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A Theory Integration Program

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Psychology's most vital challenge is to strengthen its theoretical fundament. Popper's program of competitive testing and the development of unified theories are 2 common routes toward this end. This article proposes a third and complementary route: the integration of already existing theories. To provide a systematic framework, I propose a 2-step theory integration program. The first step is integration of phenomena, that is, the study of how apparently disparate robust observations are theoretically connected, not just empirically correlated. The second step is integration of theoretical concepts, that is, the study of how apparently different explanatory concepts are linked. Links between phenomena or concepts include identity, nesting, and functional equivalence. Functional equivalence means that 2 or more psychologically distinct theoretical concepts can be shown to imply the same behavioral pattern by vicarious functioning. The 2-step program requires formalization and close attention to operational and conceptual definitions. It should not be seen as an algorithm that can be automatically applied, but as a heuristic method requiring creativity for building a network between theories.

Keywords: theory, metatheory, integration, functional equivalence

This article addresses what is arguably the most critical task of psychology, the continuing development of its theoretical fundament. Two routes toward this end have been taken. The first is the competition between existing theories, as envisioned by Karl Popper: science progresses by successively eliminating theories until ideally one survives that cannot be rejected. This program emphasizes the "context of justification" and has fueled progress in statistical hypothesis testing and model selection criteria. At the same time comparatively little attention has been paid to the "context of discovery," which Popper tried to eliminate from the philosophy of science. For him, discovery was a matter of intuition and other nonlogical factors not worthy of attention, consistent with his out-of-hand dismissal of psychology as "riddled with fashions, and uncontrolled dogmas" (Popper, 1970, pp. 57–58). In this view, proper scientific discourse is about testing theories, not constructing theories.

The second route taken is the formation of unified theoretical frameworks, as exemplified in J. R. Anderson's (1983, 1990) and Allen Newell's (1990) efforts to generate unified theories of cognition. In the field of decision making, similar efforts have been undertaken, among others, by decision field theory (Busemeyer, Jessup, Johnson, & Townsend, 2006) and by my own work on the ecological rationality of heuristics (Gigerenzer, Hertwig, & Pachur, 2011). Among the social sciences, neoclassical economics has pursued the second route most rigorously, transforming economics from its pre-1930s verbal and diagrammatic mode into the mathematical and quantitative mode that has unified the field since, with rational choice theory as the template for all behavior, micro and macro (Samuelson, 1947).

These two programs are not the same, and they can conflict. On the one hand, adhering to a unifying framework can push competitive testing of theories into the background. For instance, models inspired by rational choice theory are rarely tested against competing models outside this framework, tend to be driven by auxiliary assumptions, and are sometimes up-

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held despite contradicting data (Jones & Love, 2011; Simon, 1991). On the other hand, a sole emphasis on competitive testing of low-level theories or on null hypothesis testing may divert from the ideal of building unified theories.

This article is about a third, complementary way toward theoretical development: the integration of *existing* theories. Scientific progress can result not only from the elimination of theories but also from integration. Whereas the growth of knowledge is sometimes pictured in analogy to the survival of the fittest and elimination of weak theories (Popper, 1972), the theory integration program envisions growth through building networks between theories. Its general task is to detect coherence among current theories. This program differs from my earlier work on the tools-to-theories heuristic (Gigerenzer, 1991; Gigerenzer & Goldstein, 1996), which is about the coherence between scientific tools and theories. Both programs, however, are intended to contribute to our understanding of the context of discovery, liberating it from Popperian exile.

Theory integration is not a new idea. Charles Darwin tried to explain inheritance by pangenesis, not having read Gregor Mendel's work. Only when Mendelian genetics and Darwinian theory were combined in the early 20th century did biologists begin to understand the mechanisms of inheritance, eventually leading to the discovery of DNA. Albert Einstein spent the latter part of his life unsuccessfully searching for a unified field theory and is said to have been so obsessed with unification that he continued the search on his sickbed up to the day before he died.[1] Other physicists have since devoted their careers to integrating general relativity and quantum theory.

In contrast to the fields of biology and physics, psychology as a whole is not known for striving to integrate theoretical concepts from different theories into a common network. Concern about lack of integration has been voiced for years (Fiedler, 1991; Kagan, 2012). Contact between theories is mainly in the form of competition rather than integration (Katsikopoulos & Lan, 2011), a form of rivalry with a long tradition. For instance, the schism between the experimental and the correlational subdisciplines has been repeatedly taken up in the presidential addresses before the *American Psychological Association:* In the 1938 address, John F. Dashiell complained about both the autonomy of frameworks and their direct antagonism. In the 1957 address, Lee J. Cronbach repeated the diagnosis, and in 1975 he judged "theoretical progress to have been disappointing" (Cronbach, 1975). The resulting patchwork of theories resembles the political map of Germany and Italy before 1870: mostly small and loosely related territories that occasionally battle but mainly ignore each other. As Walter Mischel (2008) put it, "Psychologists treat other people's theories like toothbrushes—no self-respecting person wants to use anyone else's."

A Two-Step Program

In this article, I sketch out a program for theory integration in two steps: the integration of empirical phenomena and that of theoretical concepts. The term *step* does not imply a linear sequence; I use it in an analytical, not necessarily temporal sense. Nor is the program intended to be a recipe for an automatic route toward integration. Rather, it is a heuristic method, one that provides a direction of search but also requires analysis and creativity.

Above all, integration requires meticulous attention to details, operational definitions, and clarity of explanatory concepts. It cannot be achieved at an abstract level alone. Rather, it may begin by analyzing a single pair of phenomena or concepts that first need to be operationally defined, followed by an investigation of how they are theoretically connected. If the connection can be worked out, the next phase is to add further phenomena (concepts) to create a network with precise relations. The two steps build on each other, but there is a feedback loop: clarifying the relation between concepts can hone our understanding of what exactly the phenomena are, while a better understanding of the relation between phenomena can enhance the identification of concepts (Figure 1).

In following these steps, the goal of the theory integration program is not reductionism, such as trying to reduce psychology to physiol-

[1] http://www.aps.org/publications/apsnews/200512/history.cfm

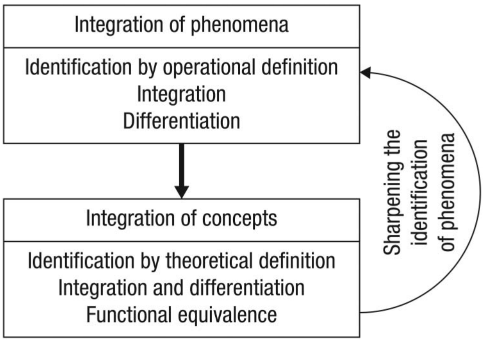

Figure 1. A two-step program for theory integration.

ogy and mental processes to neural ones. Instead, its goal is to connect existing theories. Nor does the program aim to replace all psychological theories with a single one. Its goal is more modest: to achieve a higher degree of coherence within psychology.

To illustrate the general program of integration, I draw on my own areas of expertise, but the program can and should be applied to all areas of cognitive science. These illustrations have been selected with the intention of showing *how* integration can be achieved in a number of small steps and by attention to operational details.

Step 1: The Integration of Phenomena

A phenomenon is a replicable empirical observation or empirical generalization, typically demonstrated by means of an experiment. One common class consists of functions that specify the *quantitative* relation between two variables. Examples are Weber's law ($\Delta I/I = k$, where ΔI is the jnd and I is the stimulus intensity, both measured in physical units, and k is a constant) and Fechner's law ($S = k \log I$, where S is the sensation). Another class of phenomena describes the conditions for the emergence of *qualitative* experiences. Wertheimer's (1912) phi phenomenon is a case in point, where the rapid temporal succession of two static pictures in different locations, such as two dots, causes us to perceive a continuous movement. Psychological research has uncovered hundreds of phenomena, which are often grouped in terms of the cognitive "faculties" involved: visual illusions such as the phi phenomenon, memory phenomena such as the hindsight bias, or judgment phenomena such as preference reversals. A phenomenon may or may not have an explanation—determining this is the task of explanatory concepts and theories.

A necessary first step toward theory integration is to analyze whether and how two phenomena are theoretically related. Establishing a theoretical relation entails more than an empirical demonstration that two phenomena are correlated (although the latter can be a cue to search for the former): It requires showing that one phenomenon is part of the second or that some other functional relationship exists between the two.

Before investigating the relation between two phenomena, it is necessary to specify clearly what these phenomena actually are. The label for a phenomenon needs to be separated from its operational definition, given that one and the same label is sometimes used for operationally different phenomena and a single phenomenon may have multiple labels (Mousavi & Gigerenzer, 2011). For instance, "framing" is not a phenomenon but a label for a class of phenomena that can be operationally quite distinct; the same holds for "priming" (Shanks et al., 2013). Defining a phenomenon operationally requires close attention to the experimental design that produces it. This facilitates determining whether two phenomena are connected and whether phenomena with the same label are different.

Thus, Step 1 encompasses three objectives:

1.1. Identification of phenomena by operational definition.
1.2. Integration of phenomena.
1.3. Differentiation of phenomena.

The goal of Step 1 is to create, piece by piece, a network of phenomena that specifies their relations, based on their operational definitions. With such a network in place, it is possible to make predictions about when a phenomenon is to be expected or not and about the size of the effect. Why a phenomenon appears is not explained; that is the task of the next step. At Step 1, integration is obtained not by deduction from theory (see Step 2) but by careful attention to the *cognitive processes implied by the experimental task.*

Example of Procedure

Consider two apparently distinct phenomena: the *reiteration effect* and the *hindsight bias*. In research and textbooks, the two phenomena are listed separately and treated as unrelated. I will define them in detail; as we will see, these operational specifications are necessary.

A reiteration effect occurs if (a) people's (average) confidence in the truth of an assertion increases after the assertion is repeated, and (b) this effect is independent of the actual truth and falsity of the assertion (Hasher, Goldstein, & Toppino, 1977).

Numerous politicians, from the Roman statesman Cato, who is said to have reiterated his call to destroy Carthage at the end of each speech, to Napoleon to Ronald Reagan have exploited it. Research on this effect is a good illustration of the strategy of taking an observation from the real world and studying it in the laboratory. The phenomenon can be operationally defined in a precise way. In a *reiteration design*, a set of assertions is presented at multiple, successive time points (typically 2 or 3 times, one week apart), and participants are asked each time to rate their confidence that the assertions are correct. The confidence that a person has in an assertion P (e.g., "Prohibition was called the noble experiment") is measured on a scale from 0% to 100%:

$$\text{Reiteration effect: Confidence } c \text{ in an assertion } P \text{ increases with each repetition of } P. \tag{1}$$

The size of the reiteration effect is $a = c_1 - c$, where c is the confidence before the first repetition and c_1 the confidence after it, with $a > 0$. The effect size for the second repetition is typically smaller and can be calculated in the same way. The reiteration effect has been documented in numerous experimental studies, with both convenience samples of students (Arkes, Hackett, & Boehm, 1989) and representative samples of the general public (Gigerenzer, 1984).

In a *hindsight design*, the dependent variable is not belief in P, but recall of one's belief in it. Confidence is measured in the same way as in the reiteration design. At Time 1, participants are asked to state their confidence c in the truth of an assertion P. Later, at Time 2, they learn whether the assertion is true or false (e.g., "The assertion 'Prohibition was called the noble experiment' is true"), and at Time 3, they are asked to recall their confidence judgment for each P at Time 1. A hindsight bias occurs if (a) the (average) recalled confidence r systematically deviates from c, and (b) in the direction of the feedback provided (true or false):

$$\begin{aligned}\text{Hindsight bias: } & \text{If } P \text{ is true, then } r > c;\\ & \text{If } P \text{ is false, then } r < c.\end{aligned} \tag{2}$$

The absolute difference $|r - c|$ is the size of the hindsight bias. For instance, if a person was 60% confident in the truth of P at Time 1, then learned that P is true, and finally recalled having been 80% confident, a hindsight bias occurred with a size of 20 percentage points. The size of the hindsight bias is typically larger than that of the reiteration effect. A puzzling observation is that for true assertions, the size of the hindsight bias is larger than for false ones. Hindsight bias in confidence is one of the best-documented memory phenomena (Hawkins & Hastie, 1990; Hoffrage & Pohl, 2003). Similar to the reiteration effect, the hindsight bias has been evaluated by some researchers as a cognitive fallacy and by others as a byproduct of adaptive memory. Moreover, it is a phenomenon without explanation in terms of a formal process model; the only exception I am aware of is Hoffrage, Hertwig, and Gigerenzer (2000).

The details given here and the operational definitions are essential because, as we will see, other phenomena are also called hindsight biases. Now one can ask: are the two phenomena connected, and if so, how? "Connected" can mean that they are identical (one can be reduced to the other), that they are nested (one is part of the other), or that they are related in some other way. A closer analysis of the hindsight design reveals that, unlike in the *knew-it-all-along design* (see below), participants encounter the assertion P twice, first at Time 1 and then when they are asked to recall their original confidence (Hertwig, Gigerenzer, & Hoffrage, 1997). Thus, the observed hindsight bias $r - c$ includes a genuine hindsight effect β and a reiteration effect a:

$$\text{If } P \text{ is true: } r - c = a + \beta;$$
$$\text{If } P \text{ is false: } r - c = a - \beta. \quad (3)$$

That is, the two phenomena are nested in the hindsight bias design. Uncovering this relation also explains the asymmetry of the observed hindsight bias: The effect is larger for true assertions because a and β add up, whereas for false assertions, a and β pull in opposite directions. Moreover, Equation 3 enables the asymmetry to be quantified.

Resolving Apparently Inconsistent Results

Connecting two phenomena leads to new predictions as well as to understanding the logic behind apparently inconsistent results in previous research. Equations 1 to 3 imply that the asymmetry in the hindsight bias occurs when the bias is tested with assertions (as above), but not with questions (e.g., "How long is the river Nile?"). A question does not assert a truth, and thus the reiteration effect does not apply; $|r - c| = \beta$, independent of the veracity of an assertion. Choosing assertions or questions was previously considered a matter of taste rather than theory, and inconsistent results were viewed as a puzzling fact rather than a theoretical implication of the nesting of the two phenomena. Similarly, the fact that the two phenomena are nested leads to the nontrivial and counterintuitive prediction that even when no feedback is given at Time 2 in a hindsight design, recalled confidence is larger than original confidence ($r - c = a$). These theoretical predictions are supported by experimental evidence (Hertwig et al., 1997).

Integration Enables Differentiation

Integration also leads to differentiation of phenomena that have previously been labeled identically. For instance, it clarifies that the hindsight bias, as defined here, differs from the *knew-it-all-along effect*, although these terms are sometimes used interchangeably. Unlike the hindsight bias, this effect is obtained in an experimental setting without recall: The task is to estimate the probability that an outcome X is obtained (e.g., children were accidentally killed) when an action Y is taken (e.g., drone attack on a suspected site). The knew-it-all-along effect occurs when participants estimate the probability $p(X|Y)$ to be higher after being told that X actually occurred than when told that it did not. The knew-it-all-along design involves feedback about the truth of X but not memory about an earlier judgment (no β) or the repetition of assertions (no a). Thus, these two phenomena are not the same.

More generally, experimental observations with one and the same label may turn out to deal with (partially) unrelated phenomena. Another case is the "overconfidence bias," which is a label for half a dozen logically independent phenomena (Juslin, Winman, & Olsson, 2000; Moore & Healy, 2008; Olsson, 2014). For instance, one common definition of overconfidence is $c - pc > 0$, that is, mean confidence is larger than percent correct. A second definition is *miscalibration*, that is, a mismatch between confidence and percent correct across all levels of confidence. For instance, when people say 100% confident, the percent correct is 80%, and when people say 80% it is 60%, while when people say 0% it is 20%, and when they say 20% it is 40%. Yet a difference of zero ($c - pc = 0$; that is, no overconfidence of the first kind) is compatible with any degree of overconfidence of the second kind, from perfect calibration to extreme miscalibration (Gigerenzer, Fiedler, & Olsson, 2012). Moreover, neither of these two phenomena are the same as the *better-than-average effect* (Larrick, Burson, & Soll, 2007), which is also sometimes called *overconfidence*. The practice of using the same label for logically and operationally different phenomena impedes progress in Step 2.

Similarly, priming appears to be not a phenomenon but instead a set of observations whose relations are unclear. It includes both precise computational models (e.g., Schooler, Shiffrin, & Raaijmakers, 2001) and less clear observations that lack both operational definition and a theory that implies what the phenomenon is (see Figure 1, feedback arrow). For instance, the priming phenomenon (if it exists at all) that individuals answer more general knowledge questions correctly after being asked to write down the attributes of a professor as opposed to those of a soccer hooligan appears to differ from the priming of self-related stereotypes—such as when the stereotype of an "African American" is activated for African American individuals, raising state anxiety (Shanks et al., 2013).

Precise identification of a phenomenon and differentiation between phenomena are the sine qua non for replication, and these measures aid understanding what would otherwise be considered puzzling empirical inconsistencies or failures of replication (Pashler & Harris, 2012).

Step 2: The Integration of Concepts

Theoretical concepts explain and predict phenomena. Examples include *chunks* and *buffers* in theories of memory, *aspiration levels* and *lexicographic search* in theories of heuristic decision making, and *criterion setting* and *sensitivity* (d') in signal detection theory. A theoretical concept is not the same as a theory, which is a network of concepts. For instance, criterion setting is a central concept in signal detection theory (Tanner & Swets, 1954) and error management theory (Johnson, Blumstein, Fowler, & Haselton, 2013) that balances the hit rate and false alarm rate, but it is not the theory itself.

Conceptual integration is as challenging a task as the integration of phenomena. This second step comprises four objectives (including one feedback loop):

2.1. Identification of concepts by theoretical definition.
2.2. Integration and differentiation of concepts.
2.3. Analysis of functional equivalence of concepts.
2.4. Using 2.1–2.3 to improve the identification of phenomena.

Theoretical definition of a concept is as important as the operational definition of a phenomenon. Integration and differentiation are not possible without a certain level of precision. For instance, the concept *availability heuristic* has been used for at least five vaguely characterized cognitive processes: ease, imagined ease, number, recency, and salience (Gigerenzer, 2006), which appear to be not even empirically correlated (Sedlmeier, Hertwig, & Gigerenzer, 1998). As a consequence, integration into a larger theory has not occurred. To remedy this, Steps 2.1 and 2.2 need to be taken. In Step 2.3, the term *functional equivalence* means that two different concepts are equivalent in producing the same phenomenon, but with different cognitive means.

The following example illustrates Steps 2.1 to 2.4. Again, the emphasis is on the process of integration, not on its content. To begin with, integration requires clearly defined concepts. In order to study the relation between two concepts, it can hence be of advantage if one of them stems from a theory in which the network of concepts is formally defined.

Example of Procedure

Consider *fast-and-frugal trees*, a class of heuristics used by experts to categorize people or objects in situations of high uncertainty. Formally, a fast-and-frugal tree with n binary cues has $n + 1$ exits, one at each cue and two at the final cue, which enables a categorization to be made as soon as the first exit is hit (Martignon, Vitouch, Takezawa, & Forster, 2003). In comparison, a full tree has 2^n exits. Figure 2 shows four fast-and- frugal trees, each with three cues. Consider the tree on the top left side. Every year, British magistrates make millions of decisions about whether to bail a defendant unconditionally or to react punitively by bailing with conditions such as curfew or imprisonment. How do they make these bail decisions, based on dozens of varying pieces of information available about the defendant? The tree models how London magistrates make their decisions (Dhami, 2003). When the prosecution requested conditional bail or opposed bail, the magistrates also made a punitive decision. If not, or if no information was available, a second reason came into play: whether a previous court had imposed conditions or remanded in custody. If the answer was yes, a punitive decision was made. Otherwise, a third cue led to the final decision.

The tree on the top right models how emergency physicians in Michigan hospitals decided whether to assign patients with severe chest pain to the coronary care unit (i.e., suspicion of heart attack) or to a regular nursing bed (no suspicion of heart attack; Green & Mehr, 1997). Like the magistrates, they went through a sequence of cues, after each of which a decision could be made. The bottom left tree models how soldiers at checkpoints in Afghanistan should decide whether an incoming car is likely to

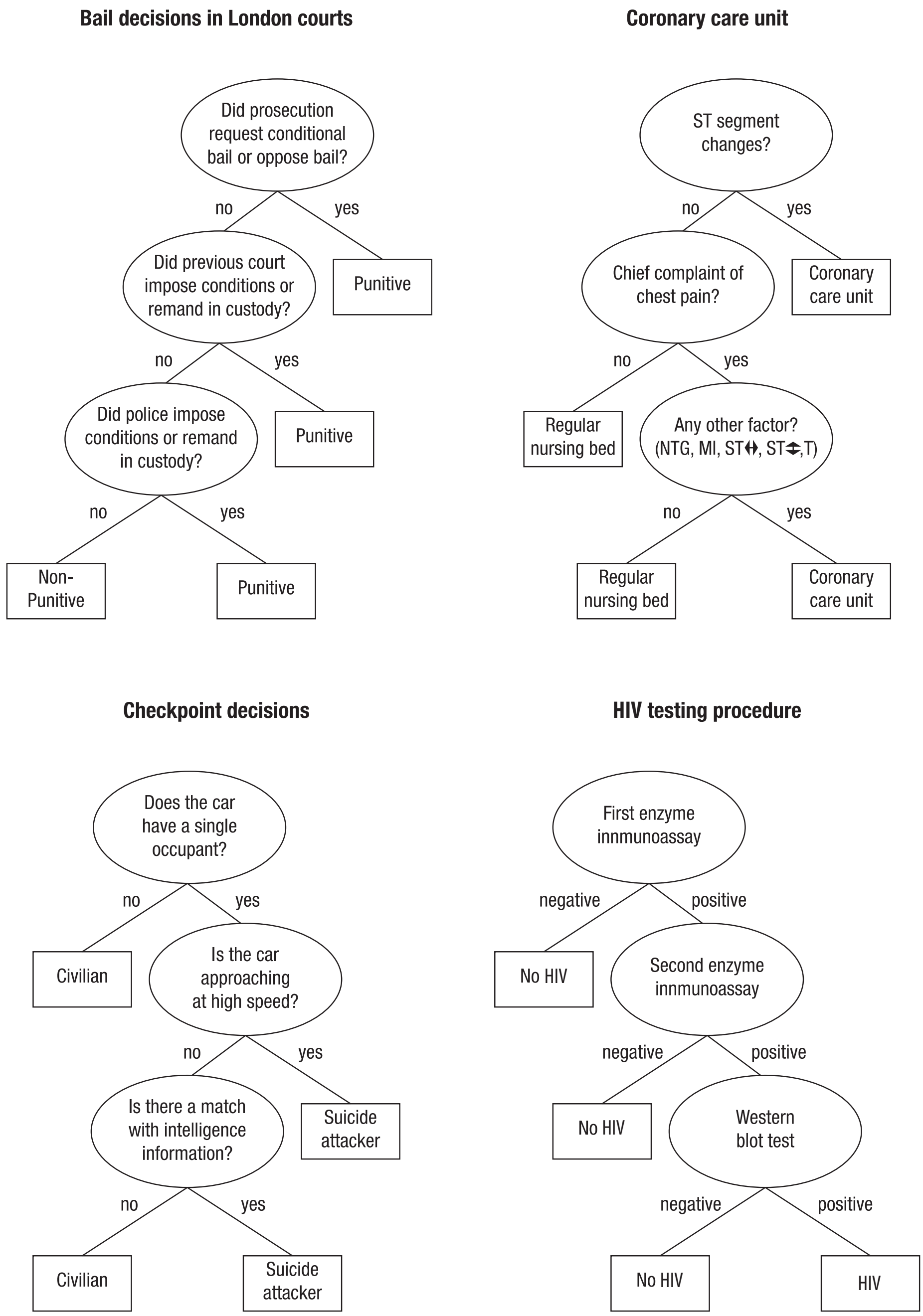

Figure 2. Illustrations of four structurally different fast-and-fugal trees. (top left) A model of how London magistrates make bail decisions (Dhami, 2003). (top right) A tree used by emergency room physicians in Michigan hospitals for deciding whether patients with severe chest pain should be allocated to the coronary care unit or to a regular nursing bed (Green & Mehr, 1997). (bottom left) A tree designed to reduce civilian casualties at checkpoints in Afghanistan in collaboration with the German Federal Armed Forces (Keller & Katsikopoulos, 2016). (bottom right) The typical decision procedure in HIV screening (Gigerenzer, 2002). The four trees differ in their exit structure. For explanations, see text.

carry suicide attackers or civilians (Keller & Katsikopoulos, 2016). The bottom right tree shows the standard procedure used in HIV screening. Note that in each case, the decision process is sequential and noncompensatory, that is, values on lower cues cannot overrule a decision made on the basis of a higher-ranked cue (see Figure 2).

Despite the widespread use of fast-and-frugal trees in practice, their theoretical properties are largely unknown. One key property of categorization is the balance between misses and false alarms: If the miss rate (i.e., overlooking a signal if there is one) is reduced, the false alarm rate (i.e., concluding that there is a signal if there is none) increases, and vice versa. Thus, the question is, what concept(s) in the fast-and-frugal tree determine the balance of errors: the order of cues, the validity of cues, or something else?

Until recently, the answer to this question was unknown. To find an answer, one strategy is to use a structure that is well understood and has a theoretical concept that balances misses and hits, and then map this concept onto the fast-and-frugal tree. Signal detection theory is such a model (top part of Figure 3) that deals with the same categorization problem as a fast-and-frugal tree, but its concepts are strikingly different. Unlike fast-and-frugal trees, signal

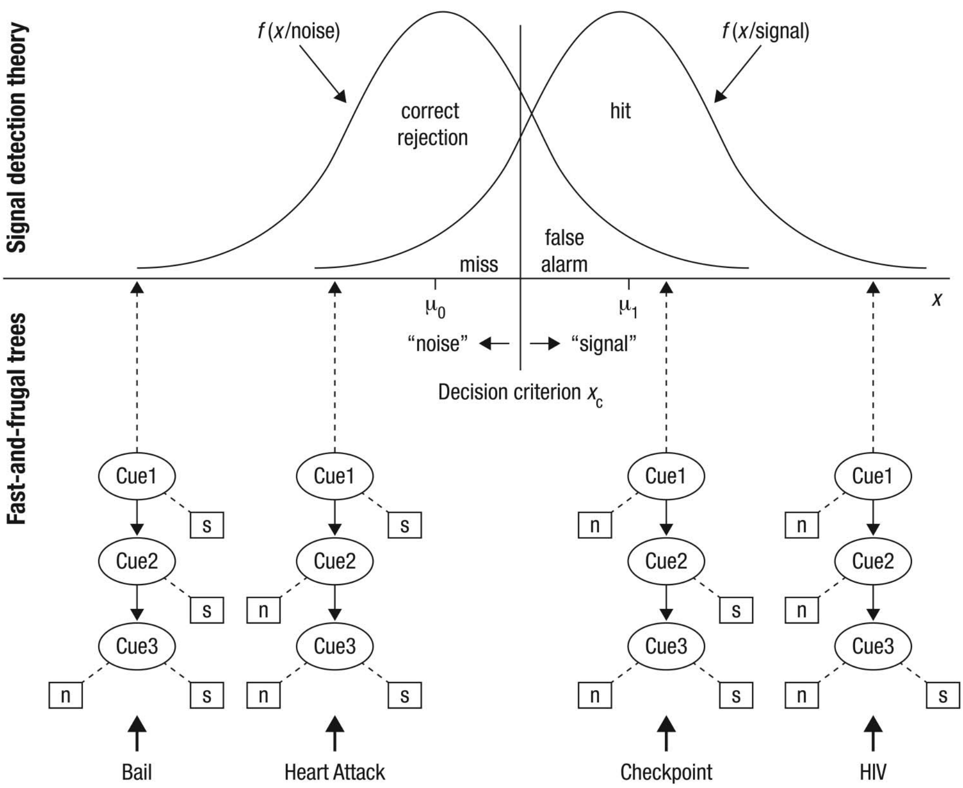

Figure 3. Illustration of a successful mapping of two theoretical concepts from different theories. Shown are two models of categorization: signal detection theory (top) and fast-and-frugal trees (bottom). According to signal detection theory, a mind balances the two errors in categorization—misses and false alarms—by adjusting the decision criterion. In a fast-and-frugal tree, a mind does the same by adjusting the exit structure of a decision tree. Fast-and-fugal trees with three cues can have four different exit structures, each of which maps onto the position of the decision criterion as marked. Each formal exit structure corresponds to one of the fast- and-frugal trees in Figure 2. Trees with a "signal" exit ("s") on each cue minimize misses at the cost of false alarms (leftmost tree), while trees with a "noise" exit ("n") on each cue minimize false alarms at the cost of misses (rightmost tree).

detection theory explicitly models how a mind balances the miss rate and the false alarm rate, although it cannot easily deal with several cues. In signal detection theory, the desired balance is arrived at by setting the decision criterion (see Figure 3, top). Thus, our integration question can be reformulated: Where is the decision criterion in a fast-and-frugal tree?

Given that no concept of a decision criterion exists in the tree, we might ask: is there something functionally equivalent? An analysis of the formal components of the tree confirmed that there is (Luan, Schooler, & Gigerenzer, 2011): The exit structure of the tree, which defines the formal differences between the four trees in Figure 2, is functionally equivalent to the decision criterion. This structure sets the balance between misses and false alarms and can be directly mapped onto the criterion setting in signal detection theory, as shown in Figure 3. Specifically, the four possible exit structures for $n = 3$ map onto four points on the receiver operating curve in signal detection theory, while the order of cues maps onto d' in signal detection theory.

In each of the four fast-and-frugal trees, the exit structure determines the desired balance between misses and false alarms. For instance, magistrates try to minimize misses (e.g., granting bail to a defendant who subsequently commits a crime), possibly because this is the only error for which they can be blamed, whereas a false alarm (e.g., imprisoning a defendant who would not have committed a crime) can hardly be detected. This exit structure with a "signal" exit (here: a punitive decision) on all cues minimizes misses at the cost of false alarms. The coronary care unit allocation tree has a more balanced way of dealing with misses and false alarms, although it also shows a bias toward avoiding misses (allocating patients who subsequently do have a heart attack to a regular nursing bed). The key problem at checkpoints in Afghanistan are false alarms when soldiers kill civilians, mistaking them for suicide attackers. The tree in Figure 2 (left, bottom) is designed to reduce civilian casualties and was validated against 1,060 critical "escalation of force incidents"; its implementation could have reduced the number of civilians killed or wounded from 204 to 78 (Keller & Katsikopoulos, 2016). Finally, the standard HIV test procedure used has "noise" exits (here, "no HIV") on each cue and thus reduces the rate of false positives, which is the typical problem of screening for every rare disease.

The mapping shown in Figure 3 proves the equivalence of two questions: how a mind sets the decision criterion and how a mind sets the exit structure. The two concepts are functionally equivalent. This analysis also shows how an optimizing model (signal detection theory) can be connected with a heuristic model (fast-and-frugal trees).

Functional Equivalence

According to Brunswik (1955), the functional equivalence of cognitive processes—vicarious functioning—is the signature of living organisms, to be distinguished from simple cause-effect relationships in the inorganic world (Hammond & Stewart, 2001). Functional equivalence means that the mind has not one but multiple roads toward a goal. If knowledge about the shape of the two distributions is available, as assumed in signal detection theory, setting the decision criterion is a means of balancing hits and false alarms. If that knowledge is not available, such as in bail decision-making and coronary care unit allocations, then setting the exit structure in a fast-and-frugal tree is a vicarious means toward the same goal. With distribution knowledge, the balance can be adjusted in a continuous way and without it, in a discrete way (see Figure 3).

When two concepts are proven to be functionally equivalent, it is possible to return to Step 1.1 and review the precise identification of a phenomenon. For instance, the terms "balancing misses and false alarms" and "setting the decision criterion" are sometimes used interchangeably. However, they are not equivalent because balancing errors can be modeled by setting either a criterion or an exit structure. Consider the phenomenon that fear of malpractice suits motivates doctors to avoid all misses (overlooking a disease) at the cost of frequent false alarms, which can result in unnecessary surgery or other treatment. However, the very same doctors accept some misses in order to reduce false alarms when treating members of their own family (Domenighetti, Casabianca, Gutzwiller, & Martinoli, 1993). This observation is not identical to saying that doctors move the decision criterion from the extreme left (for patients) to the moderate left (family members). The latter statement is already an explanation, which becomes clear when a functionally equivalent concept such as the exit structure is discovered. Another explanation for the same phenomenon is that doctors use different exit structures for patients (left-hand tree in Figure 3) and family (second tree from the left). Exit structure and decision criterion are functionally equivalent means to achieve the same goal but refer to different psychological processes.

Functional equivalence of concepts in different theories is probably more frequent than assumed. For instance, the Allais paradox and other violations of expected utility theory have been attributed to overweighting of small probabilities and underweighting of large probabilities as proposed by prospect theory. However, these very violations are logically implied by the priority heuristic *without* any overweighting and underweighting of probabilities. Instead, the violations are the product of sequential search through cues and a stopping rule, a search process similar to fast-and-frugal trees (Brandstätter, Gigerenzer, & Hertwig, 2006). That is, without transforming values and probabilities (and without any free parameters), the priority heuristic *implies* the same phenomena that prospect theory *fits* by transforming values and probabilities in a nonlinear way (Drechsler, Katsikopoulos, & Gigerenzer, 2014; Katsikopoulos & Gigerenzer, 2008).

The discovery of functionally equivalent but psychologically different concepts that explain the same behavioral pattern is essential for the feedback loop in Figure 1. In the present case, it clarifies that weighting probabilities, like sequential search, is not the phenomenon but part of the explanation. In this way, demonstrating functional equivalence helps identify more clearly what the phenomenon actually is.

Extensions

The two-step program can be extended in several directions. As it stands, it is about discovering links between phenomena and concepts that explain these phenomena. Thereby, it creates a "horizontal" network of relations between phenomena and between concepts at the same level of analysis. This horizontal integration can be extended to a "vertical" integration, where theoretical constructs at different levels of explanation are linked. In general, theories refer to various levels of analysis, from molecular to molar, such as the levels of individual neurons, neural circuits, brain networks, core cognitive capacities, higher-order intelligent processes, and collective behavior (Newell, 1990). Vertical integration across levels refers to the connection of two or more theories that focus on different levels. (The hierarchy of levels is by no means easy to define, but that is another issue.)

Consider two heuristics from the adaptive toolbox of humans, the recognition heuristic (Goldstein & Gigerenzer, 2002) and the fluency heuristic (Kelley & Jacoby, 1998). The recognition heuristic can be used to infer which of two objects, a and b, has a higher value on a criterion y, and is defined as follows: if a is recognized but b is not, infer that $a_y > b_y$. The fluency heuristic applies when the recognition heuristic is not applicable, that is, when both objects are recognized, and is defined as follows: if a is recognized faster than b, infer that $a_y > b_y$. Both heuristics model the inference process but are mute about the underlying recognition process, which is taken as given. Yet understanding the recognition process might help in understanding the accuracy of the resulting heuristic inferences. Schooler and Hertwig (2005) explored the potential for vertical integration by implementing the recognition heuristic and the fluency heuristic in the adaptive control of thought–rational (ACT-R; Anderson, 2007) cognitive architecture. As a result, they could show how memory parameters in ACT-R, such as information decay, affect the inferential accuracy of the heuristics. Moreover, this vertical integration led to models of the mechanisms underlying the time-honored thesis that forgetting is indispensable to the proper functioning of memory. Schooler and Hertwig (2005) also showed that a memory system that systematically (as opposed to randomly) loses information generates the input that simple heuristics need in order to make accurate inferences. Thus, integrating models for the recognition process and models for inference aids understanding how forgetting and heuristics mutually support each other and how accuracy of inferences depends on the nature of the recognition process (see also Nellen, 2003; Pleskac, 2007).

Toward a Balance of Integration and Elimination of Theories

The growth of knowledge is sometimes pictured in analogy to the survival of the fittest, with scientific disciplines competing like species and theories being selected like genes (Popper, 1972). The view taken in this article diverges from that form of evolutionary epistemology. Progress is less a blind variation-plus-selection process than a carefully reflected process, where scientific growth can result from deliberate integration rather than elimination of theories. Instead of seeing theories as fierce competitors, or as toothbrushes that no one wants to share, the theory integration program sees them as pieces of a puzzle that, carefully combined, might form a greater picture.

In this article, I have outlined a program toward achieving that goal. It is not the only possible program, and its elements can be easily modified and adapted. It also carries several constraints and limitations. First, the program requires more detailed analyses of the phenomena and formal definitions of the concepts than is currently the practice in some areas of the cognitive and behavioral sciences. Second, it pursues a more modest goal than what is often praised as the ideal type of theory integration, reductionism. The reduction of heat to motion in the kinetic theory of gas is one of the few great successes of reductionism. In psychology, reduction has sometimes been attempted, as in behaviorists' proposed reduction of all cognitive phenomena to behavior (Skinner, 1957), but rarely achieved. Finally, although integration increases the coherence between existing theories, it is unlikely to result in a single metatheory that provides a common skeleton of concepts for all theories. Evolutionary theory has been proposed as a candidate for such a grand metatheory of psychology (Tooby & Cosmides, 1992) or, combined with game theory, of the social sciences in general (Gintis, 2007). In contrast to successful neural or behavioral reductionism and the establishment of a metatheory, which aims at unification, the theory integration program is a more modest and realistic alternative.

To get the theory integration program running, editors might consider encouraging researchers to submit articles that work out the connection between apparently different phenomena and concepts. Theoretically oriented journals might consider opening a section on theory integration to signal the vital importance of this type of work. Psychological institutions, including tenure and hiring committees, might pay special attention to contributions toward this goal. All this would change the view that the royal road to tenure and fame lies in presenting multiple experimental findings with little need for much else. These measures would also signal a change in professional culture and pave the way for more theoretical coherence. Rethinking psychology's relation to theory is likely crucial for the future of psychology as a science.

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