From One, Many: How to Personalise Nudges?

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Abstract

Personalised nudging promises greater policy effectiveness and accuracy. However, developments in personalised nudging are hindered by clashing terms and diverse methodological outlooks. This article presents a framework for personalised nudging, the PeN framework. The framework distinguishes impersonal nudging from five ‘levels’ of personalisation. Levels are determined by (1) how a nudge can be personalised, (2) the data required for personalisation, and (3) the malleability required of the choice environment. This framework contributes a foundation for future personalised nudging research, and this article discusses the merits of it for researchers, policymakers and public welfare.

Introduction

Personalised nudging (PeN) is receiving increased attention (Mills, 2021; Sunstein, 2023a). For behavioural scientists, PeN offers the possibility of producing more effective interventions. Impersonal nudges, based on a "one-size-fits-all" approach, suffer from what might be called the problem of local maxima. An impersonal nudge can only ever be as effective as the average effect exhibited by the population to which it is applied (e.g., Sunstein, 2013). PeN potentially solves this problem, realising greater intervention effectiveness, by targeting smaller segments of the population—down to the individual, in some instances—with interventions which integrate relevant group variations (Mills, 2022; Peer et al., 2020). Given recent criticism of the small effect sizes of impersonal nudges (e.g., Maier et al., 2022), the promise of enhancing effectiveness through personalisation is an attractive one for behavioural scientists.

For policymakers, in addition to enhanced effectiveness, personalised nudges may be elegant solutions to some of the negative distributional effects which can arise from impersonal interventions (Sunstein, 2023a) as well as producing cost-saving benefits (e.g., Sunstein, 2013). For technologists, enthusiasm may be driven by emerging technological opportunities. In the past decade or so, malleable digital environments have come to dominate the spaces in which everyday choices are made. People buy, sell, bank, meet, and manage their health, all through the media presented on screens (Benartzi, 2017). Coupled with data-driven technologies such as artificial intelligence (AI), opportunities for personalisation have never been greater (Mills, Costa and Sunstein, 2023; Mills and Sætra, 2022).

While some technological innovations may be recent, frameworks for effective nudging have often included elements related to personalisation, including the "salience" element (to make it personally relevant) in MINDSPACE (Dolan et al., 2012), the "attractive" factor in EAST (BIT, 2014), and the "subjective" element in the 4S framework (Mills & Whittle, 2023). Yet, despite some acknowledgement, and despite growing interest generally, substantial challenges surround PeN. For instance, several studies highlight the limits of impersonal nudges (e.g., Kim et al., 2023; Thunstrom et al., 2018), but few directly test and demonstrate the effectiveness of personalisation strategies, either in comparison to a control group (e.g., Chiam et al., 2024; Hirsh et al., 2012) or to an impersonal nudge (e.g., Auer and Griffiths, 2023; Castleman and Page, 2015; Peer et al., 2020). Furthermore, some studies analyse the potential for personalisation only post-hoc, exploring heterogeneity in responses to different nudges between sub-groups (e.g., Murakami et al., 2022). As such, much of the enthusiasm around PeN must be understood as excitement about an interesting hypothesis, rather than excitement about an established approach whose time has now come.

To an extent, a lack of detailed evidence can be explained by the nascency of personalisation technologies (as above, perhaps less than a decade old), and even nudging itself (perhaps fifteen to twenty years old). Certainly, as personalisation methodologies mature and access to requisite technologies grows, there is likely to be substantial growth in empirical PeN research (Mills, 2021). Current enthusiasm, rather than putting the cart before the horse, may instead be understood as a means to catalyse further research which will answer many of the unknowns around PeN (e.g., Dalecke and Karlsen, 2020).

More empirical work is certainly necessary to understand PeN and interrogate the validity of its promises, particularly around enhanced effectiveness (Bergram et al., 2022; Mills, Costa and Sunstein, 2023). Yet, as this article demonstrates, the term ‘personalisation’—almost by necessity—captures many different techniques, approaches, and strategies, each drawing on a different assortment of resources (Karlsen and Andersen, 2022). Before the research agenda into PeN takes off, a conceptual footing is necessary to chart a coherent course. This is the main contribution of this article.

Towards a Framework for Personalised Nudging

This article presents a framework for PeN which distinguishes between different 'levels' of personalisation. Levels are determined through three criteria. Firstly, what aspect(s) of the nudge is personalised? Secondly, what data are required to personalise the nudge? Thirdly, how malleable must the choice environment be given the desired personalisation? Before presenting the framework, it is helpful to briefly discuss each criterion, which also offers an opportunity to review conceptual work surrounding PeN to date.

What Aspect of the Nudge is Personalised?

PeN discussions often distinguish between personalising the content of a nudge, versus personalising the method of nudging itself (Dalecke and Karlsen, 2020; Peer et al., 2020). For instance, all might be nudged using a social norm, but the norm itself may be personalised (Schultz et al., 2016). Or, one might nudge one person using a social norm, and another using a framing nudge, and so on (e.g., Peer et al., 2020). Some discussions of personalisation have also considered personalising the *audience* to generic content, versus personalising the content itself (Matz et al., 2024). The latter example is often implicit in discussions surrounding targeted advertising on social media (e.g., Matz et al., 2017).

Yet, some distinguish between personalising the method of nudging, versus personalising the outcomes towards which a person is nudged (Mills, 2022). This is to say, if individual (1) were to prefer A over B, and individual (2) B over A, (1) should be nudged towards A and (2) towards B. This notion is often what is meant by personalisation in discussion of recommendation algorithms and, increasingly, so-called 'choice engines' (Goldstein et al., 2008; Johnson, 2021; Sunstein, 2023b; Thaler and Tucker, 2013). Yet, there is good reason to consider personalising outcomes as being quite different from personalising nudges. Consider recommendation algorithms. If some option is always going to be recommended, and always recommended with a predetermined design (e.g., prominently in a banner on a website), while the selection of the outcome involves personalisation, the design of the nudge remains generic. Recommendation algorithms personalise insofar as the option towards which a person is nudged is personalised, but not insofar as the nudge itself varies according to the individual being nudged (Mills, 2022).

Normatively, this distinction is relevant. Personalising outcomes necessarily involves some deliberation over the merits and demerits of particular outcomes given particular individual characteristics. It is what has previously been dubbed "personalised paternalism" (Sunstein, 2013, p. 1871; Sunstein, 2023b). In this guise, personalisation must be understood as a component of libertarian paternalism (Thaler and Sunstein, 2003). In this article, PeN is understood as an approach to the *design* of nudges, irrespective of the outcome being nudged towards. Therefore, the framework does not focus on personalising outcomes. Relatedly, the framework does not consider whether the outcome being nudged towards is the "right" or "best" outcome, nor does it pertain to whether nudging is the best means to achieve said outcome. The framework developed in this article is largely descriptive, with some prescriptive elements insofar as recommendations for how to use PeN are offered. Yet, whether PeN *ought* to be used is contingent on many of the same ethical questions as impersonal nudging, which is not a topic of concern here.

What Data are Required?

Data is important in discussions of PeN for several reasons. The availability of data naturally impacts how a nudge can be personalised (Dalecke and Karlsen, 2020; Mills, 2022). For instance, if one does not know the target's name, one cannot include it in a text message. Furthermore, different types of data are likely to produce different nudge designs, and different designs may yield different effects (e.g., Hauser et al., 2014; Karlsen and Andersen, 2022). A nudge which personalises using gender data is likely to look very different to one which uses personality traits. This may also be observed when considering how data could be combined to arrive at even smaller stratifications of the population. Combining data on gender with personality data would allow personalised nudges to be designed for extroverted women, introverted men, and so on (Chiam et al., 2024).

Considerations around data reveal the limitations of the term ‘personalised nudging’ and push for conceptual distinctions between different ‘levels’ of personalisation. For instance, both nudges which incorporate a person’s name, and those which draw on insights into individuals’ psychology (or more; Mills and Sætra, 2022) could be described as ‘personalised’ nudges, despite obvious differences in sophistication (e.g., Auer and Griffith, 2023; Castleman and Page, 2015; Chiam et al., 2024; Peer et al., 2020; Sayed et al., 2023). Conceptual clarity around the qualitative differences between various levels of PeN is necessary to develop empirical specificity (e.g., Valenčič et al., 2023).

Finally, emphasising the role of data in PeN highlights important aspects of personalisation methodologies. One may be able to determine the targets of a personalised nudge *ex ante*, with the design of the nudge personalised to those targets. This ‘top-down’ approach relies on one’s means of predicting the likely behavioural responses of a target to a personalised design. Some work around ‘website morphing,’ where webpage aesthetics and content are reconfigured based on data such as user gender, age, and cultural background, may align with ‘top down’ approaches (e.g., Hauser et al., 2014; Reinecke and Gajos, 2014; also see Chiam et al., 2024; Hirsh et al., 2012). Alternatively, one may test many different nudge designs on many different individuals, and *ex post* determine through inferential statistics which subgroups react more strongly to different nudges. This ‘bottom-up’ approach demands A/B testing and relies on various experimental parameters. It is the method which has been deployed in studies of personalisation in behavioural science (Peer et al., 2020; Schöning et al., 2019) and other fields, such as marketing (e.g., Moon, 2002). Thus, data does not just influence the design of the personalised nudge but has an important role in *how* personalised nudges are designed.

How Malleable is the Choice Environment?

Finally, any discussion of PeN must account for the malleability of the choice environment. Malleability is to be understood as the flexibility afforded to the choice architect to change (and thus personalise) a nudge (Weinmann et al., 2016). It is closely related to the question of data availability but differs insofar as the availability of data is a necessary, but not sufficient, aspect of malleability (Dalecke and Karlsen, 2020). For instance, knowledge that a person is best nudged through a social norm mechanism is functionally less useful than it otherwise might be if the only means of nudging a person is by changing the default option (Thaler, 2021).

Some, more speculative contributions (e.g., Mills, 2022; Yeung, 2017) have considered PeN within a hypothetical setting where the choice environment is completely malleable, thus offering a choice architect maximum freedom to influence individuals, typically through personalised interventions (e.g., Frischmann and Selinger, 2018). Discussions of 'smart nudges' often draw on a similar principle (e.g., Karlsen and Andersen, 2022; Mele et al., 2021; Sadeghian and Otarkhani, 2023).

These discussions are interesting insofar as they highlight important policymaker considerations given the emergence of new technologies. For instance, technologies such as virtual reality are increasingly discussed as tools for nudging (e.g., Blom et al., 2021; Ramirez et al., 2021), in part because of links to PeN (Krpan and Urbaník, 2021). Yet, most environments have limits on malleability, and these limits in turn determine how and when PeN can be used. For instance, one may have much more data about a target individual than just their name. But, if one can only communicate—and thus nudge—the target via a letter, the only feasible personalised nudge may be personalising the letterhead or a message in the letter.

In recent years, as choice environments have become more malleable given new technologies and changing technological habits (Thaler and Sunstein, 2021), malleability has come to be seen more as an opportunity than a limitation (e.g., Mills, Costa and Sunstein, 2023). Still, malleability remains a constraint of PeN which should not be ignored.

The PeN Framework

Simply put, *personalised nudging is designing behavioural interventions such that they manifest to the target of the intervention differently, based on some systematic (non-random and non-arbitrary) individual difference variable(s) that is pre-defined by the choice architect.* This definition captures a variety of design approaches, which can be further divided into the nudge's *mechanism* ('what psychological or behavioural process is being levered?'), the nudge's specific *design* ('how is the nudge constructed, presented or delivered?') and the nudge's *content* ('what information or details are used within the nudge?'). Personalisation may arise when adjustments to only one of these components occurs, but in principle all components could be personalised provided data is available and the choice environment is sufficiently malleable.

Bringing these features of personalisation together (content, design, mechanism, data, malleability), the PeN framework conceptualises personalisation as occurring in levels. Error: Reference source not found summarises the framework. The current section elaborates on each level, while the following section discusses the implications of the framework on future PeN research.

Impersonal Nudges

While initially counter-intuitive, it is important to include impersonal nudges within any PeN framework. In almost all instances where nudging is considered a viable strategy, impersonal nudging will be the default design position. The decision to use an impersonal nudge or a personalised nudge is not a question of whether to nudge, or not, but rather, one of nudge design. Impersonal nudging is thus a (rudimentary) level of personalised nudging, as it is a legitimate nudge design one may choose, even if one can personalise.

An interesting example comes from the world of retirement savings. Evidence suggests that those who experience ‘mental distress’ save significantly less for retirement than those who do not (Arulsamy and Delaney, 2022). Thus, data about mental distress could be used to personalise an intervention for those who suffer, to encourage them to save more. However, evidence also shows that an impersonal automatic enrolment nudge for workers in the UK eliminated the savings gap between those suffering from mental distress, and those not, while all workers increased their overall contributions (Arulsamy and Delaney, 2022). Thus, the possibility of personalisation should not imply its priority. Even where personalisation is possible, impersonal nudging should still be considered, even if only to be rejected.

Named Nudges

Perhaps the most basic level of active personalisation is the idea of the personal message. Instead of sending a letter or text message to “Dear Sir/Madam,” it may often be possible to integrate the first or full name of the receiver into the message. In the PeN framework, this is a named nudge.

Table 1: The PeN Framework, exemplified by a social norm nudge.

Level	Design Factors (either fixed or variable between subjects)			Data Requirements [a]	Malleability Requirements	Examples
	Mechanism	**Design**	**Content**			
Impersonal	Social proof	Message	"Most people are getting vaccinated."	No personal data.	N/A	
Named nudge	Social proof	Message	Varies by name only: "Alex, most people are getting vaccinated."	A person's name.	Specific adjustments to content are possible. Accurate matching of the nudge to the individual.	Named messages to increase fine payments (Haynes et al., 2013)
Individualised nudge	Social proof	Message	Varies in the individually relevant content: "80% of people in your age group of 30-35 are getting vaccinated."	Data about subjects' age group and adherence rates.	Broad adjustments to content are possible. Accurate matching of the nudge to the individual.	Home Energy Reports (Allcott, 2011)
Tailored nudging	Framing risks vs. benefits	Message	Varies by individual differences: "Getting a flu shot can protect your health" Or, "Not getting a flu shot can jeopardize your health."	Personality or other individual difference data that correlates or predicted to correlate with susceptibility to different message framing	Broad adjustments to content are possible within the given design, Accurate matching of the nudge to the individual.	Personalized persuasion messages to personality traits (Hirsh et al., 2012)
Targeted nudging	Social Proof vs. Present Bias	Message vs. Default option	Varies by individual differences: Social Norm: "Most people are getting vaccinated, get yours now" Or: Default: "We scheduled you an appointment to get vaccinated next Tuesday at noon. Click here if you'd like to change or cancel."	Personality or other individual difference data that correlates or predicted to correlate with susceptibility to the different types of nudges	Comprehensive adjustments to content and design are possible. Accurate matching of the nudge to the individual.	Reducing meat consumption by fitting interventions to stage of behavioural change (Lacroix & Gifford, 2020); Personalized password nudges (Peer et al., 2020)
Adaptive nudging	Variable	Variable	Varys by type and level of nudge. E.g., First send	The above, plus data on past responses to	Comprehensive, real-time adjustments to content and design	

			impersonal social norm nudge, if no effect, send another nudge (e.g., named or individualised), etc.	nudges of different content, design, and mechanisms	are possible, Formatting is updated in real-time. Mechanisms are organised into a hierarchy of most likely to affect behaviour, which is updated in real-time. Hyper accurate (near perfect) matching of the nudge to the individual.	
[a] Data examples given relate specifically to the example given in the 'Content' heading. Different designs may require different data, and data may come from different sources.						

A named nudge only requires trivial personal data, typically a person's name, and potentially their title and gender. The instrumental design of the nudge, such as whether the nudge is delivered via a paper letter or an SMS text message, remain unchanged. So too does most of the content of the nudge. Two letters nudging a person to get vaccinated, one named and the other impersonal, will only differ by the use of naming, and not in terms of the information therein contained, or the structure or language of the letter. Finally, the nudge mechanism will also be the same for all individuals.

Naming affects behaviour because most people have positive associations with themselves (implicit egotism; Pelham et al., 2005), and thus treat messages with their names as more personal and relevant to them (Maslowska et al. 2016). In many instances, names are not related to the goal of the nudge. Rather, they capture greater attention and better position the nudge to affect behaviour. Naming thus indirectly enhances on the behavioural effect of the nudge. For instance, named text messages have been found to be more effective than impersonal messages at increasing payment rates of delinquent fines (Haynes et al., 2013). The use of a name would be irrelevant to this behaviour, but the name is likely to have directed attention to the message itself, which is relevant.

Perhaps the most famous example of named nudges is Coca Cola's personalised 'Share a Coke' campaign, which replaced the typical Coca Cola branding on bottles with common first names. In 2014, a year after the campaign's launch, it was credited with reversing a decade-long decline in Coca Cola's sales (Esterl, 2014). Again, naming did not change the content of the product, but attracted attention to it by making the product more personal and thus more engaging and desired. In the same vein, a personally addressed letter could make the recipient feel that the message is more personally relevant, and not part of a generic appeal, which could increase the message's effect.

Individualised Nudges

Individualised nudges vary their content or specific details according to the target and, differently from named nudges, use personal information to make the content and details of the nudge relevant to the goal of the nudge. For instance, Home Energy Reports (HERs) include information about an individual's electricity consumption in relation to the usage of others (Schulz et al., 2016), a common social norm nudge (e.g., Allcott, 2011). Individualised nudges like those found in HERs are similar to named nudges insofar as only the content is changed. The design and the mechanism of the nudge remain unchanged. However, they differ from named nudges because the content is personalised such that the details given in the nudge directly enhance the behavioural effect of the nudge. For instance, in the HER social norm nudge, some consumers understand their consumption is higher than average, and are encouraged to reduce it (i.e., a negative injunctive norm), while others see that their consumption is lower than average, and are encouraged to maintain it (i.e., a positive injunctive norm). Other forms of individualised nudges could be to provide different default savings rates (e.g., based on income levels) or to set pre-scheduled medical appointments at different times (e.g., based on previous kept appointments times) for different patients. In all these cases, the mechanism of the nudge, be it a social norm or a default, is administered to all targets, but the contents of the nudge, and its specific details, differ according to the individual.

Individualised nudges have been found to increase the frequency of withdrawals by gamblers from gambling websites, as well as the amount of money withdrawn (Auer and Griffiths, 2023). Encouraging more frequent withdrawals reduces gambler losses and may allow players to avoid losses they later come to regret. Messages can be personalised to appear when a gambler is on a winning streak, with an individualised message emphasising the benefits of taking one's winnings now, rather than continuing to play. Another interesting example is the use of 'fresh starts,' in savings nudges. Fresh starts encourage people to commit to saving on a particular, personally important date (e.g., a birthday or an anniversary). They lever the positive associations one may have with personal events to overcome the negative effects which can be experienced ‘losing’ money to saving (Beshears et al., 2021). Both examples demonstrate how individualised nudges apply the same design and mechanism to all targets, but change the specific details in the content of the nudge to make it personal.

Tailored Nudging

Tailoring nudges involves personalising the behavioural design of a given nudge such that different versions, conditions or variations of the nudge are delivered or presented to different individuals. This may often also involve personalising the content of the nudge. For instance, a nudge aimed to encourage hybrid vehicle adoption may highlight the potential gains of fuel savings for one person, but the added costs associated with combustion engine vehicles for another. Similarly, framing nudges can be tailored by providing different individuals with different framing conditions. For example, to encourage vaccinations, some targets can be presented with a positive framing condition (e.g., stressing the benefits of getting vaccinated)while others a negative framing condition (e.g., stressing the risks of not getting vaccinated). Warning messages, too, can be tailored to emphasise different risks to different individuals. For example, one can discourage smoking by warning men about the risk of impotence while warning women about pregnancy hazards. Reminders can be tailored by setting their timing differently for morning-type vs. evening-type individuals. Social norm nudges can also be tailored such that the reference group for the comparison of energy consumption would be different between individuals (e.g., similar consumers for some vs. all consumers for other, see Peer, 2024).

In each instance, the nudge itself (whether it is a persuasive message, framing, warning, reminder, norm, and so on) remains the same for all individuals, but the specific design and delivery mechanism is different for different individuals.

Tailored nudging necessarily requires data about a person which may be applicable in several domains. For instance, data about a person's risk preferences may have applications in healthcare and financial decision-making, and more. Thus, tailored nudging (and beyond) also require data about the relationship between key individual-level data and different nudge designs.

Relationship data could be determined in several ways. One may conduct pre-studies in which different nudges are randomly assigned to a sample, before stratifying the sample using measurements of heterogeneity (e.g., personality) to infer the most effective variation for each subsample (e.g., Ingendahl et al., 2020; Schöning, Matt and Hess, 2019). This follows a 'bottom up' approach where the relationship between individual traits and nudges are not hypothesised ex-ante, but rather revealed ex-post.

'Top down' approaches use theory and past results to create personalised nudges, before comparing these designs against an impersonal nudge or a control group. This can be seen in some studies which design nudges based on theories about different personality traits (e.g., an introverted-orientated message vs. a consciousnesses-orientated message) before investigating whether congruent individuals (those individuals whose personality matches the message) are more effected by the nudge, compared to incongruent individuals (e.g., Hirsh et al., 2012 Moon, 2002; Schöning, Matt and Hess, 2019). Top-down approaches assume that a population can be divided into known sub-groups that map well onto heterogeneity in individuals' responses to different nudges. While this is possible, it is more likely for bottom-up approaches to capture higher degrees of heterogeneity and thus enable more accurate personalisation of different nudges to different individuals (Veltri, 2023).

Targeted Nudging

Targeted nudging involves personalising the nudge mechanism used and may also involve personalising the content and the design of nudges. This is to say, rather than targeting different people with different variations of a nudge that derive from the same psychological mechanism (e.g., conformity in social norms nudges or status-quo bias in defaults), targeted nudging personalises by selecting the optimal mechanism for influencing a specific person's behaviour and assigns different types of nudges to different individuals. Some individuals may receive a pre-commitment nudge to encourage them to exercise more, while others might receive a loss aversion nudge, or a social norm nudge, and so on. This also means that, in some settings, some individuals may be nudged, while others may receive a different, non-nudge intervention, such as financial incentives. Targeted nudging thus involves identifying (or presuming) different reasons, barriers or motives that underlie why different people engage in an undesired behaviour, and applying different nudges (or other interventions) to different people.

Naturally, targeted nudging requires one to know even more about an individual. In particular, targeted nudging requires psychological and psychometric data which capture insights into how an individual interacts with choice architecture (Dalecke and Karlsen, 2020). For instance, nudges have been personalised to encourage stronger passwords by using personality data – specifically, on decision-making styles – to predict the effectiveness of different nudge mechanisms for different individuals, before targeting individuals with these personalised nudges. This approach led to stronger password setting, compared to a group receiving impersonal nudges (Peer et al., 2020). In another example, researchers designed group-matched behaviour change strategies to reduce meat consumption according to individuals' measured stage in a behavioural change model, and found these targeted interventions effective (Lacroix and Gifford, 2020). Related work in the field of 'website morphing' also emphasises how online designs can be targeted at different people depending on psychological factors such as colour and media preferences (e.g., Benartzi, 2017).

Yet, beyond these obvious design aspects, targeted nudging reveals nuances about the role of the target population. This is owing to the added data and environmental malleability associated with targeted nudging.

Specifically, as insights into individual differences increase, an option which may become available to the choice architect is to choose who *not to nudge* (Sunstein, 2022; Thunström et al., 2018). For instance, a recent review of nudges promoting vaccination uptake emphasises the need to target interventions using attitudinal data about vaccination and public health (Reñosa et al., 2021). Many people get vaccinated when the opportunity is present; some are hesitant due to behavioural factors (e.g., fear) which a nudge may overcome; and some resist due to strong opposition to vaccination generally. Nudging the first or third groups to get vaccinated is unlikely to have a substantial positive impact, though for different reasons. Indeed, nudging the third group may even have backfire effects (Attwell and Freeman, 2015). Targeting interventions *only* at the second group may be most beneficial. Further examples, from nudges to reduce spending (Thunström et al., 2018) to nudges to reduce water usage (Schultz et al., 2016) suggest that, in some instances, *not nudging* is best for some people.

The discussion of targeted nudging reveals another important aspect of personalised nudging. Namely, that in personalising a nudge, a choice architect must select both *who* will receive a nudge and *what* nudge they will receive. When considering the vaccination example, targeting using attitudinal data is primarily advocated as a means of selecting a specific sub-population to nudge. Having selected this sub-population, all in the sub-population could receive the same nudge design. Or, in the case of the password example, the whole population could be nudged, but the nudge mechanism personalised to each person in the population. This distinction risks producing another dichotomous scale on which PeN is discussed. Yet, this can be avoided by simply recognising that *not nudging* a person is still a form of personalised nudging. Indeed, it is a form of targeted nudging insofar as one is personalising the nudge mechanism to an individual given specificities surrounding said individual.

Individualised vs. Tailored vs. Targeted Nudging

It is worthwhile to clarify the differences between the previous three levels of personalised nudging. Individualised nudging only alters the content and details of the nudge that has been designed, without changing its behavioural design or the psychological mechanism that underlies the nudge. For example, all patients get a reminder for their upcoming appointment with individual-level content (when and where it is and what do they need to bring to their doctor). The differences in content vary by individuals, but only in the specific details and not in their gist and purpose.

Tailored nudging employs different variations or conditions of a specific nudge, which typically requires also changes in content, but the general mechanism of the nudge remains the same for all. For example, all patients get a reminder for their upcoming appointment, but some may get it only once, while others may receive several reminders; some may receive it in the morning, others in the evening; and for some it could be sent several days ahead of time, or only on the day of the appointment. These design changes maximize the potential effectiveness of the reminder for each individual, ensuring that the unchanged, underlying mechanism (e.g., reducing forgetfulness) exerts its full potency. This implicitly or explicitly assumes that the behavioral reason for not performing the desired behavior (showing up to the appointment) is similar across individuals.

In contrast, targeted nudging presumes the opposite: that the reasons for the behavior among different individuals are variate, and thus each person should receive a different type of treatment, employing a different mechanism that can target each specific reason. For example, if it known (or assumed) that some forget their appointment while others do not forget, but think missing the appointment is costless to others, then some may get a reminder while the others may get a persuasive message emphasizing the cost to other patients when missing appointments. That is, each person would be targeted with a different nudge that relies on a different mechanism to affect their behavior.

In summary, nudges can be personalised by individualising the content and details, tailoring the design and condition, and/or targeting different mechanisms using different interventions.

Adaptive Nudging

Prediction is an important aspect of both tailored and targeted nudging, as they involve predicting which nudges and which mechanisms will be best for a given individual (e.g., Dalecke and Karlsen, 2020; Mills, Costa and Sunstein, 2023). Adaptive nudging emerges from this notion of prediction by incorporating an individual's past behaviours, and specifically their past adherence to nudging, into targeted nudging. For instance, a person may be nudged to begin saving for retirement at the start of every tax year. If they chose not to save last year, despite a personalised social norm nudge encouraging them to do so, this year they may receive a personalised loss aversion nudge emphasising the savings benefits they have lost out on over the course of the year. If that is still not effective, they can be nudged the following year using a nudge of a different type, such as assigning them a default saving rate (from which they can opt-out).

Data about a person's past adherence can be a powerful tool for personalising an intervention because it captures information about the relationship between a person and a nudge design which may not be possible to observe *a priori* (e.g., Chiam et al., 2024; Saponaro et al., 2021). Say two people are predicted to respond to nudge A; one responds well, and the other does not. All else being equal, this response to the nudge represents a datapoint from which later nudges can be personalised.

While such adaptive personalisation implies choice environments must be extremely malleable, adaptive nudges may be possible in less malleable settings, too. For instance, the concept of 'responsive regulation' emphasises how regulatory approaches might adapt in response to an individual's actions. A debt holder might initially receive a basic letter encouraging them to repay their dept. Those who do not pay may get more threatening letters, followed by personal phone calls, and so on (e.g., Braithwhite, 2011).

Equally, malleability can (and often is) a key component of adaptive nudging (e.g., Dalecke and Karlsen, 2020; Mills, 2022). For instance, real-time physical activity data, in combination with demographic data and AI, have been used to predict the most effective of four different nudging mechanisms (framing, gamification, reminders, social influence) to use to encourage increased physical activity (Chiam et al., 2024). This also included personalising the content of the nudge message, and the design of the message. The literature on adaptive gamification strategies for behaviour change also offers interesting examples of how adaptive feedback can shape design approaches (Lopez and Tucker, 2021). For instance, a recent study investigates adaptive personalisation of feedback to encourage student learning, using AI to predict and adapt lesson presentation (where gamification elements are used) and feedback messages to students' learning styles as they progress through an online course (Sayed et al., 2023). This strategy was found to have positive learning outcomes for students.

Summary

Adaptive nudging thus presents the highest level of sophistication in the PeN framework. The levels of the framework are determined by the degree and types of changes that can be identified between nudges given to different individuals, in their content, design and mechanism.

While named nudges only personalise a single piece of content, individualised nudges personalise various aspects of content and details to achieve greater effectiveness. Tailored nudging personalises design elements of the nudge, providing it uses different variations or conditions to enhance its delivery. Targeted nudging utilises different types of nudges, targeting different underlying mechanisms, to encourage behaviour change. Lastly, adaptive nudging also takes advantage of past adherence to nudge designs to adapt future nudges and maximize effectiveness of the intervention. In this sense, adaptive nudging can be regarded as a kind of "meta-personalisation" as adherence data is used to select optimal nudge designs, rather than generate new personalised designs.

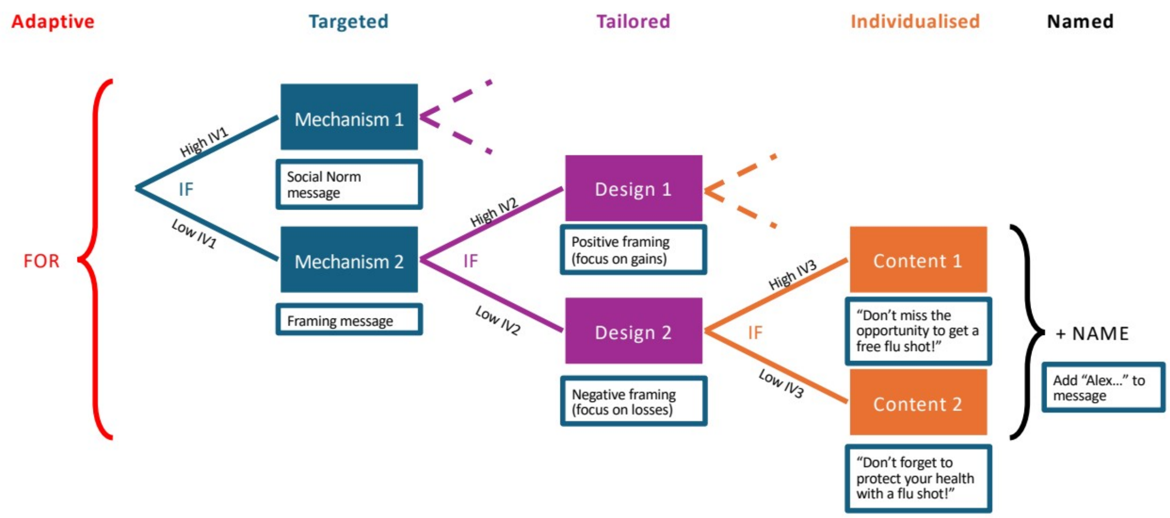

Figure 1: An Algorithmic Description of Personalised Nudges

Figure 1 illustrates the process of nudge personalisation as a series of IF-THEN statements that are satisfied to achieve different levels of personalisation. Each statement uses some independent variable (IV) to determine the individuals that would receive different nudges. For example, one IV can be used to determine if a target receives a social normor a framing message nudge; next, another IV can be used to tailor the message framing as either positive or negative; next, another IV can be used to provide individualized content for each target; and a name can be added to the message to create a named nudge. Lastly, this algorithm of IF-THEN statements can be repeated based on responses to the nudge to achieve a process of adaptive nudging, hence the FOR-loop in the diagram (e.g., *for n observations…*). Naturally, not all levels must be used in any nudge personalisation process, and it is possible to skip or omit steps in the process described in Figure 1, especially where practical feasibility restricts some personalisation capabilities.

Discussion

From one, rather vague and ill-defined notion, the PeN framework organises many ideas surrounding personalised nudging and offers several benefits for research and policy.

The benefits for research include enabling better and clearer definitions of personalisation that can be used in the design and implementation of future studies. Specifically, the framework enables different researchers to talk about personalisation in a common language, rather than having to traverse the confusing terrain of adjectives which presently represents the landscape of PeN. Further, the framework allows researchers to explore different levels of personalisation in the same study, thus drawing deeper insights into the effectiveness of personalisation, rather than approaching personalised nudging as either personalised, or not.

Opportunities abound, given such a framework, and given emerging methods within behavioural science. For instance, mega-studies examine a large number of different nudges and other behavioural interventions across large and diverse samples (e.g., Duckworth and Milkman, 2022; Milkman et al., 2021). Such studies increasingly incorporate individual-level data and offer insights into nuances of behaviour at the individual-level (e.g., Buyalskaya et al., 2023). One natural extension of mega-study approaches is thus designing more diverse, personalised interventions, which the proposed framework enables. A mega-study on different levels and versions of personalised nudging to promote a certain goal, for example, can now become more feasible and desirable.

By incorporating discussions of requisite data and malleability, the PeN framework also enhances understanding of the skills and resources necessary for undertaking research on personalised nudges (e.g., Mills, Costa and Sunstein, 2023). This should further support researchers and practitioners in designing, conducting, and evaluating personalised nudging studies. For instance, by encouraging ex ante planning of studies through active consideration of what technologies and skills are required to achieve a given level of personalisation. Furthermore, such planning should also encourage transparent reporting of research practices, supporting replication and scaling efforts ex post.

Lastly, the PeN framework enables researchers to more readily identify existing personalisation techniques which may already be used in industry, and in other fields such as marketing and computer science. Doing so should foster better integration of these techniques within behavioural science, and prompt investigation into the behavioural mechanisms which underpin such techniques, and their applicability to applied behavioural science. As the body of personalised nudging studies grows, this could also lead to a meta-analysis of personalised nudges in which the level of personalisation is a key moderating variable.

The framework also presents an important contribution to behavioural policymaking. Policymakers, as with researchers and practitioners, have been interested in personalised nudging, with regulatory voices in particular placing greater scrutiny on personalisation strategies given recent advances in generative AI (e.g., Colback, 2024; CMA, 2024, p. 79, 2021; Matz et al., 2024). For instance, concerning the risk of personalised misinformation and fraud tactics (CMA, 2024). Broadly, the conceptual clarity offered by the PeN framework should support efforts to develop effective regulatory positions on personalised choice architecture (Mills, 2024).

Specifically, the framework should enhance the behavioural auditing capabilities of regulators when auditing online services that deploy personalised nudges (e.g., Morozovaite, 2022). Behavioural auditing is a broad classification of behavioural science tools which are increasingly of interest to regulators as a means of protecting consumers and citizens from deceptive, online practices (Mills, 2024). Personalisation is a challenge in this regard because, as above, there are many different ways to personalise choice architecture, meaning regulatory tools and principles may not always be applicable or appropriate. The PeN framework offers recourse to this challenge by conceptualising personalisation as occurring in levels and pointing to practical requirements for each level of personalisation. By connecting data, malleability, and personalisation within nudge design, the PeN framework can support regulators insofar as they are interested in auditing the *potential* or *capabilities* of an online service to utilise personalised nudges.

An additional area where personalised nudging should be relevant for policymakers is that of the distributional effects of nudges. It has been argued that impersonal nudges may have distributional effects when relevant, but ignored, individual differences lead to substantially different outcomes (Sunstein, 2023a). For instance, a nudge to promote healthier lifestyles might have greater benefits for those who are already healthy because they are more receptive to the *risk* of being unhealthy than those who already indulge in an excess of unhealthy behaviours. Such individual differences may impact the 'nudgeability' of individuals, thus skewing the distributive benefits (and costs) of nudges (de Ridder et al., 2022). Given this, personalised nudging emerges as a promising policy approach, as such differences could be integrated into nudge designs (Sunstein, 2023a). While interesting, this is an area where more research into the effects of personalised nudging is needed. It is a tangible example of where the proposed framework can contribute to research efforts in support of policymaking objectives.

One ambition of the PeN framework is to prompt greater criticality surrounding not only *how* personalisation may be used, but also *when* and *if* personalised nudges are preferable policy approaches. While technologies such as AI are spurring interest in the possibilities of a more personalised behavioural science (e.g., Mills, Costa and Sunstein, 2023; Sunstein, 2023b), it is vital that evidence, rather than more readily accessible technology, drives the usage of personalised nudges.

To this end, it is helpful to understand what is meant by 'levels' within the PeN framework. The language is used to emphasise the increase in data, malleability, and multiplicity of design decisions which must be undertaken as one progresses from an impersonal nudge through to adaptive nudging. There *may* be an increase in the effect size associated with traversing these various levels of personalisation, though there is insufficient evidence at present to make this determination, with some (e.g., Auer and Griffiths, 2023; Chiam et al., 2024; Peer et al., 2020) suggesting positive effects of personalisation, and others (e.g., Lipman, 2020; Malkin et al.,

2017) providing less supportive results. Thus, progressing from one ‘level’ to another should not be considered as necessarily *improving* the personalisation of the nudge, insofar as it increases the effectiveness of the intervention. Rather, each level simply emphasises a different way of personalising. As such, the PeN framework may be better used as a *map* of personalisation. Just as a far-off island is no better than any other by virtue of being further away, so too is one ‘level’ of personalisation no better than another by virtue of, say, using more data, more complex technology, and demanding more malleability. For different outcomes and scenarios, different levels of personalisation are likely to perform differently.

One way of arriving at this conclusion is by considering the marginal effectiveness of personalisation. As one progresses through the levels of the PeN framework, the resources required for personalisation increase, as may the costs. One important cost, for instance, would be privacy costs associated with collecting and handling more ‘intimate’ data such as personality styles and behavioural traits. If these costs outweigh the benefits from greater personalisation, progressing to a ‘higher’ level of personalisation (so to speak) will not be worthwhile (Sunstein, 2013). Or, from a more statistical perspective, if the insights gleaned from an additional variable are less than the costs associated with it—both in terms of gathering the data, and in terms of the predictive power of the model—then endeavouring to achieve a ‘higher’ level of personalisation with it will not be worthwhile. When personalisation is understood to carry costs as well as benefits, one must be careful not to conflate more personalisation with greater benefit (e.g., Frischmann and Selinger, 2018).

Conclusion

This article has presented a framework which classifies and outlines different levels personalised nudging. Levels are determined by considering the design aspects of the nudge, and the resources required to incorporate personalisation. In terms of design, personalisation may vary depending on how the content, design, and mechanism of the nudge is changed. When a nudge is personalised by adding only a personal address (e.g., the name) to the content, this is a named nudge. When content is personalised to directly support the nudge mechanism, this is an individualised nudge. Tailored nudging occurs when personalisation impacts the design of the nudge, such as the nudge's framing, often in combination with personalising the content of the nudge. Targeted nudging goes beyond tailored nudging by personalising the nudge mechanism which is used. Adaptive nudging responds to past behaviours to adapt personalised nudges further.

Each level of personalisation requires more personal data than the previous level, as well as a more malleable choice environment. To personalise a nudge, one needs to have information about a person to inform design choices and behavioural predictions. Once one has arrived at a design, the choice environment must change to accommodate the design. Data and malleability are thus constraining factors on personalised nudging, which the PeN framework emphasises in addition to the design factors of content, design, and mechanism.

This article has also discussed the uses of the PeN framework. Levels should not imply more personalisation is 'better' than less personalisation. Rather, the framework showcases different design choices available to those wishing to personalise nudges. Many aspects of personalised nudging benefit from further research and experimentation. Investigations into the effectiveness of personalised nudging versus impersonal interventions, and the distributional effects of personalised nudges, are likely to be important in future research. The PeN framework supports future research agendas by offering a conceptually consistent language and organising rationale for the study of personalised nudges. The framework is also likely to support policymaker and practitioner efforts in this space by disentangling different perspectives on personalised nudges, allowing for more precise specification and evaluation of different personalisation strategies.

References

Allcott, H. (2011) 'Social norms and energy conservation' *Journal of Public Economics*, 95(9-10), pp. 1082-1095

Arulsamy, K., Delaney, L. (2022) 'The impact of automatic enrolment on the mental health gap in pension participation: Evidence from the UK' *Journal of Health Economics*, 86, e. 102673

Attwell, K., Freeman, M. (2015) 'I Immunise: An evaluation of a values-based campaign to change attitudes and beliefs' *Vaccine*, 33(46), pp. 6235-6240

Auer, M., Griffiths, M. D. (2023) 'Nudging Online Gamblers to Withdraw Money: The Impact of Personalized Messages on Money Withdrawal Among a Sample of Real-World Online Casino Players' *Journal of Gambling Studies*, DOI: 10.1007/s10899-023-10276-1

Benartzi, S. (2017) '*The Smarter Screen: Surprising Ways to Influence and Improve Online Behaviour*' Portfolio Penguin: USA

Bergram, K., Djokovic, M., Bezençon, V., Holzer, A. (2022) 'The Digital Landscape of Nudging: A Systematic Literature Review of Empirical Research on Digital Nudges' *CHI'22*, DOI: 10.1145/3491102.3517638

Beshears, J., Dai, H., Milkman, K. L., Benartzi, S. (2021) 'Using fresh starts to nudge increasing retirement savings' *Organizational Behavior and Human Decision Processes*, 167, pp. 72-87

BIT (2014) '*EAST: Four simple ways to apply behavioural insights*' Available at: https://www.bi.team/wp-content/uploads/2015/07/BIT-Publication-EAST_FA_WEB.pdf

Blom, S. S. A. H., Gillebaart, M., de Boer, F., van der Laan, N., de Ridder, D. T. D. (2021) 'Under pressure: Nudging increases healthy food choice in a virtual reality supermarket, irrespective of system 1 reasoning' *Appetite*, 160, e. 105116

Braithwaite, J. (2011). The essence of responsive regulation. *UBCL Rev.*, *44*, 475.

Buyalskaya, A., Ho, H., Milkman, K. L., Li, X., Duckworth, A. L., Camerer, C. (2023) 'What can machine learning teach us about habit formation? Evidence from exercise and hygiene' *Proceedings of the National Academy of Science*, 120(17), e. 2216115120

Castleman, B. L., Page, L. C. (2015) 'Summer nudging: Can personalized text messages and peer mentor outreach increase college going among low-income high school graduates?' *Journal of Economic Behavior and Organization*, 115, pp. 144-160

Chiam, J., Lim, A., Nott, C., Mark, N., Shinde, S., Teredesai, A. (2024) '*Co-Pilot for Health: Personalized Algorithmic AI Nudging to Improve Health Outcomes*' Arxiv. Available at: https://arxiv.org/pdf/2401.10816.pdf

CMA (2024) '*AI Foundation Models: Initial Report*' Competition and Markets Authority. Available at: https://assets.publishing.service.gov.uk/media/65081d3aa41cc300145612c0/Full_report_.pdf

CMA (2021) '*Algorithms: How they can reduce competition and harm consumers*' Competition and Markets Authority. Available at: https://www.gov.uk/government/publications/algorithms-how-they-can-reduce-competition-and-harm-consumers/algorithms-how-they-can-reduce-competition-and-harm-consumers

Colback, L. (2024) '*Personalisation and the battle for customers' attention*' The Financial Times. Available at: https://www.ft.com/content/eae952f8-5290-449b-9447-b17b395e3643

Dalecke, S., Karlsen, R. (2020) 'Designing Dynamic and Personalized Nudges' *WIMS'20*, DOI: 10.1145/34059623405975

De Ridder, D., Kroese, F., van Gestel, L. (2022) 'Nudgeability: Mapping Conditions of Susceptibility to Nudge Influence' *Perspectives on Psychological Science*, 17(2), pp. 346-359

Dolan, P., Hallsworth, M., Halpern, D., King, D., Metcalfe, R., Vlaev, I. (2012) 'Influencing behaviour: The MINDSPACE way' *Journal of Economic Psychology*, 33(1), pp. 264-277

Duckworth, A. L., Milkman, K. L. (2022) 'A guide to megastudies' *PNAS Nexus*, 1, e. 214

Esterl, M. (2014) ''*Share a Coke' Credited With a Pop in Sales*' The Wall Street Journal. Available at: https://www.wsj.com/articles/share-a-coke-credited-with-a-pop-in-sales-1411661519

Goldstein, D. G., Johnson, E. J., Herrmann, A., & Heitmann, M. (2008). Nudge your customers toward better choices. *Harvard Business Review*, *86*(12), 99-105.

Hauser, J. R., Liberali, G., Urban, G. L. (2014) 'Website Morphing 2.0: Switching Costs, Partial Exposure, Random Exit, and When to Morph' *Management Science*, 60(6), pp. 1594-1616

Haynes, L. C., Green, D. P., Gallagher, R., John, P., Torgerson, D. J. (2013) ‘Collection of delinquent fines: An adaptive randomized trial to assess the effectiveness of alternative text messages’ *Journal of Policy Analysis and Management*, 32(4), pp. 718-730

Hirsh, J. B., Kang, S. K., Bodenhausen, G. V. (2012) ‘Personalized Persuasion: Tailoring Persuasive Appeals to Recipients’ Personality Traits’ *Psychological Science*, 23(6), pp. 578-581

Ho, S. Y., Lim, K. H. (2018) ‘Nudging mood to induce unplanned purchases in imperfect mobile personalization contexts’ *MIS Quarterly*, 42(3), pp. 757-778

Ingendahl, M., Hummel, D., Maedche, A., Vogel, T. (2020) ‘Who can be nudged? Examining nudging effectiveness in the context of need for cognition and need for uniqueness’ *Journal of Consumer Behavior*, 20, pp. 324-336

Johnson, E. (2021) ‘*How Netflix’s Choice Engine Drives Its Business*’ Behavioral Scientist. Available at: https://behavioralscientist.org/how-the-netflix-choice-engine-tries-to-maximize-happiness-per-dollar-spent_ux_ui/

Karlsen, R., Andersen, A. (022) ‘The Impossible, the Unlikely, and the Probable Nudges: A Classification for the Design of Your Next Nudge’ *Technologies*, 10(110), pp. 1-17

Kim, J., Yoon, Y., Choi, J., Dong, H., Soman, D. (2023) ‘Surprising Consequences of Innocuous Mobile Transaction Reminders of Credit Card Use’ *Journal of Interactive Marketing*, DOI: 10.1177/10949968231189505

Krpan, D., Urbaník, M. (2021) ‘From libertarian paternalism to liberalism: behavioural science and policy in an age of new technology’ *Behavioural Public Policy*, DOI: 10.1017/bpp.2021.40

Lacroix, K., & Gifford, R. (2020). Targeting interventions to distinct meat-eating groups reduces meat consumption. *Food Quality and Preference*, *86*, 103997.

Levin, I. P., Gaeth, G. J., Schreiber, J., & Lauriola, M. (2002). A new look at framing effects: Distribution of effect sizes, individual differences, and independence of types of effects. *Organizational behavior and human decision processes*, *88*(1), 411-429.

Lipman, S. A. (2020) ‘One size fits all? Designing financial incentives tailored to individual economic preferences’ *Behavioural Public Policy*, DOI: 10.1017/bpp.2020.21

Lopez, C. E., Tucker, C. S. (2021) 'Adaptive Gamification and Its Impact on Performance' in Fang, X. (eds.) *HCI in Games: Experience Design and Game Mechanics* (2021). Springer: USA

Maier, M., Bartoš, F., Stanley, T. D., Shanks, D. R., Harris, A. J. L., Wagenmakers, E. (2022) 'No evidence for nudging after adjusting for publication bias' *Proceedings of the National Academy of Science*, 119(31), e. 2200300119

Malkin, N., Mathur, A., Harbach, M., Egelman, S. (2017) 'Personalized Security Messaging: Nudges for Compliance with Browser Warnings' *EuroUSEC'17*, DOI: 10.14722/eurousec.2017.23008

Maslowska, E., Smit, E. G., van den Putte, B. (2016) 'It is all in the name: A study of consumers' responses to personalized communication' *Journal of Interactive Advertising*, 16(10, pp. 74-85

Matz, S. C., Kosinsky, M., Nave, G., Stillwell, D. J. (2017) 'Psychological targeting as an effective approach to digital mass persuasion' *Proceedings of the National Academy of Science*, 114(48), pp. 12714-12719

Matz, S. C., Teeny, J. D., Vaid, S. S., Peters, H., Harari, G. M., Cerf, M. (2024) 'The potential of generative AI for personalized persuasion at scale' *Scientific Reports*, 14, e. 4692

Mele, C., Spena, T. R., Kaartemo, V., Marzullo, M. L. (2021) 'Smart nudging: How cognitive technologies enable choice architectures for value co-creation' *Journal of Business Research*, 129, pp. 949-960

Milkman, K. L., et al. (2021) 'Megastudies improve the impact of applied behavioural sciencei' *Nature*, 600, pp. 478-483

Mills, S. (2024) 'Deceptive Choice Architecture and Behavioral Audits: A Principles-Based Approach' *Regulation and Governance*, DOI: 10.1111/rego.12590

Mills, S. (2022) 'Finding the 'nudge' in hypernudge' *Technology in Society*, 71, e. 102117

Mills, S. (2021) '*The Future of Nudging Will Be Personal*' Behavioral Scientist. Available at: https://behavioralscientist.org/the-future-of-nudging-will-be-personal/

Mills, S., Costa, S., Sunstein, C. R. (2023) 'AI, Behavioural Science, and Consumer Welfare' *Journal of Consumer Policy*, 46, pp. 387-400

Mills, S., Sætra, H. S. (2022) 'The autonomous choice architect' *AI and Society*, DOI: 10.1007/s00146-022-01486-z

Mills, S., Whittle, R. (2023) 'Seeing the nudge from the trees: The 4S framework for evaluating nudges' *Public Administration*, DOI: 10.1111/padm.12941

Moon, Y. (2002) 'Personalization and personality: Some effects of customizing message style based on consumer personality' *Journal of Consumer Psychology*, 12(4), pp. 313-325

Morozovaite, V. (2022) 'Hypernudging in the changing European regulatory landscape for digital markets' *Policy and Internet*, 15(1), pp. 78-99

Murakami, K., Shimada, H., Ushifusa, Y., & Ida, T. (2022). Heterogeneous treatment effects of nudge and rebate: Causal machine learning in a field experiment on electricity conservation. *International Economic Review*, *63*(4), 1779-1803.

Peer, E., Egelman, S., Harbach, M., Malkin, N., Mathur, A., Frik, A. (2020) 'Nudge me right: Personalizing online security nudges to people's decision-making styles' *Computers in Human Behavior*, 109, e. 106347

Pelham, B. W., Carvallo, M., Jones, J. T. (2005) 'Implicit Egotism' *Current Directions in Psychological Science*, 14(2), pp. 106-110

Purohit, A. K., Holzer, A. (2019) 'Functional Digital Nudges: Identifying Optimal Timing for Effective Behavior Change' *CHI'2019*, DOI: 10.1145/3290607.3312876

Ramirez, E. J., Elliot, M., Milam, P. (2021) 'What it's like to be a : why it's (often) unethical to use VR as an empathy nudging tool' *Ethics and Information Technology*, 23, pp., 527-542

Reinecke, K., Gajos, K. Z. (2014) 'Quantifying Visual Preferences Around the World' *CHI'14*, DOI: 10.1145/2556288.2557052

Reñosa, M. D. C., Landicho, J., Wachinger, J., Dalglish, S. L., Bärnighausen, K., Bärnighausen, T., McMahon, S. A. (2021) 'Nudging toward vaccination: a systematic review' *BMJ Global Health*, 6, e. 006237

Sadeghian, A. H., Otarkhani, A. (2023) 'Data-driven digital nudging: a systematic literature review and future agenda' *Behaviour and Information Technology*, DOI: 10.1080/0144929X.2023.2286535

Saponaro, M., Vemuri, A., Dominick, G., Decker, K. (2021) 'Contextualization and individualization for just-in-time adaptive interventions to reduce sedentary behavior' *CHIL'21*, DOI: 10.1145/3450439.3451874

Sayed, W. S., Noeman, A. M., Abdellatif, A., Abdelrazek, M., Badawy, M. G., Hamed, A., El-Tantawy, S. (2023) ‘AI-based adaptive personalized content presentation and exercises navigation for an effective and engaging E-learning platform’ *Multimedia Tools and Applications*, 82, pp. 3303-3333

Schöning, C., Matt, C., Hess, T. (2019) ‘Personalised Nudging for more Data Disclosure? On the Adaption of Data Usage Policies Design to Cognitive Styles’ *Proceedings of the 52nd Hawaii International Conference on System Sciences*, 52, pp. 4395-4404

Schultz, P. W., Messina, A., Tronu, G., Limas, E. F., Gupta, R., Estrada, M. (2016) ‘Personalized Normative Feedback and the Moderating Role of Personal Norms: A Field Experiment to Reduce Residential Water Consumption’ *Environment and Behavior*, 48(5), pp. 686-710

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J., Griskevicius, V. (2007) ‘The Constructive, Destructive, and Reconstructive Power of Social Norms’ *Psychological Science*, 18(5), pp. 429-434

Sunstein, C. R. (2023b) ‘*Behavioral Biases, Choice Engines, and Paternalistic AI*’ SSRN. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4539053

Sunstein, C. R. (2022) ‘The distributional effects of nudges’ *Nature Human Behaviour*, 6, pp. 9-10

Sunstein, C. R. (2013) ‘The Storrs Lectures: Behavioral Economics and Paternalism’ *The Yale Law Journal*, 122(7), pp. 1670-2105

Thaler, R. H. (2021) ‘What’s next for nudging and choice architecture?’ *Organizational Behavior and Human Decision Processes*, 163, pp. 4-5

Thaler, R. H., Sunstein, C. R. (2021) ‘*Nudge: The Final Edition*’ Penguin Books: UK

Thaler, R. H., Sunstein, C. R. (2008) ‘*Nudge: Improving Decisions about Health, Wealth and Happiness*’ Penguin Books: UK

Thaler, R. H., Sunstein, C. R. (2003) ‘Libertarian Paternalism’ *American Economic Review*, 93, pp. 175-179

Thaler, R. H., Tucker, W. (2013) ‘Smarter Information, Smarter Consumers’ *Harvard Business Review*, 91(1-2), pp. 44

Thunström, L., Gilbert, B., Jones-Ritten, C. (2018) ‘Nudges that hurt those already hurting – distributional and unintended effects of salience nudges’ *Journal of Economic Behavior and Organization*, 153, pp. 267-282

Valenčič, E., Beckett, E., Collins, C. E., Seljak, B. K., Bucher, T. (2023) 'Digital nudging in online grocery stores: A scoping review on current practices and gaps' *Trends in Food Science and Technology*, 131, pp. 151-163

Veltri, G.A. (2023). Harnessing heterogeneity in behavioural research using computational social science. *Behavioural Public Policy,* 1-18

Weinmann, M., Schneider, C., vom Brocke, J. (2016) 'Digital Nudging' *Business and Information Systems Engineering*, 58, pp. 433-436

Yeung, K. (2017) 'Hypernudge: Big Data as a mode of regulation by design' *Information, Communication and Society*, 20(1), pp. 118-136