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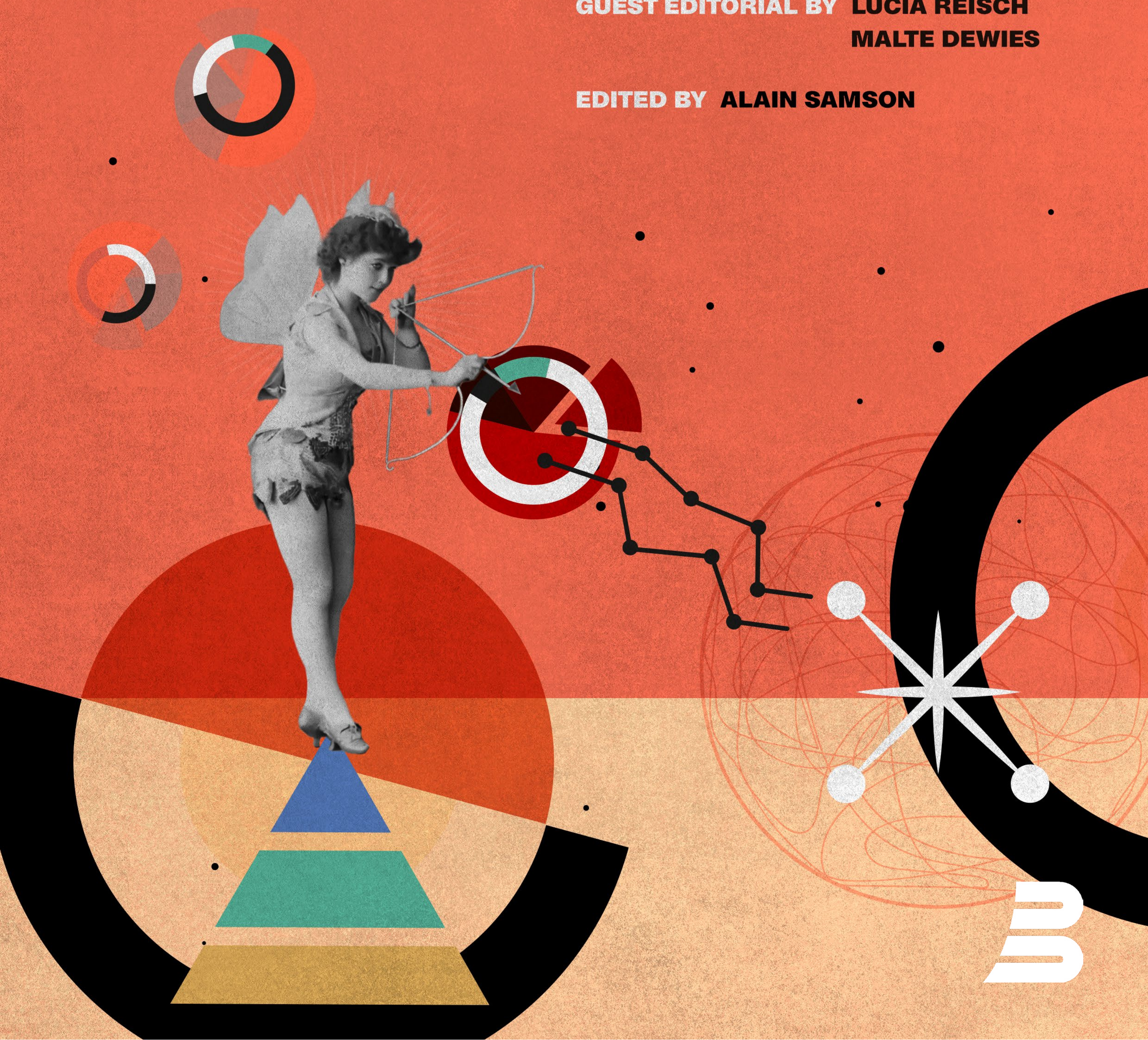

People Are Different! And So Should Be Behavioural Interventions

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Behavioural economics is increasingly recognising the key role of individual heterogeneity in understanding human behaviour. People differ in many ways: preferences, attitudes, beliefs, socio-cultural and economic backgrounds and cognitive responses to external stimuli. Effective behavioural interventions (BIs), designed to influence and change human behaviour, must therefore account for this heterogeneity. Today, there is a spectrum of BIs beyond the popular "nudges" for influencing behaviour, including boosts, thinks and nudge+. Responses to these are complex and varied, driven by numerous psychological mechanisms. We illustrate this point by reviewing experimental evidence from a recent stream of behavioural economics experiments on food choices, which highlights the role of individual heterogeneity in behavioural responses. We recommend that behavioural economists must systematically and holistically test a wide range of BIs, complement the analysis of average treatment effects with localised effects and use computational social science methods to adaptively tailor and test BIs for different population segments.

Introduction

One of the main contributions of behavioural economics to date has been to enrich and augment the standard model of economic behaviour and decision-making by acknowledging the central role played by human diversity and heterogeneity (Thaler, 1985, 1988, 1990, 2016; Loewenstein, 1987; Camerer, et al., 1989; Loewenstein & Prelec, 1993). There is not just one type of representative human agent: people are different. One of the earliest areas of interest for pioneering behavioural economists was the conceptual and empirical analysis of fundamental economic preferences such as risk, time and social preferences, with the immediate recognition that there is indeed a remarkable heterogeneity in human preferences, as witnessed by the many instances of so-called "behavioural anomalies" and "exotic preferences" documented in early studies (Kahneman & Tversky, 1974; Loewenstein & Thaler, 1989; Camerer & Thaler, 1995; Charness & Rabin, 2002; Frederick, et al., 2002; Fehr & Schmidt, 2006; Loewenstein, 2007).

There are indeed multiple sources of heterogeneity characterising human behaviour. To start with, people have very rich and diverse preferences. Take risk preferences, for example: arguably one of the most developed and influential streams of behavioural economics research has been the experimental analysis of heterogeneity in individual risk preferences (Kahneman & Tversky, 1974; Camerer, 1989; Hey & Orme, 1994; Loomes & Sugden, 1995; Ballinger & Wilcox, 1997; Wakker et al., 1997; Starmer, 2000; Abdellaoui et al., 2007, 2008; Harrison & Rutström, 2009; Bruhin et al., 2010; Wakker, 2010; von Gaudecker, et al., 2011; Vieider et al., 2015; Burghart et al., 2020). Similarly striking diversity and heterogeneity in individual preferences has been documented by behavioural economists for time and social preferences, too (Andreoni, 1988; Prelec & Loewenstein, 1991; Loewenstein & Prelec, 1992; Laibson, 1997; Bolton & Ockenfels, 2000; Fehr & Gachter, 2000; Andreoni & Miller, 2002; Frederick, et al., 2002; Dana, Cain & Dawes, 2006; Dana, et al., 2007; List,

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2007; Bardsley, 2008; Cohen, et al., 2019). Alongside diverse preferences, people have very heterogeneous attitudes, beliefs and perceptions, and they make very heterogeneous decisions (Loewenstein, 1996; Loewenstein et al., 2001, 2003; Slovic et al., 2004; Della Vigna, 2009; Galizzi et al., 2024). Of course, people are different in many more dimensions, shapes and forms: from their cultural, evolutionary, historical and geographical backgrounds to their socio-economic conditions, from their personality traits to their cognitive and neurological differences. In parallel to how biodiversity has substantially reshaped natural and environmental sciences in the last decades, neurological diversity is now radically reshaping science, medicine and social sciences, championing differences in terms of how brains and neurological systems work in different people; for instance, about 15% of the global population are estimated to be "neurodivergent", having conditions such as attention deficit hyperactivity disorder (ADHD), autistic spectrum condition, dyslexia, dyspraxia or dyscalculia, among others.

If people are inherently so different, it should not surprise us that they can also respond differently to behavioural interventions (BIs) and policies aiming at changing behaviours. One of the most exciting current developments in behavioural economics is in fact the recognition of the richness, diversity and nuances of behavioural responses to policies, interventions and stimuli. Bryan et al. (2021) describe a nascent 'heterogeneity revolution' defined by the recognition that most 'treatment effects' of policies and BIs are heterogeneous. For example, a BI or policy that is effective in changing behaviour for the majority or a group of people can still have negative consequences for a minority or backfire for another segment of the population (Galizzi et al., 2022; Sunstein, 2022). One size does not fit all, then, and so it is likely that a policy or BI that works for one group of individuals will not work for others (Beshears et al., 2020; Brody et al., 2024; Galizzi et al., 2024). The traditional focus of behavioural economists on simple averages and "average treatment effects" (ATEs) should thus be complemented by paying more attention to the study of heterogeneous treatment effects, over and above simple averages. Localised average treatment effects (LATEs), for example, that measure differential effects of the treatment in given subgroups, are often more informative than ATEs to behavioural economics practitioners, as they offer more granularity on the individual uptake of BIs and policies.

This granularity and diversity of behavioural responses to policies and BIs, and the related heterogeneity in treatment effects, calls for a systematic approach to sampling and moderation in order to account for variations in effect estimates when making conclusions about reproducible and generalisable findings (Bryan et al., 2021; Ghai & Banerjee, 2024). Recent attempts to synthesise available evidence on the effectiveness of BIs, such as nudging (Mertens et al., 2022), have limited generalisability due to the wide disparities in types of BIs and to the specificity of their domains of applications and/or their underlying causal mechanisms, especially when these interventions are clubbed together and compared to one another. These contextual differences further add to the inherent variations in the above-described individual characteristics, as well as in situational constructs in which BIs are implemented and taken up by people.

On the other hand, understanding heterogeneity in the uptake of BIs enables a more tailored approach to delivery, either via market segmentation or by developing micro-targeted, customised or personalised interventions (Mills, 2020). Recent developments in computational social science methods (Sha et al., 2023; Veltri, 2023) now make it possible to infer individual heterogeneities causally in the uptake of BIs (Banerjee & Veltri, 2024), which in turn opens up the possibility of administering and testing the broadest range of BIs. There are also issues of scalability, transferability, legitimacy and public support in relation to BIs and policies, in that not all forms of "one-size-fits-all" BIs generalise or scale up equally well, or receive equal public support or approval, and so understanding individual differences is key to improving their effectiveness and legitimacy (Soman & Hossain, 2021; List, 2022; Sunstein, 2022; Sha et al., 2023; Saccardo et al., 2024). For all these reasons, strategies and policies aiming at influencing – and possibly changing – human behaviour should therefore fully account for the extraordinary richness in individual heterogeneity (Bryan et al., 2021; Veltri, 2023).

In this piece, we illustrate the key role of human behaviour heterogeneity in the context of behavioural interventions aiming at promoting sustainable dietary choices. We review nudges and two new behaviour change intervention toolkits – boosts and nudge+ interventions – that have been proposed as alternatives to traditional nudges. Both toolkits aim to improve human agency and autonomy (Banerjee et al., 2024), have different causal cognitive underpinnings (Banerjee, 2021) and therefore place different demands on different individuals. We summarise key differences in their operationalisation and draw on growing empirical evidence that suggests differences in the effectiveness of these BIs, especially when systematically compared to each other experimentally in the same sample and at the same time. Specifically, we highlight the case of sustainable diets, where experimental evidence has shown that nudge+ can be more effective than boosting or nudging, for example. We conclude with the suggestion to test a wide variety of BIs systematically in multiple experimental setups, to analyse the heterogeneity in their effectiveness and to ultimately develop a set of common patterns that enables behavioural economics researchers and practitioners to choose one BI over the other.

The rest of the chapter is organised as follows. The next section summarises boosts and nudge+ interventions and highlights key differences in their workings. We then summarise findings from a range of recent experimental studies to compare and contrast these BIs in relation to promoting sustainable diets. We conclude with three recommendations for behavioural economics practitioners to account better for individual heterogeneity in practical applications.

Pluralism in Behavioural Economics Interventions

Nudges

Following the eponymous best-selling book by Thaler & Sunstein (2008), "nudges" are now largely popular mainstream BIs. To qualify as a nudge, a BI must meet some specific features, namely to modify the decision environment (the so-called "choice architecture") without limiting individual freedom and the number of choices, and without altering the economic incentives and the set of available information (Thaler & Sunstein, 2008; Banerjee & John, 2023b). The so-called 'libertarian paternalism' approach has been invoked as the main conceptual framework to justify nudges as politically and ethically acceptable BIs (Sunstein & Thaler, 2003). Such an approach, as well as nudges, has not been exempt from criticisms, arguing, for example, that they seem to rely critically on the assumption that individual decision-makers are largely uneducable because they are inherently cognitively biased (Gigerenzer, 2008, 2015).

Alongside nudges, a growing number of tools have recently been added to the behavioural economics intervention toolbox. This increasing pluralism of tools speaks to the inherent richness and diversity of human behaviour, as well as to the need to be fully reflected by the objectives and strategies of public and corporate decision-makers. Below, we outline two such tools – boost and nudge+.

Boosts

Boosting refers to a behaviour change strategy that seeks to improve people's competencies and upgrade their 'repertoire of skill-sets' (Hertwig & Grüne-Yanoff, 2016). Interventions designed with this principle of enhancing human capacities are referred to as "boosts" (see Hertwig, 2017). As the name suggests, boosts were conceived to empower individuals and enable them to undertake welfare-improving behaviours, which they do fundamentally by promoting people's cognitive capabilities (Herwig & Grüne-Yanoff, 2017). While nudges focus on influencing final behaviours, boosts take a step back and work by influencing people's competencies, which are then expected to change the end behaviour of the individual. Boosts and nudges are rooted in different behavioural schools of thought. For example, nudging and its precedents are based in the "heuristics and biases" paradigm, which links every sub-optimal deviation in human behaviour ("bias") to a given cognitive shortcut ("heuristic") that humans follow: nudging enables decision architects to alter the presentation of choices to people and predictably leads to certain well-defined outcome behaviours ("ends"). Contrarily, boosts relate to the "simple heuristics" paradigm, which assumes that humans often follow simple shortcuts to make *reasonable* choices (also see Madsen et al., 2024); sometimes, they may go wrong, but they do not happen systematically. Furthermore, boosts can be short-term whereby competency-building exercises are tied to a specific context of decision-making. Long-term boosts relate to broader human competences, such as rules to infer statistics or manage uncertainty better, which can then be applied to a wide range of human decision scenarios. A more detailed overview of differences between nudging and boosting can be found in Hertwig and Grüne-Yanoff (2017; see Table 1, p. 974).

Nudge+

Nudge+ refers to a set of BIs that prompt reflection ("plus") in citizens in addition to nudging them (Banerjee & John, 2024a). Nudge+ interventions are successors of large-scale reflective tools in public policy called "thinks" (John et al., 2011), i.e., citizen forums or deliberative democracies in which people come together in groups to think about a problem and find ways to solve it collectively. While these large-scale thinks were originally effective, they were often too costly to administer (John et al., 2011), so in order to overcome the substantial costs of facilitating group-led thinking, a more pragmatic way to deliver individual mini-thinks was proposed (John & Stoker, 2019). This eventually led to the development of nudge+ – an intervention combining a traditional nudge policy with a deliberative "think", either fused into one another or made proximate to each other. An essential requirement for a BI to classify as a nudge+ is the need to prompt active reflection. Specifically, the nudge+ is based on the psychological phenomenon of "perspective transformation," which works as follows: a nudge+ tool must first prompt reflection on a certain topic, which then allows decision-makers to articulate their priors genuinely, following which they either reassess and transform their prior beliefs (when there is dissonance) or they simply go as they are nudged (Banerjee & John, 2024b). Similar to a nudge, the nudge+ is rooted in the heuristics and biases paradigm. However, like a boost, it is motivated by the need to improve human agency, especially when making decisions under the influence of a nudge. In this way, the nudge+ combines the "best of both worlds," namely the convenience of delivering the nudge, as well as the agency-enhancing capacities like the boost or think. The design and delivery of a nudge+ depend on two aspects: the combination strategy of the nudge and the plus, and the timing of delivery of the plus, which can be either simultaneous or sequential (before or after) to the nudge (Banerjee & John, 2023a). A more detailed overview of the differences between a nudge, a boost and a nudge+ is outlined in Banerjee (2021; see Table 1, p10).

Individual differences and BIs

Nudges, boosts and nudge+ interventions place different cognitive demands on decision-makers. It is thus natural to expect that some people, or groups of people, respond more positively to nudging, boosting or nudge+ interventions than others. For example, one can expect that nudging is better suited and more effective in changing the behaviour of people who might face self-control failures or lack the intrinsic motivation to engage in a certain task, compared to already motivated decision-makers, for whom boosting or nudge+ can be more effective.

Many People, Many Tools

Changing dietary behaviours is a complex problem, as dietary choices are highly individual-specific and subject to the influence of many external factors, such as culture, social network, habits and norms, among others (Rozin, 1996). A shift in diets is necessary for meeting many of the Sustainable Development Goals (SDGs), ranging from mitigating greenhouse gas emissions from livestock farming for climate action, to promoting animal welfare or reducing pressures on land and water use to preserve our ecosystem services and promote biodiversity. This impending 'protein transition', in turn, necessitates the uptake of 'planetary health diets' (Willet et al., 2019), which are diets rich in plant-based food items and low in meat and dairy. This poses an interesting challenge: how can we effectively change people's dietary choices in the long term?

Traditional economic tools, such as standard command and control policies (like a meat ban) or pricing interventions (such as a meat tax or vegan subsidy), are often disliked by citizens[2]. The support for these hard policies has been shown to differ across the population based on individual preferences, such as their political ideologies, which further correlate with differences in basic human values (Morren & Banerjee, 2024). Softer policies such as nudges,

2 See Alderson (2024): https://www.thetimes.com/business-money/money/article/meat-tax-uk-news-rishi-sunak-pay-fj6kx-3z6n

however, have gained popularity. For example, in order to increase the share of plant-based food orders, the Swedish burger chain Max Burgers has set the vegetarian burger as the default option in their digital ordering stations (Gravert, 2023). Gravert & Kurz (2021) conducted a field experiment with a popular business lunch restaurant in Sweden, where they randomly handed out to customers two versions of the same lunch menu: one version of the menu listed the meat option first, while the other one listed the vegetarian option first. After the 3-week experimental period, Gravert & Kurz (2021) found that the share of meat dishes was 46% in the meat-first group while it was only 21% in the vegetarian-first group – a large and statistically significant reduction. A review of the literature suggests that changing the default from meat to vegetarian options is consistently effective in reducing meat-based consumption (Meier et al., 2022). Experimental evidence suggests that nudging food choices consistently has low-to-moderate effect sizes, varying across the exact nature of the intervention deployed (see Byerly et al., 2018; Cadario & Chandon, 2020). However, this light-touch approach is also criticised because these nudged dietary behaviours often reverse once the nudges are removed, thereby lacking persistence in effects.

Banerjee et al. (2023a) started this debate by administering to a large sample of 3,074 UK individuals an online randomised controlled experiment involving ten different BIs. Participants were first asked to consider a food menu and then to place an order for an online delivery, with some participants being paid for their orders. The BIs varied across four different toolkits, namely nudges (default and labelling), boosts (quick rules and implementation intentions), a think (a full pledge) and nudge+ interventions (default and labelling with information disclosures and default combined with parts of a pledge before or after) besides the control condition. While all these BIs were found to be effective in significantly reducing orders of carbon-intensive food items, the nudge+ intervention, which combined the option to pledge first before defaulting people into the green menu, was the most effective. Following this, the implementation intention boost, which allowed people to develop personalised “if-then” eating plans, ranked second-best. More recently, Thamer, Banerjee & John (2024) validated these findings for the nudge+ in a field experiment based in a German cafeteria, where they found that an eco-labelled nudge combined with reflection, either on the nudge itself or one’s own goals, reduced meat orders by 5-7 per cent. Both these experiments highlight the importance of letting individuals develop and clearly articulate their dietary preferences before letting a BI influence their food choices.

Banerjee & Picard (2023) extended this line of research by generalising this evidence in the context of social norm nudges. Using a large online sample of 5,555 UK citizens, they showed that norm internalisation, especially matching personal and social norms emphasising vegetarianism, is key to improving the effectiveness of these interventions. Using a similar online food delivery set-up as in Banerjee et al. (2023a), they randomised people into four different conditions: control condition; a social norm treatment, where individuals were presented with a dynamic, descriptive norm highlighting the proportion of UK nationals who were vegetarian; a personal-social norm treatment, where people were additionally asked to reveal their personal preferences around vegetarianism; and finally a personal-social norm with pledge treatment, where people were asked additionally to think if they could pledge to align their personal norms with the social norm. Building on this element of reflection, the social norm nudge almost doubled the effectiveness of the nudge in promoting plant-based orders.

Besides heterogeneous responses to different tools and BIs, there is also the issue of the heterogeneous uptake of treatment owing to individual characteristics. For example, using a subset of the sample in Banerjee et al. (2023a) (N=605 individuals), Banerjee et al. (2023b) established that people’s intrinsic motivations, as measured by their short- and long-term intentions, moderated the effect of these BIs. Comparing the think with the nudge+ treatments, they found that when people were nudged towards a green menu after they had openly articulated their preferences (versus being let to think fully), those individuals who had strong short-term positive intentions reacted negatively to the nudge by increasing their meat consumption. However, this “psychological reactance” effect was attenuated when the estimations controlled for their long-term intentions. This reinforces our prior discussion on the prerequisites of different BIs, suggesting that motivation is a strong predictor of behaviour change for nudge+ (and boosting) interventions.

Along similar lines, Banerjee & Picard (2023) showed in their experiment that a subset of people in their sample – those who had negative personal norms for meat reduction to begin with were nudged – reacted negatively to this social norm nudge by increasing their meat choice. A closer demographic profiling further revealed that people who were more liberal, educated, geographically mobile and female were more likely to respond positively to reflective BIs compared to their counterparts. Psychological reactance in subgroups of people that have been nudged has been documented more widely in the literature (for a review, see Osman, 2020).

A related point requires an assessment of whether people who have been influenced by certain BIs either engage in secondary "promoting" welfare-improving behaviours or simply feel "permitted" or "licensed" to subsequently act poorly. This phenomenon, known as positive or negative 'behavioural spillovers' (Galizzi & Dolan, 2015; Galizzi & Whitmarsh, 2019), is important because different people, given their psychological, socio-economic and personal characteristics, are influenced to act differently in follow-up actions. Understanding individual differences in such behavioural spillovers, especially when influenced by a specific BI, is also key to understanding how different behaviours manifest. For example, using a subset of participants, Picard & Banerjee (2023b) find that while the social norm nudge was effective in increasing intentions to choose vegetarian food, this was driven by a particular subgroup, and there was also a positive spillover, whereby choosing vegetarian food increased donations.

Overall, this section highlights the nuances inherent in applying different BIs. We must account for these individual differences carefully, which then translate into the differential uptake of different BIs in the form of either primary or secondary behaviour change.

Conclusion

We assert the need to employ different BIs owing to the rich individual diversity in human behaviour. Increasingly, efforts are being made to refine the BI toolkit, but they must be stepped up, especially if we are to meet the global challenges we currently face (Banerjee & Galizzi, 2024). To encourage behavioural economics practitioners to account fully for heterogeneity, and to better utilise this richness and pluralism in the behavioural toolbox, we conclude by making three practical recommendations.

Recommendation 1: Behavioural economists must test a wide range of BIs systematically and holistically in order to produce comparative, rigorous evidence on what works. This is the necessary first step to create rules of thumb that practitioners can use to choose between different BIs. Systematic comparisons of BIs are increasing, either through 'mega studies' (Duckworth & Milkman, 2022) or via multi-country comparisons (Ruggeri et al., 2024; Banerjee et al., 2024; Steinert et al., 2022), or by using integrative approaches (see Almaatouq et al., 2023). However, they are not the common standard yet. To build a knowledge repository around what works, it is therefore essential to test different BIs together systematically and in different settings and samples.

Recommendation 2: Behavioural economists must complement the analysis of average treatment effects by considering localised or differential average treatment effects. A wide range of computational social science methods can be used to analyse individual heterogeneity in the uptake of BIs. Focusing on average treatment effects often hides valuable information on specific mechanisms of BIs and their most effective target subgroup, which can inform behavioural analysts on whom – and why – BIs work. It is imperative that we recalibrate our focus now and use 'data science to identify the ways in which an intervention or situation appears to increase inequalities, and reduce them' (Hallsworth, 2023, p. 316).

Recommendation 3: Behavioural economics practitioners must be able to use heterogeneity to adaptively tailor and test BIs for groups and segments of individuals. A growing proposition in behavioural economics, and in behavioural science more generally, is to personalise interventions to improve their efficacy and/or legitimacy. Understanding heterogeneity will be key to this personalisation, as different individuals will respond differently to the BIs.

Through new contexts, multiple samples and innovative methods, understanding and fully accounting for heterogeneity in human behaviour will continue to remain key for behavioural economics in years to come.

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