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Advancing applied behavioral science: the GAP framework

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Growing acceptance of applied behavioral science in public policy and organizational decision-making has resulted in ambitions to go beyond nudging, particularly following developments in new technologies. To support these ambitions, this paper presents the GAP framework. Building from established behavioral science concepts (General Tools), GAP incorporates new technologies like artificial intelligence (AI) into the behavioral science toolkit (Algorithms), as well as practical considerations for implementing behavioral science within organizational settings (Practical Considerations). The framework unifies diagnostic, design, and scalability considerations to support practitioners in tailoring behavioral capacities to their organizational contexts. GAP is developed as a 'modular' framework, allowing practitioners to draw on its insights to supplement existing knowledge and adapt knowledge to organizational demands.

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Introduction

Applied behavioral science has emerged as a pivotal tool in policy and organizational decision-making (Bhanot and Linos 2020; Mazar and Soman 2022). It leverages insights from various disciplines, such as psychology, economics, and sociology, to change people's behavior (Hallsworth 2023). Among large institutions (e.g., United Nations, European Commission, World Bank and OECD), governments (e.g., USA, UK, Canada, Australia, France, Germany, Singapore, and India) and large firms (e.g., Google, Meta, Walmart, PepsiCo and Morningstar), key behavioral science ideas—such as nudging (Thaler and Sunstein 2008)—are becoming well-embedded.

Such interest has spurred (and been spurred by) the development of various frameworks for designing behavioral science interventions (e.g. COM-B, EAST, MINDSPACE). Some, such as COM-B (Michie et al. 2011) and MINDSPACE (Dolan et al. 2012) offer valuable insights that help overcome gaps between diagnosis and implementation[1]. Yet, few existing frameworks integrate diagnostic and design elements, while also appreciating practical considerations and evaluation needs (e.g., 4S; Mills and Whittle 2024). A comprehensive framework integrating diagnostic and design components (extending beyond choice architecture) alongside practical constraints and technological innovations, may be worthwhile to challenge the popular view of applied behavioral science as just 'off-the-shelf', simple nudges (De Ridder et al. 2024). This need is compounded as emerging technologies, like artificial intelligence (AI), change both the tools available to behavioral science and the behavioral dynamics of organizations themselves (Mills et al. 2023). Prior frameworks have largely seen behavioral science as independent of prevailing technologies. But for many organizations, the link between technology and behavior is not one that can be abstractly cut.

In response to this evolving applied landscape, we contribute the GAP framework. GAP (Fig. 1) consists of three components. *General Tools* captures existing techniques within applied behavioral science. These include actionable insights (SHELL), behavioral audits, and choice architectural interventions. *Algorithms* concern advances in data-processing technologies, such as AI, and the intersection of behavioral science with these technologies. *Practical Considerations* examines the organizational dimensions of behavioral science, from establishing behavioral insights (BI) teams to facilitating the transfer of a team's insights throughout an organization

GAP has a modular design so it can adapt to different organizations' capabilities and needs. For organizations that lack behavioral science capabilities, GAP presents an immediate guide to developing behavioral science capabilities. For an organization already equipped with some capabilities, modularity allows GAP to supplement 'gaps' in those capabilities.

This article presents the GAP framework before concluding with some reflections of the limitations of the framework in relation to current challenges within applied behavioral science.

General tools

General Tools considers existing practices within applied behavioral science. The approaches discussed are not exhaustive, but they do represent important pillars of the field today.

Actionable insights. Behavioral science investigates many decision-making approaches involving various degrees of conscious deliberation (Dhami and Sunstein 2022). These insights can be captured with the mnemonic SHELL (Table 1): social influence (S), habits (H) and emotions (E), limited cognitive processing (L) and limited willpower (L). SHELL broadly summarizes, though does not exhaust, common insights from behavioral science, and serves as a heuristic to encourage organizations to adopt a 'behavioral lens' when aiming for behavior change (Hallsworth 2023).

Social influence encompasses dynamics such as social norms (Bicchieri 2017), peer influence (Laursen 2018) and herd behavior (Banerjee 1992). It arises in various domains, from the stock markets (Aslam et al. 2022) to online misinformation sharing (Van Der Linden 2023) and workplace culture Naji et al. (2022). Leveraging social influence can often be an effective way of influencing behavior. (e.g., Bergquist et al. 2023). This may be through emphasizing ideas such as reciprocity or authority (e.g., Cialdini 2021).

Habits are repeated actions requiring limited conscious deliberation (Wood and Rünger 2016). This repetitive quality makes them important in sustaining behavior change (Carden and Wood 2018). Habits, good and bad, have been studied in areas such as health (Rothman et al. 2015), finance (Furnham 1999), environmental sustainability (Walker et al. 2015) and political participation (Coppock and Green 2016). They form through an interplay of contextual cues and the frequency of those cues (Clear 2018; Eyal 2014; Wood 2019), and can be induced through interventions such as temporary financial incentives (e.g., Loewenstein et al. 2016) sometimes allowing behavior change to persist after the intervention is removed. However, most 'induced' habits gradually disappear post-intervention (Carden and Wood 2018), suggesting habits are not a silver bullet. To this end, technologies which automate and adapt contextual cues, rewards, and the frequency of cues, are

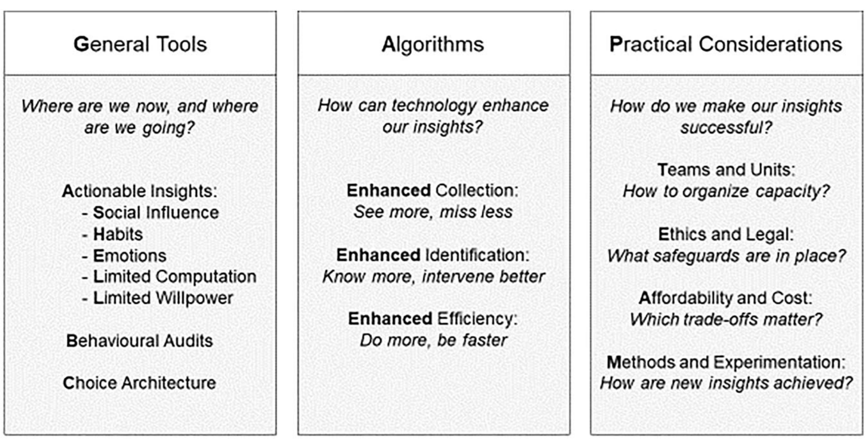

Fig. 1 The GAP-framework for advanced applied behavioral science, including General tools (G), AI enhancements (A) and practical considerations (P).

Table 1 The SHELL mnemonic.

Concept	Detail
Social Influence	Social dynamics often affect decisions, and leveraging social influence can enhance behavior change interventions.
Habits	Habits arise through the frequency of action and guide actions automatically. Recognizing and modifying habits can help people change their behavior and sustain behavior change.
Emotions	Emotions significantly influence choices. Acknowledging and managing emotions is vital to aligning emotional experiences with desired outcomes.
Limited Cognitive Processing	Limited cognitive processing can frustrate information-processing tasks, leading to the use of heuristics or 'rules of thumb'. Heuristics can often produce biases.
Limited Willpower	Limited willpower can undermine self-control, influencing a person's ability to do (or not do) something. Cognitive stressors can sap willpower, with interventions needing to foster self-regulation and target influencing factors.

increasingly of interest in habit formation research (e.g., Carden and Wood 2018; Conklin et al. 2010).

Emotions exert profound influence over decision-making (Phelps et al. 2014). They can focus limited attention, assisting rather than opposing reason (Simon 1997), though can also distract from or undermine effective decision-making. Emotions are considered a dominant driver of most significant life decisions (Ekman and Davidson 1994; Keltner et al. 2019; Loewenstein and Lerner 2003). This claim is grounded in much research highlighting the role of emotional decision-making in areas such as mental and physical health (Taylor 2018), welfare policy preferences (Small and Lerner 2008), creativity (Fredrickson 2001) and economic choices (Loewenstein 2000). The importance, though, of encouraging reasoned and considered decision-making, at least in principle, has seen emotions as a *tool* of behavioral science be relatively under-utilized. Nevertheless, their persistence as a driver of behavior means they cannot be overlooked.

Limited information processing is an important conceptual pillar of behavioral science today. For instance, discussions of emotions often draw upon the observation that people have limited information-processing capacities (Simon 1955). Instead, people often use intuitive heuristics (i.e., 'rules of thumb') to guide decision-making, enabling choices to be made when there is both too much and too little information (Hjeij and Vilks, 2023; Simon 1955), or other constraints on information-processing, such as too little time (Gigerenzer and Selten, 2001). Heuristics are not always well-adapted to modern day organizations, leading to systematic mismatches, or biases. For instance, people tend to rely on easily accessible information (Tversky and Kahneman 1973) and that which confirms pre-held beliefs (Nickerson 1998). Thus, practitioners may employ strategies that enhance information accessibility, simplify (statistical) formats, and improve trust in information (Compton et al. 2021) to influence behavior.

Finally, *limited willpower* influences a person's self-control. Research on limited will-power and self-control (e.g., Friese et al. 2017; Willems et al. 2019) shows that intentional cognitive effort to do or not do some activity is limited (Baumeister et al. 2018). People can be prone to suboptimal decision-making when faced with temptations, internal conflicts, or fatigue (Inzlicht et al. 2021). These self-control failures contribute to various policy issues, including obesity (VanEpps et al. 2016), retirement saving (Thaler and Benartzi, 2004) and educational achievement (Duckworth et al. 2016). While willpower is limited, situational factors such as poverty or financial worry may also contribute to these limitations by sapping one's available cognitive effort (Duckworth et al. 2019; Adamkovič and Martončik 2017). Appreciating both the behavioral impact of willpower, and the factors that may counteract it, can be important to maximize behavioral outcomes (Curchin 2017; Mills 2024a).

The SHELL mnemonic captures an array of established behavioral science insights and serves as a foundation to elaborate upon (see Table 1). It introduces a structured diagnostic 'behavioral lens' to identify behavioral drivers from a boundedly rational perspective (e.g. covering drivers captured in other models, such as MINDSPACE, but extending them as well), rather than defaulting to more traditional explanations, such as inadequate rewards or information gaps. However, SHELL also demonstrates the drivers of behavior that might be at play in a policy scenario or organizational setting. Many drivers, insofar as they are the cause of problems, may point to many different behaviorally-informed solutions. SHELL is thus an element of the diagnostic orientation of GAP, preceding the design of an intervention.

Behavioral audits. With an understanding of behavioral drivers, one must identify those drivers relevant to the policy or organizational problem. To this end, behavioral auditing procedures have started to emerge as diagnostic tools (Mills 2024b). While behavioral auditing remains a nascent area of applied behavioral science, auditing approaches are developing around behavioral phenomena, such as sludge (Sunstein 2022c), bias (Fang et al. 2019; Morewedge et al. 2023), and noise (Kahneman et al. 2021).

Sludge audits examine bureaucratic processes within organizations to identify and eliminate unnecessary barriers to individual action (Sunstein 2022b). 'Sludge' thus refers to excessive or unjustified frictions that waste time, money, and effort (Sunstein 2022c). In online settings, sludge audits are increasingly used from a consumer protection perspective (e.g., Behavioural Insights Team 2022; Mills et al. 2023). The benefits of such auditing can thus be diverse. For organizations, sludge audits can streamline processes and realize cost savings, ensure regulatory compliance, and support interactions with citizens or consumers.

Bias audits are review policies, practices, and decision-making processes to identify biases, both implicit and explicit, within an organization. They can be used to promote fairness, equity, and inclusivity by uncovering and rectifying discriminatory practices (i.e., diversity audits, Fang et al. 2019; Emerson and Lehman 2022). They can also involve ex-post analysis of organizational decisions, such as hiring and promotion decisions (Bendick and Nunes 2012; Espinosa and Ferreira 2022) to change and improve processes in the future. Similarly, internal auditing can provide insights into (biased) organizational cultures, as has been shown in the finance sector to uncover a link between an organization's disclosure behavior and risk profile (Suss et al. 2021). Recently, bias audits have been proposed as a vital element of algorithmic design within organizations and public policy institutions (Morewedge et al. 2023).

Finally, noise audits examine the random and inconsistent factors that introduce unwanted variability into decision-making processes (Kahneman et al. 2021). Noise arises from sources like personal mood, inconsistent application of rules, and random

Table 2 Distinct nudging related concepts ('choice architecture').

Concept	Definition	Example
Nudge	A non-coercive intervention designed to influence individual behaviors in a predictable direction by altering their choice environment.	Placing fruits at eye level in a cafeteria to encourage healthier choices.
Nudge+	A nudge intervention with a reflective strategy embedded into it.	A fitness app reminds you to exercise but also to reflect on your fitness goals and how exercising aligns with them.
Self-nudging	Individuals nudge themselves to influence their own behavior and align it with their long-term objectives.	Automatically enabling "Do Not Disturb" mode on your phone during your work hours to reduce distractions and promote better focus.
Boost	Using strategies like training, education, and transparent communication to enhance individual abilities to make better choices.	Short financial educational messages about budgeting, saving, and investing, equipping people with the knowledge and skills to make informed financial decisions.
Shove	Coercively intervening to change behavior, often through means such as regulation.	Legislation that bans the sale of sugary beverages in large sizes to reduce sugar consumption.
Sludge	Excessive or unjustified frictions that discourage behavior and cost time or money.	Completing a government form to apply for a simple permit, but the process involves filling out numerous pages of paperwork, creating excessive bureaucratic hurdles and wasting time.

Table 3 Adapted version of Münscher et al.'s (2016) taxonomy of choice architecture interventions.

Intervention Type	Psychological Barrier	Behavioral Techniques
Decision Information	Limited access to information processing capacity.	Translate information; make information visible; provide social reference points.
Decision Structure	Limited capacity to evaluate choice options and a proclivity to minimize effort.	Change choice defaults; change effort; change range or composition of options.
Decision Assistance	Limited attention and self-control.	Provide reminders; facilitate commitment; facilitate self-regulation.

encounters. As a result, outcomes may be unreliably predictable, show unwanted variation, and reflect influences from irrelevant events and experiences.

Noise can be identified by comparing differences in separate intra-observer or inter-observer evaluations in situations where a similar response is expected (e.g., medical decision-making; Mullins and Coughlan 2022). Greater variability is indicative of greater noise and thus inconsistency in human decision-making for situations where a consistent evaluation is required. For instance, insurance company executives have been found to believe that expert judgments vary by no more than 10%. However, via a noise audit, the researchers discovered that the actual differences were much larger, with variation ranging from 43 to 55% (Kahneman et al. 2021). Similar examples of noise can be found in areas such as peer reviews in academic journals (Bonavia and Marin-Garcia 2023), medical decision-making (Mullins and Coughlan 2022), software development (Grimstad and Jørgensen 2007) and commercial property evaluations (Adair et al. 1996).

Behavioral auditing supports problem identification, in conjunction with SHELL, to diagnose the behavioral drivers of an organizational problem and the areas that need improvement.

Choice architecture. Once behavioral drivers have been understood (SHELL) and specific drivers diagnosed (audits), interventions must be designed to change behavior and solve the organizational or policy problem. This is often achieved through choice architecture (or 'nudging'), which concerns the design of decision contexts (see Table 2 for an overview of nudging related concepts).

Choice architecture interventions have demonstrated success across various domains (e.g., Banerjee and John 2021; Mertens et al. 2022; Maier et al. 2022; DellaVigna and Linos 2022; Hallsworth 2023), including for example health (e.g., Milkman et al. 2021b; Johnson and Goldstein 2003), financial decision-making (e.g., Thaler and Benartzi 2004) and pro-environmentalism (e.g., Bergquist et al. 2023).

Münscher et al. (2016) categorize choice architecture interventions into three clusters (see Table 3). Decision Information (DI) choice architecture enhances accessibility to decision-relevant information, given cognitive limitations in information processing capacity. Decision Structure (DS) choice architecture acknowledges the context-dependent nature of decision-making (e.g., whether an option is presented preferentially) and the role of effort minimization in decision making. Decision Assistance (DA) choice architecture focuses on bolstering self-regulation, reducing unintentional behaviors arising from cognitive limitations such as limited cognitive attention and self-control.

These categories are necessarily broad, but so is the array of choice architecture one might encounter when designing or experiencing a policy or acting within an organizational setting. We will not linger on choice architecture here, as this is probably the most widely understood element of behavioral science, owing to works like *Nudge* (Thaler and Sunstein 2008). What this section has done, however, is to contextualize choice architecture. Choice architecture is not the totality of applied behavioral insights. Rather, it is design philosophy for developing solutions which comes after other behavioral tools that diagnose the problem.

Having outlined these *General Principles* (G) relating behavioral diagnosis to behavioral design, we now turn to the question of technology, specifically, algorithms.

Algorithms

Algorithms are a growing feature of applied behavioral science (Sunstein 2023). When trained on diverse datasets, some algorithms can reduce cognitive biases and reduce variability, in comparison to human decision-making. For instance, Kleinberg et al. (2017) find algorithms predict reoffending rates better than human judges using the same data available to said judges at the time of the hearing. In some ways, algorithms might be understood as automated decisions, and this perspective belies the affinity—now coming to the fore—between algorithms and behavioral science.

Increasingly sophisticated algorithms may offer further possibilities, and in particular, artificial intelligence (AI) holds transformative potential for behavioral science (Aonghusa and Michie 2020; Wang et al. 2023), by providing new methods for studying human behavior and behavior change strategies (Gruetzemacher and Whittlestone 2022; Mills et al. 2023; Tyler et al. 2023). Such opportunities are driven by data. Broadly, one may distinguish three categories: (1) how AI transforms data collection ('Enhanced Collection'); (2) how AI transforms data analysis ('Enhanced Identification'); and (3) how AI transforms intervention design and evaluation ('Enhanced Efficiency'). With a view to advancing behavioral science, such enhancements can contribute to diagnostic capabilities and design possibilities available to practitioners.

Enhanced collection. AI can enhance data collection through unlocking existing data sources through the development of new data analysis procedures, such as sentiment analysis (Babu and Kanaga 2021; Marshall and Wallace 2019; Wang et al. 2023). This, in turn, encourages the collection of more, and more diverse data.

One worthwhile example may be seen in the rise of 'mega-studies' within behavioral science. Mega-studies are "massive field experiment[s] in which the effects of many different interventions are compared in the same population on the same objectively measured outcome for the same duration" (Milkman et al. 2021a, p. 1). Interest in this approach is growing because mega-studies enable apples-to-apples comparisons of dozens of different behavioral interventions, providing more incremental insights into behavior change techniques (i.e., for who does it work, and why?) (Milkman et al. 2021a; Milkman et al. 2021b). Furthermore, their 'mega' scale supports efforts to replicate important behavioral results, bolstering external validity (Ruggeri et al. 2020).

Yet, mega-studies require a lot of data—commonly millions of observations—creating data handling challenges and increasing the likelihood that researchers miss important details. To this end, AI technologies may support behavioral researchers in data handling and exploration within mega-study projects (Mills et al. 2023). This is a much more academic take on a broader opportunity to integrate AI and behavioral science. Organizations will often collect much more data than they can analyze given their existing technical and knowledge capabilities. Just as behavioral science can supplement knowledge capabilities for organizations, so too might AI technologies supplement technical requirements.

Such capabilities may yield new organizational insights. AI technologies are increasingly used to synthesize knowledge to overcome limited information processing. The Human Behaviour Change Project (HBCP) has developed a Theory & Techniques Tool (HBCP 2023b), based on work of Carey et al. (2018). It uses machine-learning methods to synthesize literature on behavior change mechanisms and behavior change outcomes. These insights can then be used to inform policy, behavior change programs, and further research.

More comprehensive syntheses of existing literature can also support ambitions of integrating more diverse, heterogeneous human experiences into behavioral science (Bryan et al. 2021). Understanding individual differences (or similarities) allows behavioral scientists using AI technologies to optimize timing, content, and delivery methods. The HBCP Prediction Tool (HBCP 2023a), based on work by Michie et al. (2017), is an example of an evidence-based behavior change tool that uses AI to synthesize literature and propose specific behavior change techniques dependent on the problem situation (e.g., smoking cessation) and target population at hand (e.g., 50 years old; also see Aonghusa and Michie 2020).

In sum, the analytical capabilities of AI algorithms change the practical usefulness of data. In turn, this is encouraging wider and more diverse data collection.

Enhanced identification. As above, simply collecting data is rarely an organizational or policy objective. Deriving insights from data is perhaps the most common use of AI algorithms. It is the use which is most reflective of the interests of behavioral scientists (e.g., Ludwig and Mullainathan 2022; Mills et al. 2023). Mills et al. (2023) argue behavioral biases can be understood as patterns within datasets. As AI algorithms are adept pattern detection tools, they are ideally suited to support behavioral science perspectives (see e.g., Kleinberg et al. 2017; Mullainathan and Obermeyer 2021). Such behavioral algorithms may support regulation of other algorithms through real-time bias monitoring (e.g., recommender systems in e-commerce, Lee and Hosanagar 2019), and by contributing insights into the auditing of algorithm designs (Morewedge et al. 2023).

Further to this point, Mills et al. (2023) argue behavioral noise often captures statistical variance which is yet to be appropriately identified. AI is likely to enhance explorations of noise, and thus may be understood as a noise reducing technology within data analysis. Ludwig and Mullainathan (2022) suggest that AI-empowered behavioral science will be best placed to identify and target behavioral anomalies within organizations and policy-making circles. For instance, delineating between decisional processes where human expertise is likely to enhance outcomes, and processes where expertise is diminished owing to prevalent expert biases (also see Sunstein 2023).

Emerging studies support these positions. As above, habit formation is a crucial aspect of behavioral science, owing to the relative mysticism of how habits form (Wood and Rünger 2016), the common desire to deter bad habits, and the frequent requirement to encourage good habits to realize long term behavior change (Carden and Wood 2018). Buyalskaya et al. (2023) machine learning to identify habit formation effects. Examining two big data sets (i.e., 12 million observations of gym attendance and 40 million of hospital handwashing), they find that it takes generally several months to form habits of going to the gym, but only weeks to develop handwashing habits in hospitals. Such studies demonstrate the potential of AI technologies to enhance understanding of contextual habit formation and bolster the behavioral scientist's toolkit for affecting long term behavior change.

Another emerging tool is behavioral systems mapping. AI technologies can be used to construct complex behavioral causal networks by analyzing interactions between contextual factors and behavioral outcomes (Greener et al. 2022). Such networks thus capture the psychological drivers of, and contextual barriers to, desired behaviors (Randlane 2016). Recent contributions have argued that such approaches can guide the development of interventions targeting key leverage points (Hallsworth 2023). The benefits are two-fold.

Firstly, identifying behavioral factors (be it an individual, or an environmental factor), which exert on outsized influence on overall behavior, may result in more effective interventions, depending on the initial 'cost' of the intervention (Mills et al. 2023). Secondly, mapping systemic causal networks offers some recourse to recent concerns within the literature that behavioral science is losing

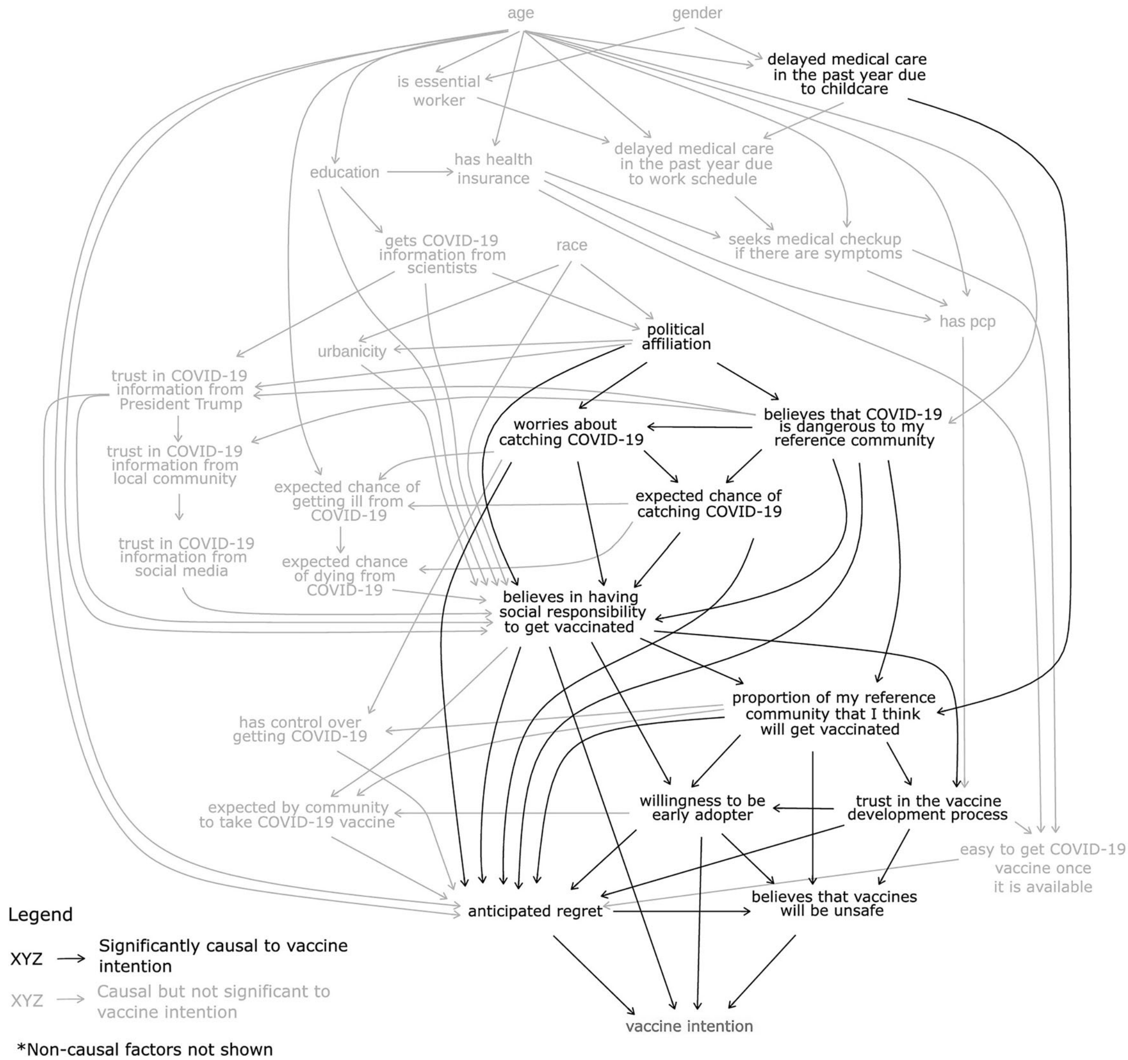

Fig. 2 A representation of causal factors influencing vaccine intention (Fung et al. 2023).

perspective on the necessary system changes required to affect substantiate behavioral change (e.g., Chater and Loewenstein 2022; Schmidt and Stenger 2021; Mills and Whittle 2023).

Fung et al. (2023) provide an example of such causal mapping (i.e., causal Bayesian network) for COVID-19 vaccine intentions (see Fig. 2), using unsupervised, hypothesis-free causal discovery algorithms and data from a COVID-19 vaccine hesitancy survey. This analysis reveals three key causal factors (i.e., social responsibility, vaccine safety and anticipated regret) to target policy interventions and a complex network of variables mediating their influence. Such a use of algorithms, in conjunction with behavioral science, enhances the diagnostic capabilities of practitioners.

Enhanced efficiency. AI technologies can automate behavior change strategies with varying levels of (retrospective) human supervision (Mills et al. 2023; Tyler et al. 2023). Algorithms can streamline behavior change processes and enable the delivery of behavioral interventions at scale without constant human involvement. Mills and Sætra (2024) conceptualize AI systems as 'autonomous choice architects,' which operate autonomously to influence people. They note that such systems already exist in areas such as online recommendation algorithms, integrating real-time feedback to maximize the likelihood of a target behavior. Peer and Mills (2024) call such algorithmic systems *adaptive nudging*. Similarly, Mele et al. (2021) discuss 'smart nudging' strategies that integrate various data streams into intervention designs to efficiently and effectively support behavior change.

Such perspectives emphasize the use of AI and automated systems to personalize and scale behavioral science interventions. Emerging evidence suggests personalization is an important component of effective intervention design (Mills 2022b). Personalization also meets the call for a more heterogeneous outlook within behavioral science (Bryan et al. 2021), and may respond to calls to consider the distributional effects of behavioral interventions, too (Sunstein 2022a).

On the other hand, these technologies may exacerbate manipulation and harm (Kertysova 2018; Monteith et al. 2023). Automated behavior change processes raise substantial questions about ethics and the role of human oversight in behavior change strategies (Mills and Sætra 2024; Ryan 2020; Susser 2019), including—but not limited to—questions around acceptable surveillance of behavior (e.g., at work) and questions about respect for people's autonomy (e.g., when real-time feedback might lead to immediate re-intervention).

Practical considerations

Such questions are only a subsection of wider practical considerations that arise as organizations seek to integrate behavioral science into their practice. Successfully applying behavioral science demands several practical considerations (Bhanot and Linos 2020; Mazar and Soman 2022). These include considerations about institutional capacity and organizational structures; ethical and legal considerations, including regulatory compliance; costs and affordability; and methodological support given practical demands. Continuing the modularity of the GAP approach, we discuss these considerations under the mnemonic TEAM.

Teams and units. Behavioral insights (BI) units can establish behavioral science competencies within organizations (Mazar and Soman 2022). These units are often hubs for diagnosing problems, designing solutions, and evaluating their impact. Using experimentation to see 'what works', units can support a culture of evidence-based decision-making within the organization (Halpern 2016). Nevertheless, a unit's success depends on their structure and power within the organization (Hallsworth and Kirkman 2020).

Firstly, should units be centralized within an organization, or decentralized throughout departments and decision-making clusters within the organization? The World Bank (2019) reports substantial variation among governmental BI units in ten leading countries. Germany follows a 'centralized' model (i.e., one central unit), while the UK and US follow 'decentralized' approaches (i.e., departments coordinating own BI projects and functions). The Netherlands follows a 'networked' model, with one team per ministry, but a common secretariat across teams. Cultural and political processes tend to influence the adopted structures, as well as the common problems faced by respective organizations determining the most appropriate structure (World Bank 2019). Hallsworth (2023) emphasizes the need to adopt a 'behavioral lens' and to diffuse knowledge and unleash the full potential of 'behaviorally enabled organizations', avoiding the mere centralization of a BI team, which, as above, can cause behavioral science to be viewed as a form of 'off-the-shelf' problem solving. This aligns with Soman and Yeung (2020), who argue that BI expertise should be structured depending on specific goals or problem areas, with a BI strategist coordinating the dissemination of behavioral science knowledge throughout the whole organization. Such an approach may act like a 'networked' model.

Secondly, what knowledge should members of the BI unit have? Multidisciplinary teams enrich applied behavioral science, pooling expertise from disciplines including psychology, economics, sociology, neuroscience, anthropology, law and, increasingly, computer science (Soman and Yeung 2020). Such interdisciplinary can help address complex problems (Hallsworth 2023). However, multi-disciplinary may increase the costs of establishing a BIT unit (Hallsworth 2023), especially when skills are relatively scarce. For instance, the prevalence of people skilled in both behavioral science and machine learning remains scarce (Mills et al. 2023).

Thirdly, should BI units do? Soman and Feng (2023) discuss several prescriptions for developing 'healthy' BI units. Drawing on practical experience, they argue that many (underperforming) units lack a clear vision and a strategic 'positioning statement' (Soman and N-Marandi 2022). Such statements should articulate the unique function of the unit (e.g., health & safety) compared to other departments (e.g., marketing teams), and also include details regarding the target audience for the unit and the core benefits arising from the unit. Units can have multiple statements depending on their functions and capabilities, but at least one is advised to counter the observed 'naive belief that [behavioral] science will be effortlessly embraced by other stakeholders' (Soman and Feng 2023, Prescription 4 section, para. 1).

Ethical and legal considerations. Ethical considerations are also critical. Several scholars have explored the ethical dimensions of choice architecture (and the related concept of 'libertarian paternalism', see Sunstein and Thaler 2003), given the potential for manipulative applications (Chowdhury 2021; Lin et al. 2017).

To this end, various ethical behavioral science tools have emerged in recent years. The FORGOOD framework (Lades and Delaney 2020) highlights several factors practitioners are advised to consider when applying behavioral interventions. It encourages practitioners to consider alternative actions, perspectives, and outcomes to arrive at informed positions about the use of behavioral insights. Such a perspective further reiterates the above considerations about the structure and purpose of BI units.

As above, recent developments in technology, including potential autonomous applications, render ethical considerations even more pressing (Mills et al. 2023; Ryan 2020), as do regulatory developments, which are increasingly motivated by concerns over manipulative behavioral strategies (cf. AI Act of the European Commission, see EU 2023).

One aspect that combines both the technological and regulatory aspects of ethics for behavioral science is data protection law. Data collection is a key component of behavioral science, particularly in conjunction with AI technologies (Michie et al. 2017). However, it must comply with ethical and legal standards, such as the General Data Protection Regulation (GDPR) (EU 2016). Gathering and using personal data to inform interventions must be done responsibly, with a focus on privacy and data security. Non-compliance can lead to legal challenges and erode public trust (Gille and Brall 2021; Shark 2022). In considering the skills and knowledge BI units should possess, knowledge of ethical tools like FORGOOD, as well as regulatory and data compliance, are likely essential.

Affordability and cost-effectiveness. The cost-effectiveness of behavioral interventions, from simple nudges to broad behavioral systems mapping, is a critical consideration for embedding behavioral competency within organizations.

Choice architectural interventions often deliver a high cost-effectiveness ratio because of their low development and implementation costs. In their call for governments to invest more in nudging, Benartzi et al. (2017) show that nudges can achieve remarkable return on investment (ROI) ratios outperforming standard interventions such as tax incentives and educational campaigns. For example, a nudge promoting retirement saving raises $100 for every dollar spent (Carroll et al. 2018), while in comparison tax incentives only led to a $1.24 dollar increase per dollar spent (Duflo et al. 2007). Social influence interventions were able to reduce energy consumption by 27.3 kWh per 1 dollar spent (Allcott 2011), while incentives and education resulted in a reduction of only 14.0 kWh (Arimura et al. 2012). While ROI's may vary and matters of 'effectiveness' are often more nuanced than just an ROI ratio (Mills and Whittle 2024), in general choice architecture interventions are relatively cheap to develop and implement, allowing modest effect sizes to still have a worthwhile impact at scale (DellaVigna and Linos 2022). However, in a revision by Tor and Klick (2022) of the Benartzi et al study, they argue that the original findings might in some cases overstate the benefits of nudges compared to traditional interventions. To select the most efficient strategies, they highlight the need to conduct cost-benefit analyses of all competing interventions. This reaffirms the importance of emphasizing the diagnostic component of applied behavioral science, in conjunction with design components like choice architecture.

Beyond the efficiency of interventions, behavioral audits can reveal organizational *in*efficiencies. Kahneman et al. (2021) estimate noise audits may save the insurance underwriting industry hundreds of millions of dollars each year, based on preliminary investigations in conjunction with industry partners. Sunstein (2022b) estimates that the benefits of sludge audits performed on programs such as the Transportation Security Administration (TSA) Precheck Program are easily in the hundreds of millions of dollars after costing for development and implementation. Milkman et al. (2009) argue that the benefits of bias audits are self-evident given the significant impact biased decision-making can have in certain areas, such as medical decision-making, criminal law or even the (collective) decision to start a war.

Central to all behavioral audits is estimating the potential cost of flawed decision-making. Initially, to substantiate the need for an audit and subsequently, after completing the audit, to weigh the costs and benefits of countermeasures. Growing regulatory pressure is adding a new dimension to this calculation, with the misuse of behavioral insights carrying growing legal and reputational costs. For instance, the UK's Consumer Duty regulation now requires financial companies to act in the best interests of their customers, including avoiding the use of manipulative or deceptive behavioral strategies (FCA 2023). To this end, behavioral audits are increasingly likely to benefit organizations by serving as a safeguard from the costs of accidentally harming individuals (Mills 2024a).

Technologies like AI algorithms may also require substantial initial investments but hold the potential, as above, to deliver scaled and personalized behavior change interventions (Gruetzemacher and Whittlestone 2022). Cost-benefit analyses are important to indicate if the problems to solve are worth the investment, balancing the level of algorithmic complexity and data costs with the severity of the problems to solve (Xu et al. 2021). For instance, while personalized behavioral interventions may be able to influence behavior better than generic interventions (e.g., Peer et al. 2020), personalization often requires far more data and computational resources than impersonal approaches (Mills 2022b). The marginal benefits of ever more personalized interventions must therefore be weighed against the marginal costs of personalization.

Methods and experiments. Research methods are vital in revealing underlying mechanisms of behavior and gathering evidence to determine which behavior change strategies work, and which do not.

The OECD (2023) outlines a roadmap for choosing adequate methods related to specific goals and contextual limitations (e.g., limited sample size, no control groups or inability to randomize). Experimental approaches, such as Randomized Controlled Trials (RCTs) and similar A/B testing techniques, enable researchers to examine causality and intervention efficacy. Conversely, non-manipulative methods like longitudinal studies, correlational analyses, and qualitative research offer valuable insights into naturally occurring behavioral patterns and the persistence over time, allowing for a holistic understanding of complex phenomena (Privitera 2022). Employing a combination of these methods equips behavioral scientists with a comprehensive toolkit for advancing knowledge of human behavior and promoting positive behavioral outcomes (Baggio et al. 2021; Lunn 2014), hence the importance of interdisciplinary in the skillset of BI unit members.

Both lab experimentation and field research are important for evidence-based practices (Cartwright 2007; Samek 2019). For field experiments often hold an advantage over other methods because their scale allows for greater generalizability (Milkman et al. 2021a). However, such studies can be more expensive or less practical, undermining cost-effectiveness. Lab experiments often carry lower costs, though this is traded off against questions around external validity. Many more methods exist, each with a suite of pros and cons. The immediate takeaway is that the appropriate method for a given policy challenge is, and will remain, an important practical implication for applied behavioral science.

While no panacea, and culture of continuous experimentation and evaluation is likely essential to developing effective methodological practice. BI units need to embed experimentation into their everyday practice—not experimentation with behavioral interventions, but experimentation with best practice itself.

Comparison to other models and frameworks

The GAP framework offers a modular and integrative approach to applied behavioral science, designed to support organizations in navigating the increasingly complex landscape of behavior change. Rather than positioning itself in opposition to existing models such as COM-B[2], MINDSPACE[3], or EAST[4], GAP draws upon and connects their respective strengths. Its central contribution lies in offering a flexible structure. This captures behavioral diagnosis and intervention design, as well as implementation aspects like emerging technologies and practical organizational considerations.

COM-B, for instance, has rightly been recognized as a general and adaptable model that links behavioral diagnosis with intervention design, particularly through its placement within the Behaviour Change Wheel (Michie et al. 2011; Dolan et al. 2012). EAST builds on this by presenting more accessible design principles, making behavioral science more approachable for practitioners (Behavioural Insights Team 2024).

What GAP adds to this landscape is a way to situate these models within a broader system of organizational behavior change. Where COM-B and MINDSPACE excel in linking causes and interventions, GAP offers a structure for embedding these tools in institutional practice—whether through behavioral audits, algorithmic support, or the development of behavioral science teams. The framework does not attempt to replace existing models but to act as connective tissue between them, especially for organizations operating with limited behavioral science experience or in contexts requiring adaptation to new technologies and constraints. The SHELL framework aids in this regard by captivating behavioral drivers that are specific to the bounded rationality perspective, while COM-B can be interpreted more broadly (e.g. 'capabilities' and 'motivations'), and by grouping these behavioral drivers in broad categories (e.g. 'Social Influence', 'Limited Information-Processing' and 'Limited Self-Control') that extend beyond specific drivers highlighted by MINDSPACE (e.g. 'Messenger' or 'Norms' that are part of 'Social Influence').

In comparison to the Behavioral Drivers Model (Petit 2019), which is comprehensive in mapping behavioral influences in development settings and emphasizes participatory, contextual diagnosis, GAP shares an appreciation for complexity but differs in its emphasis on organizational and operational applicability. The Behavioral Drivers Model provides valuable insight into the drivers of behavior, particularly in community and humanitarian contexts, but offers less guidance on how to institutionalize behavior change processes across large-scale organizations or incorporate technological enhancements like AI.

The modular nature of the GAP framework allows it to complement rather than compete with existing models. Practitioners can use it to identify where they may need diagnostic clarity (e.g., via SHELL or behavioral audits), technological support (e.g., through algorithmic tools), or operational guidance (e.g., via TEAM). In this way, it serves as an adaptive platform that can incorporate established tools like COM-B or MINDSPACE where appropriate, while also preparing organizations for the evolving demands of behavioral science in the digital era. By acknowledging and building upon the contributions of earlier frameworks, GAP aims to enhance—not diminish—the behavioral science toolkit available to policymakers and organizations today.

Discussion

The GAP framework gives structure to existing approaches within behavioral science, emphasizing tools and techniques beyond nudging, while also integrating promising if still emerging technologies, and important practical considerations. In this sense, the GAP framework is offered as a modular approach for building behavioral competency into organizations (Dhami and Sunstein 2022). SHELL (Carden and Wood 2018; Gelfand et al. 2024; Lerner et al. 2015), behavioral audits (Bonavia and Marin-Garcia 2023; Sunstein 2022b), and increasingly algorithmic behavioral science (Mills et al. 2023), are examples of important innovations which are influencing and enhancing applied behavioral science (Benartzi et al. 2017). The GAP framework offers a concise yet comprehensive guide for governments and organizations navigating this intricate landscape by situating these insights alongside practical limitations.

In comparing the GAP framework with existing behavioral science frameworks like COM-B, EAST, and MINDSPACE, the GAP framework distinguishes itself through its integrative and modular structure. Unlike the other models, which each address more specific facets of behavior change, the GAP framework aims to unify these dimensions into a cohesive, flexible tool for practitioners. By incorporating the SHELL mnemonic, the GAP framework introduces a robust diagnostic lens, enabling deeper exploration of behavioral drivers via subsequent behavioral audits. Furthermore, its inclusion of emerging technologies, like AI, and practical implementation considerations equips practitioners with a comprehensive, adaptable guide that goes beyond mere nudging. While other models retain their value and are compatible for addressing specific aspects of behavior change (with varying degrees of specificity, e.g. COM-B being widely applicable), the GAP framework provides a comprehensive approach, offering practitioners a unifying structure that combines diagnostic tools with design, evaluation, technological advancements and scalability practical considerations for effective organizational interventions.

GAP has some limitations. *General Tools* covers important bounded rationality principles for affecting behavior change. Yet, it is not an exhaustive review of all behavior change techniques, and in isolation, might be regarded as an overly simplistic approach, or at least one which is intellectually rooted in the choice architecture paradigm which has defined so much of modern behavioral science to date. The *General Tools* component should thus not be regarded as definitive, and there is much scope for further elaboration and debate.

Furthermore, while GAP is offered to give structure, it may also constrain some discussions, and cause some important debates to be missed or sidelined. For instance, most behavioral change strategies to date are investigated in isolation (Beshears and Kosowsky 2020). Comparative studies between various existing strategies (including explicitly paternalistic ones, such as nudging), and their combinations, could help to better define the behavior change formula ('what works') for specific societal challenges. The focus on behavioral diagnosis may miss the 'meta' diagnostic problem of understanding whether an organizational problem is fundamentally behavioral, or not, to begin with. Figuring out how to integrate behavioral science optimally within an organization and its current practices (i.e., adopting a 'behavioral lens') remains one of the main problems to resolve (Hallsworth 2023; Mazar and Soman 2022; Soman and Yeung 2020), and while GAP aims to provide further guidance in this area, ongoing efforts are needed to bridge the gap with a wider system-approach. In addition, currently GAP functions as an integrative framework synthesizing core domains to advance applied behavioral science. Future work may formalize or operationalize elements of GAP using state-of-the-art design science methodologies to uncover underlying dynamics within and across GAP components, increasing the testability and applicability of the framework, along with the intended impact.

Finally, ethical considerations are of increasing importance given rapid developments in technology, and technology's immediate application to behavioral science (Mills et al. 2023; Ryan 2020). Besides guidelines for ethical conduct (Lades and Delaney 2022), comprehensive regulations are emerging to prevent (un)intentional harm (e.g., EU AI Act 2023). This poses a challenge, but equally an opportunity for applied behavioral science. Behavioral science practitioners are likely best placed to advise on any future regulation within this space, and done with sensitivity and proper oversight, such a privileged position may allow behavioral science to become more embedded in the policy landscape than ever before. However, a changing regulatory landscape could lead to difficult administrative challenges for practitioners, including limitations on the use of some of the technologies and methods discussed here. We have briefly discussed some regulatory implications. However, in relation to behavioral audits and ethical and legal considerations, regulation is likely to have a substantial role in shaping the applied behavioral science landscape in the future, and it is area where—in the future—some aspects of GAP might benefit from revision.

Conclusion

The GAP framework offers a comprehensive yet flexible approach for applying behavioral science in public policy and organizations, integrating foundational tools, emerging technologies like AI, and essential practical considerations. By focusing on behavioral tools that extend beyond nudging (e.g., behavioral audits and SHELL) and adopting a modular structure, GAP unifies diagnostic, design, and scalability considerations to support practitioners to tailor behavioral capacities to their organizational contexts. This might involve supplementing existing capacities, say in response to new technologies, or developing wholly new capacities. As applied behavioral science advances, GAP paves a foundation for the use of innovative tools to tackle complex social and organizational challenges.

Data availability

No new data were generated. All relevant references and resources have been cited within the paper.

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Notes

1 See section 'Comparison to other models and frameworks' for a more elaborate overview.
2 Capability, Opportunity, Motivation and Behaviour (COM-B)
3 Messenger, Incentives, Norms, Defaults, Salience, Priming, Affect, Commitments and Ego (MINDSPACE)
4 Easy, Attractive, Timely and Social (EAST)

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Competing interests

The authors declare no competing interests.

Additional information

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