CAMBRIDGE UNIVERSITY PRESS

ARTICLE

META BI: A tool for describing behavioural interventions

Malte Dewies¹ (D) and Lucia A. Reisch^{1,2} (D)

 1 El-Erian Institute of Behavioural Economics and Policy, Cambridge Judge Business School, University of Cambridge, Cambridge, UK and 2 Department of Management, Society and Communication, Copenhagen Business School, Copenhagen, Denmark

Corresponding author: Malte Dewies; Email: m.dewies@jbs.cam.ac.uk

(Received 27 January 2025; revised 11 July 2025; accepted 5 August 2025)

Abstract

A lack of common terminology and shared understanding of behavioural interventions across academic disciplines and professional groups limits the multidisciplinary application of such interventions and our collective ability to share and compare their effects. The current study attempts to narrow this gap by developing a comprehensive classification system of nudges and similar behavioural interventions that can aid researchers and practitioners in understanding and describing such interventions to steer desired behaviour change. We develop an initial classification system drawing on our expert knowledge and subsequently validate it in an iterative procedure with 44 experts from various fields, disciplines and sectors during two feedback rounds (i.e. a Delphi approach). The result is META BI (Mapping of Environment, Target group and Agent for Behavioural Interventions), a classification system describing interventions across 20 dimensions and using 17 distinct psychological mechanisms. META BI is aligned with a system lens, shifting the focus from single true effects to contextualised assessments. It can help to understand, compare and evaluate nudges and selected interventions for the desired effects.

Keywords: behavioural interventions; classification; Delphi; mechanisms; nudge

Introduction

Organisations, businesses and governments worldwide are increasingly making use of nudges to steer behaviour (Hallsworth, 2023). They have been applied successfully in various sectors and regions of the world, for instance to improve health and sustainability (Hummel and Maedche, 2019; Beshears and Kosowsky, 2020; Hubble and Varazzani, 2023). As an umbrella term, nudge is often used for a large variety of interventions. For instance, highlighting social norms, sending reminders, setting defaults and simplifying forms can be considered nudge interventions (Sunstein *et al.*, 2014).

[©] The Author(s), 2025. Published by Cambridge University Press. This is an Open Access article, distributed under the terms of the Creative Commons Attribution licence (http://creativecommons.org/licenses/by/4.0), which permits unrestricted re-use, distribution and reproduction, provided the original article is properly cited.

2 Malte Dewies and Lucia A. Reisch

Accordingly, there have been various attempts to define the scope of nudging (Hansen, 2016; Congiu and Moscati, 2022) and categorise different nudge types (e.g., Münscher et al., 2016). The current research contributes to this research by developing a novel, transdisciplinary classification system called META BI (Mapping of Environment, Target group and Agent for Behavioural Interventions). META BI serves as a tool to understand and describes key characteristics of nudge interventions, including their mechanisms, and establishes guidelines for their categorisation.

The need for a comprehensive and transdisciplinary classification of nudges

Although there is no final consensus on what defines nudges (Hansen, 2016; Congiu and Moscati, 2022), we follow the seminal definition from Thaler and Sunstein (Thaler and Sunstein, 2008, p. 6) and consider nudges 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 cost-effective in many cases (Benartzi et al., 2017), constitute a comparatively new policy tool that is not well understood (Sunstein, 2018; Leong and Howlett, 2022), and can be relatively easy and quick to implement. Other individual-level interventions (e.g. education, deliberative platforms, social marketing) tend to involve more extensive programs and interaction between behaviour change agents and targets. Moreover, they are often built on different theoretical assumptions (John et al., 2009; French, 2011; Hertwig and Grüne-Yanoff, 2017), complicating a shared classification. Therefore, the present study focuses on nudges and similar behavioural interventions such as debiasing (Morewedge et al., 2015). For better readability, we use the terms nudge and behavioural interventions interchangeably.

Generally, classification systems provide decision rules to categorically assign interventions to mutually exclusive and exhaustive groups (Doty and Glick, 1994). In Table 1, we describe some frequently used nudge classification systems. Acknowledging the complex nature of nudges, many such systems are multidimensional, meaning that nudges are assigned to several groups simultaneously (i.e. 'faceted classifications'; Stavri and Michie, 2012). TIPPME, for instance, classifies interventions in a matrix-like structure according to the type of intervention and the intervention's spatial focus. Without a clear scope of the objects to classify, classification systems risk becoming inconsistent or ambiguous. Therefore, the *first of three principles* that guided the development of META BI was the establishment of a clearly defined scope and consistent classification criteria.

The diverse nature and various disciplines (e.g. psychology, economics, political science) and sectors (e.g. industry, politics) involved in nudge research and application can make communicating about nudges complex and hinder shared understandings. Previous nudge classifications tended to focus on one or a small number of characteristics typically associated with specific disciplines, for instance, underlying cognitive mechanisms (psychology) or welfare effects (economics). However, such aspects are related and involve complex trade-offs necessitating a detailed and rich understanding of nudges and application contexts (Hallsworth, 2023). For instance, the Behaviour Change Intervention Ontology (Michie *et al.*, 2021) maps relevant aspects

 Table 1. Overview of frequently used classifications for nudges

Name	Authors	Focus	Development process	Domain and discipline
Taxonomy of choice architecture techniques	Münscher et al., 2016	Intervention formats	Inductively generated based on example interventions, empirical validation	Domain- independent, decision- making
Tools of a choice architecture	Johnson <i>et al.</i> , 2012	Intervention formats	Not provided	Domain- independent, marketing
MINDSPACE	Dolan <i>et al.</i> , 2012	Intervention formats and strategies	Not provided	Domain- independent, cross- discipline
EAST	Behavioural Insights Team, 2024	Intervention strategies (e.g. make it easy)	Not provided	Domain- independent, cross- discipline
TIPPME	Hollands et al., 2017	Intervention format and spatial focus	Literature review, expert consultation, empirical validation	Food, cross- discipline
Three degrees of nudge	Baldwin, 2014	Intervention mechanisms and their impact (i.e., on autonomy)	Not provided	Domain- independent, law
Framework for the responsible use of nudge	Hansen and Jespersen, 2013	Intervention mechanisms and transparency	Not provided	Domain- independent, cross- discipline
Behavioural policy cube	Oliver, 2015; Oliver, 2018	Intervention impact and relation to rationality	Not provided	Domain- independent, economics
Behaviour change techniques taxonomy	Michie et al., 2013	Intervention strategies	Literature review, expert consultation, validation	Health, psychology
Meta-analytic cognitive frame- work of nudge and sludge	Luo et al., 2023	Intervention mechanisms, impact and relation to behaviour	Not provided	Domain- independent, cognition
Nudging: An organising framework	Ly et al., 2013	Intervention mechanisms, intervention agents and relation to behaviour	Not provided	Domain- independent, cross- discipline

4 Malte Dewies and Lucia A. Reisch

of behavioural interventions, such as their outcome behaviours and context. However, its technical focus on behaviour change means it does not include aspects such as autonomy and the objectives of interventions, frequently the interest of philosophers, policymakers and economists. To complicate things further, different communities use different terminologies to describe the same interventions, demonstrating a lack of common understanding. For example, an influential psychological distinction relies on individuals' perceptions of nudges as pro-self or pro-social (Hagman et al., 2015), whereas the economics literature employs a similar but more objective distinction between interventions that target consequences for oneself (i.e. internalities; Allcott and Sunstein, 2015) or consequences for others (i.e. externalities; Oliver, 2018; Carlsson et al., 2021). Therefore, we think researchers and practitioners will benefit from a clarifying classification system that integrates disconnected areas of knowledge and bridges different communities acting as a shared reference (Osman et al., 2020a). Such a system may facilitate the transdisciplinary debate needed to leverage nudges for addressing complex societal changes such as ill-health and climate change (Lang et al., 2012). Consequently, our second principle guiding the development of the classification is to acknowledge and integrate knowledge from diverse disciplines.

Recently, researchers suggested viewing behavioural interventions as part of adaptive systems, emphasising that interventions and the context in which they are deployed mutually influence each other (Schill et al., 2019; Hallsworth, 2023). That is, interventions are regarded as 'events in systems' (Hawe et al., 2009) rather than fixed solutions that have the same or similar effects across contexts (Bryan et al., 2021; Szaszi et al., 2022; Schmidt, 2024). However, very few classifications view interventions as configurations across system-level elements. The psychological mechanisms that nudge interventions rely on to change behaviour are a key aspect in that regard. Mechanisms are essential for understanding why interventions work (Grüne-Yanoff, 2016; Marchionni and Reijula, 2019) and how they interact with their context (Findley et al., 2021). For example, a nudge can activate different mechanisms and lead to different outcomes depending on who launches it (Tannenbaum et al., 2017). Yet, existing classifications and review studies predominantly focus on the format (e.g. salience of options) of interventions; or they group mechanisms into overly broad categories (e.g. Cane et al., 2012; Connell et al., 2019). As an example, classifications often distinguish mechanisms according to general psychological processes (e.g. attention, memory; Yoeli et al., 2017; Luo et al., 2023). A more detailed overview of mechanisms seems necessary for assessing the external validity of interventions and their suitability for a particular application. Therefore, the third principle for developing the classification system was to adopt a system's lens and acknowledge the importance of contexts and mechanisms.

Methodological approach

In the early stages of the project, both authors together considered ways of carrying out the project and decided on a stepwise development procedure which was preregistered online (https://doi.org/10.17605/osf.io/duj8v). The steps involved in developing META BI are outlined in Figure 1. We began by drafting an initial version of META



Figure 1. Development procedure for META BI showing methods (left) and ouptuts (right) per step.

BI, drawing on our expert knowledge of relevant theories and evidence. This was followed by a structured Delphi process involving a panel of international nudge experts, who reviewed successive iterations of META BI. Delphi is a widely used research method for achieving expert consensus and was employed to systematically gather feedback and refine the classification system (Linstone and Turoff, 1975; Diamond et al., 2014). In addition, we incorporated feedback from practitioners who apply behavioural interventions, and assessed how effectively interventions could be coded using the mechanisms included in META BI. Overall, the development process relied heavily on expert input, including our own, to ensure that META BI was consistent with existing knowledge and met the needs of the community (Norris et al., 2021).

All materials created during this research (e.g. surveys) and results (e.g. versions of META BI, codebooks, search outputs) can be viewed online in the accompanying data repository (https://doi.org/10.17605/osf.io/6yucj). The Ethical Review Board of the Cambridge Judge Business School gave a favourable assessment (23-12).

Step 1: initial development

For this step, we developed an initial classification system based on our knowledge of nudge theories and evidence. Such an integrative step building on previous work is a common starting point in classification development (e.g. Michie et al., 2013; Hollands et al., 2017). In following the third guiding principle, we defined the structure of the initial version of the classification systems ex ante as encompassing the agent launching an intervention, the intervention, the target group at which the intervention is aimed, the behaviour intended to change and the environment in which all other elements operate (originally named 'context') as structural system-level elements. This structure was adapted from the Behaviour Change Intervention Ontology (Michie et al., 2021) and corresponds to aspects commonly integrated in reporting checklists for behaviour change interventions, such as TIDieR (Hoffmann et al., 2014) and CONSORT (Schulz et al., 2010). We then characterised those elements by defining and assigning characteristic dimensions to each element (e.g. "preferences" were assigned to the target group). The dimensions were identified in 31 relevant literature sources, many of which were highly influential classifications of nudges (e.g. high number of citations). They were selected to come from various academic disciplines, in line with principle two. The complete mapping of the literature sources, dimensions and elements is available in the online data repository. The resulting initial version of META BI displayed and described 16 dimensions, each characterising one of the five structural elements (e.g. "legitimacy" of the agent).

Mechanisms (originally named 'functions' based on Hawe *et al.*, 2004) were one dimension characterising behavioural interventions, based on our third principle. To arrive at descriptions of mechanisms, we relied on an inductive approach reviewing 188 descriptions of behavioural interventions from five structured attempts to organise behavioural interventions (Johnson *et al.*, 2012; Münscher *et al.*, 2016; Hollands *et al.*, 2017; Cadario and Chandon, 2020; Jesse and Jannach, 2021) and four unstructured lists of the most common nudges (Dolan *et al.*, 2012; Datta and Mullainathan, 2014; Sunstein, 2014, 2016). We generated definitions of underlying psychological mechanisms in a spreadsheet (see online data repository) for these interventions and added new definitions whenever interventions could not be mapped onto previously defined mechanisms. Interventions could rely on an unlimited number of mechanisms. For ease of comprehension, the resulting 15 mechanisms were grouped into five categories based on topical similarities.

The following steps served to develop and validate the initial version of META BI.

Step 2: rapid expert feedback

Researchers recommend piloting data-collection methods before conducting Delphi studies (Hasson *et al.*, 2000). Therefore, this step served to obtain initial feedback on the classification system (v.1.0) to start developing it and improve the methods used in the following step. Specifically, we conducted two interviews and one workshop with four participants who together formed our small convenience sample (n = 6) of

¹Note that this step was added after the preregistration. For more details on the procedure and the analysis during this step, please view the Supplementary Information.

academics and practitioners from our networks. Interviews and the workshop were semi-structured, closely following the classification's structure while inquiring about any missing aspects, coherence and accuracy. During the interviews and the workshop, the researchers realised the limitations of eliciting feedback using a predetermined structure because it required experts to comment on aspects of the classification (e.g. dimensions, mechanisms) they were less familiar with based on their backgrounds. Instead, unstructured interviews used in Step 3.1 encouraged interviewees to take a more active role during the interview and provide more constructive and substantiative feedback. This observation aligns with the distinction between interactional expertise, here allowing interviewees to understand and converse without actively contributing new knowledge, and contributory expertise as the advanced understanding of key theories and methodologies to the extent of being able to use and apply them to contribute new knowledge independently (Collins and Evans, 2007). We believe that we tapped into the second form of expertise using an unstructured interview approach.

For the analysis of our pilot data, field notes summarising the feedback obtained during each interview and the workshop were analysed in Atlas.ti using thematic analysis (Braun and Clarke, 2006). In this step, we used only 17 feedback codes related to superficial changes (e.g. changing examples), simplifications (e.g. deleting superfluous dimensions) and obvious inconsistencies (e.g. overlapping descriptions of mechanisms) to update the classification system (v.2.0) because of the small sample size. The remaining feedback was included in the analysis in Step 3.1.

Step 3.1: first Delphi round

The Delphi method is a repeated feedback process commonly used in the social sciences to integrate expert views, develop new frameworks and reach agreement (Hasson *et al.*, 2000; Brady, 2015). For the credibility and effectiveness of Delphi studies, the composition of expert panels is crucial (Hasson *et al.*, 2000; Okoli and Pawlowski, 2004; Brady, 2015). Therefore, in line with the second guiding principle, we aimed for the experts to represent the breadth of relevant academic disciplines and various positions in the field. Interviews were chosen as a method for this step because they signal a personal approach and because they are well-suited to obtain data from busy experts.

We considered experts identified through four complementary approaches (see also Okoli and Pawlowski, 2004): (1) authors of the literature sources used to develop the initial version of META BI in Step 1; (2) authors of articles published in three field journals; (3) authors of articles identified through a systematic search of the Web of Science; and (4) advisory board members of two relevant scientific associations. To be eligible, experts were expected to have published works relating to either the classification of behavioural interventions or general nudge reviews. From the 218 identified experts, we invited a total of 45 academics to participate in this study with different disciplinary backgrounds and positions, plus one more expert who was recommended by one invitee. In total, 23 academics provided feedback during an unstructured interview, and five offered written feedback (n = 28; total response rate 61%). All participants

²The complete sampling process is described in more detail in the Supplementary Information.

8

Discipline Number participants Percentage Psychology 10 26 **Economics** 9 24 4 Sociology 11 Philosophy 3 8 Behavioural science 3 8 Political science 2 5 2 **Nutritional sciences** 5 Public policy 1 3 1 Marketing 3 1 3 Law Information systems 1 3 Design 1 3

Table 2. Disciplinary background of experts involved in the development of META BI until step 4

received the classification system in advance and were prompted to reflect on any missing aspects, coherence of the system and any changes to improve it. In addition, we presented and discussed the classification system at a scientific conference where we received written, unstructured feedback from another four participants.

A list of all experts who took part in the development process and agreed for their names to be published is available in the Supplementary Information. This list evidences the participation of experts of various positions in the field. Moreover, Table 2 shows that despite most experts having a background in psychology or economics, both disciplines strongly represented in the study of behavioural interventions, we successfully recruited a multidisciplinary sample.

The analysis followed the same approach used in Step 2 (i.e. thematic analysis) and included Feedback from Step 2 that had not been used to update the classification system before. As a result, field notes from 30 interviews and two workshops were analysed and yielded 106 distinct feedback points (i.e. codes assigned during the analysis) used to update the classification (v.3.1). Many of those points were associated with the elements of the classification system (total 33, 31%), the 'mechanisms' dimension (31 codes, 29%) and the general approach and conceptualisation (9, 8%). We summarised those feedback points and considered them individually in updating the classification (see online data repository). Table 3 illustrates this process showing some frequent feedback points and how we responded to them. Maintaining consistency and staying within the scope of the classification system were essential in this process, in line with our first principle. For instance, experts suggested describing the relations between dimensions included (e.g. how the objectives of interventions are related to their underlying mechanisms). Yet, we decided against this suggestion because claims about such relations, in our view, required theorising and evidence beyond our scope. Moreover, experts pointed to ambiguities in what kind of interventions were meant to be included, which led us to clarify the description of the intervention element, in line with the first principle.

Code/feedback	Response
Relations between the dimensions should be acknowledged. (30 times applied)	We did not integrate this aspect because it falls outside our scope to make claims about such relations.
There is overlap between the different mechanisms. (11)	We acknowledged in the description of the dimensions that mechanisms are not mutually exclusive.
The classification lacks the ability to describe and differentiate different intervention formats. (10)	We added a novel dimension to acknowledge this aspect.
Interventions are not always about outcomes, but sometimes improve procedural aspects of decision making. (6)	We added this aspect in the description of the 'Objectives' dimension.

Table 3. Exemplary codes during the first Delphi round and responses

Step 3.2: second delphi round

The purpose of the second feedback round of the Delphi was to give the experts who provided feedback during the first Delphi round (Step 3.1), as well as the two experts interviewed for the rapid expert feedback (Step 2) an opportunity to review the classification system (v.3.1) again and assess its development. To increase the response rate and reduce social desirability, we conducted an anonymous online survey. Of the 30 invited experts, a total of 19 completed the survey (response rate of 63%). Experts were asked to comment on and rate the classification's (v.3.1) description and content, its comprehensiveness and the coherence of its structure. Answers were analysed again using thematic analysis and descriptive statistics for participant ratings.

The analysis yielded 29 feedback codes used to further improve the classification system (v.3.1) (see online data repository). Nonetheless, the feedback was largely positive, with most finding META BI's its content meaningful and correct (79% indicating agreement), its structure (v.3.1) coherent (74%) and it providing a comprehensive overview of factors relevant for behavioural interventions (79%), which suggests that principle one was applied successfully. Beyond the agreement rate, both the interquartile range and standard deviation of the experts' assessments indicated sufficient agreement to conclude consensus regarding these criteria (Giannarou and Zervas, 2014).

Step 4. Practitioner interviews

This step served to investigate the usefulness and comprehensiveness of the classification system (v.3.2) using semi-structured interviews with practitioners developing and applying behavioural interventions. Engaging practitioners can help connect research to practice and generate 'actionable knowledge' (Argyris, 1993; Antonacopoulou, 2009). Because of limited resources, we did not use purposive sampling until saturation was reached, as preregistered initially, but instead recruited a small convenience sample of six practitioners from our networks and using social media. Yet, the sample represented a diverse group of practitioners from different sectors (NGO, research, government, business), varying levels of policymaking (local, supranational) and employing different approaches (analytic, design-based).

The classification system (v.3.2) was shared with interviewees in advance together with questions prompting reflection on its usefulness and comprehensiveness. Interview field notes were again analysed using thematic analysis, which yielded 56 distinct feedback points. Of these, 42 codes related to feedback that was used to update classification details (e.g. changing examples; see online data repository) and to add one dimension reflecting how interventions relate to other levers of change because of this dimension's high practical relevance. Eight codes concerned the usefulness of the classification system, with practitioners indicating that it can be useful, for instance, to understand and explain what nudges are and to select interventions that will likely be successful in specific target contexts. The remaining six codes indicated that practitioners found META BI clear and comprehensive.

Step 5: intercoder agreement

Assessing intercoder agreement served to investigate how effectively two independent coders could assign mechanisms included in META BI (v.4.0) to a set of 65 behavioural interventions. These interventions were taken from a previous coding task for classification development (Münscher *et al.*, 2016) and complemented by us with 10 additional interventions to ensure all mechanisms were represented a minimum of three times based on the coding of one author. Coders were trained and instructed to code for each intervention an ordered number of mechanisms with no maximum number. Agreement between the two independent coders implies that mechanisms can be assigned consistently and reliably, in line with our first guiding principle. This does not mean, however, that interventions must rely on the coded mechanisms because coding is interpretative.

Analysis of the coded interventions yielded a moderate fuzzy kappa (Kirilenko and Stepchenkova, 2016) of 0.49 as a measure of agreement. Fuzzy kappa was calculated because it allows assigning multiple labels (here mechanisms) to one entity (here interventions). Conventional kappa was 0.47, when considering only the main mechanism coded by each coder. This suggests that while mechanisms might overlap and interact for a single intervention, primary mechanisms can be assigned with moderate reliability. Complete intercoder agreement (i.e. identical codes being assigned to an intervention by both coders) was achieved for 34% of the interventions. Reasons likely preventing higher intercoder agreement were the unobservable and speculative nature of mechanisms and ambiguities in the descriptions of interventions. Given these explanations and the fact that the short descriptions of interventions focused on intervention formats (e.g. 'Offering people to commit themselves to a goal online'), we were satisfied with the observed intercoder agreement and changed the description of mechanisms only marginally. In addition, descriptions were short and in applied contexts (e.g. when coding interventions for meta-analyses) more relevant information is likely to be available for coders.

Step 6: refinement

This step involved reviewing the language and display of META BI (v.6.0), polishing the presentation, and creating an interactive document. For this, the research team hired

a language editor and a graphic designer to improve readability and overall usability. In the following, we briefly summarise META BI, while the full detailed classification system is provided in the Supplementary Information.

META BI

META BI describes behavioural interventions across five system-level elements (see Figure 2) each characterised by three to five dimensions. In the following, we describe each element and each dimension included in META BI. In addition, we illustrate classifying one intervention (i.e. an energy default based on Ebeling and Lotz, 2015) using META BI in Table 4.

Intervention

The classification system considers single discrete nudges, rather than repeated or interactive interventions. The *mechanisms* dimension refers to immediate changes in mental states in response to the intervention sought to influence behaviour. META BI suggests 17 such mechanisms listed in Table 5 grouped into five categories based on topical similarity. *Format* refers to the appearance of the manipulated component of the intervention (i.e. the nudge). We do not suggest any rules or labels to code formats because there are many possible approaches beyond our scope (e.g. Hollands *et al.*, 2017; Congiu and Moscati, 2020). *Intrusiveness* refers to the extent to which the intervention interferes with or disrupts people's lives and their goals, and if targets can avoid and exit the intervention (Lemken *et al.*, 2024). *Personalisation* refers to whether different members of the target group receive different versions of the same intervention (e.g. using different messengers) based on their characteristics (e.g. gender, postcode).

Agent

Agents are the organisations, institutions and individuals that define the behaviour to be changed, identify the target group and launch interventions. Objectives refer to the agent's goal motivating the nudge. We differentiate between nudges aiming to improve quality of decision-making (e.g. attention to one's choice; Dold and Lewis, 2023), as well as nudges targeting internalities (i.e. consequences for oneself), externalities (i.e. consequences for others) and social or group characteristics (e.g. polarisation, groupthink). Legitimacy refers to the agent being reasonably allowed to deploy the nudge and promote the targeted behaviour. Reputation is a multifaceted construct that refers to the subjective perception of the agent by the target group (e.g. trust, authenticity and attractiveness) (Krijnen et al., 2017; Tannenbaum et al., 2017). Sameness refers to the relation between the agent and target group, namely whether agents are identical to target groups (e.g. self-nudging; Reijula and Hertwig, 2022), equal (e.g. employees influencing peer behaviour) or different (e.g. government influencing citizen behaviour). Many of these dimensions can be assessed both subjectively and objectively, and assessments may show heterogeneity across individuals.

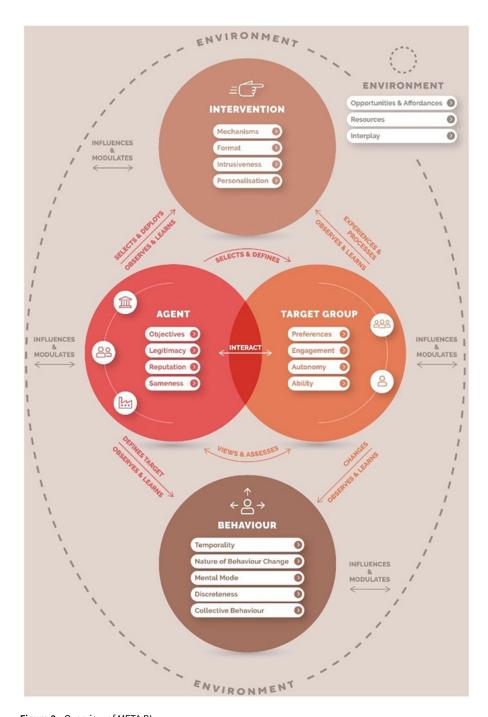


Figure 2. Overview of META BI.

Table 4. Dimensions, classification questions and categories/labels relating to each dimension of the META BI classification system

Dimension	Classification question	Categories/labels	Energy default example
Intervention			
Format	What does the intervention look like? How is it administered?	Not provided	Pre-selected checkbox when choosing a tariff.
Mechanisms	What mechanism(s) does the intervention rely on?	17 mechanisms	Endorsement; Social norms; Physical effort and ease
Personalisation	Do different members of the target group receive different versions of the intervention based on their characteristics?	Personalisation vs no personalisation	No personalisation – Intervention is the same for all customers.
Intrusiveness	To what extent does the intervention interfere in or disrupt people's lives?	Low to high	Low – Intervention can be ignored and avoided when choosing a different provider.
Agent			
Objectives	What is the purpose of deploying the intervention?	Quality of decision-making vs internalities vs externalities vs social and group characteristics	Externalities – Benefits for the environment.
Legitimacy	To what extent is the agent reasonably allowed to deploy the intervention?	Low to high	High – Providers determine their product, but pre-selected options may be viewed as manipulative.
Reputation	What is the perception of the agent by the target group?	Low to high	High—Customers trust the energy provider.
Sameness	How similar or different are the agent and the target group?	Identical vs equal vs unequal	Unequal—The provider determines product features for customers.

(Continued)

Table 4. (Continued.)

Dimension	Classification question	Categories/labels	Energy default example
Target group			
Preferences	How aligned are the intervention's target behaviour and objective with the target group's own evaluation?	Aligned vs unaligned	Aligned, weak, heterogenous – Customers are somewhat concerned about the environment and prefer green energy tariffs, but do not like
	How strong is the preference (perceived importance)?	the preference (perceived Weak to strong higher costs.	
	How is the preference structured?	Homogenous vs heterogenous vs time-inconsistent	-
Engagement	To what extent does the target group become aware of relevant aspects of the intervention?	Unaware to aware	Aware – Most customers actively notice the pre-selected option.
	To what extent does the target group take an active role in the development and delivery of the intervention?	Passive vs active	Passive – No active role in the development or deployment of the intervention.
Autonomy	To what extent are choice options constrained and manipulated?	Constraining vs maintaining freedom of choice	Freedom of choice maintained – Tariff options remain unaffected.
	To what extent does the outcome of the intervention align with the interests, preferences and desires of the target group?	Unaligned to aligned	Somewhat aligned – Customers prefer green energy, but they may desire more structural investment and policy action.
	To what extent is the decision-making process in response to the intervention fair and well-reasoned?	Supporting vs limiting process autonomy	Low process autonomy – Customers are not prompted to reflect and are not educated about energy options.
Ability	To what extent does the target group possess the means to process and act upon the intervention as planned?	Low to high	High – Most customers understand the intervention and can pay for green energy.

(Continued)

Malte Dewies and Lucia A. Reisch

Table 4. (Continued.)

Dimension	Classification question	Categories/labels	Energy default example
Behaviour			
Temporality	How frequently does the target behaviour occur?	One-off vs repeated	Repeated – Customers choose tariffs multiple times.
	For how long does the target behaviour need to be maintained?	Time-bound vs enduring	Time-bound: Customers choose tariffs on specific occasions and dates only.
Nature of behaviour change	Does the intervention aim to avoid, reduce, maintain, or intensify previous behaviours?	Avoid vs reduce vs maintain vs intensify	Avoid – Choosing a different tariff.
	Does the intervention aim to instigate novel behaviours?	No novel behaviour vs novel behaviour	Novel behaviour – Choose green tariff instead.
Mental mode	What is the mental process of the target group producing the behaviour?	Not provided	Customers likely reflect on their choice after noticing the check box.
Discreteness	To what extent is the behaviour linked to other behaviours of the target group?	Discrete to linked	Linked—Related to other pro-environmental behaviours.
Collective behaviour	To what extent is the behaviour influenced by others and/or linked to their behaviour?	Individual to collective	Mostly individual – Choice is made in agreement with other household members only.
Environment			
Opportunity and affordances	To what extent do different levels (immediate choice situation, context) and facets of the environment (cultural, political, social, physical, economic, technological) support and/or limit the target behaviour?	Supporting to limiting	Medium support, heterogeneous influence – Political and sociocultural context are positive toward green energy, but economic factors are negative because of increased costs.
	To what extent are the influences of environment in the same direction?	Heterogenous to homogenous	

(Continued)

Table 4. (Continued.)

Dimension	Classification question	Categories/labels	Energy default example
Resources	What information is the agent communicating alongside the intervention?	No information vs information	Information – Information on pricing is provided.
	What relevant behaviours is the agent banning or permitting?	No authority vs authority	No authority – All tariffs remain available.
	What financial sanctions and incentives is the agent using alongside the intervention?	No financial vs financial	No financial – No additional incentives or sanctions.
	What goods and services does the agent deliver alongside the intervention?	No material vs material	No material – No additional services.
	What symbols and signals of approval/disapproval is the agent sending alongside the intervention?	No symbols vs symbols	No symbols – No additional services.
Interplay	How does the intervention affect other levers of change?	Neutral vs supportive vs countervailing	Supportive – Increased demand for green energy can lead to a larger investment in and supply of green energy.

Table 5. Names and descriptions of mechanisms included in META BI

Name of mechanism	Description
Social influence	
Endorsement	Target groups view others as endorsing (opposing) the behaviour.
Social standards	Target groups view others as (not) engaging in the behaviour.
Reciprocity	Target groups are more (less) likely to perform the behaviour because they reward (punish) previous or expected acts.
Status seeking	Target groups view the behaviour as contributing to their positive social standing.
Expectations	
Material expectation	Target groups expect to personally receive tangible consequences for performing the behaviour.
Immaterial expectation	Target groups expect to personally receive non-tangible consequences for performing the behaviour.
Emotions	Target groups associate the behaviour with direct positive (negative) emotions or mental states.
Effort and ease	
Physical effort and ease	Target groups associate the behaviour with a lot of (little) physical effort.
Cognitive effort and ease	Target groups find it easier (more difficult) to understand and act on information.
Ease of use	Target groups find the use of services, products, etc. easier (more difficult).
Choice processing	
Thinking mode	Target groups change from one mode of thinking (automatic or deliberate) to another.
Frames	Target groups adopt different frames of reference, which alter the meaning and interpretation of specific behaviours.
Cognitive operation	Target groups respond to a familiar choice context with a specific and different cognitive operation.
Goals and self-regulation	
Goals and commitment	Target groups set/confirm goals and are committed to the behaviour.
Performance comparison	Target groups compare their behaviour against a performance standard.
Normative comparison	Target groups evaluate their behaviour in light of values and beliefs (e.g. moral, religious).
Remembering	Target groups perceive cues that remind them of the behaviour.

Target group

The target group consists of those individuals whose behaviour the agent aims to influence. Those individuals evaluate the agent, experience the intervention and show a response in behaviour. *Preferences* refer to the target group's evaluations of the target behaviour and the objective of a nudge. They can differ in direction (aligned vs

unaligned with the goal of the nudge) and perceived importance. Moreover, they can be homogeneous (e.g. positive smell and positive taste), heterogeneous (e.g. negative smell but positive taste) or time-inconsistent (e.g. alcohol now, but no hangover tomorrow) (Sunstein, 2015a; de Ridder et al., 2021). Engagement refers to the target group's involvement with the nudge, namely the extent to which the target group becomes aware of the intervention (e.g. its purpose, source, mechanism; Hansen and Jespersen, 2013) and if the target group takes an active role in its development and/or delivery (Richardson and John, 2021). Autonomy refers to a multifaceted concept that describes the extent to which choice options are constrained (freedom of choice), how the intended behavioural outcome aligns with the interests, preferences and desires of the target group (outcome autonomy), and to what extent the decision-making process in response to the nudge is fair and well-reasoned (process autonomy) (Engelen and Nys, 2020; Vugts et al., 2020). Lastly, ability is defined as the extent to which the target group has the means to process and act upon the nudge as planned (Baldwin, 2014; Howlett, 2018).

Behaviour

This element refers to the behaviours targeted by the nudge. *Temporality* refers to the behaviour's relationship to time. We differentiate between one-off behaviours and frequently repeated behaviours. It also refers to whether there is a specific period during which behaviour is influenced or not (one-off vs repeated behaviour change) (Chatterton & Wilson, 2014). *Nature of behaviour change* refers to the direction of and type of change. Nudges can aim to avoid, reduce, maintain or intensify existing behaviours. Additionally, they can aim to instigate novel behaviours or not. *Mental mode* refers to the mental processes of the target group that bring about the desired behaviour change. We do not suggest any rules and labels to code mental modes because there are many different approaches and theoretical orientations that researchers can rely on to describe them (e.g. Gollwitzer *et al.*, 1990; Kahneman, 2011). *Discreteness* refers to the degree to which target behaviours are linked to other behaviours, for instance, through one's identity, motivations or the context (Chatterton & Wilson, 2014). *Collective behaviour* refers to the extent to which the behaviour is influenced by others and linked to their behaviour.

Environment

The environment encompasses all other structural elements, influences them and is influenced by changes within them. It includes the cultural, political, social, physical, economic and technological aspects of the immediate choice situation as well as the wider context. *Opportunities and affordances* refer to the extent to which the environment supports and invites or blocks and limits the intended behaviour change (Schill *et al.*, 2019; Van Dessel *et al.*, 2022; Schmidt, 2024). *Resources* refer to the means that the agent uses to support the intended behaviour change beyond the nudge. These resources include information provided alongside the intervention, using authority to ban or permit options, financial sanctions or incentives, services and goods offered to the target group and symbols and signals of approval or disapproval sent

alongside the intervention (John, 2013; Howlett, 2018). *Interplay* refers to the relationship between nudges and structural/systemic levers of change (Brownstein *et al.*, 2022; Chater and Loewenstein, 2023). Nudges can be neutral to such levers when they do not affect each other, they can be supportive when they reinforce or complement each other and they can be countervailing when they prevent or limit each other.

Discussion

We developed META BI as a multidisciplinary, context-rich classification system of nudge interventions. It is based on a stepwise development procedure where an initial version of the classification system drawing on our expert knowledge was subsequently developed further and validated in a Delphi exercise with an interdisciplinary group of academic experts who reviewed several versions of it. We call the result META BI, which stands for Mapping of Environment, Target group and Agent for Behavioural Interventions. META BI is a tool for understanding and describing interventions across 20 dimensions, each relating to one of five system-level elements. As one of the 20 dimensions, we also generated a list of 17 underlying mechanisms (see Table 5). The goal of META BI is to provide a common language for a fruitful exchange about behavioural interventions across disciplines and professions. It helps prevent an overemphasis on buzzword-driven behavioural interventions (Oliver, 2025) and potentially facilitates evidence synthesis and systematic reviews. In the following, we contrast META BI with previous classification systems, illustrate potential use cases and reflect on our methodological approach.

Previous classifications listed in Table 1 focus on maximum four aspects of nudges at a time, often suggesting a limited number of clearly defined nudge types. In contrast, META BI 'zooms out' to integrate 20 dimensions across five system-level elements (e.g. behaviour, target group) used to classify nudges. It thus considers nudges as configurations across those dimensions, providing a syntax to describe and understand nudges in their context from various perspectives. The few classification systems capturing similar systems level elements (e.g. Ly et al., 2013; Stenger and Schmidt, 2025), tend to be less comprehensive. Without a comprehensive system, however, those interested in nudges risk thinking about them in an overly simplistic way, focusing on a few salient attributes while not considering others (Hauser et al., 2018). Addressing this, META BI provides an organising device and coding scheme for its users to reduce the messy nature of real-world interventions to 20 key dimensions, shifting the focus from single true effects of specific interventions ('Nudge type A produces result B') to more contextualised assessments (e.g. 'When C and D are present, a nudge relying on mechanism E produces result B'). Such a shift is extremely important when estimating the likely effects of interventions in implementation and scaling, that is applying interventions in novel contexts (Pawson and Tilley, 1997; Schill et al., 2019; Soman, 2024). To illustrate, the framework might explain why a planning intervention for tax payments successfully scaled even though the goal-setting component was excluded when scaling the intervention (goal-setting refers to the Mechanisms and Engagement dimensions in META BI). Namely, because the tax context meant that fines and penalties ensured extrinsic motivation (Resources dimension) compensating for individually set goals

(Robitaille *et al.*, 2024). It is difficult to imagine how any of the previous classifications listed in Table 1 could inform scaling in a similar fashion.

Secondly, META BI adds several dimensions not included in previous classifications. For instance, the classification system's 'resources' dimension distinguishes between interventions steering free choice (e.g. consumption choices) and interventions increasing adherence with pre-existing laws and regulations (e.g. tax payment). This way, META BI helps overcome the misconception that behavioural interventions are incompatible with traditional regulatory tools such as bans and sanctions (Sunstein, 2018). In fact, such traditional instruments may be essential for the effectiveness of behavioural interventions; a notion supported by a recent review finding that financial incentives combined with nudges are highly effective in encouraging proenvironmental behaviour (Alt et al., 2024). Many previous classification systems view nudges as standalone approaches, lacking conceptual links to other interventions with which nudges might form policy mixes (Howlett et al., 2015; Mukhtarov, 2024). Put differently, META BI acknowledges that traditional instruments can be re-analysed and re-interpreted from a behavioural perspective (see Schneider and Ingram, 1990; John, 2013; Howlett, 2018) and as part of configurations that make up behavioural interventions.

Thirdly, META BI integrates knowledge and experience from different disciplinary and sectoral perspectives leading to consensus. An example is the 'objectives' dimension, where the distinction between nudges targeting internalities or externalities present in several classification systems from economics (Oliver, 2018; Carlsson *et al.*, 2021) is complemented by two novel categories, namely nudges targeting decision-making procedures irrespective of outcomes (Sunstein, 2015b, 2017; Dold and Lewis, 2023) and nudges aiming to change social and group characteristics (e.g. group-think, polarisation; Dudley and Xie, 2022; Mattis *et al.*, 2024). Thanks to the latter two categories, META BI can accommodate nudges that do not fall squarely into pre-defined economic categories. In addition, the classification system is evidently transdisciplinary with several dimensions that can be linked to specific disciplines (e.g., "mechanisms" and psychology; "interplay" and public policy).

Fourthly, META BI was developed through an empirically robust, stepwise procedure that incorporated several best practices to enhance the credibility and reliability of our findings. We began by pilot testing and refining our Delphi data collection method (Hasson et al., 2000). To ensure practical relevance, we actively involved practitioners experienced in applying behavioural interventions. Moreover, we assessed interrater agreement for the most concrete component of META BI (i.e. the mechanisms dimension) demonstrating that this aspect can be coded reliably and consistently by future users. This stepwise process of iterative refinement likely led to clearer definitions, more precise labels and well-defined boundaries for our classification system. Compared to many earlier classifications, which often lack empirical validation during development (see Table 1), META BI stands out for its methodological transparency and validation. That said, it is worth acknowledging that some widely used frameworks, such as EAST (Behavioural Insights Team, 2024), have gained practical legitimacy through extensive application in the field (e.g. Arboleda et al., 2024), despite not being developed through a formal empirical process. In sum, META BI is a comprehensive and context-sensitive classification system, shaped by interdisciplinary input and empirical testing.

Goals META BI **Describe and understand your nudge**Utilize dimensions to understand your nudge and its context Code your nudge on each dimension by answering the classification questions provided in Table 4. - Direct attention to the most relevant characteristics of your nudge to get a comprehensive understanding Communicate about your nudge across - Use clear labels to communicate about the characteristics of your nudge Compare nudges and structure evidence Code tested nudges and build a searchable - Filter for nudge characteristics relevant for your situation - Identify differences and similarities with previous nudges **Generate evidence** Understand the state of the field and study nudge effects Code relevant nudges and analyse the coded data. - Explore co-occurrences and the relations between reviews, meta-analysis) - Study features of nudges and their effects (e.g., on behaviour) . the dimensions included in META BI. - Estimate the impact of various dimensions on key outcomes of interest

Figure 3. Usage of META BI.

Usage of META BI

While META BI offers a novel theoretical perspective on nudges, it may also hold potential for practical innovation. As illustrated in Figure 3, the classification system can support the application of individual nudges, the comparison of nudges and learning from relevant nudge applications. First, META BI might enable users to think more systematically and comprehensively about the nudges they are applying. Its 20 dimensions can serve as a mental organising device, helping practitioners and researchers focus on the most relevant aspects of an intervention. By answering the classification questions outlined in Table 4, users can structure their thinking and avoid common pitfalls, such as overlooking contextual influences, negative spillovers or unintended backfiring effects (Meder et al., 2018; Osman et al., 2020b). Second, META BI might be used to structure and search behavioural evidence. A repository of coded interventions could function similarly to filters used when selecting a new laptop to buy: instead of filtering by screen size, processor speed and working memory, users could filter by mechanisms, agent objectives and target group preferences, for instance. This would allow for more targeted evidence retrieval and facilitate the identification of comparable interventions. For illustration, we have coded a set of well-known interventions in the Appendix. Third, META BI can support field mapping and evidence synthesis . By analysing a carefully selected and consistently coded set of interventions, researchers might better understand the current landscape of behavioural science. This is particularly valuable for literature reviews and meta-analyses. META BI captures many of the key factors that influence external validity, such as mechanisms, the nature of the intervention, its target group and behavioural outcomes - factors identified by Findley et al (2021) as essential for generalisability. Yet, META BI does not explicitly code for time as the last factor identified by Findley and colleagues. As such, it may help explain the substantial heterogeneity often observed in review studies of nudge interventions. We recommend users with limited resources to start with the first of the three use cases as it is least resource intensive.

Limitations

There are at least four potential limitations concerning the methods and results of this study. First, in our approach to developing the classification system we relied on our subjective judgement. Specifically, the initial version of the classification was shaped by our understanding of the need for a classification and early design choices. For instance, we conceptualised the mechanisms of interventions on the individual level (e.g. conformity with social norms) rather than the social level (e.g. herd behaviour). Although the following steps served to further develop and validate META BI, a different initial version is likely to have produced other results. In addition, in developing the classification system and integrating views from different disciplinary experts, we relied on our professional expertise and judgement - an approach known as 'integration by leader. This approach to transdisciplinary integration is different from more collaborative approaches, such as group deliberation and negotiation (Rossini and Porter, 1979). However, we considered the practical constraints of other integration modes, which often demand more from the participating experts (e.g. scheduling efforts, travel, resolving group conflicts) making it unlikely to achieve similar levels of expert involvement. Consequently, META BI might be viewed prescriptive, offering subjective recommendations, rather than an objective description of dimensions and rules describing nudges. Yet, the agreement from academics and practitioners may give credibility to this classification.

As a second limitation, our sample was mostly Western, educated, industrialised, rich and democratic ('WEIRD'; Henrich *et al.*, 2010). This limitation likely stems from our reliance on sampling academic experts who are statistically more likely to exhibit those characteristics. Exploring and achieving agreement among those experts was deemed more important than generalisability to other samples. Consequently, a different classification may have emerged from a different panel.

Third, the classification system may be considered overly abstract and disconnected from individual disciplines, which is a common challenge for transdisciplinary research (Lang *et al.*, 2012). Evidence of this may be seen in the fact that users of META BI will need to operationalise the classification's dimension and agree on observable criteria before codifying interventions (e.g. using objective or subjective criteria to assess "objectives" of an intervention). Yet, this also applies to several previous classifications (e.g. Baldwin, 2014; Behavioural Insights Team, 2024).

Fourth, we caution readers against the risk of treating META BI's classification codes as fixed or self-contained labels without considering underlying dynamics. It is important to recognise that the dimensions are unlikely to be entirely independent. For example, a shift in one dimension (e.g. "reputation" of the agent) may moderate others (e.g. "mechanism" of the intervention). These interdependencies are difficult

to capture using the structure of META BI. Moreover, the relevance of specific dimensions may vary across different applications, complicating count-based comparisons of coded interventions. Two interventions may appear similar across most dimensions, yet differ significantly if the one divergent dimension holds greater contextual importance. However, this limitation reflects a broader challenge in classification systems: the tension between analytical clarity and the complex, often fluid nature of real-world phenomena (Medin and Ortony, 1989) and is likely to apply in a similar fashion to previous classifications.

Conclusion

To sum up, META BI offers a conceptual synthesis between literature and application. It aims to avoid misunderstandings, improve implementation and support evidence synthesis by striking a balance between an exhaustive mapping of factors influencing nudges and overly simplistic descriptions. Researchers and practitioners can employ the classification system to investigate and make sense of specific behavioural interventions, ensuring that the most relevant aspects of a nudge are considered. We hope that it might help close the gap between highly detailed technical classifications 'zooming in' on specific aspects (e.g. intervention techniques; Michie *et al.*, 2013) and general behaviour-change typologies, in which nudges are one intervention type among many (e.g. behaviour change wheel; Michie *et al.*, 2014).

Supplementary material. The supplementary material for this article can be found at https://doi.org/10. 1017/bpp.2025.10015.

Acknowledgments. The authors are grateful to Aiswarya Sunil, Mariam Abdelnabi and Sorin Thode for their excellent research assistance, and to numerous conference and seminar participants for their helpful comments and discussions. We particularly thank the experts for the time they devoted to the Delphi interviews.

Funding statement. This work was supported by the Novo Nordisk Foundation (Grant number NNF21SA0069203).

Competing interests. The authors declare no competing interests.

Author contributions. M.D.: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft. L.A.R.: Conceptualization, Funding acquisition, Investigation, Methodology, Writing – review & editing.

Data availability statement. All data, analysis code and research materials including all versions of the classification are available in an online repository (https://doi.org/10.17605/osf.io/6yucj).

References

Allcott, H. and C. R. Sunstein (2015), 'Regulating internalities', *Journal of Policy Analysis and Management*, **34**(3): 698–705. doi:10.1002/pam.21843

Alt, M., H. Bruns, N. DellaValle and I. Murauskaite-Bull (2024). 'Synergies of interventions to promote proenvironmental behaviors – a meta-analysis of experimental studies', *Global Environmental Change*, **84**: 102776. doi:10.1016/j.gloenvcha.2023.102776

Antonacopoulou, E. P. (2009), 'Impact and scholarship: unlearning and practising to co-create actionable knowledge,' *Management Learning*, **40**(4): 421–430. doi:10.1177/1350507609336708

- Arboleda, J., L. F. Jaramillo, A. Velez and J. E. Restrepo (2024), 'EAST framework to promote adherence to nutritional supplementation: a strategy to mitigate COVID-19 within health workers', *Behavioural Public Policy*, **8**(4): 639–651. doi:10.1017/bpp.2024.11
- Argyris, C. (1993), Knowledge for Action: A Guide to Overcoming Barriers to Organizational Change, San Francisco: Jossey-Bass.
- Baldwin, R. (2014), 'From regulation to behaviour change: giving nudge the third degree,' *The Modern Law Review*, 77(6): 831–857. doi:10.1111/1468-2230.12094
- Behavioural Insights Team. (2024), 'EAST: four simple ways to apply behavioural insights Revised and updated edition'. https://www.bi.team/publications/east-four-simple-ways-to-apply-behavioural-insights/ (accepted 13 August 2025).
- Benartzi, S., J. Beshears, K. L. Milkman, C. R. Sunstein, R. H. Thaler, M. Shankar, W. Tucker-Ray, W. J. Congdon and S. Galing (2017), 'Should governments invest more in nudging?', *Psychological Science*, 28(8): 1041–1055. doi:10.1177/0956797617702501
- Beshears, J. and H. Kosowsky (2020), 'Nudging: progress to date and future directions', Organizational Behavior and Human Decision Processes, 161: 3–19. doi:10.1016/j.obhdp.2020.09.001
- Brady, S. R. (2015), 'Utilizing and adapting the Delphi Method for use in qualitative research', *International Journal of Qualitative Methods*, **14**(5). doi:10.1177/1609406915621381
- Braun, V. and V. Clarke (2006), 'Using thematic analysis in psychology', *Qualitative Research in Psychology*, 3(2): 77–101. doi:10.1191/1478088706qp063oa
- Brownstein, M., Kelly, D. and Madva, A. (2022), Individualism, structuralism, and climate change. Environmental Communication, 16(2), 269–288. doi:10.1080/17524032.2021.1982745
- Bryan, C. J., E. Tipton and D. S. Yeager (2021), 'Behavioural science is unlikely to change the world without a heterogeneity revolution', *Nature Human Behaviour*, 5(7): 980–989. doi:10.1038/s41562-021-01143-3
- Cadario, R. and P. Chandon (2020), 'Which healthy eating nudges work best? A meta-analysis of field experiments', Marketing Science, 39(3): 465–486. doi:10.1287/mksc.2018.1128
- Cane, J., D. O'Connor and S. Michie (2012), 'Validation of the theoretical domains framework for use in behaviour change and implementation research', *Implementation Science*, 7(1): 37. doi:10.1186/1748-5908-7-37
- Carlsson, F., C. Gravert, O. Johansson-Stenman and V. Kurz (2021), 'The use of green nudges as an environmental policy instrument', Review of Environmental Economics and Policy, 15(2): 216–237. doi:10.1086/715524
- Chater, N. and G. Loewenstein (2023), 'The i-frame and the s-frame: how focusing on individual-level solutions has led behavioral public policy astray', *Behavioral and Brain Sciences*, **46**: e147. doi:10.1017/S0140525X22002023
- Chatterton, T. and Wilson, C. (2014), The 'Four Dimensions of Behaviour' framework: A tool for characterising behaviours to help design better interventions. *Transportation Planning and Technology*, 37(1), 38–61. doi:10.1080/03081060.2013.850257
- Collins, H. and R. Evans (2007), Rethinking Expertise, Chicago: University of Chicago Press.
- Congiu, L. and I. Moscati (2020), 'Message and Environment: a framework for nudges and choice architecture', *Behavioural Public Policy*, 4(1): 71–87. doi:10.1017/bpp.2018.29
- Congiu, L. and I. Moscati (2022), 'A review of nudges: definitions, justifications, effectiveness', *Journal of Economic Surveys*, 36(1): 188–213. doi:10.1111/joes.12453
- Connell, L. E., R. N. Carey, M. de Bruin, A. J. Rothman, M. Johnston, M. P. Kelly and S. Michie (2019) Links between behavior change techniques and mechanisms of action: an expert consensus study, *Annals of Behavioral Medicine*, 53(8): 708–720. doi:10.1093/abm/kay082
- Datta, S. and S. Mullainathan (2014), 'Behavioral design: a new approach to development policy', Review of Income and Wealth, 60(1): 7–35. doi:10.1111/roiw.12093
- de Ridder, D., F. Kroese and L. van Gestel (2021), 'Nudgeability: mapping conditions of susceptibility to nudge influence,' *Perspectives on Psychological Science*, 17(2): 346–359. doi:10.1177/1745691621995183
- Diamond, I. R., R. C. Grant, B. M. Feldman, P. B. Pencharz, S. C. Ling, A. M. Moore and P. W. Wales (2014), 'Defining consensus: a systematic review recommends methodologic criteria for reporting of Delphi studies', *Journal of Clinical Epidemiology*, **67**(4): 401–409. doi:10.1016/j.jclinepi.2013.12.002

- Dolan, P., M. Hallsworth, D. Halpern, D. King, R. Metcalfe and I. Vlaev (2012), 'Influencing behaviour: the MINDSPACE way', *Journal of Economic Psychology*, **33**(1): 264–277. doi:10.1016/j.joep.2011.10. 009
- Dold, M. and P. Lewis (2023), 'A neglected topos in behavioural normative economics: the opportunity and process aspect of freedom', *Behavioural Public Policy*, 7(4): 943–953. doi:10.1017/bpp.2023.11
- Doty, D. H. and W. H. Glick (1994), 'Typologies as a unique form of theory building: toward improved understanding and modeling,' *The Academy of Management Review*, **19**(2): 230–251. doi:10.2307/258704
- Dudley, S. E. and Z. Xie (2022), 'Nudging the nudger: toward a choice architecture for regulators', *Regulation & Governance*, 16(1): 261–273. doi:10.1111/rego.12329
- Ebeling, F. and S. Lotz (2015), 'Domestic uptake of green energy promoted by opt out tariffs', *Nature Climate Change*, 5(9): 868871. doi:10.1038/nclimate2681
- Engelen, B. and T. Nys (2020), 'Nudging and autonomy: analyzing and alleviating the worries', *Review of Philosophy and Psychology*, 11(1): 137–156. doi:10.1007/s13164-019-00450-z
- Findley, M. G., K. Kikuta and M. Denly (2021), 'External validity', *Annual Review of Political Science*, 24: 365–393. doi:10.1146/annurev-polisci-041719-102556
- French, J. (2011), 'Why nudging is not enough', Journal of Social Marketing, 1(2): 154–162. doi:10.1108/ 20426761111141896
- Giannarou, L. and E. Zervas (2014), 'Using Delphi technique to build consensus in practice', *International Journal of Business Science & Applied Management*, 9(2): 65–82.
- Gollwitzer, P. M., H. Heckhausen and B. Steller (1990), 'Deliberative and implemental mind-sets: cognitive tuning toward congruous thoughts and information', *Journal of Personality and Social Psychology*, 59(6): 1119. doi:10.1037/0022-3514.59.6.1119
- Grüne-Yanoff, T. (2016), 'Why behavioural policy needs mechanistic evidence', *Economics and Philosophy*, 32(3): 463–483. doi:10.1017/S0266267115000425
- Hagman, W., D. Andersson, D. Västfjäll and G. Tinghög (2015), 'Public views on policies involving nudges', Review of Philosophy and Psychology, 6(3): 439–453. doi:10.1007/s13164-015-0263-2
- Hallsworth, M. (2023), 'A manifesto for applying behavioural science', Nature Human Behaviour, 7(3): 310-322. doi:10.1038/s41562-023-01555-3
- Hansen, P. G. (2016), 'The definition of nudge and libertarian paternalism: does the hand fit the glove?', European Journal of Risk Regulation, 7(1): 155–174. doi:10.1017/s1867299x00005468
- Hansen, P. G. and A. M. Jespersen (2013), 'Nudge and the manipulation of choice: a framework for the responsible use of the nudge approach to behaviour change in public policy', European Journal of Risk Regulation, 4(1): 3–28. doi:10.1017/s1867299x00002762
- Hasson, F., S. Keeney and H. McKenna (2000), 'Research guidelines for the Delphi survey technique', *Journal of Advanced Nursing*, 32(4): 1008–1015. doi:10.1046/j.1365-2648.2000.t01-1-01567.x
- Hauser, O. P., F. Gino and M. I. Norton (2018), 'Budging beliefs, nudging behaviour', *Mind & Society*, **17**(1): 15–26. doi:10.1007/s11299-019-00200-9
- Hawe, P., A. Shiell and T. Riley (2004), 'Complex interventions: how "out of control" can a randomised controlled trial be?', BMJ, 328(7455): 1561. doi:10.1136/bmj.328.7455.1561
- Hawe, P., A. Shiell and T. Riley (2009), 'Theorising interventions as events in systems', American Journal of Community Psychology, 43(3–4): 267–276. doi:10.1007/s10464-009-9229-9
- Henrich, J., S. J. Heine and A. Norenzayan (2010), 'The weirdest people in the world?', *Behavioral and Brain Sciences*, 33(2-3): 61-83. doi:10.1017/S0140525X0999152X
- Hertwig, R. and T. Grüne-Yanoff (2017), 'Nudging and boosting: steering or empowering good decisions', Perspectives on Psychological Science, 12(6): 973–986. doi:10.1177/1745691617702496
- Hoffmann, T. C., P. P. Glasziou, I. Boutron, R. Milne, R. Perera, D. Moher et al. (2014), 'Better reporting of interventions: template for intervention description and replication (TIDieR) checklist and guide', BMJ, 348: g1687. doi:10.1136/bmj.g1687
- Hollands, G. J., G. Bignardi, M. Johnston, M. P. Kelly, D. Ogilvie, M. Petticrew, A. Prestwich, I. Shemilt, S. Sutton and T. M. Marteau (2017), 'The TIPPME intervention typology for changing environments to change behaviour,' *Nature Human Behaviour*, 1(8): 0140. doi:10.1038/s41562-017-0140
- Howlett, M. (2018), 'Matching policy tools and their targets: beyond nudges and utility maximisation in policy design', *Policy & Politics*, **46**(1): 101–124. doi:10.1332/030557317X15053060139376

- Howlett, M., I. Mukherjee and J. J. Woo (2015), 'From tools to toolkits in policy design studies: the new design orientation towards policy formulation research', *Policy & Politics*, 43(2): 291–311. doi:10.1332/ 147084414X13992869118596
- Hubble, C. and C. Varazzani (2023, May 10). Mapping the global behavioural insights community. OECD Observatory of Public Sector Innovation. https://oecd-opsi.org/blog/mapping-behavioural-insights/
- Hummel, D. and A. Maedche (2019), 'How effective is nudging? A quantitative review on the effect sizes and limits of empirical nudging studies', *Journal of Behavioral and Experimental Economics*, **80**: 47–58. doi:10. 1016/j.socec.2019.03.005
- Jesse, M. and D. Jannach (2021), 'Digital nudging with recommender systems: survey and future directions', Computers in Human Behavior Reports, 3: 100052. doi:10.1016/j.chbr.2020.100052
- John, P. (2013), 'All tools are informational now: how information and persuasion define the tools of government', *Policy & Politics*, 41(4): 605–620. doi:10.1332/030557312X655729
- John, P., G. Smith and G. Stoker (2009), 'Nudge nudge, think think: two strategies for changing civic behaviour', *The Political Quarterly*, **80**(3): 361–370. doi:10.1111/j.1467-923X.2009.02001.x
- Johnson, E. J., S. B. Shu, B. G. C. Dellaert, C. Fox, D. G. Goldstein, G. Häubl, R. P. Larrick, J. W. Payne, E. Peters, D. Schkade, B. Wansink and E. U. Weber (2012), 'Beyond nudges: tools of a choice architecture', Marketing Letters, 23(2): 487–504. doi:10.1007/s11002-012-9186-1
- Kahneman, D. (2011), Thinking, Fast and Slow, New York: Farrar, Straus and Giroux.
- Kirilenko, A. P. and S. Stepchenkova (2016), 'Inter-coder agreement in one-to-many classification: fuzzy kappa', PLOS ONE, 11(3): e0149787. doi:10.1371/journal.pone.0149787
- Krijnen, J. M. T., D. Tannenbaum and C. R. Fox (2017), 'Choice architecture 2.0: behavioral policy as an implicit social interaction', *Behavioral Science & Policy*, 3(2): 1−18. doi:10.1177/237946151700300202
- Lang, D. J., A. Wiek, M. Bergmann, M. Stauffacher, P. Martens, P. Moll, M. Swilling and C. J. Thomas (2012), 'Transdisciplinary research in sustainability science: practice, principles, and challenges', Sustainability Science, 7(1): 25–43. doi:10.1007/s11625-011-0149-x
- Lemken, D., A. Erhard and S. Wahnschafft (2024), 'A choice architect's guide to the (autonomous) galaxy: a systematic scoping review of nudge intrusiveness in food choices', *Humanities and Social Sciences Communications*, 11: 1030. doi:10.1057/s41599-024-03555-8
- Leong, C. and M. Howlett (2022), 'Theorizing the behavioral state: resolving the theory-practice paradox of policy sciences', *Public Policy and Administration*, **37**(2): 203–225. doi:10.1177/0952076720977588
- Linstone, H. A., and M. Turoff Eds., (1975), *The Delphi Method: Techniques and Applications*, Reading: Addison-Wesley.
- Luo, Y., A. Li, D. Soman and J. Zhao (2023), 'A meta-analytic cognitive framework of nudge and sludge', Royal Society Open Science, 10(11): 230053. doi:10.1098/rsos.230053
- Ly, K., N. Mažar, M. Zhao and D. Soman. (2013), A practitioner's guide to nudging. https://www-2.rotman.utoronto.ca/facbios/file/GuidetoNudging-Rotman-Mar2013.ashx.pdf (accessed 13 August 2025).
- Marchionni, C. and S. Reijula (2019), 'What is mechanistic evidence, and why do we need it for evidence-based policy?', *Studies in History and Philosophy of Science Part A*, **73**: 54–63. doi:10.1016/j.shpsa.2018.08.
- Mattis, N., T. Groot Kormelink, P. K. Masur, J. Moeller and W. van Atteveldt (2024), 'Nudging news readers: a mixed-methods approach to understanding when and how interface nudges affect news selection', *Digital Journalism*, 1–21. doi:10.1080/21670811.2024.2350464
- Meder, B., N. Fleischhut and M. Osman (2018), 'Beyond the confines of choice architecture: a critical analysis', Journal of Economic Psychology, 68: 36–44. doi:10.1016/j.joep.2018.01.001
- Medin, D. L. and A. Ortony (1989), 'Comments on Part I: psychological essentialism', in S. Vosniadou, and A. Ortony, eds, Similarity and Analogical Reasoning, Cambridge: Cambridge University Press, 179–195. doi:10.1017/CBO9780511529863.009
- Michie, S., L. Atkins and R. West (2014), *The Behaviour Change Wheel: A Guide to Designing Interventions*, London: Silverback Publishing.
- Michie, S., M. Richardson, M. Johnston, C. Abraham, J. Francis, W. Hardeman, M. P. Eccles, J. Cane and C. E. Wood (2013), 'The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: building an international consensus for the reporting of behavior change interventions', *Annals of Behavioral Medicine*, 46(1): 81–95. doi:10.1007/s12160-013-9486-6

- Michie, S., R. West, A. N. Finnerty, E. Norris, A. J. Wright, M. M. Marques, J. Thomas, J. Hastings, M. Johnston and M. P. Kelly (2021), 'Representation of behaviour change interventions and their evaluation: development of the Upper Level of the Behaviour Change Intervention Ontology [version 2; peer review: 2 approved]', Wellcome Open Research, 5: 123. doi:10.12688/wellcomeopenres.15902.2
- Morewedge, C. K., H. Yoon, I. Scopelliti, C. W. Symborski, J. H. Korris and K. S. Kassam (2015), 'Debiasing decisions: improved decision making with a single training intervention', *Policy Insights from the Behavioral and Brain Sciences*, 2(1): 129–140. doi:10.1177/2372732215600886
- Mukhtarov F. (2024), Combining behavioural and reflective policy tools for the environment: A scoping review of behavioural public policy literature. *Journal of Environmental Planning and Management*, **67**(4), 714–741. doi:10.1080/09640568.2022.2132475
- Münscher, R., M. Vetter and T. Scheuerle (2016), 'A review and taxonomy of choice architecture techniques', *Journal of Behavioral Decision Making*, **29**(5): 511–524. doi:10.1002/bdm.1897
- Norris, E., J. Hastings, M. M. Marques, A. N. F. Mutlu, S. Zink and S. Michie (2021), 'Why and how to engage expert stakeholders in ontology development: insights from social and behavioural sciences', *Journal of Biomedical Semantics*, 12(1): 4. doi:10.1186/s13326-021-00240-6
- Okoli, C. and S. D. Pawlowski (2004), 'The Delphi method as a research tool: an example, design considerations and applications', *Information & Management*, **42**(1): 15–29. doi:10.1016/j.im.2003.11.002
- Oliver, A. (2015), 'Nudging, shoving, and budging: behavioural economic-informed policy', *Public Administration*, **93**(3): 700–714. doi:10.1111/padm.12165
- Oliver, A. (2018), 'Nudges, shoves and budges: behavioural economic policy frameworks', *The International Journal of Health Planning and Management*, 33(1): 272–275. doi:10.1002/hpm.2419
- Oliver, A. (2025), 'Clarifying by declassifying: removing the buzzwords from behavioral public policy', *Policy and Society*. doi:10.1093/polsoc/puaf010
- Osman, M., S. McLachlan, N. Fenton, M. Neil, R. Löfstedt and B. Meder (2020b), 'Learning from behavioural changes that fail', *Trends in Cognitive Sciences*, **24**(12): 969–980. doi:10.1016/j.tics.2020.09.009
- Osman, M., S. Radford, Y. Lin, N. Gold, W. Nelson and R. Löfstedt (2020a), 'Learning lessons: how to practice nudging around the world', *Journal of Risk Research*, **22**(1): 11–19. doi:10.1080/13669877.2018.1517127 Pawson, R. and N. Tilley (1997), *Realistic Evaluation*, London: Sage Publications.
- Reijula, S. and R. Hertwig (2022), 'Self-nudging and the citizen choice architect', *Behavioural Public Policy*, 6(1): 119–149. doi:10.1017/bpp.2020.5
- Richardson, L. and P. John (2021), 'Co-designing behavioural public policy: lessons from the field about how to 'nudge plus', Evidence & Policy, 17(3): 405–422. doi:10.1332/174426420x16000979778231
- Robitaille, N., J. House and N. Mažar (2024), 'Horizontally scaling of planning prompt interventions to help tax compliance in Canada', in D. Soman, ed, *What Works, What Doesn't (And When): Case Studies in Applied Behavioral Science*, Toronto: University of Toronto Press, 229–248. doi:10.3138/9781487550509-
- Rossini, F. A. and A. L. Porter (1979), 'Frameworks for integrating interdisciplinary research', *Research Policy*, 8(1): 70–79. doi:10.1016/0048-7333(79)90030-1
- Schill, C., J. M. Anderies, T. Lindahl, C. Folke, S. Polasky, J. C. Cárdenas, A.-S. Crépin, M. A. Janssen, J. Norberg and M. Schlüter (2019), 'A more dynamic understanding of human behaviour for the Anthropocene', *Nature Sustainability*, 2(12): 1075–1082. doi:10.1038/s41893-019-0419-7
- Schmidt, R. (2024), 'A model for choice infrastructure: looking beyond choice architecture in Behavioral Public Policy, *Behavioural Public Policy*, **8**(3): 415–440. doi:10.1017/bpp.2021.44
- Schneider, A. and H. Ingram (1990), 'Behavioral assumptions of policy tools', *The Journal of Politics*, **52**(2): 510–529. doi:10.2307/2131904
- Schulz, K. F., D. G. Altman, D. Moher et al. (2010), 'CONSORT 2010 Statement: updated guidelines for reporting parallel group randomised trials', BMC Medicine, 8: 18. doi:10.1186/1741-7015-8-18
- Soman, D. Ed., (2024), 'What Works, What Doesn't (And When): Case Studies in Applied Behavioral Science', Toronto: University of Toronto Press. doi:10.3138/9781487550509
- Stavri, Z. and S. Michie (2012), 'Classification systems in behavioural science: current systems and lessons from the natural, medical and social sciences', *Health Psychology Review*, **6**(1): 113–140. doi:10.1080/17437199.2011.641101
- Stenger, K. and R. Schmidt (2025), 'Navigating complexity: a pattern language approach for behavioral science in public policy,' *Behavioural Public Policy*, 1–17. doi:10.1017/bpp.2024.47

- Sunstein, C. R. (2014), 'Nudging: a very short guide', *Journal of Consumer Policy*, 37(4): 583–588. doi:10. 1007/s10603-014-9273-1
- Sunstein, C. R. (2015a), 'The ethics of nudging', Yale Journal on Regulation, 32(2): 413-450.
- Sunstein, C. R. (2015b), 'Active choosing or default rules? The policymaker's dilemma', *Behavioral Science & Policy*, 1(1): 29–33. doi:10.1177/237946151500100105
- Sunstein, C. R. (2016), 'The council of psychological advisers', *Annual Review of Psychology*, **67**(1): 713–737. doi:10.1146/annurev-psych-081914-124745
- Sunstein, C. R. (2017), 'Default rules are better than active choosing (often)', *Trends in Cognitive Sciences*, 21(8): 600-606. doi:10.1016/j.tics.2017.05.003
- Sunstein, C. R. (2018), 'Misconceptions about nudges', Journal of Behavioral Economics for Policy, 2(1): 61–67.
- Szaszi, B., A. Higney, A. Charlton, A. Gelman, I. Ziano, B. Aczel, D. G. Goldstein, D. S. Yeager and E. Tipton (2022), 'No reason to expect large and consistent effects of nudge interventions', *Proceedings of the National Academy of Sciences of the United States of America*, 119(31): e2200732119. doi:10.1073/pnas.2200732119
- Tannenbaum, D., C. Fox and T. Rogers (2017), 'On the misplaced politics of behavioural policy interventions', *Nature Human Behaviour*, 1(7): 0130. doi:10.1038/s41562-017-0130
- Thaler, R. H. and C. R. Sunstein (2008), *Nudge: Improving Decisions about Health, Wealth, and Happiness*, New Haven: Yale University Press.
- Van Dessel, P., Y. Boddez and S. Hughes (2022), 'Nudging societally relevant behavior by promoting cognitive inferences', Scientific Reports, 12: 9201. doi:10.1038/s41598-022-12964-1
- Vugts, A., M. van den Hoven, E. de Vet and M. Verweij (2020), 'How autonomy is understood in discussions on the ethics of nudging', Behavioural Public Policy, 4(1): 108–123. doi:10.1017/bpp.2018.5
- Yoeli, E., D. V. Budescu, A. R. Carrico, M. A. Delmas, J. R. DeShazo, P. J. Ferraro, H. A. Forster, H. Kunreuther, R. P. Larrick, M. Lubell, E. M. Markowitz, B. Tonn, M. P. Vandenbergh and E. U. Weber (2017), 'Behavioral science tools to strengthen energy & environmental policy', *Behavioral Science & Policy*, 3(1): 69–79. doi:10.1353/bsp.2017.0001

Cite this article: Dewies, M. and L.A. Reisch (2025), 'META BI: A tool for describing behavioural interventions', *Behavioural Public Policy*, 1–28. https://doi.org/10.1017/bpp.2025.10015