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Boosting: Empowering Citizens with Behavioral Science

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Abstract

Behavioral public policy came to the fore with the introduction of nudging, which aims to steer behavior while maintaining freedom of choice. Responding to critiques of nudging (e.g., that it does not promote agency and relies on benevolent choice architects), other behavioral policy approaches focus on empowering citizens. Here we review boosting, a behavioral policy approach that aims to foster people's agency, self-control, and ability to make informed decisions. It is grounded in evidence from behavioral science showing that human decision making is not as notoriously flawed as the nudging approach assumes. We argue that addressing the challenges of our time—such as climate change, pandemics, and the threats to liberal democracies and human autonomy posed by digital technologies and choice architectures—calls for fostering capable and engaged citizens as a first line of response to complement slower, systemic approaches.

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1. INTRODUCTION

> It is now widely recognized that great changes must be made [to our] way of life. Not only can we not face the rest of the world while consuming and polluting as we do, we cannot for long face ourselves while acknowledging the violence and the chaos in which we live. The choice is clear: either we do nothing and allow a miserable and probably catastrophic future to overtake us, or we use our knowledge about human behavior to create a social environment in which we shall live productive and creative lives and do so without jeopardizing the chances that those who follow us will be able to do the same.
>
> —B.F. Skinner, *Walden Two*

B.F. Skinner wrote this text in 1976, but it still rings true today. Although Skinner's work on reinforcement principles and how to use them to shape human behavior was enormously influential in many applied areas of psychology (but also controversial; see Czubaroff 1988), it did not, as he had hoped, result in a concerted behaviorally informed public policy. Exactly such an endeavor, however, has emerged over the last two decades. Inspired by evidence from behavioral science, a rapidly rising number of studies and interventions have addressed a range of major objectives of public policy, and what are often called behavioral insights units have been established around the world (Hallsworth 2023).

This development took root in the introduction of nudging to behavior change (Sunstein 2014, 2016). The approach reached a wide audience through Thaler & Sunstein's book *Nudge*, where they 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. To count as a mere nudge, the intervention must be easy and cheap to avoid. Nudges are not mandates. Putting the fruit at eye level counts as a nudge. Banning junk food does not. (Thaler & Sunstein 2008, p. 6)

Heuristics: simple rules of thumb that ignore information to make faster, more frugal, and/or sometimes even more accurate decisions

Bounded rationality: describes how people make "good-enough" decisions based on realistic assumptions about their cognitive constraints and the fit between strategy and environment

Features of choice architectures that can be harnessed for nudges include default settings and the position of an item in a list. Such architectural nudges were later complemented by educative nudges, which consist predominantly of warnings, reminders, and disclosure of information (Sunstein 2022) and embody a minimalist interpretation of informing and educating citizens. Nudges are almost exclusively changes in choice architecture; they mostly do not involve changing people's cognitive and motivational structures and processes. This focus on the external world resonates with Skinner's focus on positive reinforcement in environments, but the similarities end there. Whereas Skinner thought there was little of interest to say about the inner workings of the mind, nudges are based on a strong conception of how the human brain works—or does not.

Around the same time Skinner wrote his plea, psychologists became interested in demonstrating reasoning errors in people's reckonings with uncertainty, risk, and incomplete information. They invoked heuristics as the explanation for why people tend to make reasoning errors (now often called cognitive biases). The resulting heuristics-and-biases program (Kahneman 2003, 2011) has been immensely influential, contributing to the emergence of behavioral economics, behavioral law, and behavioral public policy. The program's findings serve as the conceptual foundation of nudging, raising "serious questions about the rationality of many judgments and decisions that people make" (Thaler & Sunstein 2008, p. 7). For instance, "people do not exhibit rational expectations, fail to make forecasts that are consistent with Bayes' rule, use heuristics that lead them to make systematic blunders, exhibit preference reversals (that is, they prefer A to B and B to A) and make different choices depending on the wording of the problem" (Thaler & Sunstein 2003, p. 176).

The apparent weakness of human cognition is compounded by a weakness of will, bringing about "mindless choosing" (Thaler & Sunstein 2008, p. 43), "inertia" (p. 8), and "self-control problems" (p. 44). Based on this conception of human cognition, motivation, and behavior, a focus on choice architectures is compelling, since the mind and self-control seem to be untrustworthy allies in enabling better behaviors—especially insofar as biases and blunders are assumed to be hard to correct due to a deliberate reasoning system that is no match for the dizzying complexity of the world (Kahneman 2011).

The attention that heuristics-and-biases research has received in psychology and beyond masks, however, a plurality of views within psychology and economics about just how capable boundedly rational judgment and decision making are (see, e.g., Wheeler 2020).

Bounded rationality is a concept introduced by Herbert Simon (1955, 1990) to capture the fact that people often approximate rather than optimize when making decisions in order to accommodate limited human computational powers, knowledge, and time. Simon also emphasized that environmental structures are key to understanding when and why a boundedly rational system can perform well—namely, a fit between the system's processes and the environment's structure is essential.

WHAT IS BOOSTING?

Boosting is a behavioral public policy approach to empowerment grounded in evidence from behavioral science showing that human decision making is not as flawed as the nudging approach assumes. Boosts are interventions that improve people's competences to make informed choices that conform to their goals, preferences, and desires (see **Table 1** for examples). Hertwig & Grüne-Yanoff (2017, p. 977) defined boosts as follows:

> 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. . .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.

Since its introduction, the concept of bounded rationality has sparked considerable debate. While the heuristics-and-biases approach translated bounded rationality into faulty cognitive software and error-prone inferences and decisions, another approach, with reference to Simon, has rejected this equation. Instead, even with constraints on computational resources, knowledge, and time, human judgment and decision making can be remarkably effective (and sometimes even because of them; Hertwig & Todd 2003). Importantly, this alternative interpretation of bounded rationality provides the basis for alternatives to nudging—in particular, approaches that emphasize competences, empowerment, and agency.

Next, we briefly review this alternative interpretation of bounded rationality and three reasons that empowerment in behavioral public policy is, in our view, much needed. We then review boosting, a framework that aims to empower people (Hertwig & Grüne-Yanoff 2017; see the sidebar titled What Is Boosting?) by fostering competences that are relevant for addressing a range of challenges (see **Table 1** for examples). We subsequently outline general considerations for behavioral public policy approaches and end with a discussion of the limits of empowerment approaches such as boosting, addressing the traps of individualizing responsibility, cognitive and motivational requirements, and the potential for creating or exacerbating inequality.

Ecological rationality: investigates how and why a strategy performs better than others in particular environments

Rational choice theory: assumes that people decide as if they consider all options and choose the one with the highest utility, given their circumstances

Bayesian updating of beliefs: revising prior beliefs about a hypothesis based on new evidence to form posterior beliefs

2. WHY EMPOWERMENT IN BEHAVIORAL PUBLIC POLICY IS FEASIBLE

As pointed out before, not everybody in the behavioral sciences agrees that the psychology of bounded rationality is best captured by a "study of biases" (Kahneman 2003, p. 697) that aims to reveal the systematic gap between people's actual beliefs and choices and the optimal beliefs and choices assumed in rational-agent models. Research on the ecological rationality of heuristics (for reviews, see Gigerenzer & Gaissmaier 2011, Gigerenzer et al. 2011) has demonstrated that heuristics—"efficient cognitive processes, conscious or unconscious, that ignore part of the information" (Gigerenzer & Gaissmaier 2011, p. 451)—can lead to surprisingly good judgment and decisions. In fact, heuristics can match or even surpass the performance of more complex strategies, a finding corroborated by recent work on simple and transparent models in machine learning (Rudin et al. 2022, Semenova et al. 2022).

Like the heuristics-and-biases program before it, the ecological rationality program has challenged economics' rational choice theory—but in a completely different way. The findings of the heuristics-and-biases program questioned the extent to which rational choice theory and its building blocks (e.g., Bayesian updating of beliefs) accurately describe actual human reasoning. The findings of the ecological rationality program, in contrast, challenge the core normative

Table 1 Examples of societal and individual challenges and related competences and boosts

Challenge	Competence	Boost
Failure to understand and systematic misinterpretation of statistical information (e.g., interpretation of medical test results)	Statistical competences, for example, correct interpretation of medical test results using Bayes' theorem	Training in the ability to convert statistical information (prevalence, sensitivity, and specificity of a test) into natural frequencies to make the correct interpretation apparent (Sedlmeier & Gigerenzer 2001)
Poor financial practices (e.g., microentrepreneurs blurring the boundary between their business and personal finances)	Financial competences, for example, clearly separating business and personal accounts	Training in basic accounting heuristics and procedural routines (which is more effective than conventional accounting training; Drexler et al. 2014)
Misinformation online, on social media, and in messenger services	Reliably assessing the trustworthiness of information and sources	Training in lateral reading as practiced by professional fact-checkers: Rather than critically thinking through the content itself (vertical reading), using a search engine to find what others say about the content's source (lateral reading) (McGrew 2024; see also resources at **https://cor.stanford.edu**)
Failures of self-control in online environments (e.g., mindless scrolling)	Self-management of attention and distractions	Self-nudging in online environments (Kozyreva et al. 2020, 2023; see also **https://humanetech.com**), for example, actively (re)designing one's online environment by changing notification settings and defaults
Socioeconomic gap in enrollment in higher education	Self-regulation skills	Short training in mental contrasting with implementation intentions (MCII; Wang et al. 2021) in schools can improve self-regulation and academic skills (e.g., reading) and reduce the socioeconomic enrollment gap (Schunk et al. 2022)
Lower math success in children of parents with math anxiety	Playfully, casually engaging with math with one's children despite one's own math anxiety	Bedtime Learning Together, an app that provides parents and children with math stories and playful math tasks (Berkowitz et al. 2015)
Non-adherence to hygiene regulations	Understanding the consequences of not complying with hygiene regulations	Simple, concise, and transparent communication about the effectiveness of hygiene regulations (e.g., van Roekel et al. 2022)
Unhealthy diet	Self-control management	Self-nudging (Reijula & Hertwig 2022), for example, reducing accessibility of problematic stimuli by storing tempting and high-caloric foods out of reach to minimize challenges to self-control
Maintaining physical activity	Self-control management	Training in temptation bundling: coupling a behavior that produces a delayed reward with an immediate treat (e.g., listening to audiobooks during physical activity; Kirgios et al. 2020)

For more examples, see Section 5 and **https://scienceofboosting.org**.

assumption that rational choice theory automatically provides the appropriate benchmarks for cognitive success (Schurz & Hertwig 2019). Rational choice theory and Bayesian updating are optimizing methods. They can be normative in one class of environments—especially in what Savage (1954), the founder of modern Bayesian decision theory, called "small worlds," characterized by perfect knowledge about all relevant choice options and their consequences and probabilities—but not in others, particularly "large worlds" where knowledge is, at best, incomplete (Binmore 2011).

Juxtaposing models of heuristics and optimizing models offers especially telling results in situations in which a heuristic is ecologically rational—that is, it is adapted (e.g., through a process of learning) to the structure of an environment—and part of the relevant information is unknown or can only be inferred from small samples (e.g., Gigerenzer & Gaissmaier 2011, Spiliopoulos & Hertwig 2020). In these circumstances, numerous studies have shown that in contexts such as business, health care, and law, simple heuristics offer predictions that are equally or more accurate than those of optimizing models and support better decisions on the basis of less information, less computation, and a transparent process (for a review, see, e.g., Katsikopoulos et al. 2020). Simple heuristic models can outperform optimizing models—for example, if optimizing models overfit their training data and thus fail to generalize well to new data [see, e.g., the bias-variance dilemma illustrated by Brighton & Gigerenzer (2015)].

Alongside the two programs' profoundly different views of bounded rationality are profoundly different opinions on the ability of the human mind to reckon with uncertainty. In the decades before the heuristics-and-biases program was established, psychologists thought of the mind as an intuitive statistician: A review of the judgment and decision making research of the 1950s and 1960s concluded that "probability theory and statistics can be used as the basis for psychological models that integrate and account for human performance in a wide range of inferential tasks" (Peterson & Beach 1967, p. 29). One of the likely reasons that the conclusions about human judgment and prediction abilities in the heuristics-and-biases program differed so strikingly from previous research is that the program established a new type of experimental protocol in behavioral decision research (Lejarraga & Hertwig 2021). Whereas research in the 1950s and 1960s tended to use experiential settings with frequent repetition, feedback, and physical instantiations of the experimental task, the heuristics-and-biases program used described scenarios (i.e., text-based vignettes) that were largely devoid of learning opportunities: Feedback was rarely provided and there were generally no opportunities for practice or repetition.

To conclude, human judgment and decision making is not as flawed as it is portrayed in the nudging approach (for more research making this point, see Hertwig & Grüne-Yanoff 2017, Lieder & Griffiths 2020). Even though human cognition is undoubtedly bounded and although heuristics—like complex strategies in uncertain situations—can lead to errors (Gigerenzer & Gaissmaier 2011), the conclusion that "mental illusions should be considered the rule rather than the exception" (Thaler 1994, p. 4) borders on caricature. The alleged ubiquity of such illusions should not be used to justify investing in choice architectures while ignoring the importance of human competences.

3. WHY EMPOWERMENT IN BEHAVIORAL PUBLIC POLICY IS NEEDED

Libertarian paternalism: policy approach that aims to influence behavior while preserving individuals' freedom of choice

Nudging has drawn substantial criticism. Critics have scrutinized its underlying concept of libertarian paternalism and found fault with nudging's relative neglect of autonomy and agency (e.g., Schmidt & Engelen 2020), its narrow normative focus on utility maximization (Oliver 2019), its limited view of what behavioral science can contribute to public policy (Ewert 2020), the extent to which it leads to lasting and generalizable effects (e.g., Hertwig 2017), and the size and variability of the effect of nudging interventions (e.g., DellaVigna & Linos 2022, Szaszi et al. 2022). While there is robust evidence for the effectiveness of some forms of choice architectures (e.g., the literature on default effects shows no indications of publication bias; Jachimowicz et al. 2019), in a meta-analysis Maier et al. (2022, p. 1) found "no evidence for nudging after adjusting for publication bias."

Another point of criticism concerns nudging's neglect of human competences (Grüne-Yanoff & Hertwig 2016, Hertwig & Grüne-Yanoff 2017). Nudges steer people, primarily by changing their choice architecture—they do not empower people by helping them develop existing or new competences. Competent and empowered citizens, however, are more important than ever. To effectively respond to current challenges, behavioral public policies should enable people to safely navigate exploitative commercially constructed environments that jeopardize their well-being and autonomy, to actively adapt behaviors, and to subject the choices they face to reasoned scrutiny. We turn to these goals now.

Ultra-processed environments: settings where products and choice architectures are engineered to exploit human psychology and physiology, usually to maximize profit

3.1. Ultra-Processed Environments

Substantial parts of the twenty-first-century consumer environment are ultra-processed: Many consumer products (e.g., fast food, tobacco) and commercial choice architectures (e.g., social media feeds) are carefully engineered to exploit human psychology and physiology.

With an unblinking focus on maximizing profit, these ultra-processed products and environments can be detrimental to people's health, welfare, and autonomy (Hertwig 2023). Take, for example, the food industry (Dallacker et al. 2019b), where the term "ultra-processed" was coined to refer to ready-to-eat industrially formulated products designed to be highly profitable, convenient, and hyperpalatable, often through food additives and other food-adjacent substances. More than half (57.9%) of the average American's total calorie intake is estimated to stem from ultra-processed foods, which also account for about 90% of added sugar in the American diet. A high intake of added sugars increases the risk of obesity, type 2 diabetes, high cholesterol, high blood pressure, stroke, heart disease, cancer, and untimely death (Pagliai et al. 2021). Nudging interventions deployed by benevolent public choice architects can certainly help to make food-related choice architectures healthier (e.g., by positioning healthy foods at eye level in canteens; Cadario & Chandon 2020), but most ultra-processed calories are consumed at home or in stores and restaurants, well outside the reach of public choice architects. Moreover, regularly consuming high-fat and high-sugar foods has an insidious consequence: It can create a vicious cycle by reducing people's preference for low-fat foods and increasing the brain's response to palatable foods (Edwin Thanarajah et al. 2023), leaving the consumer constantly wanting more. Ultra-processed foods appear to systematically redesign people's food preferences, ultimately undermining people's autonomy.

The online world is another ultra-processed environment that threatens people's control and autonomy over their choices. Indeed, online choice architectures are often deliberately designed to do just that (Hertwig 2023, Kozyreva et al. 2020, Narayanan et al. 2020). Enabling citizens to cope better with ultra-processed products and environments like supermarkets and social media feeds is no panacea—the ultra-processed world is simply too powerful for policy makers to rely on behavior change alone. Any behavioral approach needs to be complemented by systemic interventions (Chater & Loewenstein 2022). However, in our view, it would be highly negligent not to equip citizens with the competences they need to navigate these worlds adeptly. Systemic responses such as regulations are often slow (e.g., due to lobbying influence on legislative actions; Ennis 2023, Gilmore et al. 2023) or controversial (e.g., vaccination mandates). Furthermore, many commercial environments (e.g., online) are evolving rapidly, and systemic responses often lag behind. In such circumstances, boosting interventions are at least a first line of response to safeguard citizens' autonomy (Hertwig 2023).

3.2. Tackling Global Challenges Requires Competent and Active Citizens

A second major reason empowered citizens are indispensable lies in the active role they are expected to play in adapting to societal challenges. For example, during the COVID-19 pandemic, public health experts and policy makers appealed to people's risk competences (e.g., comprehension of health statistics; Gigerenzer et al. 2007), their understanding of unfamiliar concepts such as exponential growth (e.g., Lammers et al. 2020), their media competences in the face of the COVID-19 infodemic (Okan et al. 2020), their trust in science, their prosocial motivation, their self-control in implementing protective measures (e.g., quarantine), and their ability to adapt to a remote working environment.

The pandemic has subsided, but there is no shortage of major global challenges, including climate change and rapidly developing AI technologies. As was the case during the COVID-19 pandemic, citizens who are equipped with the skills and the motivation to actively engage and change will be crucial to addressing these issues effectively. As Welzel & Inglehart (2010, p. 44) argued, "among individuals as well as societies, the imperative of adaptability puts a premium on 'agency.' Greater agency involves higher adaptability because for individuals as well as societies, agency means the power to act purposely to their advantage." Competent agency is a goal worthy of investment (see also Banerjee et al. 2024). Not only does it benefit society but also has intrinsic value for individuals by contributing to greater life satisfaction and well-being (e.g., Ryan et al. 2022).

3.3. Ethical Value of Empowerment

A third major reason for investing in people's cognition and motivation pertains to one of the most influential frameworks for thinking about human welfare and related concepts (e.g., agency, freedom, and equality), Amartya Sen's capability framework (e.g., Sen 2002). According to this view, autonomous agents must be able to subject their "choices—of actions as well as of objectives, values and priorities—to reasoned scrutiny" (Sen 2002, p. 4). By this measure, nudging can be ethically problematic because it generally does not require, let alone encourage, a reasoned examination of one's choices. Boosts, on the other hand, do.

4. BOOSTING: A BEHAVIORAL PUBLIC POLICY APPROACH TO EMPOWERING CITIZENS

Boosting is grounded in evidence from behavioral science that shows that human decision making is not as flawed as the nudging approach assumes. Boosts are interventions that improve people's competences to make informed choices that conform to their goals, preferences, and desires (Hertwig & Grüne-Yanoff 2017; see also the sidebar titled What Is Boosting?). **Table 1** presents selected examples of boosts across a range of domains, such as understanding health statistics, coping with misinformation, addressing self-control problems, and mastering math anxiety. Section 5 reviews these and additional boosts (see **https://scienceofboosting.org** for more examples). The sidebar titled Categories of Boosts highlights different categories of boosts. Note that in this review, we focus on boosts that foster competences that are relevant for public policy problems, but boosts can also serve other, more individualistic goals (e.g., successful contract negotiation, maintaining or improving memory performance).

In order to foster competences, boosts typically impart knowledge—but their focus is on actionable and procedural, rather than declarative, knowledge (see the related distinction between "knowing how" and "knowing that"; Ryle 1945–1946). The notion of actionable knowledge has taken on different meanings over time (see Mach et al. 2020); we use the term here to indicate that information about relevant action is embedded within the knowledge (e.g., instead of simply being

CATEGORIES OF BOOSTS

Boosts can be classified along several dimensions, including the behaviors or problems being targeted (e.g., unhealthy diet, social media addiction), the competence to be established or enhanced, how specific or generalizable the competence is, the cognitive and motivational requirements an individual needs to engage with a boost, the targeted audience (e.g., first-graders versus the population at large), and whether the boost is deployed by oneself or someone else (see also Duckworth et al. 2018).

Another important distinction is between short-term and long-term boosts (Hertwig & Grüne-Yanoff 2017). Short-term boosts foster a competence that is bound to time and place and are typically deployed by someone else; for example, a health authority presents information about the reliability of a medical test by presenting its diagnostic statistics—prevalence, sensitivity, and specificity—as "natural frequencies" (McDowell & Jacobs 2017; see **Figure 1**). Long-term boosts aim at permanently changing people's cognitive and behavioral repertoire by adding a new competence or enhancing an existing one that people can deploy themselves across situations—for example, training people to autonomously convert diagnostic statistics into natural frequencies, thus making the correct interpretation apparent (Sedlmeier & Gigerenzer 2001; see **Figure 1**).

told not to trust everything online, being able to assess the trustworthiness of an online source by using a search engine to find out what others say about it; McGrew 2024). However, even providing knowledge without explicit instructions for how to act can be valuable. For instance, learning the most common but not widely known symptoms of a heart attack (Mata et al. 2014) can be enough to save a life. Identifying such crucial population-wide gaps in knowledge and designing ways to fill them are also objectives of boosting.

4.1. How Boosting Differs from Nudging

Boosts and nudges are conceptually distinct on several key dimensions (see **Table 2**). Perhaps the most striking difference between the two is their immediate intervention objective: Nudges

Table 2 Differences between nudging and boosting approaches to public policy

Dimension	Nudging (noneducative)	Boosting (long-term)
Intervention target	Behavior	Competences
Roots in research programs and evidence	Shows decision maker as systematically imperfect and subject to cognitive and motivational deficiencies	Acknowledges bounds but identifies human competences and ways to foster them
Causal pathways	Harnesses cognitive and motivational deficiencies in tandem with changes in the external choice architecture	Fosters competences through changes in skills, knowledge, decision tools, or the external environment
Assumptions about cognitive architecture	Dual-system architecture	Malleable cognitive architectures
Reversibility	Once intervention is removed, behavior reverts to pre-intervention state	For long-term boosts, effects should persist once successful intervention is removed
Programmatic ambition	Corrects momentous mistakes in specific contexts ("local repair")	Equips individuals with domain-specific or generalizable competences
Normative implications	Might violate autonomy and transparency	Necessarily transparent, cooperation is required (and can be refused)

Table adapted from Hertwig & Grüne-Yanoff (2017).

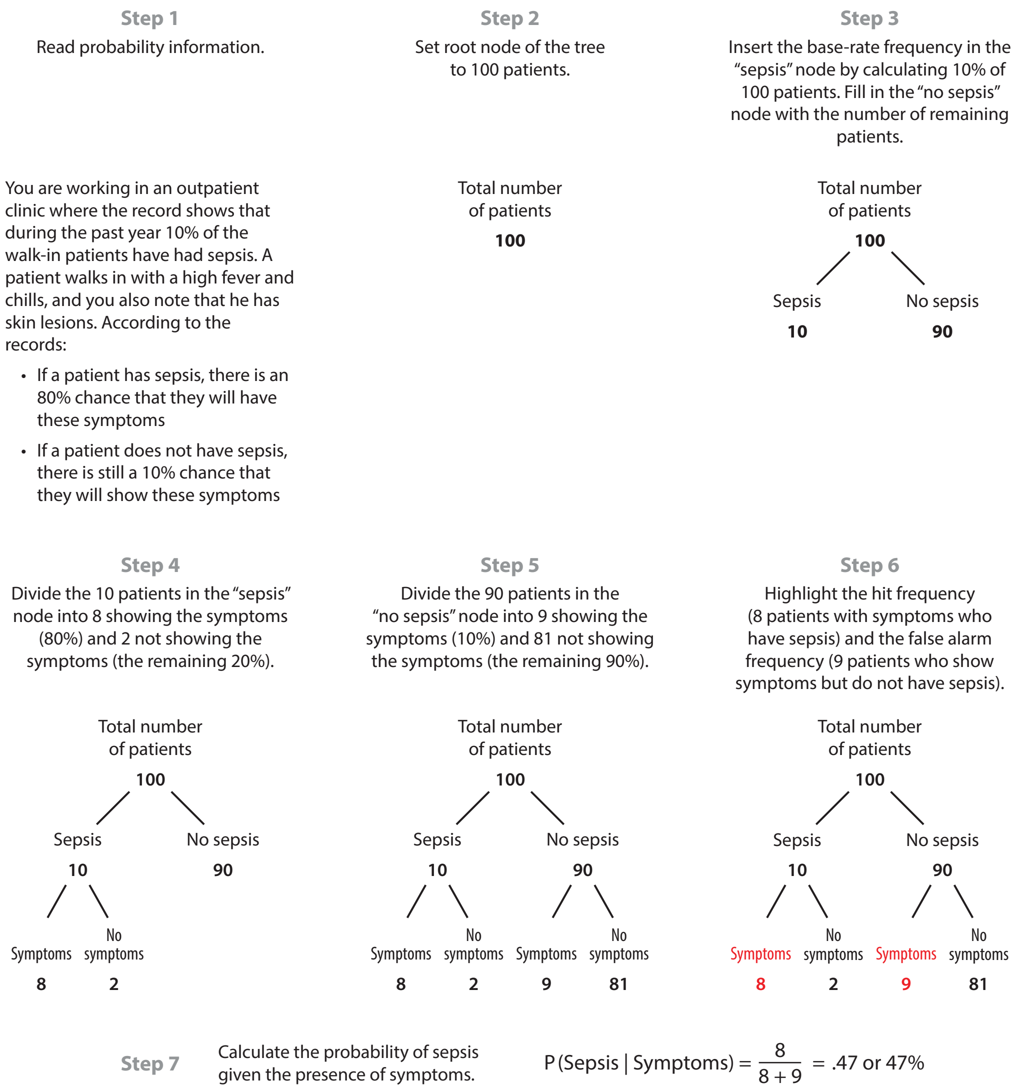

Figure 1

Boosting Bayesian reasoning competences using natural-frequency tree representations. The figure is a graphical representation of the natural-frequency representation training from Sedlmeier & Gigerenzer (2001). Step 1 starts with the description of a medical diagnostic problem expressed in the nonintuitive, conditional probabilities format. Steps 2–7 show how to translate this information into the more insightful natural-frequency tree representation, which makes the correct answer much more transparent and intelligible.

target behavior (e.g., saving more for retirement through automatic enrollment in pension plans), whereas boosts target competences and leave it to the individual to decide whether and to what extent they will use the competences to change their behavior. This distinction implies others: For example, people who are nudged may or may not notice the change in their behavior (e.g., as a result of a default setting; Jachimowicz et al. 2019) or the intervention that brought it about; by contrast, boosts require an individual's attention and cooperation and therefore cannot fly under their radar. Given the different assumptions that boosting and nudging approaches make, one,

WHEN TO CONSIDER BOOSTING OR NUDGING

Boosting and nudging make different assumptions about decision makers (see Hertwig & Grüne-Yanoff 2017 and **Table 2**). To assess whether either approach might work in a particular setting (see Hertwig 2017), consider the following. For boosting to work, the target audience needs both the cognitive ability and the motivation necessary to develop competences. If they do not have both, a boosting approach is unlikely to be effective. To assess nudging, consider the following questions:

- Is there uncertainty about people's goals?
- Is there a marked heterogeneity of goals? Do individuals have conflicting goals?
- Do nudges need to be nontransparent or invisible to be effective?
- Are there nonbenevolent choice architects or governments?
- Can the private sector create toxic choice architectures?
- Is the aim to foster generalizable and lasting behaviors?

If the answer to at least one of these questions is yes, the use of nudging is questionable.

both, or neither of the approaches might work in a particular setting (see Hertwig 2017 and the sidebar titled When to Consider Boosting or Nudging).

A burgeoning line of research on nudge plus interventions has attempted to address questions around nudging's effectiveness and legitimacy by modifying the concept of nudging to incorporate an element of reflection (Banerjee & John 2024). For instance, Banerjee et al. (2023) compared agency-enhancing interventions, including nudge plus interventions, with classic nudges (opt-out default and labeling) in the context of reducing meat consumption and individual carbon footprints. The intervention that had the biggest effect on the intention to choose sustainable food when ordering from a hypothetical food delivery service was a nudge plus: People were asked whether they would pledge to commit to a more sustainable diet before being defaulted into the environmentally friendliest order. In our view, nudge plus is a promising approach for behavioral public policy (for a brief review of nudge plus–like interventions, see Banerjee & John 2024). It has the potential to exceed the degree of behavior change achieved by standard nudges and to move nudging interventions closer to meeting Sen's (2006) criterion of reasoned scrutiny.

4.2. Boosting via Self-Nudging

One category of boosting deserves special mention. Reijula & Hertwig (2022) proposed that people can be taught to nudge themselves in order to regulate their own behavior; they called this approach self-nudging. In self-nudging boosts, people are empowered to design and structure their own choice environments—that is, to act as citizen choice architects (see also the notion of egonomics, or the art of self-management; Schelling 1978). This is possible because many of the psychological principles behind nudges (e.g., friction, defaults, positional effects) are intuitive and easy to learn. Positional effects, for example, will be familiar to anyone who has added a chocolate bar to their purchase while queuing in a supermarket. Not much explanation is needed to make the concept clear. Highlighting how positional effects can be used at home to promote healthier choices gives people the ability to design their surroundings in ways that support their personal goals: A person might decide, for instance, to stash their chocolate out of sight in order to avoid temptation. Self-nudges can be implemented in a range of ways, including via apps like one sec (Grüning et al. 2023), which delivers a self-deployed and self-imposed barrier to behavior. In one sec, the user is in the driver's seat. They first specify the websites or apps they would

Nudge plus: policy approach that informs people about a nudge and encourages them to reflect on it

Self-nudging: guiding one's own behavior toward a desired outcome by applying behavioral science principles to modify one's choice environment like to use less. Thereafter, whenever they attempt to open one, the app automatically interrupts the process, prompting the user to stop for a few seconds—or longer, depending on the user's preferences—before deciding whether they really want to proceed. This simple process, which inserts just a little friction, has been shown to decrease users' actual opening of target apps by 57% after 6 weeks. Importantly, users liked it, reporting higher satisfaction with their social media consumption.

Like all boosts, self-nudging handily addresses some of the criticisms of nudging. For one, it respects people's autonomy; people are always aware of a self-nudging intervention and can choose whether to employ it. Similarly, citizen choice architects are free to undo—and reinstate—the changes they make to their environments at any time. Self-nudging also addresses the fact that a public policy maker can never know and meet the needs of every individual in their target group. In self-nudging, the nudger and the nudged are one and the same, making it more likely that the intervention meets their needs. Furthermore, self-nudging makes it possible for individuals to introduce nudging interventions that are effective in the public sphere into their private spheres—if they want to.

5. BOOSTS FOR FOSTERING CORE COMPETENCES

In today's world, being able to read and write is no longer enough for an educated citizenry in a functioning democracy. We now examine a selection of competences that may be considered indispensable for an educated citizenry today. (Note that the categories we use to structure the competences and boosts below are for illustrative purposes only and do not represent the only way to organize competences and boosts.)

5.1. Risk Competences

Competence in reckoning with risks involves being able to understand, analyze, and reason about risks and probabilities (e.g., health statistics, distributions of financial returns). Below we review five boosts to foster risk competences: fact boxes, visual representations, interactive representations of simulated experience, minimally manipulative representations, and training in designing insightful representations.

5.1.1. Fact boxes. Fact boxes are short-term boosts designed to effectively present complex statistics and evidence in a clear and concise format (McDowell et al. 2016). For instance, McDowell et al. (2019) developed a fact box on the effects of prostate cancer screening that presents the key consequences for men who underwent screening and those who did not. It includes absolute numbers for critical outcomes such as prostate cancer mortality and the incidence of false alarms or unnecessary treatments, thus boosting an individual's ability to systematically compare the benefits and harms associated with getting screened.

5.1.2. Visual representations. Visual representations are powerful tools for communicating complex information (Fundel et al. 2019, Garcia-Retamero & Cokely 2017, Lusardi et al. 2017, Spiegelhalter et al. 2011, van der Bles et al. 2019). One example of this short-term boost is an icon array (**Figure 2**; see also Xiong et al. 2022). Similar to fact boxes, visual representations can be used to effectively communicate the benefits and harms of medical treatments, but they may be a better tool for people who cannot easily interpret nongraphical representations of probabilistic information (Garcia-Retamero & Cokely 2017).

Icon array: graphical display of shapes, with some highlighted to intuitively and transparently depict event frequencies

5.1.3. Interactive representations of simulated experience. Interactive simulations of, for instance, outcome distributions of financial returns or side effects of medical treatments are an

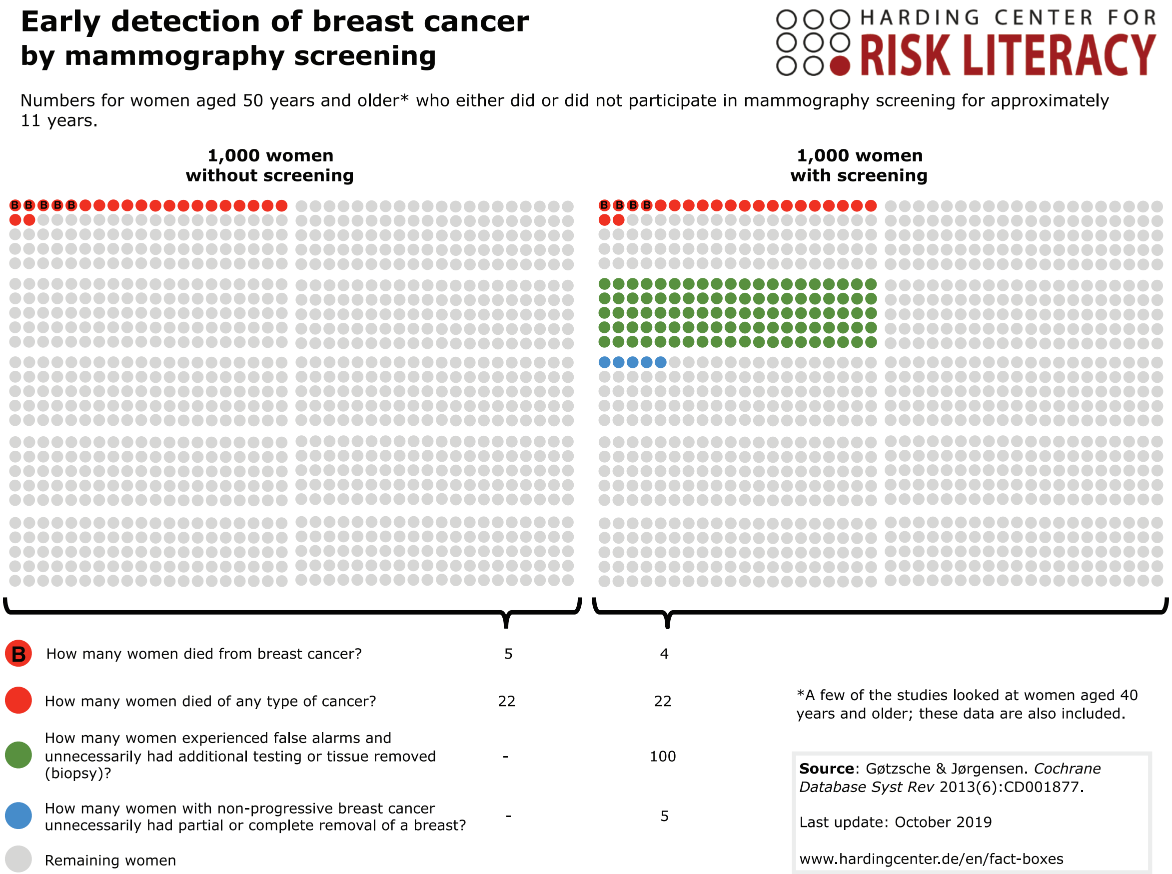

Figure 2

Icon array for early detection of breast cancer by mammography screening (**www.hardingcenter.de/en/transfer-and-impact/fact-boxes/early-detection-of-cancer/early-detection-of-breast-cancer-by-mammography-screening**). Figure reproduced with permission from the Harding Center for Risk Literacy (CC BY-NC-ND 4.0).

engaging way for people to understand and assess risks over time that do not lend themselves well to static, descriptive explanations (Hertwig & Wulff 2022). In a randomized controlled trial, simulated experience formats improved the objective and subjective risk perception of opioids' harms in patients suffering from chronic noncancer pain (Wegwarth et al. 2022). Importantly, 9 months later, patients who had seen the simulated experience format were more likely to have reduced their opioid intake or quit opioids altogether; they also showed a higher uptake of other therapies compared to patients who had seen a fact box (which was also found to increase subjective and objective risk perception).

5.1.4. Minimally manipulative representations. Representations of risk information that present an agnostic view of people's final decisions are essential for informed decision making (Gigerenzer et al. 2007, Spiegelhalter et al. 2011). One effective strategy for this type of short-term boost is to represent risks in terms of absolute frequencies instead of relative risks, which can lead to systematic misinterpretations that channel people toward options they otherwise would not have chosen. For example, in 1995 the UK Committee on Safety of Medicines stated that the third-generation contraceptive pill would double the risk of thrombosis. This framing caused a widespread "pill scare" that resulted in many women rejecting the pill and an estimated 13,000 additional abortions the following year in England and Wales (Furedi 1999). Had this risk been conveyed in absolute terms—such as "from 1 to 2 cases of thrombosis per 7,000 women"—this more informative and agnostic framing would likely have helped more women make informed decisions (Gigerenzer et al. 2007).

5.1.5. Training in designing insightful representations. Statistical reasoning has been hailed as being as important as reading and writing. Yet people seem to fail at the ultimate discipline of statistical reasoning, Bayesian reasoning (Thaler & Sunstein 2003, p. 176). A long-term boost has been shown to improve people's competence in Bayesian reasoning in under 2 hours (Sedlmeier & Gigerenzer 2001). In a training session, people learned to transform an opaque representation (i.e., single-event, conditional probabilities) into a transparent one (i.e., natural frequencies). Having done so, they were then better able to infer, for example, the probability of actually having a disease given a positive test (see **Figure 1**). Three months later, they were still able to make correct Bayesian inferences, with no drop in performance. This example highlights the broader potential for long-term boosts that foster individuals' ability to convert unhelpful and even misleading information into something more accessible and intuitive, thereby improving their reasoning and decision-making skills over the long term and removing the need for a benevolent information designer.

5.2. Financial Competences

Financial education interventions can improve financial knowledge and associated behaviors (Kaiser et al. 2022; but see also Greenberg & Hershfield 2019, p. 21). Here we review a few relatively quick, low-effort financial boosts: visual representations, interactive representations of simulated experience, and heuristics.

5.2.1. Visual representations. Graphics showing the effects of different diversification strategies on a financial portfolio's expected return improve people's understanding of investment strategies (Lusardi et al. 2017). For example, a simple line graphic showing the dramatic increase in savings resulting from doubling monthly payments into an investment improves people's accuracy in judging the effects of increasing investments and motivates them to save more for retirement (McKenzie & Liersch 2011).

5.2.2. Interactive representations of simulated experience. Allowing people to experience risks in a simulation is a promising avenue for improving their understanding of those risks (Hertwig & Wulff 2022). For example, an interactive tool that enables individuals to simulate the expected return distribution of an investment, its variability, and the likelihood of loss—rather than gauging those from a graphical description—was found to improve people's comprehension of investment risks and their willingness to invest (Kaufmann et al. 2013).

5.2.3. Heuristics. Simple heuristics can boost people's financial literacy. Training microentrepreneurs in basic accounting heuristics and routines was found to improve their financial practices (e.g., separating business and personal accounts), reporting of business outcomes (e.g., fewer errors), and business revenues (Drexler et al. 2014). For example, they were taught 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" (Drexler et al. 2014, p. 3). Crucially, the effect of the training was substantially greater than that of conventional accounting training, which typically focuses on teaching the fundamentals of double-entry accounting, working capital management, and investment decisions.

There are also heuristics that help people understand compound interest and exponential growth. For example, teaching people the rule of 72 (i.e., that an investment growing at x percent per year doubles roughly every $72/x$ years) helps them understand the dynamics of saving (Foltice 2017). Other heuristics may help people better estimate the amortization of debts (e.g., how many monthly payments are necessary to pay off a debt by a certain time; Foltice 2017, Soll et al. 2013).

5.3. Judgment and Decision-Making Competences

Most decisions that individuals face are steeped in uncertainty (Hertwig et al. 2019); knowledge about possible outcomes and their probabilities is at best incomplete, and at worst nonexistent. The risk boosts that we discussed in Section 5.1, where most if not all of the relevant information about possible outcomes was available, will therefore not suffice. There are various ways to boost people's competences for dealing with uncertainty. For example, brief training sessions in probabilistic reasoning principles can improve people's forecasts of future events (Chang et al. 2016). Here we focus on heuristics as simple decision aids to improve judgment and decision-making competences.

Heuristics have been proposed as descriptive models of how the mind deals with uncertainty (Gigerenzer & Gaissmaier 2011, Katsikopoulos et al. 2020). They allow for good judgments and decisions by exploiting the informational structure of the environment. However, heuristics can also be thought of as prescriptive models that people can use—or can be instructed to use—to make good judgments and decisions under uncertainty and adversarial conditions such as lack of time and information.

Complementing this perspective, recent research in machine learning has made remarkable progress in constructing simple and transparent decision models that generally perform about as well as more complicated and opaque models (Rudin et al. 2022). How is that possible? To see why consider that in many domains, large sets of similarly accurate models exist; these sets will therefore often contain at least one model that is simple and interpretable (Semenova et al. 2022). Thus we can expect that, in practice, simple models often exist and can be used as boosts in place of more complex, opaque models with little to no sacrifice in performance.

5.3.1. One-reason heuristics. One-reason heuristics base judgments "on one good reason only, ignoring other cues" (Gigerenzer & Gaissmaier 2011, p. 463). Here we highlight simple decision trees (Katsikopoulos et al. 2020, Wang et al. 2022), a one-reason heuristic used to support decision making in domains such as finance, medicine, and human resources (e.g., Aikman et al. 2021, Gigerenzer et al. 2022, Keller et al. 2020).

Consider a simple decision tree that was developed to identify failing banks (Aikman et al. 2021; see **Figure 3**) using expert insights from the Bank of England and statistical analyses. The tree correctly red-flagged 82% of the banks that failed during the 2008 global financial crisis (i.e., sensitivity of 82%) and correctly green-flagged 50% of the banks that survived (i.e., specificity of 50%)—a performance similar to that of a more complex logistic regression model. This decision tree shows how a boost can support policy makers and institutions as well as the general public [for another example, see a simple decision tree for evaluating the credibility of scientific information online by Osborne & Pimentel (2022)].

Simple decision tree: decision tree with few questions that often leads to a decision before all questions have been answered

5.3.2. Trade-off heuristics. A trade-off heuristic "weights all cues or alternatives equally and thus makes trade-offs" (Gigerenzer & Gaissmaier 2011, p. 469). Simple tallying heuristics fall under this category (Katsikopoulos et al. 2020). Trade-off heuristics can support decision making in domains such as forensics and medicine (as simple statistical prediction rules; see also

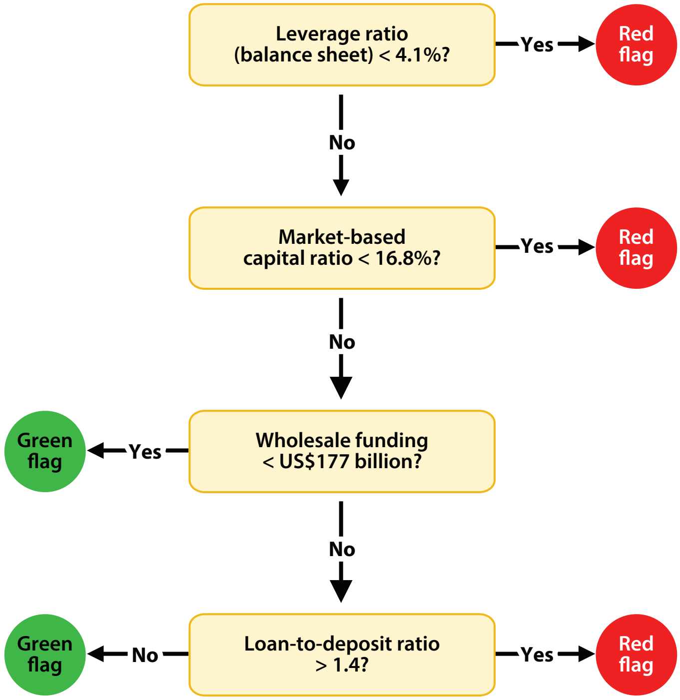

Figure 3

Simple decision tree for identifying failing banks. Figure adapted from Aikman et al. (2021) (CC BY 4.0).

Swets et al. 2000) and are promising boosts whenever only a combination of cues predicts an important outcome.

For instance, a simple predictive checklist in a hospital might include tallying heuristics such as "If M (or more) symptoms are present out of a total of N symptoms, flag the patient as critical." Zhang et al. (2021) developed machine learning techniques to construct simple predictive checklists of this form. They illustrated their approach, among other things, with a checklist for predicting whether a patient will readmit to a hospital within the next 30 days. It predicts readmission if three or more of six items are present (e.g., number of admissions in the past year $\geq$1 or length of stay $\geq$8 days). In cross-validation analyses, this checklist yielded an error rate of 34%—similar to that of a regularized logistic regression model (LASSO; 33%) and slightly better than that of a blackbox ensemble model (XGBoost; 37%).

5.4. Competences for a Digital World

Online, people face countless adversarial and exploitative environments. Misinformation campaigns (Lewandowsky et al. 2023), microtargeting (Lewandowsky et al. 2020, Lorenz-Spreen et al. 2021), and "dark patterns" in user interfaces (Narayanan et al. 2020) all undermine people's autonomy and threaten democracies (Kozyreva et al. 2020, Lewandowsky et al. 2020). To successfully confront these and other challenges, people need competences that pertain to the cognitive challenges posed by the digital world's attention economy, choice architectures, algorithmic content curation, misinformation, and disinformation (Lewandowsky et al. 2020). In this section, we highlight a selection of boosts for fostering digital citizen competences; more examples are provided by Kozyreva et al. (2020, 2023, 2024) and Zimmerman et al. (2020).

5.4.1. Attention economy. The digital world is engineered to extract people's time, attention, and data without them considering the personal or societal costs of doing so. In this environment it is crucial to be competent in critical ignoring (Kozyreva et al. 2023, p. 81), that is, "choosing what to ignore and where to invest one's limited attentional capacities." Boosts to foster critical ignoring include self-nudges (Reijula & Hertwig 2022) such as introducing friction into the use of distracting apps (e.g., by deploying the one sec app; Grüning et al. 2023) or removing tempting apps from one's phone altogether (Kozyreva et al. 2023).

Another way online environments monopolize people's attention is through microtargeting, that is, tailoring content to a target audience's psychological characteristics (e.g., personality), potentially with the goal to exploit those characteristics (Lorenz-Spreen et al. 2021, Simchon et al. 2024). Lorenz-Spreen et al. (2021) showed how a simple self-reflection intervention in which people filled out an eight-question extraversion questionnaire, either with or without subsequent feedback, improved their ability to correctly identify whether an advertisement targeted their personality type (i.e., extraverted or introverted).

Critical ignoring: strategically directing one's attention to high-quality information and ignoring low-quality information

Microtargeting: tailoring content to a target audience's psychological characteristics (e.g., personality), potentially with the goal to exploit those characteristics

5.4.2. Misinformation and disinformation. People may engage with misinformation at various stages: when selecting information sources, when choosing what information to consume or ignore, when evaluating the accuracy of the information and/or the credibility of the source, or when judging whether and how to react to the information (Geers et al. 2024). Research has produced a toolbox of interventions against misinformation (Kozyreva et al. 2024). For example, one boost psychologically inoculates people against misinformation. The rationale is that "if people are forewarned that they might be misinformed and are exposed to weakened examples of the ways in which they might be misled, they will become more immune to misinformation" (Lewandowsky & van der Linden 2021, p. 348). For example, short videos that expose common manipulation techniques such as emotionally manipulative language, incoherence, false dichotomies, scapegoating, and ad hominem attacks have been found to improve not only people's ability to recognize manipulation but also their confidence in spotting it, their ability to discern trustworthy from untrustworthy content, and their sharing decisions, both in controlled experiments and on YouTube (Roozenbeek et al. 2022). Another effective boost is to teach people simple fact-checking heuristics such as lateral reading (i.e., checking what other online sources say) (McGrew 2024; see **Table 1**).

Lateral reading: leaving an unfamiliar website to assess its credibility by efficiently consulting other relevant sources on the open Internet

Motivational boost: fostering a person's competence to autonomously adjust their motivation, cognitive control, self-control, and environment

5.5. Motivational Competences

Many people aspire to eat healthily, exercise regularly, or spend their time online in a self-determined way. Attempts to withstand temptations and distractions through sheer force of will are likely doomed to fail, especially in environments that actively promote the behavior a person is trying to avoid, such as overeating (Brownell 2005) or getting distracted online (Kozyreva et al. 2023).

Based on what is known about motivation, cognitive control, self regulation, and habit formation (Duckworth et al. 2018, Inzlicht et al. 2021, Oettingen & Gollwitzer 2015, Wood & Rünger 2016; see also the sidebar titled Motivational Boosting Interventions), motivational boosts (Hertwig & Grüne-Yanoff 2017, Reijula & Hertwig 2022) can be designed to foster people's motivational competences. For example, people can be taught to use temptation bundling, that is, coupling a behavior that produces a delayed reward with an immediate treat (e.g., listening to audiobooks during physical activity; Kirgios et al. 2020).

Some motivational boosts are highly specific. For example, to prevent hitting cyclists when opening their car door, drivers can learn and practice the simple Dutch Reach method (Large et al. 2018): Reach toward the door with the hand that is furthest from it and, as you pivot, check your blind spot for cyclists coming up behind you. Once people have established this habit (e.g.,

MOTIVATIONAL BOOSTING INTERVENTIONS

Motivational boosting interventions can incorporate strategies such as expressive writing (e.g., regularly writing about a stressful topic; Pennebaker 2018), attention and attention state training (e.g., "training programs that...involve effortless practices or experiences, such as nature exposure and flow experience"; Tang et al. 2022, p. 568), psychological connectedness training (e.g., writing a letter to yourself 20 years into the future; Hershfield 2019), reward-bundling exercises (e.g., coupling a behavior that produces a delayed reward with an immediate treat; Ainslie 2021, Kirgios et al. 2020), the strategic use of automatic processes (e.g., mental contrasting with implementation intentions, that is, spelling out in advance what one will do, how, and when, while considering potential obstacles; Oettingen & Gollwitzer 2010), training in precommitment strategies (e.g., using a savings bank account in which the saved-up money only becomes available at a future date; Bryan et al. 2010), and other self-control strategies (e.g., self-imposed penalties or rewards for reaching exercise goals; Fishbach & Shen 2014).

with the help of a small reminder placed on the door handle), they no longer need to remind or motivate themselves to check for cyclists before getting out of a car.

Other motivational boosts foster general competences that can be applied broadly. For example, people are more likely to achieve their goals if they use mental contrasting with implementation intentions (MCII; i.e., spelling out in advance what they will do, how, and when, while considering potential obstacles) (Cross & Sheffield 2019, Gollwitzer & Sheeran 2006, Oettingen 2012, Oettingen & Gollwitzer 2010, Wang et al. 2021). Schunk et al. (2022), for example, demonstrated that children who received a short training in self-regulation based on MCII improved their self-regulation and academic skills (e.g., reading).

When using self-nudges (Reijula & Hertwig 2022) as a motivational boost, citizen choice architects can outsource parts or all of the motivational demands to the environment. For example, people who want to waste less time online can deactivate notifications (Kozyreva et al. 2020, 2023). By making people aware of the control their environment has over their behavior, self-nudging can help them turn their environment into an ally rather than an obstacle.

5.6. Health Competences

One of the United Nations's 17 Sustainable Development Goals is to "ensure healthy lives and promote well-being for all at all ages" (**https://sdgs.un.org/goals/goal3**). A mix of policies is key to achieving objectives like this. Subgoals such as ensuring universal health coverage or reducing deaths and diseases from hazardous chemicals and pollution require government action, but individual competences also play an important role. Health competences include many that we have already discussed here, such as risk competences and motivational competences (see also Rouyard et al. 2022). In health matters, however, an ounce of prevention is worth a pound of cure. A key competence is therefore avoiding threats to health altogether.

Mental contrasting with implementation intentions (MCII): planning what to do, and how and when to do it, considering potential obstacles

Obesity is a chronic, multifactorial, and relapsing disease, and the most compelling response to it is prevention. Prevention in childhood holds particular promise, as this is when eating habits are formed. One entry point for policy intervention is to empower parents to become competent architects of their own food environment—and, by extension, of their children's food environment. Parents are usually their children's nutritional gatekeepers: Two-thirds of a child's daily calories come from food prepared at home (Poti & Popkin 2011). Furthermore, frequent family meals are associated with a lower risk of overweight and higher diet quality in children (Dallacker et al. 2018). Building on this finding, another meta-analysis identified family meal routines that are associated with healthier diets and body weight in children (Dallacker et al.

2019a) and that could serve as boosting interventions for parents by enabling them to effectively design the family meal environment: parental modeling, no TV during meals, preparing meals at home, involving children in meal preparation, longer meal duration, and positive mealtime atmosphere. A randomized clinical trial that focused on the most beneficial routine, longer mealtimes, found that a simple intervention of lengthening family mealtimes by about 10 minutes improved children's diet quality and eating behavior (Dallacker et al. 2023).

Health interventions that aim to enhance people's competences abound. Take, for instance, the growing interest in mental health apps. These apps target a range of competences, including practicing meditation, performing breathing exercises, or practicing acts of kindness toward others. A recent meta-analysis of the still-limited evidence suggests that mental health apps can "promote emotion regulation, positive mental health, and well-being in the general population" (Eisenstadt et al. 2021). Although these interventions primarily respond to individual, not societal, health problems, a recent analysis found that "a change in mental health has an effect on absenteeism [among prime age workers] more than three times greater than a change in physical health" (Bryan et al. 2021b, p. 1519). Therefore, "the prevention and alleviation of chronic health conditions, particularly common mental disorders such as depression and anxiety that are highly prevalent in prime age workers, will deliver significant benefits" (p. 1519).

6. CONSIDERATIONS FOR BEHAVIORAL PUBLIC POLICY APPROACHES

We now discuss three topics that are relevant to boosting as well as to behavioral public policy approaches in general: harnessing existing evidence and concepts; designing, disseminating, and implementing boosts; and studying and evaluating boosts.

6.1. Harnessing Existing Evidence and Concepts

The pursuit of efficient and evidence-informed ways to educate and empower people is part of a time-honored tradition across research fields such as judgment and decision making (in particular, debiasing research; Milkman et al. 2009, Morewedge et al. 2015, Soll et al. 2015), educational science (Weinert 2001), lifespan psychology (Baltes et al. 1999), counseling psychology (Brown & Lent 2008), clinical psychology (Blagys & Hilsenroth 2002), health science (Sørensen et al. 2012), community psychology (Zimmerman 2000), and organizational science (Conger & Kanungo 1988). The boosting approach can therefore draw on a vast toolbox of empowering interventions (e.g., math bedtime story, lateral reading; see **Table 1**). Where no suitable intervention exists, new boosting interventions can be inspired by and developed on the back of evidence from existing lines of research.

The fact that numerous research fields are developing methods for fostering people's competences is good news: There are likely many boosts yet to be harnessed and adapted for behavioral public policy. However, the interdisciplinary, distributed, and heterogeneous nature of the evidence base for boosts also makes it challenging to discover and synthesize this diverse knowledge in order to build a cumulative and coherent science of boosting. Here we offer two strategies for making this challenge more manageable.

First, use the conceptual triad of (*a*) societal challenges where citizens need to be empowered, (*b*) the human competences (cognitive and motivational) needed to tackle a particular challenge, and (*c*) boosting interventions that could promote those competences (see **Table 1** for examples; see also Kozyreva et al. 2020). From a policy perspective, the first step is typically to start with a precise description of the problem (e.g., the rapid spread of harmful misinformation online). The next step consists in analyzing the causes of and enabling reasons for the problem. Typically, several factors (e.g., insufficient regulation, commercial incentives, individual behavior) collude in causing and amplifying a problem. In a third step, behavioral policy makers aiming to help people develop relevant competences would identify what competences and motivations can support citizens in dealing with the problem (e.g., accurately and efficiently assessing the reliability of information and its sources online; Geers et al. 2024) and search the literature for suitable interventions (e.g., lateral reading; McGrew 2024).

Second, boosting research would profit from an ontology (Sharp et al. 2023) of boosting interventions along the lines of the Behavior Change Technique Taxonomy developed for behavior change interventions (Marques et al. 2023). Such an ontology would make it easier to consolidate study results from the literature into topic-specific, machine-readable databases of studies (see, e.g., Spadaro et al. 2022 for a database of 2,636 studies on human cooperation), which in turn would make conducting meta-analyses more efficient (see also the Open Research Knowledge Graph; Auer et al. 2023). More generally, bridging ontologies from different domains (e.g., education and medicine) via foundational ontologies would facilitate discoveries of new applications for existing interventions and other insights.

6.2. Designing, Disseminating, and Implementing Boosts

Many studies of boosts provide proof of concept, that is, evidence that people can, in principle, be boosted (conceptually similar to efficacy trials in the health sciences, which test interventions in tightly controlled settings and prioritize internal over external validity; Bauer et al. 2015). For example, computer simulations show that simple decision trees can promote accurate decisions in difficult circumstances (e.g., time pressure, limited information; Katsikopoulos et al. 2020), such as when triaging patients (Keller et al. 2020). However, successfully teaching medical professionals a simple decision tree in a controlled setting does not guarantee that they will use it in practice.

It will often be possible to embed the core boost (here, the simple decision tree) inside a broader, psychologically informed delivery vehicle. For example, when learning about a simple decision tree, people could be asked to specify their implementation intentions (i.e., the when, where, and how of using the decision tree in the form of if-then rules; see Gollwitzer & Sheeran 2006) and engage in mental contrasting (i.e., anticipating and planning around obstacles to using the decision tree; see Cross & Sheffield 2019, Oettingen 2012) to increase the likelihood that they will use the decision tree in the future. There are also domain-specific opportunities to design boosts that are easier to implement successfully. For example, teaching a simpler but slightly less precise decision tree instead of a more complex but slightly more accurate one can promote learning and reliable usage, resulting in the same—or better—performance in practice. The adoption and dissemination of boosts can also be supported by the use of digital tools such as apps (Grüning et al. 2023) or information formats such as fact boxes (see Reijula & Hertwig 2022).

It is crucial to consider the broader context in which a boosting intervention is implemented (e.g., Bauer et al. 2015). For example, relevant stakeholders should be consulted early on so that they can offer insight into potential opportunities and constraints (e.g., what information is available to doctors at what point in a patient's diagnosis and what could be included in a simple decision tree; Keller et al. 2020).

6.3. Studying and Evaluating Boosts

Next, we briefly discuss three research priorities in the study and evaluation of boosts and other types of behavioral public policies. These complement other, more general strategies advocated in the behavioral and other sciences for improving research and its dissemination (e.g., Holford et al. 2023, Nosek et al. 2022, Topp et al. 2018).

First, given that long-term boosts aim to have lasting effects on competences, research needs to measure their longevity. To date, very few studies have examined the long-term effectiveness of boosting interventions (e.g., Loy et al. 2016, McDowell et al. 2019, Paunov & Grüne-Yanoff 2023, Sedlmeier & Gigerenzer 2001, van Roekel et al. 2022). Longitudinal studies are more laborious and costly than cross-sectional studies, which may partly explain the dearth of longitudinal studies in behavioral public policy. One way to ease the logistical and financial burden is to collaborate in larger research teams (Forscher et al. 2023).

Second, research on behavioral interventions should, by default, be comparative in nature. Ideally, different behavioral interventions would be compared in the same trials to gain a better understanding of when each intervention works best, and for whom (see, e.g., Banerjee et al. 2023, Folke et al. 2021, Franklin et al. 2019, Paunov & Grüne-Yanoff 2023, van Roekel et al. 2022, for comparisons between boosts and nudges). Alongside key behavioral outcome measures, studies should also aim to assess the changes (or lack thereof) in the competences hypothesized to drive behavior change whenever possible. This approach would make it possible to assess the extent to which an intervention achieves its goal via its hypothesized route (e.g., via improved competences in the case of boosting, via changing behavior in the case of nudging). It would also help refine existing theory-derived guidelines for assessing whether boosting or nudging can be expected to work better in a particular setting (Hertwig 2017; see also the sidebar titled When to Consider Boosting or Nudging). Megastudies that compare a larger number of treatments (Duckworth & Milkman 2022, Hameiri & Moore-Berg 2022) could be more feasible for larger research teams (in so-called team science; Forscher et al. 2023).

Third, many studies of boosts provide promising proof of concept in the laboratory, but few have demonstrated the effects of boosts in the field (e.g., how boosting risk perceptions about infectious risks improves hand hygiene compliance among nurses in actual hospital wards; van Roekel et al. 2022). Being clear about the kind of evidence that studies provide (e.g., lab or field, populations studied, presence or absence of heterogeneous treatment effects, evidence on which psychological mechanisms produce the observed behaviors; see, e.g., Bryan et al. 2021a, Grüne-Yanoff 2016) helps both researchers and practitioners estimate the expected success of an intervention in a particular setting and supports them in identifying future research priorities.

7. THE LIMITS OF EMPOWERMENT

Boosts are not a panacea; indeed, no single approach can eradicate major threats such as climate change, poverty, or disease. One explanation for this is offered by Gilmore et al.'s (2023, p. 1194) examination of emerging research on the commercial determinants of health:

> Although commercial entities can contribute positively to health and society there is growing evidence that the products and practices of some commercial actors—notably the largest transnational corporations—are responsible for escalating rates of avoidable ill health, planetary damage, and social and health inequity; these problems are increasingly referred to as the commercial determinants of health. The climate emergency, the non-communicable disease epidemic, and that just four industry sectors (ie, tobacco, ultra-processed food, fossil fuel, and alcohol) already account for at least a third of global deaths illustrate the scale and huge economic cost of the problem. . . . [T]he shift towards market fundamentalism and increasingly powerful transnational corporations has created a pathological system in which commercial actors are increasingly enabled to cause harm and externalize the costs of doing so.

Alongside commercial determinants of health are social determinants of health (Braveman et al. 2011), such as income, knowledge gaps, educational attainment, and racial disparities.

It would be naïve to believe that just one type of intervention can solve all these issues. We argue that an evidence-based and integrated policy mix including behavioral science–informed regulation, education, boosting, choice architecture interventions, and other tools has the best chance of making a difference.

7.1. The Trap of Individualizing Responsibility

All interventions have benefits and drawbacks, and boosts are no exception. In this and the following subsection, we briefly discuss two noteworthy risks of boosts. First, policy makers need to be aware of the risk of shifting the blame. Chater & Loewenstein (2022) argued that corporations and entire industries, driven by the relentless pursuit of profit, have played a key role in creating numerous public health crises and societal problems, including the obesity, diabetes, and opioid epidemics; widespread climate change denial; and a tsunami of misinformation (see Chater & Loewenstein 2022 but also the critical commentaries of this article). One of the most consistently applied strategies that industries have used to shield themselves from accountability is to "cast societal problems as issues of individual weakness and responsibility, the solutions to which involve 'fixing' individual behavior" (Chater & Loewenstein 2022, p. 2). For example, the fossil fuel lobby championed the concept of personal carbon footprints to shift attention away from regulating the industry's carbon emissions (Schendler 2021). Similarly, credit card companies have pushed for financial literacy curricula in schools, purportedly to help people avoid financial debt. These efforts, however, can also be understood as cynical attempts to evade industry regulation (Olen 2013).

Advocating for people to gain the competences they need to confront challenges can be misappropriated as a way to place the blame and burden of responsibility on the individual. In principle, which and to what extent determinants of health and well-being are social, commercial, or individual in nature requires empirical analysis, not commercially or politically motivated finger-pointing. And, as we discussed in Section 3, we think of competent citizens as a first line of response, not the only one; system-level solutions are also required (Hertwig 2023). Furthermore, boosting could complement system-level approaches, for example, by enhancing relevant competences (e.g., financial literacy) and thus making standard policy instruments (e.g., incentives for saving) more effective and more equitable (e.g., by increasing participation rate).

7.2. Cognitive and Motivational Requirements and Social Inequality

A second risk of boosting interventions is that they will create or exacerbate inequality. All boosts require individuals to have the cognitive abilities necessary to engage with the intervention and understand the basic principles at work (Grüne-Yanoff & Hertwig 2016, Hertwig & Grüne-Yanoff 2017; see also the sidebar titled When to Consider Boosting or Nudging), and in some cases not everyone will. This depends in part on the cognitive requirements—for instance, math bedtime stories (Berkowitz et al. 2015) and decision trees are more cognitively demanding than the Dutch Reach method (Large et al. 2018). Similarly, boosting policies require the target audience to be motivated enough to acquire and use the competence offered. In the absence of such motivation, boosting interventions are unlikely to be effective. The entry costs of boosting interventions might lead them to discriminate against less educated or more disadvantaged populations. This is a serious risk, and its magnitude depends on the intervention in question (e.g., more people may be motivated to avoid injuring cyclists than to overcome math anxiety) as well as on how accessibly the boost is framed and explained and how demanding the prerequisite cognitive abilities are.

Nudging also faces the challenge of inequality (see, e.g., Schüz et al. 2021). The libertarian guardrail of nudging is the criterion of easy reversibility: The behavior change brought about by a nudge should be easy to reverse, allowing the individual to act otherwise. However, the ability to act otherwise also presupposes a minimum level of cognition and motivation. This is somewhat ironic, since some nudging interventions (e.g., those based on defaults; Jachimowicz et al. 2019) are designed to exploit people's inertia. The risk here is that nudges are more likely to be accepted by less educated, less motivated, or less well-off groups (for the latter, see, e.g., Shafir 2017); if this were the case, these interventions would no longer preserve liberty in the population as a whole.

8. CONCLUSIONS

Proponents of nudging have argued that "nudges are specifically designed to preserve full freedom of choice" (Sunstein 2014, p. 584). If this quality is ascribed to nudges, then it is all the more applicable to boosts. Boosts aim to help people make informed and good decisions by and for themselves. They also aim to maintain and promote agency, self-efficacy, and autonomy. While boosts alone are not sufficient to address the challenges of our time, it seems absurd, in the search for solutions, not to invest in the capabilities of human beings.

SUMMARY POINTS

1. Behavioral public policy garnered widespread attention with the introduction of nudging, which aims to steer behavior while maintaining freedom of choice.
2. Criticisms of nudging include that it does not promote agency and competences and that it relies—overly optimistically—on the presence of benevolent choice architects.
3. The proliferation of environments threatening people's autonomy, the slow pace of systemic approaches to tackling societal issues, and the intrinsic benefits of empowerment make empowering citizens an indispensable objective of behavioral public policy.
4. Boosting is a behavioral public policy approach to empowerment grounded in evidence from behavioral science that shows that humans' boundedly rational decision making is not as flawed as the nudging approach assumes.
5. Boosts are interventions that improve people's competencies to make informed choices that conform to their goals, preferences, and desires.
6. In self-nudging boosts, people learn to use architectural changes in their proximate choice environment to regulate their own behavior—that is, they are empowered to adapt their own choice environments.
7. There are boosts to foster core competences in many domains, including finance, online environments, and health, as well as broader, overarching areas, such as motivation, risk, and judgment and decision making. Boosts should be part of a policy mix that also includes system-level approaches.
8. When implementing boosts, policy makers need to avoid the trap of individualizing responsibility and to be mindful that, due to differences in cognition and motivation, inequalities in the desirable effects across boosted individuals may emerge.

FUTURE ISSUES

1. How can the boosting approach benefit from other relevant research, including research on empowerment and capability (Conger & Kanungo 1988, Nussbaum 2011, Zimmerman 2000), behavior change in health psychology (Michie et al. 2011),

human-centered design (Lyon et al. 2020), engineering psychology (Wickens et al. 2022), cognitive task analysis (Crandall et al. 2006), and implementation science (Bauer et al. 2015)?

2. Boosts, like other behavioral public policy interventions, need to be implemented as part of a policy mix, especially when they respond to complex problems. How can synergies between regulation, boosts, and nudges be identified and exploited? How does boosting interface with well-being public policy (Fabian & Pykett 2022)?
3. How can research that deals with human decision making for teams and organizations—for instance, fast and frugal heuristics (Gigerenzer et al. 2022) and cognitive repairs (Heath et al. 1998)—be better integrated into research on behavioral public policy?
4. How can boosts best be scaled up and disseminated (e.g., apps, fact boxes, games), and what enhances the longevity of the effects of boosting interventions?
5. What would it mean to apply boosting on a collective level (see Hofmann 2024)?
6. How can boosting enable people to better deal with digital media, online challenges (e.g., deepfakes, dark patterns, microtargeting), and emerging AI technologies (e.g., large language models and other generative AI, algorithmic decision making) (see also Herzog & Franklin 2024)?
7. Boosting is one tool to support lifelong and cumulative learning. It is not meant as a verdict on the success or lack thereof of compulsory learning. Nevertheless, one question is whether the competences that boosting addresses (e.g., risk competences, decision-making competences, digital competences) can and should be integrated into school curricula.

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