Perspectives on Psychological Science
2017, Vol. 12(6) 973–986

DOI: 10.1177/1745691617702496
www.psychologicalscience.org/PPS

Nudging and Boosting: Steering or Empowering Good Decisions

Ralph Hertwig[1] and Till Grüne-Yanoff[2]
[1]Max Planck Institute for Human Development, Berlin and [2]Royal Institute of Technology, Stockholm

Abstract
In recent years, policy makers worldwide have begun to acknowledge the potential value of insights from psychology and behavioral economics into how people make decisions. These insights can inform the design of nonregulatory and nonmonetary policy interventions—as well as more traditional fiscal and coercive measures. To date, much of the discussion of behaviorally informed approaches has emphasized "nudges," that is, interventions designed to steer people in a particular direction while preserving their freedom of choice. Yet behavioral science also provides support for a distinct kind of nonfiscal and noncoercive intervention, namely, "boosts." The objective of boosts is to foster people's competence to make their own choices—that is, to exercise their own agency. Building on this distinction, we further elaborate on how boosts are conceptually distinct from nudges: The two kinds of interventions differ with respect to (a) their immediate intervention targets, (b) their roots in different research programs, (c) the causal pathways through which they affect behavior, (d) their assumptions about human cognitive architecture, (e) the reversibility of their effects, (f) their programmatic ambitions, and (g) their normative implications. We discuss each of these dimensions, provide an initial taxonomy of boosts, and address some possible misconceptions.

Keywords
boost, nudge, choice architecture, education, public policy, autonomy, welfare

Numerous governments and international organizations such as the World Bank (2015) and the European Commission (Lourenco, Ciriolo, Almeida, & Troussard, 2016) have begun to acknowledge the enormous potential of behavioral science evidence in helping to design more effective and efficient public policies. For instance, behavioral science is now used or seriously considered as a policy tool in many of the 35 member countries of the Organisation for Economic Co-operation and Development (OECD), whose mission it is to "promote policies that will improve the economic and social well-being of people around the world" (http://www.oecd.org/about/). In fact, the OECD is currently drafting a collection of more than 100 case studies of behavioral insights in practice. Without doubt, drawing attention to the importance of behavioral science for policy making is the outstanding achievement of the *nudge* approach, presented most prominently in Thaler and Sunstein (2008). "Nudges" are nonregulatory and nonmonetary interventions that steer people in a particular direction while preserving their freedom of choice (e.g., Alemanno & Sibony, 2015; Halpern, 2015). Paradigmatic examples include automatic (default) enrollment in organ-donation schemes and pension plans unless individuals specifically choose to opt out (rather than having to actively opt in if they want to enroll), the redesign of cafeterias such that healthier food is displayed at eye level, and use of social norms (e.g., that many taxpayers pay on time; see Cialdini & Goldstein, 2004) to increase tax compliance. The nudge approach has also prompted critical and informative debates about its underlying political philosophy of libertarian paternalism (e.g., Rebonato, 2012), the ethics of nudging (e.g., Barton & Grüne-Yanoff, 2015; Bovens, 2009), the empirical success of nudging policy interventions (e.g., House of Lords Science and Technology Select Committee, 2011), and the approach's starting proposition: that deficits in human decision-making competence are pervasive and difficult to alter (e.g., Grüne-Yanoff & Hertwig, 2016).

Corresponding Author:
Ralph Hertwig, Center for Adaptive Rationality, Max Planck Institute for Human Development, Lentzeallee 94, 14195 Berlin, Germany
E-mail: hertwig@mpib-berlin.mpg.de

Table 1. Seven Dimensions on Which the Nudging (Non-educative) and Boosting (Long-Term) Approaches to Public Policy Can Be Distinguished

Dimension	Nudging	Boosting
Intervention target	Behavior	Competences
Roots in research programs and evidence	Show decision maker as systematically imperfect and subject to cognitive and motivational deficiencies	Acknowledge bounds but identify human competences and ways to foster them
Causal pathways	Harness cognitive and motivational deficiencies in tandem with changes in the external choice architecture	Foster competences through changes in skills, knowledge, decision tools, or external environment
Assumptions about cognitive architecture	Dual-system architecture	Cognitive architectures are malleable
Empirical distinction criterion (reversibility)	Once intervention is removed, behavior reverts to preintervention state	Implied effects should persist once (successful) intervention is removed
Programmatic ambition	Correct momentous mistakes in specific contexts—"local repair"	Equip individuals with domain-specific or generalizable competences
Normative implications	Might violate autonomy and transparency	Necessarily transparent and require cooperation—an offer that may or may not be accepted

The current interest in behavioral science within governments, owed to the enormous impact of the nudge approach, offers psychology a new channel for informing and influencing public policy (Teachman, Norton, & Spellman, 2015). Yet, we believe it would be a mistake to equate all public policy making informed by behavioral science evidence with nudging or to assume that all such evidence ultimately points to nudge interventions. We suggest that the scientific study of human behavior also provides support for a decidedly distinct kind of intervention, namely, *boosts* (Grüne-Yanoff & Hertwig, 2016). The objective of boosts is to improve people's competence to make their own choices. The focus of boosting is on interventions that make it easier for people to exercise their own agency by fostering existing competences or instilling new ones. Examples include the ability to understand statistical health information, the ability to make financial decisions on the basis of simple accounting rules, and the strategic use of automatic processes (we return to these examples later).

In this article, we distinguish between nudges and boosts on seven dimensions, summarized in Table 1. Not all of these dimensions are independent of each other but we believe that they are sufficiently important to merit separate discussion. Our text is structured largely along these seven dimensions. After discussing the differences between nudges and boosts with respect to their immediate intervention targets (i.e., behavior vs. competences), their roots in different research programs, and the causal pathways through which they affect behavior, we provide an initial taxonomy of boosts. We then continue to discuss the differences between nudging and boosting with respect to their assumptions about the human cognitive architecture, the reversibility of their effects, their programmatic ambitions, and their normative implications. We conclude by addressing some of the misconceptions about boosts that we have encountered in recent discussions and the literature.

A Plurality of Views on How Real People Reason and Decide

We begin by reviewing the plurality of views within the behavioral sciences on how and how well people make decisions. Our review is brief and theoretical rather than empirical and exhaustive. The goal is to illustrate the surprising range of views on the nature of human decision making and to show that the rich behavioral evidence available is indeed consistent with more than just nudging. We begin with the view on which nudging rests.

Nudging's starting point is a drastically different view of the real-world decision maker from that of the stylized, hyperrational *Homo economicus* or the Olympian model of rationality, which, according to Simon (1990), "serves, perhaps, as a model of the mind of God, but certainly not as a model of the mind of man" (p. 34). Thaler and Sunstein (2008) put it this way: "If you look at economics textbooks, you will learn that homo economicus can think like Albert Einstein, store as much memory as IBM's Big Blue, and exercise the willpower of Mahatma Gandhi" (p. 6). Yet real and boundedly rational people not only lack these heroic qualities, so the nudge approach argues, but they are fallible, inconsistent, ill-informed, unrealistically optimistic, and myopic, and they suffer from inertia and self-control problems (Sunstein, 2014; Thaler & Sunstein, 2008; see also Halpern, 2015).

This dismal portrayal of people's decision-making competence has its roots in the *heuristics-and-biases program* (e.g., Kahneman, 2003, 2011; Kahneman, Slovic, & Tversky, 1982). This program has—over more than four decades—cataloged a large set of "cognitive illusions," that is, systematic violations of norms of reasoning and decision making (e.g., logic, probability theory, axioms of rational choice models). The underlying idea is that humans, as a consequence of their inherent cognitive limitations, are unable to perform rational calculations and instead rely on heuristics. These heuristics are "highly economical and usually effective, but they lead to systematic and predictable errors" (Tversky & Kahneman, 1974, p. 1124). The cumulative weight of these errors has thus "raised serious questions about the rationality of many judgments and decisions that people make" (Thaler & Sunstein, 2008, p. 7) and necessitates as well as enables a new approach to public policy.

The innovative core of nudging is the insight that policy makers can harness individuals' cognitive and motivational deficiencies rather than having to yield to them as insurmountable obstacles to good decisions and welfare. By enlisting these deficiencies, policy makers can steer (nudge) individuals' behavior toward behaviors that are consistent with their ultimate goals or preferences—and that result in better outcomes than would otherwise be obtained (Rebonato, 2012; Thaler & Sunstein, 2008). Take, for illustration, defaults as one paradigmatic nudge. Default rules establish what will automatically happen if a person does nothing—and "nothing is what many people will do" (Sunstein, 2014, p. 9). Betting on this inertia, a policy maker can put in place a default that brings people closer to a desired behavioral outcome (Beshears, Choi, Laibson, & Madrian, 2010). For example, automatic enrollment in employer-sponsored savings plans increases employees' retirement income. Because people tend to stay with the default option, automatic enrollment raises participation rates in retirement savings plans (but not necessarily contribution rates; see Butrica & Karamcheva, 2015).

Although undoubtedly influential, the heuristics-and-biases program is not the only view about human decision makers and their competence, nor has its conclusions remained unquestioned. What some perceived as "the message that man is a 'cognitive cripple'" (Edwards, 1983, p. 508) was by no means unanimously endorsed—as illustrated by one early conceptual criticism of the heuristics-and-biases program that far preceded the more contentious discussions of the 1990s (e.g., Gigerenzer, 1996; Kahneman & Tversky, 1996):

> In the research literature [on heuristics and biases], subjects are almost never given feedback about the logical implications of their judgements, never shown their inconsistencies and invited to resolve them, rarely asked for redundant judgements so that inconsistency can be utilised as part of the assessment process, and almost never asked to make judgements in a group setting. . . . It is perfectly possible that many people, given the right tasks in the right circumstances, could make precise, reliable, accurate assessments of probability. (Phillips, 1983, p. 536)

Phillips argued that "research on heuristics and biases has become a psychology of first impressions" (p. 538) and that there is more to human decision making and problem solving than this first response. Indeed, let us briefly consider five other research programs also concerned with human decision making and problem solving that suggest different views and conclusions. Preceding the heuristics-and-biases program, a research program often referred to as *man as an intuitive statistician* (Peterson & Beach, 1967) reached a very different conclusion on how people make decisions. Reviewing studies conducted in the 1950s and 1960s that, like the heuristics-and-biases program, used probability and statistics as a benchmark against which people's intuitive statistical inferences and predictions (e.g., about proportions, means, variances, and sample sizes) were evaluated, Peterson and Beach (1967) concluded that "the normative model provides a good first approximation for a psychological theory of inference" (p. 42). Although this view of intuitive inference and prediction did not deny the existence of discrepancies between norm and intuition (e.g., probability updating being too conservative), the premise was that people "cannot help but to gamble in an ecology that is of essence only partly accessible to their foresight" and that the individual "gambles well" (Brunswik, cited in Peterson & Beach, 1967, p. 29).

Since the mid-1980s, a research program with roots in social psychology has been concerned with the dynamics of social influence and persuasion (see, e.g., Cialdini, 2001; Cialdini & Goldstein, 2004; Sherman, Gawronski, & Trope, 2014). This research shares with the heuristics-and-biases program the assumption that people are "cognitive misers" who, owing to their limited mental processing resources, aim to save time and effort when navigating the social world (Fiske & Taylor, 1991). Yet, and this is crucial, even cognitive misers can be motivated and enabled to allocate more cognitive resources and to engage more extensively with arguments. Take, for illustration, two influential models of persuasion: the heuristic-systematic model (Chaiken, 1987) and the elaboration-likelihood model (Petty & Cacioppo, 1986). In the former, an argument is processed *systematically* or *heuristically*; in the latter, information processing takes either the *central* or the *peripheral* processing route. Simply put, the models' core notion is that the quality of an argument will be systematically processed (central route) only if it has high relevance or if the listener is highly motivated. If, in contrast, listeners are on "autopilot" and do not devote mental capacities to systematically poring over arguments (see Booth-Butterfield & Welbourne, 2002; Todorov, Chaiken, & Henderson, 2002), their attitudes will be shaped by peripheral cues (e.g., the expertise of an argument's source rather than its quality).

Originating in the late 1980s, the research program on *naturalistic decision making* (Klein, 1999; Lipshitz, Klein, Orasanu, & Salas, 2001) has studied how people make decisions in complex, high-stakes, real-world settings such as firefighting, nursing, and commercial aviation. This program started from the premise that norms of rational choice are not suitable for the typically ill-defined and challenging tasks encountered by, for instance, fireground commanders, in which conditions of uncertainty and time pressure preclude any effort to generate and comprehensively evaluate sets of options and then pick the best one. Instead,

> when people need to make a decision they can quickly match the situation to the patterns they have learned. If they find a clear match, they can carry out the most typical course of action. In that way, people can successfully make extremely rapid decisions. The RPD [recognition-primed decision-making] model explains how people can make good decisions without comparing options. (Klein, 2008, p. 457)

This research program has been committed to revealing the mechanisms behind the often impressive performance of experts, without denying that failures may occur (see also the joint article by Kahneman & Klein, 2009).

Another research program, initiated in the mid-1990s (and to which one of the present authors has contributed), has studied which *simple heuristics* (or fast-and-frugal heuristics) people use to make decisions and how good those decisions are. The starting premise of this program has been that individuals and organizations cannot help but rely on simple heuristics in conditions of uncertainty, lack of knowledge, and time pressure. Rather than conceptualizing heuristics as inherently error-prone, however, the program has provided evidence that less information, computation, and time—conditions embodied by heuristics—can help *improve* inferential and predictive accuracy (but may violate norms of coherence; see Arkes, Gigerenzer, & Hertwig, 2016). This program views the cognitive system as relying on an "adaptive toolbox" of simple strategies, with the key to good performance residing in the ability to select and match the mind's tools to the current social or nonsocial environment (ecological rationality; Gigerenzer, Hertwig, & Pachur, 2011; Gigerenzer, Todd, & ABC Research Group, 1999; Hertwig, Hoffrage, & ABC Research Group, 2013). Of course, heuristics may still fail (e.g., when applied in the wrong environment), but this approach emphasizes that—relative to resource-intensive and general-purpose normative strategies—heuristics can be surprisingly efficient and robust (Gigerenzer et al., 2011).

Most recently, an approach sometimes referred to as *Bayesian rationality* (Oaksford & Chater, 2009) or *the probabilistic mind* (Griffiths, Chater, Kemp, Perfors, & Tenenbaum, 2010) has suggested that many of the reasoning problems used in studies that have purportedly found irrational behaviors are in fact better understood as probabilistic problems. From this perspective, human rationality and higher-level cognition are best captured not by logic but by probability theory. Human thought thus conceptualized has been found to be "sensitive to subtle patterns of qualitative Bayesian, probabilistic reasoning" (Oaksford & Chater, 2009, p. 69).

To conclude, the goal of this short conceptual history of psychological theorizing and evidence on how people reason and make decisions was to demonstrate that the nudge approach's portrayal of the human decision maker as systematically imperfect is not the only legitimate conception. Several others exist, and their conclusions about human decision-making competences tend to be less disquieting. Our objective here is not to champion one idea over the other. Yet if behavioral science insights into how people make decisions are to inform public policy, it is vital to acknowledge the existence of different views and findings—particularly as these different approaches may suggest different types of policy interventions, including measures that foster existing competences or build new ones.

Boosts and Nudges: Definitions and Causal Pathways to Behavior

Thaler and Sunstein (2008) defined a nudge as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" and where this intervention is "easy and cheap to avoid" (p. 6). Nudging thus defined includes *all* behavioral policies that do not coerce people or substantially change their financial incentives *and* whose point of entry is the choice architecture—that is, the external context within which individuals make decisions. Within this extensive category, nudges often come in the form of either "non-educative" or "educative" nudges (Sunstein, 2016). We first focus on non-educative nudges—the innovative core of nudging and libertarian paternalism—and return to educative nudges later when discussing boosts aimed to improve performance in the short term.

The intervention target of non-educative nudges is behavior (Table 1). To causally steer behavior, non-educative nudges harness cognitive or motivational deficiencies (e.g., inertia, procrastination, loss aversion; see also Rebonato, 2012) and effect corresponding changes in the choice architecture to steer behavior in the desired direction. In so doing, policy makers do not target features over which people have explicit preferences (e.g., money, convenience, taste, status, etc.) but rather exogenous properties of the choice architecture that people typically claim not to care about (e.g., position in a list, default settings, formulation of semantically equivalent statements). Furthermore, the behavior change brought about has to be easily reversible, permitting the chooser to act otherwise. Because this easy reversibility preserves individuals' freedom of choice, this kind of paternalism has been described as "libertarian" in nature (Thaler & Sunstein, 2008).

Building on Grüne-Yanoff and Hertwig (2016), we define boosts as interventions that target competences rather than immediate behavior (Table 1). The targeted competences can be specific to a single domain (e.g., financial accounting; Drexler, Fischer, & Schoar, 2014) or generalize across domains (e.g., statistical literacy). A boost may enlist human cognition (e.g., decision strategies, procedural routines, motivational competences, strategic use of automatic processes), the environment (e.g., information representation or physical environment), or both. By fostering existing competences or developing new ones, boosts are designed to enable specific behaviors. Furthermore, they have the goal of preserving personal agency and enabling individuals to exercise that agency. Consequently, if people endorse the objectives of a boost—say, risk literacy, financial planning, healthy food choices, or implementing goals—they can choose to adopt it; if not, they can decline to engage with it. To this end, a boost's objective must be transparent to the boosted individual. People can then harness the new or "boosted" competence to make choices for themselves (e.g., whether to undergo a medical test or consume a particular food).

We distinguish two kinds of boosts. Some are *short-term* boosts. They foster a competence, but the improvement in performance is limited to a specific context. Others are *long-term* boosts. Ideally, these permanently change the cognitive and behavioral repertoire by adding a new competence or enhancing an existing one, creating a "capital stock" (Sunstein, 2016, p. 32) that can be engaged at will and across situations.

To appreciate this distinction, consider psychologists' work on conditional probabilities, natural frequencies, and Bayesian inferences.[1] In the 1970s and 1980s, researchers within the heuristics-and-biases program (Kahneman, 2011) concluded that people systematically neglect base rates in Bayesian inference: "the genuineness, the robustness, and the generality of the base-rate fallacy are matters of established fact" (Bar-Hillel, 1980, p. 215). In the 1990s, others suggested that the mind's statistical reasoning processes evolved to operate on natural frequencies and that Bayesian computations are simpler to perform with natural frequencies than with probabilities (the information format used in the base-rate fallacy studies).[2] Consistent with this hypothesis, Gigerenzer and Hoffrage (1995) and Hoffrage, Lindsey, Hertwig, and Gigerenzer (2000) showed that statistics expressed in terms of natural frequencies improved students', patients', doctors', and lawyers' Bayesian inferences. This improvement was achieved not by explicit instruction, but by changing the information format in probabilistic reasoning problems from probabilities to natural frequencies. This boost was a short-term, context-specific fix, with no aspiration to improve Bayesian reasoning beyond the given set of problems.

A long-term boost of Bayesian reasoning, in contrast, could foster people's competence to actively translate any probabilities they encounter into frequencies and thereby simplify the Bayesian computations. Using a computerized tutorial program, Sedlmeier and Gigerenzer (2001) taught people to actively construct frequency from probability representations, and found this newly developed competence to be robust after 15 weeks, with no drop in performance.

Recently, Sunstein (2016) introduced the notion of educative nudges, citing reminders, warnings, and information such as nutrition labels as examples. In our view, educative nudges and short-term boosts largely overlap. Both represent local fixes to a given problem and require—in contrast to classic nudges, such as defaults—a modicum of motivation and cognitive skill. Yet even local fixes, if they are to be successful, require psychological knowledge on the part of the booster. The mere provision of information is often not enough. Health statistics or nutritional information, for instance, bring no benefits if they are intransparent (e.g., reliant on conditional probabilities), overwhelming (like software license agreements), or misleading (e.g., expressed as relative risk information; Gigerenzer, Gaissmaier, Kurz-Milcke, Schwartz, & Woloshin, 2007).

The rest of this section will focus on the difference between non-educative nudges and long-term boosts. To illustrate, let us contrast a paradigmatic nudge that was designed to boost retirement savings, namely, Save More Tomorrow (SMT; Thaler & Benartzi, 2004), with a boost that could be designed with the same goal in mind. Although both policies have the same objective, the psychological assumptions about the decision maker underlying the respective interventions differ greatly.

The SMT intervention assumes specific cognitive and motivational deficiencies, which it enlists to increase employees' contributions to retirement savings accounts. One deficiency is the *present bias*, a strong preference for present over future rewards, which causes people to save less for their old age than they should. This bias decreases when a present reward is projected into the near future (Loewenstein & Prelec, 1992). This change in preference would not be expected to occur if people discounted the future consistently. SMT harnesses this inconsistency in discounting by *not* asking people to choose between consumption *now* versus consumption *later*. Instead, it offers a choice between consumption in the near future (say, a year from now) and consumption later. Specifically, participants commit today to a series of increases in contributions that are timed to coincide with salary increases in the future. A second deficiency that the savings program enlists is inertia. Because "nothing is what many people will do" (Sunstein, 2014, p. 9), they typically will not opt out of a program they are enrolled in, even when future contributions escalate with every pay raise.

How, in contrast, might a boost approach achieve the goal of increasing people's retirement savings? As no paradigmatic boost has yet been proposed in this context, let us outline a hypothetical savings boost that combines two components known to be effective. The first is a "simple heuristics" module. Drexler et al. (2014) found that providing microentrepreneurs with training in basic accounting heuristics and procedural routines significantly improved their financial practices, objective reporting quality, and even their revenues. Importantly, the impact of the "rule-of-thumb" training was significantly larger than that of standard accounting training designed to teach the basics of double-entry accounting, working capital management, and investment decisions. For example, whereas standard accounting training teaches students to keep their business and personal accounts separate by instructing them how to calculate business profits, the "rule-of-thumb" training offers participants

> a physical rule to keep their money in two separate drawers (or purses) and to only transfer money from one drawer to the other with an explicit "IOU" note between the business and the household. At the end of the month they could then count how much money was in the business drawer and know what their profits were. (Drexler et al., 2014, p. 3)

Following the same rationale of replacing factual knowledge with simple heuristic procedures, a retirement savings boost would not teach participants about interest compounding, inflation, and risk diversification but instead offer simple rules of thumb (e.g., a simple $1/N$ diversification strategy; DeMiguel, Garlappi, & Uppal, 2009).

The second component of a hypothetical retirement savings boost might involve fostering people's competence to vary their sense of psychological connectedness, that is, their sense of connection with their future self (Ainslie, 1975; Parfit, 1987; Schelling, 1984). In the context of savings, this could mean that the more aware someone is of being the future recipient of today's savings, the more prepared that person will be to save for retirement. By the same logic, someone who is estranged from his or her future self—through lack of belief or imagination—is less likely to save. Following this reasoning, Hershfield et al. (2011) presented people with renderings of their future selves, made using age-progression algorithms that forecast how physical appearances will change over time. In all cases, participants who interacted with their virtual future selves, and presumably overcame or reduced disconnectedness, were more likely to accept later monetary rewards over immediate ones. In another study, participants wrote a short essay about how they wanted to be remembered by future generations (Zaval, Markowitz, & Weber, 2015). This method was found to be helpful in getting people to consider the long view and promoting proenvironmental intentions and behaviors. To the extent that people are equipped with the psychological competence to mentally bridge long time horizons, they themselves (rather than a choice architect) can choose to enlist that competence whenever they perceive asymmetries between short-term benefits and long-term costs.

In sum, the SMT nudge does *not* aim to foster people's competences. Instead, it skillfully designs an external choice architecture—involving automatic enrollment, projection of the choice to give up consumption into the near future, and dynamic adjustment of savings rates—that harnesses cognitive and motivational deficiencies to prompt behavior change. A savings boost, in contrast, would seek to foster competences that would improve individuals' saving behavior if so desired by, for instance, boosting the ability to connect with one's future self and teaching simple procedural rules. In short, the nudge approach steers behavior without taking the detour of honing new competences, whereas the boost approach invests in building on and developing people's competences.

Let us emphasize four points. First, we do not suggest that a savings boost would be more effective (in terms of the rate of savings) than the SMT nudge. This is an empirical question, and we hope that the debate on the effectiveness of financial education versus automatic enrollment (e.g., Fernandes, Lynch, & Netemeyer, 2014; Willis, 2011) will be extended to include potential (procedure-based) boosts. Second, a nudge that affects behavior repeatedly (e.g., daily food choices in a rearranged cafeteria) or that lasts a number of years (e.g., SMT) may ultimately also produce behavioral routines and engender a sense of self-efficacy (Bandura, 1997). As a consequence, the desired behavior may "survive" the removal of the scaffolding choice architecture. Yet this, again, is an empirical question. If such competences did emerge, they would be most welcome—but this is not the explicit intention of the SMT nudge or nudging interventions more generally. Third, the SMT nudge and the proposed savings boost are distinct—but not necessarily mutually exclusive—policy interventions. Different kinds of interventions can complement each other. This raises an important question that is likely to receive more attention in the future: Under what circumstances is a particular intervention—boost versus nudge—more desirable (see Grüne-Yanoff, Marchionni, & Feufel, 2016; Hertwig, in press)? Fourth, boost interventions already exist and can be enlisted across a range of domains. In the following, we illustrate this point by offering a first taxonomy of boosts.

A First Taxonomy of Long-Term Boosts

Our goal is not to provide an exhaustive account but to show just how rich this class already is (even when limiting the scope of our brief review to recent work).[3] One dimension on which boosts can be classified is according to the competence to be boosted.

Risk literacy boosts establish or foster the competence to understand statistical information in domains such as health, weather, and finances. This competence can be achieved through (a) graphical representations (e.g., Lusardi et al., 2014; Spiegelhalter, Person, & Short, 2011; Stephens, Edwards, & Demeritt, 2012), (b) experienced-based (as opposed to purely description-based) representations (e.g., Hogarth & Soyer, 2015; Kaufmann, Weber, & Haisley, 2013), (c) representations that avoid biasing framing effects (e.g., absolute instead of relative frequencies; Gigerenzer et al., 2007; Spiegelhalter et al., 2011), (d) brief training in transforming opaque representations (e.g., single-event probabilities) into transparent ones (e.g., frequency-based representations; Sedlmeier & Gigerenzer, 2001), and (e) training of math skills in general (e.g., during story time with parents; Berkowitz et al., 2015). Boosts targeting risk literacy work as long as people have access to actuarial information about risks. Often, however, people need to make decisions under uncertainty, with no explicit risk information available. In this case, they need other mental tools.

Uncertainty management boosts establish or foster procedural rules for making good decisions, predictions, and assessments under uncertain conditions with the help of (a) simple actuarial inferential methods (e.g., Dawes, Faust, & Meehl, 1989; Swets, Dawes, & Monahan, 2000), (b) simple rules of collective intelligence (e.g., Kurvers et al., 2016; Kurvers, Krause, Argenziano, Zalaudek, & Wolf, 2015; Wolf, Krause, Carney, Bogart, & Kurvers, 2015; see also Herzog & Hertwig, 2014), and (c) fast and frugal decision trees, simple heuristics, and procedural routines (e.g., Drexler et al., 2014; Gigerenzer et al., 2011, chaps. 29, 31, 32, 34, 36, 39; Hertwig & Herzog, 2009; Jenny, Pachur, Williams, Becker, & Margraf, 2013).

Motivational boosts foster the competence to autonomously adjust one's motivation, cognitive control, and self-control through interventions such as expressive writing (e.g., Beilock & Maloney, 2015), growth-mind-set or sense-of-purpose exercises (e.g., Paunesku et al., 2015; Rattan, Savani, Chugh, & Dweck, 2015), attention and attention state training (e.g., Tang & Posner, 2009; Tang, Tang, & Posner, 2013; see also Moffitt et al., 2011), psychological connectedness training (Hershfield et al., 2011), reward-bundling exercises (Ainslie, 1992, 2012), the strategic use of automatic processes (i.e., harnessing simple implementation intentions; Gollwitzer, 1999), and training in precommitment strategies (Schelling, 1984) and self-control strategies (e.g., see Table 30.1 in Fishbach & Shen, 2014).

Another dimension on which boosts could be classified is the target audience. Some boosts target specific developmental periods (e.g., childhood); others are applicable across the adult life span (e.g., risk literacy boosts). Some boosts target the population at large (e.g., Spiegelhalter et al., 2011); others target subsets of the population, such as smokers (Tang et al., 2013), general practitioners (Jenny et al., 2013), or diagnosticians (Kurvers et al., 2015).

Nudges Versus Boosts: Which Cognitive Architecture Is Assumed?

Nudges and boosts differ in the target of intervention and the causal pathways taken to prompt behavior change (Table 1). Nudges co-opt the decision maker's (internal) cognitive and motivational processes and design the (external) choice architecture such that it, in tandem with the (untouched) functional processes, produces a change in behavior. Thus, nudges target behavior directly. Boosts, in contrast, target individual competences to bring about behavior change. Their goal is either to train the functional processes or to adapt the external world (e.g., representation of information), or both, to improve decision making and its outcomes.

To appreciate these distinct pathways, let us first clarify the concept of functional processes. A construct often used in cognitive science, artificial intelligence, and other disciplines is that of the *cognitive architecture*. It specifies the "infrastructure" of an artificial or naturally evolved information-processing system, including the mental hardware such as memory structures for the storage of beliefs, goals, and knowledge, as well as the functional processes operating on that hardware, such as cognitive algorithms, heuristics, and reasoning processes (e.g., Langley, Laird, & Rogers, 2009). Although psychologists agree that the human mind is a natural information-processing system, there is much debate about the nature of its architecture and especially about the mind's functional processes and their rationality. Some proposals for a cognitive architecture of the human mind are rooted in neuroscientific findings (e.g., Anderson & Lebiere, 1998; McClelland, Rumelhart, & PDP Research Group, 1986; Rumelhart, McClelland, & PDP Research Group, 1986); others are more metaphorical, with the function of generating new research hypotheses (e.g., the mind as a Swiss army knife; Cosmides & Tooby, 1994) or summarizing existing data (Kahneman, 2011). Differing assumptions about the mind's functional processes also represent important distinguishing criteria between nudging and boosting.

Nudging

The nudge approach has its roots in the "dual-system" view of the human cognitive architecture. According to Kahneman (2003, 2011), the mind can be divided into two processing systems: System 1 (or the automatic system), which is fast, intuitive, and emotional, and System 2 (or the effortful system), which gives rise to slow, rule-governed, and deliberate reasoning and is (emotionally) neutral. System 1 is an efficient first-response system but its speed and automatic processes render it susceptible to systematic biases ("cognitive illusions"). System 2 could, in principle, supervise System 1's mental products and conclusions as well as rectify biases—but it is often too sluggish to do so.

Attempts to change behavior can thus take one of two routes: One is to engage System 2 and foster it, the other is to harness System 1's deficiencies. Nudging, at least in Thaler and Sunstein (2008; but see Jung & Mellers, 2016), predominantly takes the latter approach. Attempts to strengthen System 2 are rare for at least two reasons. One is conceptual (Kahneman, 2011, p. 28). According to the dual-process view, people's cognitive and motivational deficiencies are robust, often difficult to prevent, and largely impervious to change; debiasing attempts are often seen as futile. The fact that even experts—in business, medicine, and politics (e.g., Bornstein & Emler, 2001; Heath, Larrick, & Klayman, 1998; Kahneman & Renshon, 2007; Malmendier & Tate, 2005; Norman & Eva, 2010)—fall prey to cognitive illusions suggests that even rich learning opportunities do not equip people to escape them.

The second reason why System 2 nudges are rare relates to another unique selling point of nudges, namely, their cost efficiency. By putting in place simple nudges with a large scope (e.g., "mass" default rules, automatic enrollment), policy makers can effect substantial behavior changes at relatively low costs. Indeed, cost efficiency in combination with large-scale impact, that is, maximum net benefits, has often been highlighted as a key advantage of nudging relative to educating the public or, indeed, traditional economic policies (e.g., Weber & Johnson, 2009, p. 75).

Boosting

Unlike proponents of nudging, proponents of boosting do not share a single view of the human cognitive architecture as in the dual-system view (see also the section "A Plurality of Views on How Real People Reason and Decide"). Yet, what proponents of boosting necessarily agree on is that the functional cognitive processes and motivational processes are malleable and worth developing. Specifically, existing mental tools can be enhanced or a person can learn to employ new procedural rules. Furthermore, despite its focus on boosting the mind's competences, this policy approach is not "introversive." On the contrary, competences are often best fostered by redesigning aspects of individuals' external environment or by teaching them how to redesign them.

What are the theoretical foundations of boosting? In Grüne-Yanoff and Hertwig (2016), we discussed to what extent the necessary assumptions of nudging and boosting are implied by a theoretical commitment to the heuristics-and-biases program and to the simple heuristics (and ecological rationality) program (Gigerenzer et al., 2011), respectively. Our analysis of what we called policy–theory coherence could be read to imply that boosting's view of the mind is that of an adaptive toolbox of ecologically rational heuristics. In fact, we argue that boosts include—*but go beyond*—simple and ecologically rational heuristics. For instance, because boosts include motivational interventions, their development could benefit greatly from links with programs on mind-set (Dweck, 2012) and lay theory interventions (Yeager et al., 2016), cognitive control and attention state training (Tang & Posner, 2009), the strategic use of automatic processes (Gollwitzer, 1999), and knowledge of how people process arguments (in particular, factors that prompt them to invest cognitive effort in evaluating arguments; for reviews, see Booth-Butterfield & Welbourne, 2002; Todorov et al., 2002).

Reversibility: An Empirical Criterion for Distinguishing Between Nudges and Boosts

In theory, the conceptual distinction between non-educative nudges and long-term boosts seems clear. But once concepts hit the messy world of real-life policy interventions, matters are rarely clear cut. Let us therefore offer a pragmatic rule for distinguishing nudges from boosts. Boosts seek to foster people's cognitive and motivational competences, whereas nudges adapt a choice architecture to people's cognitive and motivational processes and leave them unaltered. This difference implies a different degree of reversibility in the behavioral effects induced (Table 1):

> If, ceteris paribus, the policy maker eliminates an efficacious (nonmonetary and nonregulatory) behavioral intervention and behavior reverts to its preintervention state, then the policy is likely to be a nudge. If, ceteris paribus, behavior persists when an intervention is eliminated, then the policy is more likely to be a boost.

This criterion is based on the assumption that boosts ultimately change behavior (e.g., healthier food choices, better financial decisions, comprehension of health statistics) by enhancing existing competences or establishing new ones and that those competences, once in place, remain stable over time. Consequently, the implied behavioral effects should persist once the intervention is removed and if the implied behavior is congruent with the person's value system. Nudges, in contrast, change behavior by adapting the choice architecture, leaving individual competences unchanged. Consequently, once the intervention is removed, behavior is likely to revert to the prenudging state.

One important qualification to this criterion is worthy of note. As mentioned earlier, nudges that affect behavior repeatedly may produce behavioral routines through learning that "survive" the removal of the nudge in the choice architecture. In such cases, our empirical criterion indicates that the nudge intervention has a boosting "side effect": By changing the choice context and harnessing cognitive and motivational deficiencies to affect behavior, the nudge inadvertently affects the cognitive and motivational processes themselves. The nudge has thus turned into a boost and had lasting effects.

The Vision Behind Boosts

In response to our distinction between nudging and boosting (in Grüne-Yanoff & Hertwig, 2016), Sunstein (2016) noted, "some of the best nudges are boosts" (p. 10), and he described educative nudges (e.g., disclosure requirements, warnings, nutrition labels, reminders) as an attempt

> to strengthen System 2 by improving the role of deliberation and people's considered judgments. One example is disclosure of relevant (statistical) information, framed in a way that people can understand it. These kinds of nudges, sometimes described as "boosts," attempt to improve people's capacity to make choices for themselves. (Sunstein, 2016, p. 52)

Given this description, one might indeed conclude that boosts are simply a special kind of nudge, even if their objectives and aspirations differ. Yet there are clear differences. Take, for illustration, the case of risk literacy, mentioned in our taxonomy of boosts. Thaler and Sunstein (2008) emphasized—and we believe rightly so—that "choice architecture is inevitable, and hence certain influences on choices are also inevitable" (p. 21). This means, however, that no governmental policy maker has full control over how, for instance, players in the medical marketplace—pharmaceutical companies, governments, doctors, patient groups, and so on—communicate health statistics. The vision behind boosting is to equip individuals with, for instance, risk literacy competences that are applicable across a wide range of circumstances, including those that will not be reached by mandated disclosure requirements, warnings, and labels. The notion of educative nudges in Sunstein (2016) does not embrace this more encompassing goal of empowering people who will inevitably face commercially constructed choice architectures and industry nudges. Nor is such empowerment part of Thaler and Sunstein's (2008) vision of nudging. In fact, the notion of enhancing competences plays, if at all, a marginal role in their book—words such as "competence," "knowledge," "skills," and empowerment do not even feature as entries in the book's index.

Nudges and Boosts and Their Normative Implications

Of course, it is important to consider efficiency, effectiveness, and welfare when choosing between the two kinds of policy interventions. In addition, nudges and boosts have different implications with respect to normative dimensions of policy interventions. We briefly discuss two such normative dimensions: transparency and autonomy.

Hard paternalistic interventions such as laws (mandatory seatbelt use), bans (on smoking in public places), and financial disincentives (taxes on cigarettes) are visible and transparent (Glaeser, 2006). Citizens can therefore scrutinize them and hold governments accountable. Some have argued that nudges are less transparent. Indeed, some nudges may operate behind the chooser's back and therefore appear manipulative (e.g., Conly, 2012; Wilkinson, 2013). Default rules can be criticized on these grounds—they take advantage of people's assumed inertia and skirt conscious deliberation, meaning that they are perhaps not as easily reversible as thought and thus fail to meet the criterion of freedom of choice. Furthermore, even if default rules are completely transparent (and they often are—think automatic enrollment in savings plans), a person's ability to discern an intervention as such (e.g., a default) is distinct from the ability to discern how it changes their behavior—particularly if the direction of the effect is counterintuitive. To the extent that people are unable to fathom the underlying mechanism that brings about the change in behavior, this reduces transparency.

Boosts, in comparison, require the individual's active cooperation. They therefore need to be explicit, visible, and transparent. The requirement of cooperation also implies individual judgment and engagement. This, in turn, implies—according to dominant notions of autonomy (Buss, 2014)—that boosts are more respectful of autonomy than nudges are. This holds in particular for those nudges that seek to bypass people's "capacity for reflection and deliberation" (Sunstein, 2016, p. 64).[4]

Individuals choose to engage or not to engage with a boost. The policy maker is therefore entitled to assume that a chosen boost reflects the individual's genuine motivation. A successful nudge does not necessarily reflect such genuine motivations. Of course, the hope is that policy makers, informed by data and the public discourse, aim to promote people's own ends, as they understand them (Sunstein, 2014). Genuine motivations are often seen as the proper evidential basis of welfare considerations (e.g., Hausman, 2012). Therefore, the distinction between boosts and nudges implies that boosts are more likely to respect such considerations. Of course, this does not necessarily mean that boosts are as successful as or more successful than nudges in achieving a desired goal (e.g., higher contributions to retirement plans).

Addressing Potential Misconceptions About Boosts

Various misconceptions and oversimplifications exist regarding nudging as a policy intervention. Some misconceptions about boosting are likewise to be anticipated. We next address some of them.

Boosting is not *the same as school education*

Boosting, as we conceptualize it, is not identical to school education, although some boosts (e.g., representation training, growth mind-set interventions) could easily be included in school curricula. Of course, schools have the task of providing students with knowledge and competences and thus *do* boost the individual mind. However, the policy interventions we have in mind differ from school education in several respects. First, the primary goal of boosts is not to offer accurate declarative knowledge and cultural skills such as reading, writing, grammar, and algebra. Instead, boosts offer competences in domains that are not typically addressed in school curricula, such as good financial decision making, accurate risk assessment, healthy food choices, informed medical decisions, and effective self-regulation. Second, boosts, like nudges, should be informed by behavioral science evidence. This is not necessarily the case for what is being taught in schools. Third, boosts aim to foster or develop new competences under conditions of limited time and resources (on the part of the target audience and the policy makers) and typically in an adult citizenry that cannot be subjected to years of additional schooling. Fourth, the focus of boosts is typically on actionable motivational and decisional competences (e.g., procedural routines, heuristics, goal implementation skills) and not on information per se. Fifth, boosts often are "just-in-time" interventions, whereas school education provides knowledge and competences on a schedule. In all likelihood, people are most motivated to develop a new competence when they experience a specific need for it. Finally, boosts, as understood here, are interventions that preserve and enable individuals' personal agency and autonomy. Admittedly, if boosts were included in a mandatory school curriculum, the autonomy of the to-be-boosted person (the student) would be curtailed.

Boosts need not *be costly*

Nudges are envisioned to be inexpensive policy measures. Indeed, some modifications of the choice architecture can be made at low cost. They scale up and promise immediate results. A default rule can, for instance, be changed by government mandate (e.g., from opting in to opting out). Changes in default rules also require minimal effort on the part of the nudged individual; in fact, sometimes the nudge rests on the very assumption that individuals will do nothing. In contrast, boosts often require investments in time, effort, and motivation on the part of both the individual and the policy maker. Yet, although boosts are rarely no-cost interventions, many of them are low cost. The necessary time investment can be as little as a few minutes (e.g., expressive writing, Beilock & Maloney, 2015), or no more than a few hours (growth mind-set and sense-of-purpose interventions, Paunesku et al., 2015; representation training, Drexler et al., 2014; Sedlmeier & Gigerenzer, 2001). Admittedly, the policy maker faces the costs of setting up learning opportunities for such interventions to be offered.

The domains of boosts are not *completely orthogonal to those of nudging*

Boosts and nudges are, of course, not perfect substitutes. For instance, no nudge has been implemented to reduce math anxiety (Beilock & Maloney, 2015; Maloney & Beilock,

2012) or foster transparent communication of health risks (Gigerenzer et al., 2007). In these cases, policy makers have only one choice. Yet there are domains in which either nudges or boosts could be used, including food choices, financial decisions, and self-control problems. In each of these classes, individuals' competences can be boosted, nudged, or both. Our introductory example of the SMT nudge versus the savings boost illustrates that policy makers have a choice. As we emphasized before, which of the two interventions is more efficient is, of course, an empirical issue. Our goal is not to champion one over the other but to highlight the need for an analysis of the respective circumstances and goals, allowing policy makers to select the more appropriate intervention (Grüne-Yanoff et al., 2016). Hertwig (in press) has discussed rules that policy makers can apply to determine under what conditions boosts, relative to nudges, are the preferable form of nonmonetary and nonregulatory intervention.

The Public Policy Maker's Choice

Conceptual clarity is the key to understanding the toolbox available to public policy makers and appreciating each tool's pros and cons. Although two tools may aim to bring about the same behavioral effects, they can tread different causal pathways. For instance, Thaler and Sunstein (2008) have strictly distinguished nudges from measures that change behavior through economic incentives. Aiming for the same kind of conceptual clarity, we have argued that (at least) two evidence-informed kinds of nonregulatory and nonmonetary interventions should be distinguished. Nudging and boosting represent different causal pathways to behavior change. Making this distinction explicit contributes to the normative debate on behavioral policies, and it offers policy makers a choice.

Acknowledgments

We are grateful to the members of the Center for Adaptive Rationality and to Cass Sunstein for many helpful discussions, and we thank Susannah Goss and Anita Todd for editing the manuscript.

Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

Funding

This research was supported by a grant from the German Research Foundation (DFG) to Ralph Hertwig (HE 2768/7-2).

Notes

1. Bayesian inferences are statistical inferences that in the simplest case encompass two exclusive hypotheses (e.g., having breast cancer or not having cancer) and a datum such as the outcome of a medical test (e.g., a mammography). Bayes's theorem is a mathematical formula that combines pieces of probability information—i.e., the base rate of the hypothesis (e.g., breast cancer is present), likelihood information (the true-positive rate and the false-positive rate of the test), and a new datum (e.g., a positive test result)—to arrive at the posterior probability (e.g., the probability that someone with a positive mammogram result actually has breast cancer).

2. Natural frequencies refer to the outcomes of natural sampling—that is, the acquisition of information by updating event frequencies without artificially fixing the marginal frequencies. Unlike probabilities and relative frequencies, natural frequencies are raw observations that have not been normalized with respect to the base rates of the event in question.

3. Comprehensive frameworks for the classification of evidence-informed behavioral change interventions already exist (e.g., Michie, van Stralen, & West, 2011). Because frameworks such as the behavior change wheel (Michie et al., 2011) include interventions that go far beyond those targeted by the nudging and boosting approach (e.g., coercion, incentivization, and restriction of choice); however, we will not consider them further here. Within the behavior change wheel, the boost interventions we consider here would be classified under "education," "training," "environmental restructuring," "modeling," and "enablement."

4. Yet boosted competences can, of course, be employed to restrain other people's autonomy. For example, by coaching parents to engage in playful bedtime math with their children (Berkowitz et al., 2015), one might boost parents' ability to steer their children's behavior. Parents then, without loss of autonomy, participate in a routine that may curtail their children's autonomy.

References

Ainslie, G. (1975). Specious reward: A behavioral theory of impulsiveness and impulse control. *Psychological Bulletin*, *82*, 463–496. doi:10.1037/h0076860

Ainslie, G. (1992). *Picoeconomics: The strategic interaction of successive motivational states within the person*. Cambridge, England: Cambridge University Press.

Ainslie, G. (2012). Pure hyperbolic discount curves predict "eyes open" self-control. *Theory and Decision*, *73*, 3–34. doi:10.1007/s11238-011-9272-5

Alemanno, A., & Sibony, A. (2015). *Nudge and the law: A European perspective*. Oxford, England: Hart. doi:10.5040/9781474203463

Anderson, J. R., & Lebiere, C. (1998). *The atomic components of thought*. Mahwah, NJ: Lawrence Erlbaum. doi:10.4324/9781315805696

Arkes, H. R., Gigerenzer, G., & Hertwig, R. (2016). How bad is incoherence? *Decision*, *3*, 20–39. doi:10.1037/dec0000043

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York, NY: Worth.

Bar-Hillel, M. (1980). The base rate fallacy in probability judgments. *Acta Psychologica*, *44*, 211–233. doi:10.1016/0001-6918(80)90046-3

Barton, A., & Grüne-Yanoff, T. (2015). From libertarian paternalism to nudging—And beyond. *Review of Philosophy and Psychology*, *6*, 341–359. doi:10.1007/s13164-015-0268-x

Beilock, S. L., & Maloney, E. A. (2015). Math anxiety: A factor in math achievement not to be ignored. *Policy Insights From the Behavioral and Brain Sciences*, *2*, 4–12. doi:10.1177/2372732215601438

Berkowitz, T., Schaeffer, M. W., Maloney, E. A., Peterson, L., Gregor, C., Levine, S. C., & Beilock, S. L. (2015). Math at home adds up to achievement in school. *Science*, *350*, 196–198. doi:10.1126/science.aac7427

Beshears, J., Choi, J. J., Laibson, D., & Madrian, B. C. (2010). The impact of employer matching on savings plan participation under automatic enrollment. In D. A. Rise (Ed.), *Research findings in the economics of aging* (pp. 311–327). Chicago, IL: University of Chicago Press. doi:10.7208/chicago/9780226903088.003.0012

Booth-Butterfield, S., & Welbourne, J. (2002). The elaboration likelihood model. In J. P. Dillard & M. Pfau (Eds.), *The persuasion handbook: Developments in theory and practice* (pp. 153–173). Thousand Oaks, CA: Sage.

Bornstein, B. H., & Emler, A. C. (2001). Rationality in medical decision making: A review of the literature on doctors' decision-making biases. *Journal of Evaluation in Clinical Practice*, *7*, 97–107. doi:10.1046/j.1365-2753.2001.00284.x

Bovens, L. (2009). The ethics of nudge. In T. Grüne-Yanoff & S. O. Hansson (Eds.), *Preference change: Approaches from philosophy, economics and psychology* (pp. 207–219). Berlin, Germany: Springer. doi:10.1007/978-90-481-2593-7_10

Buss, S. (2014). Personal autonomy. In E. N. Zalta (Ed.), *The Stanford encyclopedia of philosophy* (Winter 2014 ed.). Retrieved from https://plato.stanford.edu/entries/personal-autonomy/

Butrica, B. A., & Karamcheva, N. S. (2015). *The relationship between automatic enrollment and DC plan contributions: Evidence from a national survey of older workers* (Center for Retirement Research at Boston College Working Paper, CRR WP 2015-14). Retrieved from http://crr.bc.edu/wp-content/uploads/2015/06/wp_2015-14.pdf

Chaiken, S. (1987). The heuristic model of persuasion. In M. P. Zanna, J. M. Olson, & C. P. Herman (Eds.), *Social influence: The Ontario symposium* (Vol. 5, pp. 3–39). Hillsdale, NJ: Lawrence Erlbaum.

Cialdini, R. B. (2001). *Influence: Science and practice* (4th ed.). Boston, MA: Allyn & Bacon.

Cialdini, R. B., & Goldstein, N. J. (2004). Social influence: Compliance and conformity. *Annual Review of Psychology*, *55*, 591–621. doi:10.1146/annurev.psych.55.090902.142015

Conly, S. (2012). *Against autonomy: Justifying coercive paternalism*. Cambridge, England: Cambridge University Press. doi:10.1017/cbo9781139176101

Cosmides, L., & Tooby, J. (1994). Beyond intuition and instinct blindness: Toward an evolutionarily rigorous cognitive science. *Cognition*, *50*, 41–77. doi:10.1016/0010-0277(94)90020-5

Dawes, R. M., Faust, D., & Meehl, P. E. (1989). Clinical versus actuarial judgment. *Science*, *243*, 1668–1674. doi:10.1126/science.2648573

DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naïve diversification: How inefficient is the 1/N portfolio strategy. *Review of Financial Studies*, *22*, 1915–1953. doi:10.1093/rfs/hhm075

Drexler, A., Fischer, G., & Schoar, A. (2014). Keeping it simple: Financial literacy and rules of thumb. *American Economic Journal: Applied Economics*, *6*, 1–31. doi:10.1257/app.6.2.1

Dweck, C. S. (2012). *Mindset: How you can fulfill your potential*. New York, NY: Constable & Robinson.

Edwards, W. (1983). Human cognitive capabilities, representativeness, and ground rules for research. *Advances in Psychology*, *14*, 507–513. doi:10.1016/S0166-4115(08)62254-2

Fernandes, D., Lynch, J. G., & Netemeyer, R. G. (2014). Financial literacy, financial education and downstream financial behaviors? *Management Science*, *60*, 1861–1883. doi:10.1177/1745691612460685

Fishbach, A., & Shen, L. (2014). The explicit and implicit ways of overcoming temptation. In J. W. Sherman, B. Gawronski, & Y. Trope (Eds.), *Dual process theories in the social mind* (pp. 454–467). New York, NY: Guilford.

Fiske, S. T., & Taylor, S. E. (1991). *Social cognition* (2nd ed.). New York, NY: McGraw-Hill.

Gigerenzer, G. (1996). On narrow norms and vague heuristics: A reply to Kahneman and Tversky (1996). *Psychological Review*, *103*, 592–596. doi:10.1037/0033-295X.103.3.592

Gigerenzer, G., Gaissmaier, W., Kurz-Milcke, E., Schwartz, L. M., & Woloshin, S. (2007). Helping doctors and patients to make sense of health statistics. *Psychological Science in the Public Interest*, *8*, 53–96. doi:10.1111/j.1539-6053.2008.00033.x

Gigerenzer, G., Hertwig, R., & Pachur, T. (Eds.). (2011). *Heuristics: The foundations of adaptive behavior*. Oxford, England: Oxford University Press. doi:10.1093/acprof:oso/9780199744282.001.0001

Gigerenzer, G., & Hoffrage, U. (1995). How to improve Bayesian reasoning without instruction: Frequency formats. *Psychological Review*, *102*, 684–704. doi:10.1037/0033-295X.102.4.684

Gigerenzer, G., Todd, P. M., & ABC Research Group. (1999). *Simple heuristics that make us smart*. New York, NY: Oxford University Press.

Glaeser, E. L. (2006). Paternalism and psychology. *University of Chicago Law Review*, *73*, 133–156.

Gollwitzer, P. M. (1999). Implementation intentions: Strong effects of simple plans. *American Psychologist*, *54*, 493–503. doi:10.1037/0003-066X.54.7.493

Griffiths, T. L., Chater, N., Kemp, C., Perfors, A., & Tenenbaum, J. B. (2010). Probabilistic models of cognition: Exploring representations and inductive biases. *Trends in Cognitive Sciences*, *14*, 357–364. doi:10.1016/j.tics.2010.05.004

Grüne-Yanoff, T., & Hertwig, R. (2016). Nudge versus boost: How coherent are policy and theory? *Minds and Machines*, *26*, 149–183. doi:10.1007/s11023-015-9367-9

Grüne-Yanoff, T., Marchionni, C., & Feufel, M. (2016). *The ecological rationality of behavioural policies: How to choose between boosts and nudges*. Manuscript submitted for publication.

Halpern, D. (2015). *Inside the nudge unit: How small changes can make a big difference*. New York, NY: Random House.

Hausman, D. M. (2012). *Preference, value, choice, and welfare*. Cambridge, England: Cambridge University Press. doi:10.1017/CBO9781139058537

Heath, C., Larrick, R. P., & Klayman, J. (1998). Cognitive repairs: How organizational practices can compensate for individual shortcomings. *Research in Organizational Behavior*, *20*, 1–37.

Hershfield, H. E., Goldstein, D. G., Sharpe, W. F., Fox, J., Yeykelis, L., Carstensen, L. L., & Bailenson, J. N. (2011). Increasing saving behavior through age-progressed renderings of the future self. *Journal of Marketing Research*, *48*(suppl.), S23–S37. doi:10.1509/jmkr.48.SPL.S23

Hertwig, R. (in press). When to consider boosting? Some rules for policymakers. *Behavioural Public Policy*.

Hertwig, R., & Herzog, S. M. (2009). Fast and frugal heuristics: Tools of social rationality. *Social Cognition*, *27*, 661–698. doi:10.1521/soco.2009.27.5.661

Hertwig, R., Hoffrage, U., & ABC Research Group. (2013). *Simple heuristics in a social world*. New York, NY: Oxford University Press.

Herzog, S. M., & Hertwig, R. (2014). Harnessing the wisdom of the inner crowd. *Trends in Cognitive Sciences*, *18*, 504–506. doi:10.1016/j.tics.2014.06.009

Hoffrage, U., Lindsey, S., Hertwig, R., & Gigerenzer, G. (2000). Communicating statistical information. *Science*, *290*, 2261–2262. doi:10.1126/science.290.5500.2261

Hogarth, R. M., & Soyer, E. (2015). Providing information for decision making: Contrasting description and simulation. *Journal of Applied Research in Memory and Cognition*, *4*, 221–228. doi:10.1016/j.jarmac.2014.01.005

House of Lords Science and Technology Select Committee. (2011). *Behaviour change* (2nd report of session 2010-12, HL Paper 179). London, England: Stationery Office Limited. Retrieved from http://www.publications.parliament.uk/pa/ld201012/ldselect/ldsctech/179/179.pdf

Jenny, M. A., Pachur, T., Williams, S. L., Becker, E., & Margraf, J. (2013). Simple rules for detecting depression. *Journal of Applied Research in Memory and Cognition*, *2*, 149–157. doi:10.1016/j.jarmac.2013.06.001

Jung, J. Y., & Mellers, B. A. (2016). American attitudes toward nudges. *Judgment and Decision Making*, *11*, 62–74.

Kahneman, D. (2003). A perspective on judgment and choice: Mapping bounded rationality. *American Psychologist*, *58*, 697–720. doi:10.1037/0003-066X.58.9.697

Kahneman, D. (2011). *Thinking, fast and slow*. New York, NY: Macmillan.

Kahneman, D., & Klein, G. (2009). Conditions for intuitive expertise: A failure to disagree. *American Psychologist*, *64*, 515–526. doi:10.1037/a0016755

Kahneman, D., & Renshon, J. (2007). Why hawks win. *Foreign Policy*, *158*, 34–38.

Kahneman, D., Slovic, P., & Tversky, A. (1982). *Judgment under uncertainty: Heuristics and biases*. Cambridge, England: Cambridge University Press. doi:10.1017/CBO9780511809477

Kahneman, D., & Tversky, A. (1996). On the reality of cognitive illusions. *Psychological Review*, *103*, 582–591. doi:10.1037/0033-295X.103.3.582

Kaufmann, C., Weber, M., & Haisley, E. (2013). The role of experience sampling and graphical displays on one's investment risk appetite. *Management Science*, *59*, 323–340. doi:10.1287/mnsc.1120.1607

Klein, G. (1999). *Sources of power: How people make decisions*. Cambridge, MA: MIT Press.

Klein, G. (2008). Naturalistic decision making. *Human Factors*, *50*, 456–460. doi:10.1518/001872008X288385

Kurvers, R. H. J. M., Herzog, S. M., Hertwig, R., Krause, J., Carney, P. A., Bogart, A., . . . Wolf, M. (2016). Boosting medical diagnostics by pooling independent judgments. *Proceedings of the National Academy of Sciences USA*, *113*, 8777–8782. doi:10.1073/pnas.1601827113

Kurvers, R. H. J. M., Krause, J., Argenziano, G., Zalaudek, I., & Wolf, M. (2015). Detection accuracy of collective intelligence assessments for skin cancer diagnosis. *JAMA Dermatology*, *151*, 1–8. doi:10.1001/jamadermatol.2015.3149

Langley, P., Laird, J. E., & Rogers, S. (2009). Cognitive architectures: Research issues and challenges. *Cognitive Systems Research*, *10*, 141–160. doi:10.1016/j.cogsys.2006.07.004

Lipshitz, R., Klein, G., Orasanu, J., & Salas, E. (2001). Taking stock of naturalistic decision making. *Journal of Behavioral Decision Making*, *14*, 331–352. doi:10.1002/bdm.381

Loewenstein, G., & Prelec, D. (1992). Anomalies in intertemporal choice: Evidence and an interpretation. *Quarterly Journal of Economics*, *107*, 573–597. doi:10.2307/2118482

Lourenco, J. S., Ciriolo, E., Almeida, S. R., & Troussard, X. (2016). *Behavioural insights applied to policy: European Report 2016* (EUR 27726 EN). Brussels, Belgium: European Commission Joint Research Centre. doi:10.2760/903938

Lusardi, A., Samek, A. S., Kapteyn, A., Glinert, L., Hung, A., & Heinberg, A. (2014). *Visual tools and narratives: New ways to improve financial literacy* (Global Financial Literacy Excellence Center Working Paper No. 2014-1; Becker Friedman Institute for Research in Economics Working Paper No. 2585231). Retrieved from https://ssrn.com/abstract=2585231

Malmendier, U., & Tate, G. (2005). CEO overconfidence and corporate investment. *Journal of Finance*, *60*, 2661–2700. doi:10.1111/j.1540-6261.2005.00813.x

Maloney, E. A., & Beilock, S. L. (2012). Math anxiety: Who has it, why it develops, and how to guard against it. *Trends in Cognitive Sciences*, *16*, 404–406. doi:10.1016/j.tics.2012.06.008

McClelland, J. L., Rumelhart, D. E., & PDP Research Group. (1986). *Parallel distributed processing: Explorations in the microstructure of cognition* (Vol. 2). Cambridge, MA: MIT Press.

Michie, S., van Stralen, M. M., & West, R. (2011). The behaviour change wheel: A new method for characterising and designing behaviour change interventions. *Implementation Science*, *6*(1), 42. doi:10.1186/1748-5908-6-42

Moffitt, T. E., Arseneault, L., Belsky, D., Dickson, N., Hancox, R. J., Harrington, H., . . . Caspi, A. (2011). A gradient of childhood self-control predicts health, wealth, and public safety. *Proceedings of the National Academy of Sciences USA*, *108*, 2693–2698. doi:10.1073/pnas.1010076108

Norman, G. R., & Eva, K. W. (2010). Diagnostic error and clinical reasoning. *Medical Education*, *44*, 94–100. doi:10.1111/j.1365-2923.2009.03507.x

Oaksford, M., & Chater, N. (2009). Precis of Bayesian rationality: The probabilistic approach to human reasoning.

Behavioral & Brain Sciences, *32*, 69–84. doi:10.1017/S0140525X09000284

Parfit, D. (1987). *Reasons and persons*. Oxford, England: Clarendon.

Paunesku, D., Walton, G. M., Romero, C., Smith, E. N., Yeager, D. S., & Dweck, C. S. (2015). Mind-set interventions are a scalable treatment for academic underachievement. *Psychological Science*, *26*, 784–793. doi:10.1177/0956797615571017

Peterson, C. R., & Beach, L. R. (1967). Man as an intuitive statistician. *Psychological Bulletin*, *68*, 29–46. doi:10.1037/h0024722

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In L. Berkovitz (Ed.), *Advances in experimental social psychology* (pp. 123–205). New York, NY: Academic Press.

Phillips, L. D. (1983). A theoretical perspective on heuristics and biases in probabilistic thinking. *Advances in Psychology*, *14*, 525–543. doi:10.1016/S0166-4115(08)62256-6

Rattan, A., Savani, K., Chugh, D., & Dweck, C. S. (2015). Leveraging mindsets to promote academic achievement: Policy recommendations. *Perspectives on Psychological Science*, *10*, 721–726. doi:10.1177/1745691615599383

Rebonato, R. (2012). *Taking liberties: A critical examination of libertarian paternalism*. New York, NY: Palgrave Macmillan.

Rumelhart, D. E., McClelland, J. L., & PDP Research Group. (1986). *Parallel distributed processing: Explorations in the microstructure of cognition* (Vol. 1). Cambridge, MA: MIT Press.

Schelling, T. C. (1984). Self-command in practice, in policy, and in a theory of rational choice. *American Economic Review*, *74*, 1–11.

Sedlmeier, P., & Gigerenzer, G. (2001). Teaching Bayesian reasoning in less than two hours. *Journal of Experimental Psychology: General*, *130*, 380–400. doi:10.1037/0096-3445.130.3.380

Sherman, J. W., Gawronski, B., & Trope, Y. (Eds.). (2014). *Dual-process theories of the social mind*. New York, NY: Guilford.

Simon, H. (1990). *Reason in human affairs*. Palo Alto, CA: Stanford University Press.

Spiegelhalter, D., Person, M., & Short, I. (2011). Visualizing uncertainty about the future. *Science*, *333*, 1393–1400. doi:10.1126/science.1191181

Stephens, E. M., Edwards, T. L., & Demeritt, D. (2012). Communicating probabilistic information from climate model ensembles: Lessons from numerical weather prediction. *Wiley Interdisciplinary Reviews: Climate Change*, *3*, 409–426. doi:10.1002/wcc.187

Sunstein, C. R. (2014). *Why nudge? The politics of libertarian paternalism*. New Haven, CT: Yale University Press.

Sunstein, C. R. (2016). *The ethics of influence: Government in the age of behavioral science*. Cambridge, England: Cambridge University Press.

Swets, J. A., Dawes, R. M., & Monahan, J. (2000). Psychological science can improve diagnostic decisions. *Psychological Science in the Public Interest*, *1*, 1–26. doi:10.1111/1529-1006.001

Tang, Y.-Y., & Posner, M. I. (2009). Attention training and attention state training. *Trends in Cognitive Sciences*, *13*, 222–227. doi:10.1016/j.tics.2009.01.009

Tang, Y.-Y., Tang, R., & Posner, M. I. (2013). Brief meditation training induces smoking reduction. *Proceedings of the National Academy of Sciences USA*, *110*, 13971–13975. doi:10.1073/pnas.1311887110

Teachman, B. A., Norton, M. I., & Spellman, B. A. (2015). Memos to the president from a "Council of Psychological Science Advisers." *Perspectives on Psychological Science*, *10*, 697–700. doi:10.1177/1745691615605829

Thaler, R., & Benartzi, S. (2004). Save More Tomorrow: Using behavioral economics to increase employee savings. *Journal of Political Economy*, *112*, 164–187. doi:10.1086/380085

Thaler, R., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth and happiness*. New York, NY: Simon & Schuster.

Todorov, A., Chaiken, S., & Henderson, M. D. (2002). The heuristic-systematic model of social information processing. In J. P. Dillard & M. Pfau (Eds.), *The persuasion handbook: Developments in theory and practice* (pp. 195–211). Thousand Oaks, CA: Sage.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*, 1124–1131.

Weber, E. U., & Johnson, E. J. (2009). Mindful judgment and decision making. *Annual Review of Psychology*, *60*, 53–85. doi:10.1146/annurev.psych.60.110707.163633

Wilkinson, T. M. (2013). Nudging and manipulation. *Political Studies*, *61*, 341–355. doi:10.1111/j.1467-9248.2012.00974.x

Willis, L. (2011). The financial education fallacy. *American Economic Review*, *101*, 429–434. doi:10.1257/aer.101.3.429

Wolf, M., Krause, J., Carney, P. A., Bogart, A., & Kurvers, R. H. J. M. (2015). Collective intelligence meets medical decision-making: The collective outperforms the best radiologist. *PLoS ONE*, *10*, e0134269. doi:10.1371/journal.pone.0134269

World Bank. (2015). *World development report 2015: Mind, society and behaviour*. Washington, DC: Author. Retrieved from http://www.worldbank.org/en/publication/wdr2015

Yeager, D. S., Walton, G. M., Brady, S. T., Akcinar, E. N., Paunesku, D., Keane, L., . . . Gomez, E. M. (2016). Teaching a lay theory before college narrows achievement gaps at scale. *Proceedings of the National Academy of Sciences USA*, E3341–E3348. doi:10.1073/pnas.1524360113

Zaval, L., Markowitz, E. M., & Weber, E. U. (2015). How will I be remembered? Conserving the environment for the sake of one's legacy. *Psychological Science*, *26*, 231–236. doi:10.1177/0956797614561266