponding N and P measures and in turn to decrease the correlation between them, which in itself is a reason to discount the identity model. On the other, measuring behavior using a laboratory task (e.g., using a Stroop task to assess executive control rather than a more realistic intertemporal choice assessment) might increase the association between the "behavioral" measure and other measures acquired at that session by reducing the time between the measurements. The drawback of that option is that such laboratory measures of behavior (e.g., response time tasks) are distal from the phenomena of interest and might just as easily be classified as P-indicators as B-indicators. Indeed, Kievit et al. even seem to include laboratory measures that technically require "behavior" as such (e.g., "solving puzzle x", p. 8). We discuss this issue further in the next section, on the two kinds of behavior.

Behavior and the Supervenience Model

In the supervenience model presented in the target article, mental processes "supervene" on neural processes in the sense that the difference between two mental processes must be attributable to neural differences but that neural differences are not sufficient to produce different psychological states. Hence, the mapping of neural states to mental states can be many-to-one (see target article, Figure 4).

Behavior is easily integrated into this model because behavior supervenes on mental processes in just the same way that mental processes supervene on neural processes (Figure 1). This structure follows logically given the reasonable assumptions that (a) behavioral differences are attributable to mental state differences and (b) a difference in mental states does not imply different behaviors. In other words, there will be no differences in behavior if there are no differences in mental state, but different mental states don't necessarily imply different behaviors. Together, these imply that the mapping of mental states to behavior is many-to-one (e.g., there are many mental states that can lead one to engage in prosocial behavior). In terms of the "executive control ability" example, a supervenience relationship between behavior and mental states suggests that overcoming a temptation can be accomplished through a number of mental processes (e.g., distraction, self-control, or reappraisal), which together form the construct of executive control. This is a *formative* model in the sense that the mental components cause the behavior, and not vice versa, and are not ontologically substitutable.

This model has several implications that fit nicely with traditional social psychological models. First, supervenience allows for a given behavior to be determined by multiple constellations of mental states. For instance, the same behavioral output, for example, avoiding a temptation, might be determined by strong response inhibition but weak attentional distraction or strong distraction and reappraisal but weak response inhibition. A many-to-one mapping between mental processes and behavior is a logical way to resolve the apparent conflict between strong consistency in behavior across persons in some situations and enormous idiographic variation in P-indicators (e.g., experience or personality). Another elegant implication is that the correlation among the P-indicators need not be high (Bollen, 1984; see target article section on formative model properties). This less restrictive property captures situational variability in the psychological factors that determine behavior; the mental processes that are necessary and sufficient to generate a behavior in one context may not be the same in another. Finally, the supervenience relationship between behavior and mental states explains why for the same psychological processes might be involved in a divergent number of behaviors. For example, in the last 5 years "mindfulness" has been implicated in improved emotion regulation (Arch & Craske, 2006), relapse prevention of depression (Kuyken et al., 2008), improved attention (Jha, Krompinger, & Baime, 2007), reduced aggression (Borders, Earleywine, & Jajodia, 2010), improved learning (Schroevers & Brandsma, 2010), suicide prevention (Williams, Duggan, Crane, & Fennell, 2006), improved ethical (Riskin, 2009) and management decision making (Williams & Seaman, 2010), health behavior change (Dutton, 2008), and romantic relationship quality (Barnes, Brown, Krusemark, Campbell, & Rogge, 2007) just to name a few. The point is not that the construct of "mindfulness" is too broad to be useful but rather that behavior is multiply determined by a number of psychological processes operating in concert but in different ways under different contexts and goal sets.

Comparing the Two Models: Two Kinds of Behavior?

One of the key advances of Kievit et al.'s framework is that it provides an empirical way to compare identity and supervenience models. We do not dwell on the details here as they are explained in the target article. Instead, we briefly discuss one important factor to consider when integrating behavioral indicators into the models: the distinction between *proximal* and *distal* measures of behavior. We refer to *proximal* measures as those relatively close in time of measurement and conceptual definition to N- and P-indicators. For example, if fMRI BOLD signal during a go/no-go task is used as an N-indicator of "response inhibition," then behavioral performance during that task (e.g., response time or error rate) would be considered a proximal behavioral indicator of response inhibition because it is measured concurrently with the N-indicator and using the same task. In contrast, *distal* behavioral measures are relatively further away in time and conceptual space from the N- and P-indicators. Intertemporal choice about eating among dieters (rather than go/no-go performance) is an example of a *distal* behavioral measure that could be used with the N- and P-indicators from the previous example because it would be measured at a different time using a separate task from the other indicators.

Methodological and Statistical Considerations

We distinguish between these two types of behavior because the choice between them is likely to impact the correlations between the B-indicator and the other indicators, which in turn will differentially affect the fit of the models. Specifically, due to measurement effects (Podsakoff, Mackenzie, Lee, & Podsakoff, 2003) higher B–N and B–P correlations are more likely with proximal indicators and lower B–N and B–P correlations are more likely with distal indicators. Consequently, proximal behavior indicators will be biased toward identity models, and distal behavior indicators will be biased toward supervenience models. These facts are not necessarily a problem on their own—researchers could employ both types of behavioral variables in their models to account for these biases. A problem arises because neuroscientists tend to employ proximal behavioral measures and social psychologists tend to employ distal ones (Berkman & Lieberman, 2009), which could lead these two fields to adopt divergent theoretical models with regard to behavior (i.e., identity vs. supervenience, respectively) by virtue of a statistical artifact.

An obvious solution is for neuroscience investigations to add distal behavioral measures to their studies (which already include proximal ones along with the N-indicators). Some researchers have begun to do so, and we review several such studies next. But the more general problem with the model comparison approach that is illustrated by the "two types of behavior" issue is that models will be constrained by the quantity and quality of the data that go into them (Pitt & Myung, 2002; Roberts & Pashler, 2000). Further, as noted in the target article, the number of indicators used to define a construct can also significantly impact the construct (Diamantopoulos & Winklhofer, 2001), and this is especially relevant to the formative parts of the model shown in Figure 1. As stated earlier, these are not necessarily problems with the approach per se but can become problems to the extent that researchers are unaware of how their design decisions might impact results and therefore theoretical interpretation.

These issues are particularly relevant to the cognitive neurosciences where (a) subject time is expensive, (b) relatively small samples by the standards of structural equation modeling (<50) are the norm, and (c) multiple measures of any construct are rarely assessed. We present several studies next that begin to address some of these issues. Although we don't claim to have found the perfect way to integrate behavioral measures into models with P- and N-indicators, we believe that the studies discussed next point the way for future studies to do so while balancing many of the concerns raised in this commentary.

Examples of Research Integrating Behavior With P- and N-Indicators

The target paper by Kievit and colleagues comes at an opportune time for cognitive neuroscience, and particularly for social and affective neuroscience. The field is beginning to take stock of its past work, which can largely be characterized as exploratory in the sense that it was primarily concerned with identifying brain regions involved in particular psychological processes, and contemplate its path for the future with a particular emphasis on how it can best answer psychological questions (see Diener, 2010; Miller, 2010; Poldrack, 2010; Shimamura, 2010). We have contemplated this question and believe that one of the best ways is to recover the emphasis on actual behavioral measures that was lost by social psychology during the cognitive revolution (e.g., Cialdini, 2009). Along with our colleagues, we have begun a program to do just that. Next we describe a few such studies, discuss how they might fit within the conceptual framework offered in the target article and elaborated here, and explain a few of the methodological and statistical advances that we made in the process.

Cigarette Smoking Reductions and Response Inhibition

"Response inhibition" refers to the process of preventing or stopping a prepotent behavioral response before it is fully executed. As an important subcomponent of executive control, response inhibition has been studied extensively in the cognitive neurosciences, mostly using simple response time tasks such as the Stroop, stop-signal, and go/no-go. Success on these tasks presumably requires engagement of the psychological process of "response inhibition" (P-indicator) and the relative neural activation during the tasks (e.g., *no-go* or *stop* trials relative to *go* trials) is taken as a measure of the brain systems engaged by response inhibition (N-indicators). However, a key reason to study response inhibition (and executive control more generally) is to understand how it impacts behavior in the real world (B-indicators), and this goal has been largely neglected by neuroscience studies.

We conducted a study to integrate behavioral indicators of response inhibition into an existing paradigm in the context of cigarette smoking cessation (Berkman, Falk, & Lieberman, 2011). Thirty-one heavy smokers who intended to quit smoking (but had not yet begun to reduce intake) were scanned using fMRI during a standard go/no-go response inhibition task. This task provided concurrent N- and P-indicators of response inhibition based on task-related neural activation and task performance, respectively. (We follow Kievit et al. here in considering task performance to be a P-indicator but note that it may also be considered a proximal B-indicator.) Measures taken at this session are referred to here as "baseline" measures.

We also collected a novel behavioral indicator of response inhibition following the scan. As participants embarked on their quit attempts following the baseline session, we tracked their progress in detail for 3 weeks using dense experience sampling throughout each day. Participants reported their immediate craving for cigarettes and their recent cigarette smoking (i.e., smoking since the previous signal) at each of eight daily time points by responding to a text message from the experimenter. These measures allowed us to calculate an ecological behavioral measure of response inhibition based on the prospective relationship between craving and subsequent smoking. For example, a subject who reported high levels of craving at 10 a.m. and then reported having smoked two cigarettes at the following signal (at 12 p.m.) was treated as having had a response inhibition failure between 10 a.m. and 12 p.m. These self-reports of smoking behavior were corroborated with two biological measures of cigarette smoking (urinary cotinine and exhaled carbon monoxide).

Using hierarchical linear modeling, we estimated the time-lagged within-day slope between craving (at time t) and smoking (at time $t+1$) for each participant. Estimates of response inhibition-related neural activation from the baseline session were entered into the model and allowed to moderate the craving-smoking slope. Results showed that our neural measure of response inhibition from the baseline session significantly moderated the behavioral indicator of response inhibition that was derived using experience-sampling data (Figure 2). Task performance during the baseline scan (a presumptive P-indicator) was relatively high and uniform across subjects and consequently did not relate to the craving-smoking link (a relatively distal behavioral indicator).

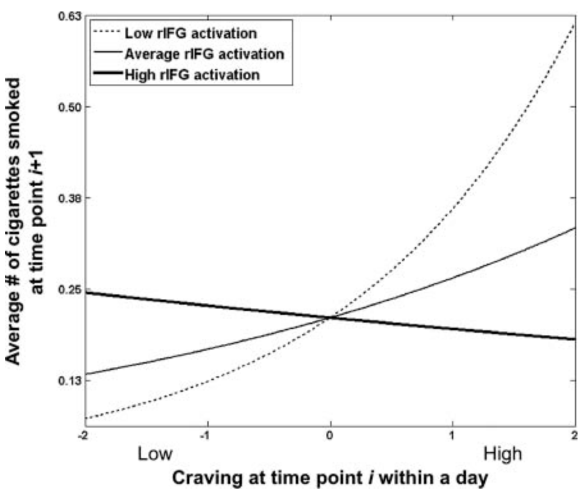

Figure 2. The moderating effect of response inhibition at baseline on the association between craving and smoking across 3 weeks of in situ smoking cessation (Berkman et al., in press). *Note.* Activation in right inferior frontal gyrus (rIFG) in the response inhibition contrast (no-go > go) moderates the relationship between cravings at one time point and smoking at the subsequent time point (log-slope = –0.29, $SE = 0.12$), $t(2391) = 2.38$, $p < .05$. Individuals with low activation in rIFG (–1 *SD* of the mean) in the [no-go > go] contrast showed a strong positive relationship between cravings and subsequent smoking (simple slope (log units) = 0.53), $t(25) = 2.79$, $p < .01$, individuals at the mean showed a modest positive relationship (simple slope (log units) = 0.24), $t(25) = 1.20$, *ns*, and individuals with high activation (+1 *SD* of the mean) showed no relationship between craving and smoking (simple slope (log units) = –0.04), $t(25) = 0.21$, *ns*. This analysis controls for the linear decline in smoking across days, the negative quadratic pattern of smoking within each day, and baseline nicotine dependence.

These results are interesting not only because they demonstrate the ecological validity of neural measures of response inhibition but also because they illustrate a couple of the key points made in this commentary. First, this study shows that real-world behavior can realistically be integrated into traditional cognitive neuroscience studies with meaningful results. Taken together with the statistical models described in the target article, these results point the way forward in bringing behavioral measures back together with P- and N-indicators. Second, the lack of association between the P-indicator (task performance on the go/no-go task at baseline) and the B-indicator (daily craving-smoking link) is consistent with our analysis on distal behavioral measures. Countless other factors might influence behavior when it is observed in situ outside of the laboratory—factors that are important to identify and understand. For example, in another paper on this data set we found that negative mood was an important moderator of the daily craving-smoking link (Berkman, Dickenson, Falk, & Lieberman, 2011). This finding is consistent with a *multiple-indicators multiple-causes* model of P-indicators to B-indicators and provides further evidence of the value of real-world behavioral data in addition to psychological and neural indicators.

Health Behavior Change and Persuasion

The discrepancy between stated attitudes about health behavior and actual changes in health behavior continue to be a hot topic of study in health psychology (e.g., Webb & Sheeran, 2006). We sought to address this problem in a series of studies led by Falk by attempting to explain additional variance in health behavior, above and beyond self-report measures, using neuroimaging (Falk, Berkman, & Lieberman, 2011; Falk, Berkman, Mann, Harrison, & Lieberman, 2010). To use the terminology of Kievit et al., we added N-indicators to an area that traditionally only uses B- and P-indicators.

In a first study, participants were scanned using fMRI while they were shown persuasive messages about increasing sunscreen use (Falk et al., 2010). Sunscreen use was chosen because it is a common health behavior, and our participants were preselected to have weak preexisting attitudes about it. We measured attitudes and intentions about sunscreen use before and immediately after the message exposure (P-indicators), and then measured change in sunscreen use 1 week later (a distal B-indicator). Neural activation in a predefined region of interest in the medial prefrontal cortex (MPFC) uniquely explained about 25% of the variance in behavior change above and beyond self-report. In other words, just as in the study on response inhibition and smoking, part of the neural activation that related to behavior was not explained by traditional self-report measures of psychological processes. A second study replicated these results using cigarette smoking cessation, a more meaningful and health-relevant behavior (Falk et al., 2011). This study found that neural activation in MPFC during exposure to persuasive messages (quit smoking television advertisements) was predictive of quitting behavior above and beyond self-reported intentions and attitudes.

An important implication of these studies is that the psychological processes that drive behavior may be only partially known or accessible to self-report. As a consequence, any study based purely on P-indicators may be missing important moderating factors. Neural indicators together with behavior can help triangulate missing psychological processes that might be relevant. For example, the fact that activation in MPFC—a region often associated with self-related processing—predicts behavior change above and beyond reported persuasion hints that self-related processing (e.g., a match between the message and current personal goals) might be an important psychological process in health behavior change that people do not typically include in their subjective reports of persuasiveness. Distal measures of behavior may be particularly useful because they can capture subtle situational and personal factors that may be overlooked or inaccessible to introspection or narrow experimental measures of psychological processes. In this way, measures of behavior that occur in the context of ongoing daily experience are critical to building a complete model of the link between neural measures and psychological processes.

Concluding Remarks

Kurt Lewin's (1943) famous formula states that behavior is a joint function of person and environment. Kievit et al.'s target article exemplifies a trend in recent years in psychology and neuroscience to focus on the "person" piece of the equation in exquisite detail by examining neural and internal mental processes. However, much of this detail has come at the expense of neglecting the other two components—behavior and environment. We have argued here that Lewin is essentially correct in two ways, and modern empirical psychology would benefit from revisiting his theory. First, Lewin (and others) believed that the fundamental goal of psychology should be to explain human behavior and that mental processes are important insofar as they are mediators of that behavior. Second, behavior must be understood as an interaction between the person and the environment. Because the psychological processes that are reflective of the environment can be difficult to assess with self-report (e.g., contextual primes or cue-induced mood), measuring behavior and psychological processes in situ using methods such as experience sampling are critical to obtaining a complete understanding of behavior.

Careful theoretical work is necessary to integrate behavior into existing models of the relationship between neural and psychological processes. Kievit et al. have done much of this work by providing a psychometric framework for empirically comparing models of this relationship. We have extended their model to include behavior and have suggested a few other issues to consider, particularly the distinction between *proximal* and *distal* measures of behavior. Of course, there is still considerable work to be done both statistically and theoretically. To give two examples, it would be useful to have an SEM model (similar to Figure 1) that allowed for hierarchical nesting of multiple behavioral measures, or for the latent behavioral construct (in the formative model from psychological to behavioral processes) to be better specified. We hope that the framework described here provides a foundation for future studies to address these and other outstanding issues.

Note

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