

Personalized nudging

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Abstract: A criticism of behavioural nudges is that they lack precision, sometimes nudging people who – had their personal circumstances been known – would have benefitted from being nudged differently. This problem may be solved through a programme of personalized nudging. This paper proposes a two-component framework for personalization that suggests choice architects can personalize both the choices being nudged towards (choice personalization) and the method of nudging itself (delivery personalization). To do so, choice architects will require access to heterogeneous data. This paper argues that such data need not take the form of big data, but agrees with previous authors that the opportunities to personalize nudges increase as data become more accessible. Finally, this paper considers two challenges that a personalized nudging programme must consider, namely the risk personalization poses to the universality of laws, regulation and social experiences, and the data access challenges policy-makers may encounter.

Introduction

Behavioural nudges have proven to be valuable tools for public policy-makers (Halpern, 2015; Sanders *et al.*, 2018). However, nudges are often criticized for their one-size-fits-all approach (Carroll *et al.*, 2009; Yeung, 2017; Peer *et al.*, 2019). For instance, Thunström *et al.* (2018) find that nudges that encourage saving can have a negative impact on individuals who already over-save. Such phenomena occur because populations are heterogeneous – individuals and groups are different from one another, and these differences may result in different responses to nudges (Sunstein, 2012).

In many domains, it is desirable to respect heterogeneity (Sunstein, 2012; Thaler & Tucker, 2013; Porat & Strahilevitz, 2014; Beshears *et al.*, 2015; Peer *et al.*, 2019). Sunstein (2013) argues that this may be achieved by incorporating data about heterogeneity into behavioural science, producing

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personalized nudges. However, it remains unclear what would be personalized under a personalized nudging programme, as well as how much additional data is required to produce effective personalized nudges.

This paper contributes to these discussions. From a review of the small body of literature discussing personalized nudging, this paper presents a two-component framework of personalization – choice and delivery. The choice/delivery framework is then used to evaluate the fresh-start nudge proposed by Beshears *et al.* (2016). This paper argues that the fresh-start nudge is a personalized nudge that can be achieved with relatively few additional data. However, by considering how more detailed data could be incorporated into the nudge, this paper supports the arguments of Sunstein (2013) and Porat and Strahilevitz (2014) that personalization opportunities increase as data become more accessible.

The ability for policy-makers to access data, however, remains a challenge. Additionally, personalized nudging may create a new challenge for policy-makers, as personalization undermines universality in areas such as law and regulation. This paper explores these challenges before concluding.

Personalization and nudging: a review

The first considerable attempt to conceptualize personalized nudging is offered by Sunstein (2012, 2013). In his 2012 paper, Sunstein considers the potential advantages personalized default nudges may offer compared to impersonal default options and active choosing. The author argues that “impersonal default rules should generally be preferred to active choosing,” because active choosing can often be burdensome, but that “personalized default rules should generally be preferred to impersonal ones in the face of relevant heterogeneity.” Furthermore, Sunstein states that “personalized default rules (if accurate and in the face of heterogeneity) have significant advantages over active choosing, because they produce benefits without requiring people to devote time and effort to choosing” (Sunstein, 2012, p. 6).

Sunstein (2013) re-emphasizes his position that personalization should be a response to heterogeneity in the population being nudged, arguing that “personalized default rules would reduce the problems posed by one-size-fits-all approaches,” before expanding on some of the practical ways personalized nudging may be achieved. Sunstein writes, “[Personalization] might be based on demographics,” or “could be very narrowly targeted,” with opportunities to personalize defaults growing as “enough information [becomes] available about someone’s past choices or personal situation” (Sunstein, 2013, p. 1871). Porat and Strahilevitz (2014) also adopt this argument in their discussion of personalized default rules in contract law.

While Sunstein (2012, 2013) positions personalized nudging as a response to heterogeneity, the analysis remains grounded in a discussion of the default option nudge, and Sunstein does not consider how personalization may manifest in other nudges.

Thaler and Tucker (2013) consider personalized nudging from a different perspective from Sunstein (2012, 2013). The authors discuss how information disclosure nudges can significantly influence people's behaviour, before noting that the amount of information available to decision-makers is fast becoming unmanageable. In response, they propose the creation of "choice engines" (Thaler & Tucker, 2013, p. 44), which would use huge amounts of data – including personal data – to "generate personalized recommendations" (Thaler & Tucker, 2013, p. 51). These recommendations would aid consumers in processing information and making decisions by personalizing what information is disclosed. Thus, Thaler and Tucker begin to consider personalized nudging beyond default options, but still focus on personalizing the outcomes nudged towards.

Thaler and Tucker's choice engines are similar to the concept of hypernudging proposed by Yeung (2017). Yeung defines a hypernudge as "nimble, unobtrusive, and highly potent, providing the data subject with a highly personalised choice environment." She further states, "[H]ypernudging relies on ... algorithmically determined correlations ... dynamically configuring the user's informational choice context in ways intentionally designed to influence decisions" (Yeung, 2017, p. 122). Yeung's hypernudge does not offer a specific framework for personalized nudging, but does significantly expand the notion of personalization beyond that suggested by Sunstein (2012, 2013) or Thaler and Tucker (2013).

Taken together, choice engines and hypernudges represent attempts to describe personalized nudging, but with an emphasis on data and technology. This is unsurprising, however, as Yeung (2017) and Thaler and Tucker (2013) approach personalized nudging as an opportunity following the expansion of data resources, while Sunstein (2012, 2013) approaches the subject as a response to the shortcomings of impersonal nudging.

Peer *et al.* (2019) also approach personalized nudging as a response to the heterogeneity problem encountered by impersonal nudges in their empirical study of personalized nudging in cybersecurity. The authors argue that heterogeneity represents an opportunity to personalize nudges and in turn improve the effectiveness of nudge interventions. Yet, where Sunstein (2012, 2013) only considers personalization within one type of nudge – the default option nudge – Peer *et al.* "distinguish between the personalization of *a certain nudge*... vs. personalizing *the selection of the nudge*" (Peer *et al.*, 2019, p. 3, emphasis in original).

Schöning *et al.* (2019) adopt the same approach to personalization in their study of online privacy settings and user preferences. By collecting individual-level psychometric data about decision-making and cognitive styles, respectively, Peer *et al.* and Schöning *et al.* personalize the selection of the nudge. This rationale seems to follow from Beshears *et al.* (2015), who suggest some people may be more cognitively predisposed to some nudges than to others. Peer *et al.* and Schöning *et al.* both find personalizing the selection of the nudge to be more effective when compared to nudges assigned impersonally.

In summary, two outstanding questions surrounding personalized nudging can be identified within the literature. Firstly, what is being personalized with the addition of heterogeneity data? Secondly, what are the heterogeneity data required for personalized nudging?

Choice and delivery personalization: a two-component framework

Addressing this first question, this paper argues that two key dimensions of personalized nudging emerge from the literature, which we call choice personalization (Sunstein, 2012, 2013; Porat & Strahilevitz, 2014) and delivery personalization (Peer *et al.*, 2019; Schöning *et al.*, 2019):

- *Choice personalization* utilizes various heterogeneity data to determine what is the best outcome to nudge a decision-maker towards when the method of nudging has already been determined. For instance, if a default nudge is being used to increase pension saving, one individual might have a higher contribution product set as the default because they frequently under-save, while another might have a low contribution product set because they frequently over-save (Sunstein, 2013; Porat & Strahilevitz, 2014). Choice personalization, therefore, is personalization *within nudges*.
- *Delivery personalization* utilizes various heterogeneity data to determine what is the most effective method of nudging an individual. For instance, some individuals might be impatient and respond well to default nudges, while others might greatly value the opinions of their peers and respond better to social norm nudges (Beshears *et al.*, 2015; Peer *et al.*, 2019; Schöning *et al.*, 2019). Delivery personalization, therefore, is personalization *across nudges*.

While presented as distinct strategies, it is reasonable to consider choice and delivery personalization being used in conjunction. For instance, it has been reported that Facebook personalizes the medium (e.g., text, photo, video) of advertisements depending on the preferences of the user, before personalizing what product is advertised to the user through that medium (Luckerson,

2015). This is illustrative of delivery and choice personalization being used together.

Equally, there may be policies that benefit from only one personalization strategy. For instance, where an active choice is desirable, such as creating a password, choice personalization may not be suitable, but delivery personalization may be effective (Peer *et al.*, 2019). Alternatively, when active choices are cumbersome, such as selecting from many retirement savings plans, choice personalization using a simple nudge like a default option may be preferable to delivery personalization, which may add complexity (Sunstein, 2012; Porat & Strahilevitz, 2014).

The data demands of personalized nudging

Personalization requires data that capture heterogeneity, although what form these take (e.g., demographic data versus personal data versus big data) is left unspecified in the choice/delivery framework. This is because choice architects may not be able to predict what data are relevant when personalizing their interventions. They may also face difficulties acquiring some data (Thaler & Tucker, 2013).

Thaler and Tucker (2013) and Yeung (2017) argue that huge amounts of personal data and big data will be necessary to reliably target individuals with personalized nudges. While Sunstein (2012, 2013) places less emphasis on these types of data, he also acknowledges the personalization opportunities that more detailed data create. The data requirements of personalized nudging – big or otherwise – remain a key aspect of personalized nudging that should be considered.

To explore this, this paper analyses the fresh-start nudge proposed by Beshears *et al.* (2016) using the choice/delivery framework and argues that this nudge is a personalized nudge, before discussing the heterogeneity data that the authors use to adapt a formerly impersonal present bias nudge into a personalized fresh-start nudge.

The fresh-start nudge

Beshears *et al.* (2016) investigate how the present bias can be used to nudge people to save more. They investigate the work of Thaler and Benartzi (2004) and find that encouraging people to begin saving in the future can have the unintended effect of suggesting to some would-be savers that saving is something that can continually be deferred. As such, when the agreed date to begin saving comes, some people do not start saving.

In response to this behaviour, Beshears *et al.* (2016) develop the ‘fresh-start’ nudge (Beshears *et al.*, 2016, p. 2). This intervention nudges people to begin saving on a personally important date in the future (e.g., a birthday or wedding anniversary). The authors call these dates “temporal landmarks” (Beshears *et al.*, 2016, p. 3) and suggest that having a landmark between today and a future commitment date makes the latter feel more distinct. By coinciding the future commitment date with a landmark date, Beshears *et al.* argue that this will make the future seem closer and reduce the inference that saving is unimportant, while retaining the behavioural advantages of using a present bias nudge outlined by Thaler and Benartzi (2004).

While not proposed as a personalized nudge, the fresh-start nudge is characteristic of choice personalization: a present bias nudge has been selected, and now data about individually important events (heterogeneity data) are being used to adapt this nudge by selecting a specific date (out of any day in the future) that choice architects believe will most effectively encourage saving.

The heterogeneity data required for the fresh-start nudge could be quite basic and easy to access; for instance, an employee’s date of birth (Beshears *et al.*, 2016). However, as Sunstein (2012, 2013) and Porat and Strahilevitz (2014) argue, more data may expand personalization opportunities. The use of date of birth data, for instance, supposes that this is a significant date for all employees, but additional data might be used to identify landmark events that are specific to individuals and which of these events is most important to those individuals. For instance, an individual might consider their wedding anniversary or child’s birthday to be a more significant temporal landmark than their own birthday.

Furthermore, the fresh-start nudge may be one of several potential nudge strategies that could be used to address the problem identified by Beshears *et al.* (2016). Psychometric data could be used to select from several methods of nudging (delivery personalization), with choices architects selecting nudges predicted to best align with an individual’s circumstances or characteristics (Beshears *et al.*, 2015; Peer *et al.*, 2019; Schöning *et al.*, 2019).

Personalized nudging and public policy

Personalized nudging reveals opportunities for public policy-makers, but also creates significant challenges. Personalization undermines universality, which is crucial to identity formation (Verbeek, 2006; Yeung, 2017) and social cohesion (O’Shea, 2019), as well as ensuring transparency in areas such as the law and regulation (Porat & Strahilevitz, 2014). There are also technical challenges such as accessing data (Thaler & Tucker, 2013; Hall & Pesenti, 2017), as well

as accountability concerns (Hardinges *et al.*, 2019) such as maintaining individual data privacy (Sunstein, 2012; O'Hara, 2019).

Universality and personalization

While the universal (one-size-fits-all) nature of impersonal nudges can produce issues due to heterogeneity, several authors attest to the benefits of universality that a programme of personalization may undermine. Yeung (2017) argues that common environments are crucial for the development of individual identity. Without common experiences for individuals to draw upon and compare with others, a sense of identity and autonomy cannot emerge (Verbeek, 2006; Yeung, 2017). Furthermore, O'Shea (2019, p. 75) argues that personalization (specifically within social media recommendation systems, which Yeung considers to be hypernudges) “[does] not just reproduce traditional social fault lines but also ... exacerbate[s] them” by personalizing along lines such as age, gender and class. Thus, by attempting to respect heterogeneity, personalized nudging may exaggerate individual differences and reduce universal experiences.

Universality is also important in law and regulation (Porat & Strahilevitz, 2014). Rawls' (1971) publicity principle argues that laws and regulations should be sufficiently transparent so as to be easily scrutinized by the public and rejected if necessary. Universality enables policies to be compared, promoting transparency and facilitating scrutiny. Personalized nudging, however, may undermine this.

For instance, a choice architect might wish to increase retirement saving and change the default option for workplace pensions from opt-in to opt-out (Service, 2015). If this change is implemented for all employees (i.e., impersonally), the policy is very transparent because everyone experiences the same nudge. By contrast, personalizing this nudge (e.g., opting some employees in and some out) renders the actions of the choice architect opaque because the criteria used to personalize the nudge are not immediately clear. In areas where transparency is crucial and is mediated by universality, personalization risks undermining effective scrutiny.

Access to data and data protection

The problem of data access by policy-makers has been explored by Thaler and Tucker (2013) in their discussion of choice engines, in the hypernudge literature (Beer, 2017; Yeung, 2017) and in the literature regarding big data technologies such as artificial intelligence (Hall & Pesenti, 2017). As discussed, some heterogeneity data used to personalize nudges may be rather easy to access (e.g., date of birth data). However, because opportunities to personalize

grow as data become more accessible, gaining access to more sensitive (personal) data and the accompanying responsibilities of data management such as privacy, security and trust are important challenges facing choice architects within a personalized nudging programme.

The first challenge of accessing sensitive data is interesting because much of these data already exist (e.g., health trackers record personal health data and social media companies have extensive databases of user data). For policy-makers, the challenge of data access is not so much collecting new data, but accessing existing data that are currently held by private firms (Hall & Pesenti, 2017).

One solution may be to purchase access to data, although this will potentially produce inhibitive costs, undermining any cost–benefit advantage of personalized nudging (Sunstein, 2012). Alternatively, policy-makers could look to the new data ownership models that are emerging (Hardinges *et al.*, 2019; Lawrence & Laybourn-Langton, 2018; Lundy-Bryan, 2018; Young *et al.*, 2019).

Hardinges *et al.* (2019) and Hall and Pesenti (2017) discuss the possibility of establishing data trusts to encourage data sharing, possibly as public–private partnerships (Young *et al.*, 2019), while Lawrence and Laybourn-Langton (2018) and Lundy-Bryan (2018) each develop the idea of a data commons, where data are easily accessible and collectively shared. Hardinges *et al.* (2019) report successful trial results of several data trusts, while initiatives such as New Zealand’s ‘Data Commons NZ’ demonstrate the potential of the data commons model (Data Commons Project, 2017).

These models tackle the second challenge of responsible data management by enshrining user obligations within a regulated and legal framework (O’Hara, 2019). This framework may contain stewardship obligations that bind policy-makers to data privacy requirements and require them to be transparent about the uses of data (Hardinges *et al.*, 2019). As such, the role of a choice architect expands in a personalized nudge environment, demanding that they act not just paternalistically in nudge-setting (Thaler & Sunstein, 2008), but responsibly in data management.

Conclusion

Personalized nudging is fast becoming a reality. Given that impersonal nudges may produce issues by not respecting the heterogeneity within the target population, personalized nudges represent a powerful tool for choice architects and may offer substantial benefits for decision-makers (Sunstein, 2012).

Two aspects of personalized nudging have been considered in this paper. Firstly, this paper has addressed the question of what personalization means

by proposing a two-component framework for personalized nudging, choice and delivery. Choice personalization uses heterogeneity data to personalize the outcome being nudged towards (e.g., high-savings products or low-savings products), while delivery personalization uses heterogeneity data to personalize the method of nudging (e.g., default option or social norm nudge). Secondly, this paper has considered the data demands of personalized nudging and has argued that personalization can be achieved with relatively few data, but as data become more accessible, the opportunities to personalize also increase.

However, personalized nudging also presents new challenges for policy-makers. Personalization may undermine important principles such as universality. Furthermore, as desires to capture ever-more heterogeneity grow, this will raise data access challenges for choice architects. For a personalized nudging programme, these challenges will be defining.

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