From one, many: How can nudges be personalized?

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Abstract

Personalized nudging (PeN) promises greater intervention effectiveness, especially for heterogenous populations. However, developments in PeN are hindered due to a lack of conceptual clarity and high methodological variability. We present a framework for PeN to tackle these challenges. We argue that personalization is contingent on personal data availability and choice environment malleability. Applying these factors to a nudge's content, design, and underlying mechanism, we suggest that various levels of PeN exist, from simple name changes to more technologically sophisticated adaptive approaches. These levels highlight various novel methodological considerations, which we split into theory-driven (top down) and data-driven (bottom up) approaches. Finally, we discuss how our framework supports practitioner goals and reveals future research directions.

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Personalized nudging (PeN) is receiving increased attention for its promise of overcoming problems associated with impersonal, one-size-fits-all nudges.[1–4] Namely, impersonal nudges are only as effective as the average effect observed in the target population, which may often be smaller than some individual-level effect sizes.[5–8] PeN promises to overcome some criticism of the small effect sizes of impersonal nudges[9] by enhancing the effectiveness of nudge interventions. Additionally, by targeting individuals or policy-relevant groups, PeN may avoid some of the negative distributional effects that can arise from impersonal nudges,[3,10] which in turn may produce cost–benefit savings.[8]

Enthusiasm for PeN is also driven by emerging technologies. In recent years, malleable digital environments have come to dominate the spaces where everyday choices are made. People buy, sell, bank, meet, order their food, and manage their health, all through adjustable screen-based user interfaces.[11] Coupled with data-driven technologies like AI, opportunities for personalization have never been greater.[12,13]

Yet, despite these promised benefits and technological opportunities, research on PeN has been relatively sparse, and substantial challenges remain. Conceptually, the term personalization—almost by necessity—captures many different techniques, approaches, and strategies, each drawing on an assortment of different resources.[14] A lack of coherent conceptual footing is likely to undermine research into PeN at almost every step of the process. Methodologically, several studies have highlighted the limits of impersonal nudges,[15,16] but few directly tested or demonstrated the effectiveness of PeN, either in comparison to a control group[17,18] or to impersonal nudges.[7,19,20] Furthermore, some studies assess personalization potential only after the fact (ex post) by analyzing how different groups responded differently to the same impersonal nudges rather than testing personalized nudges from the outset (ex ante).[21] These differing approaches render personalization an ill-defined technique in behavioral science and have stymied research to date.

A lack of detailed evidence or consistent conceptual and methodological approaches is in part explained by the nascency of personalization technologies. Inevitably, as methodologies develop and access to requisite technologies grows, so too will the body of empirical evidence surrounding PeN.[2] Nevertheless, much of the enthusiasm around PeN must be understood as excitement about an interesting hypothesis, rather than excitement about an established idea whose time has now come. Before PeN's research agenda takes off, a robust conceptual footing is necessary to chart a coherent course. This is the main goal and contribution of this article.

Toward a Framework for PeN

The first conceptualization of personalized nudges focused on the popular default nudge and distinguished between mass defaults and personalized defaults.[1] Personalized defaults use some individual or group-level data to customize the default choice (as an example, for retirement savings plans) and set an optimal smart default for different groups or people (for example, different default rates based on income level).[22,23] This framework is highly useful for optimizing default nudges. Yet, it does not consider other available nudging strategies. Thus, one of our objectives in this paper was to develop a framework applicable to various nudges and other behavioral change strategies.

We present a framework for PeN that distinguishes between different levels of personalization. Levels are determined through three criteria: First, what aspect of the nudge is personalized? Second, what data are required for personalization? And third, what is the requisite malleability of the choice environment?

What Aspect of the Nudge Is Personalized?

PeN discussions often distinguish between personalizing the content of a nudge versus the method of nudging itself.[7,24] For instance, a group may be nudged with a personalized social norm nudge.[25] Or some group members might receive a social norm nudge and others a framing nudge, and so on.[7] Other discussions distinguish between personalizing the method of nudging versus personalizing the outcomes toward which a person is nudged.[6] This is to say, if Individual 1 were to prefer A over B, and Individual 2 prefers B over A, Individual 1 should be nudged toward A and Individual 2 toward B. This approach is often what is meant by personalization in discussions of recommendation algorithms and choice engines.[1,26–28]

Yet, personalizing outcomes should be considered as distinct from personalizing nudges. Consider recommendation algorithms. If some option is always going to be recommended, and always via a predetermined design (for example, prominently in a banner on a website), the design aspects of the nudge remain impersonal. The nudge itself does not vary according to the individual being nudged.[6]

This distinction has important normative implications. It raises questions about how well a choice architect can know or predict the preferences of someone else,[29] which is why tailoring outcomes to individuals has been called "personalized paternalism."[8,27] In our article, PeN is understood as an approach to the design of nudges, irrespective of the outcome being nudged toward. In turn, the proposed framework is largely descriptive, with some prescriptive elements insofar as recommendations for how to use PeN offered. Whether PeN ought to be used is a separate question of ethics, politics, and public policy. We briefly return to these questions at the end of this article.

Thus, we focus on three aspects of a nudge's design that are important for personalization:

1. The nudge's *mechanism* (What psychological or behavioral process is being levered?), with personalization involving the use of different types of nudges for different individuals.
2. The specific *design* of the nudge (How is the nudge framed, presented, or delivered?), with personalization involving different variations of a given nudge to different individuals.
3. The nudge's *content* (What information or details are used within the nudge?), with personalization involving different stimuli within a given nudge.

What Data Are Required?

Data availability impacts PeN's potential use and design.[6,24] For instance, lacking a target's name, one cannot include it in a text message. Different types of data are likely to produce different nudge designs, which in turn may yield different effects.[14,30] Designs using gender data may look different from those using personality data, while combining gender and personality may produce a wholly different set of designs.[17]

Data-related considerations necessitate distinguishing between different levels of personalization. For instance, nudges that use a recipient's name and those that draw on their personality[13] could both be described as personalized nudges, despite obvious differences in sophistication.[7,17,19,20,31] Conceptual clarity on the qualitative differences between various levels of PeN is necessary to develop empirical specificity.[31]

Finally, the data highlight important aspects of personalization methodologies. Broadly, two approaches can be found in the literature. One may determine targets of a personalized ex ante nudge, with the nudge's design personalized to those targets. This theory-driven, top-down approach relies on one's means of predicting the likely behavioral response of a target to a design. Some personalization methods, in which different messages are predesigned based on various individual data, employ this top-down approach.[18,30] Another, more data-driven approach is to test many different nudge designs on different groups, and through inferential statistics determine which subgroups react more strongly to different designs based on actual results. This bottom-up approach has been deployed in some studies of personalization in behavioral science[7,32,33] and other fields, such as marketing.[33]

What Is the Requisite Malleability?

Finally, PeN depends on the malleability of the choice environment. Malleability is understood as the flexibility afforded to the choice architect to change (and thus personalize) a nudge.[34] It is closely related to data availability but differs insofar as data are a necessary, but not sufficient, condition for malleability.[24] For instance, knowing a person is best nudged with a social norm mechanism is not practically useful if the individual can only be nudged via changing the default option.[35]

Recent speculative contributions[36,37] have considered PeN in hypothetical settings where the choice environment is completely malleable. Discussions of "smart nudges" sometimes draw on a similar assumption.[14,38,39] Others still highlight the malleability affordances that arise from technologies such as virtual reality and speculate about these technologies becoming tools for behavior change in the future.[40–42] In recent years, as choice environments have become more malleable—given new technologies and changing technological habits[35,43]—malleability has come to be seen more as an opportunity than a limitation.[12] Nevertheless, most choice environments have limited malleability, which in turn determines when and how nudges can be personalized.

The PeN Framework

Simply put, PeN is designing behavioral interventions such that they manifest to the target of the intervention differently, based on some systematic (nonrandom and nonarbitrary) individual difference variables that are predefined by the choice architect. This definition relates the design aspects of a nudge (mechanism, design, and content) to the factors that constrain personalization (data and malleability). In bringing these features of PeN together, the PeN framework distinguishes between different levels of personalization.

Impersonal Nudges

Impersonal nudges are one-size-fits-all interventions that are commonly used in behavioral public policy.[1] They are included in this framework as the "zeroth" level of PeN, because the decision to nudge impersonally, or to use a personalized nudge, may itself be a decision based on the expected response of an individual or group. Impersonal nudging is thus a rudimentary level of PeN when not personalizing is a deliberate decision made in response to the predicted response of the target group or individual.

One relevant study to consider investigated retirement saving decisions for those suffering from mental distress.[44] Those in distress have been found to save less than those not in distress, owing to this individual circumstance. Hypothetically, one could design a personalized intervention targeting these suffering individuals. However, evidence also shows that an impersonal automatic enrollment nudge for workers in the United Kingdom eliminated the savings gap between those suffering and those not, while increasing contributions from all workers.[44] Thus, the possibility of personalization should not imply its priority. Even where personalization is possible, impersonal nudging should still be considered, even if only to be rejected.

Named Nudges

The most basic level of personalization is the personal message. Instead of sending a letter or text message to "Dear Sir/Madam," it is often possible to incorporate the receiver's name into the message. Such content personalization is a named nudge. Named nudges only require trivial personal data—a person's name, and potentially a title and gender. Naming affects behavior because most people have positive associations about themselves.[45,46] Naming is thus not directly related to the goal of the nudge. Rather, it indirectly enhances the behavioral effect of the nudge by attracting attention to relevant information.

For instance, evidence suggests that named text messages are more effective than impersonal messages at increasing payment of delinquent fines. This is because the name draws attention to delinquency information that may otherwise be ignored.[47] Perhaps the most famous named nudge is Coca-Cola's personalized "Share a Coke" campaign, which replaced the typical Coca-Cola branding with common first names. A year after the campaign's launch, it was credited with reversing a decade-long decline in Coca-Cola sales.[48] As with delinquent fines, the naming's effect was not to change the content of the product but to attract attention to the product itself. Named nudges do not change the instrumental design of the nudge; how the nudge is delivered remains unchanged. Neither does naming change the substantive content of the nudge, its design, or the psychological mechanism underpinning the intervention.

Individualized Nudges

Nudges become individualized when the substantive content of the intervention is personalized to directly, rather than indirectly, support the goal of the nudge. One example is the social norm nudge used in Home Energy Reports, which include information about an individual's electricity consumption as it relates to others' usage.[25,49] In the Home Energy Reports social norm, some consumers understand their consumption is higher than average and are encouraged to reduce it, while others see that their consumption is lower than average and are encouraged to maintain it.

Other examples effectively employ similar approaches to encourage behavior change. For instance, so-called fresh start nudges encourage people to commit to saving on a personally important date, such as a birthday, to lever the positive associations of the personal event to overcome the negative associations of losing money to savings.[50] Similarly, smart defaults[1] can apply different retirement savings based on individuals' income to produce an individualized default nudge better suited for different people. In these examples, individualized nudges change the content of the nudge in ways that directly impact the goal of the intervention. However, the specific type and design of the nudge—in terms of framing, presentation, or delivery—and the mechanism affecting behavior change are not personalized.

Tailored Nudging

Tailored nudging involves personalizing how the nudge is delivered, framed, or presented, to produce various versions of the intervention for different groups or individuals. This may often involve personalizing a nudge's content.

Examples of tailored nudging abound. Nudges to encourage hybrid vehicle adoption may personalize the framing to highlight the potential gains from fuel savings for one person or the added costs of combustion engine vehicles for another. Similarly, vaccination nudges may be tailored to emphasize the benefits of vaccination to one group while emphasizing the risks of not being vaccinated to another. Beyond framing effects, warning messages could be personalized around gender, such as discouraging smoking by warning men about the risk of impotence while warning women about pregnancy hazards. Reminders could be personalized to be delivered at different times (for example, early morning for morning people versus nighttime for night owls). Tailoring the time that withdrawal messages appear on gambling websites, such that the messages align with recent winning streaks, was found to increase the frequency of withdrawals made by gamblers at these sites and the amount of money withdrawn.[19]

Social norm interventions, too, can benefit from tailoring, as can default option nudges. For social norms, the comparison group could be tailored depending on the strength of one's association with a particular comparison.[51] For smart defaults, tailored nudging may involve predetermining who should receive the nudge's opt-in or opt-out option. In each instance, the nudge mechanism remains the same for all individuals, but specific design details regarding framing, presentation, and delivery are personalized to affect behavior change.

Tailored nudging highlights the importance of understanding the relationship between design choices and individual differences. It points to the importance of developing robust methodological approaches, particularly concerning top-down versus bottom-up perspectives, to determine personalized nudge designs when used in practice. Some methodological nuances are already being debated, and advanced computational methodologies are being put forward.[52] For instance, it has been argued that bottom-up approaches are more likely to capture higher degrees of heterogeneity and enable more accurate personalization as this approach may be more amenable to controlled testing.[53]

Targeted Nudging

Targeted nudging involves personalizing the nudge mechanism and may also involve personalizing specific designs and content. Thus, rather than targeting different people with variations of the same nudge (for example, different comparison groups in a social norm nudge), targeted nudging personalizes by selecting the optimal mechanism to affect behavior change. For instance, some people may receive a precommitment nudge to encourage greater exercise while others might receive a social norm nudge, or timely reminders, and so on.

In one study using personality data relating to decision-making styles, targeted nudging approaches were found to result in creating stronger passwords, compared to an impersonal nudge.[7] In this study, each person was given a different nudge mechanism that had previously been determined as most effective given their decision-making style. This personalization increased intervention effectiveness compared to impersonal nudging.

In another example, researchers designed behavior change strategies to reduce meat consumption by monitoring which stage of a behavior change model participants occupied and matching interventions to these stages.[54] Related work in website morphing (that is, automatically adjusting a website's design and content to match visitors' cognitive styles) also emphasizes how online designs can be targeted at different groups depending on psychological factors such as color and media preferences.[11]

Targeted nudging raises an intriguing conceptual question because some individuals might be more likely to change their behavior when they receive a nonnudge intervention, such as a financial incentive, in certain settings. This is because targeted nudging fundamentally involves identifying (or predicting) the different reasons, barriers, or motives that underlie why people engage in undesired behaviors. Furthermore, targeted nudging also implies that choice architects may personalize a nudge by identifying who should not be nudged.[3,16] For instance, a recent review of nudges promoting vaccine uptake found that many people get vaccinated when the opportunity is present, while some are hesitant due to behavioral factors such as fear, and some resist due to strong opposition to vaccination.[55] However, nudging the first or third groups to get vaccinated is unlikely to have a substantial positive impact for different reasons and may even have backfire effects.[56] Targeting nudges only at the second group may be most beneficial. Further examples, ranging from nudges to reduce spending[16] to nudges to reduce water usage,[25] suggest that, in some instances, not nudging could be best for some people.

Adaptive Nudging

Prediction is an important aspect of PeN.[12,24] Adaptive nudging emerges from prediction by incorporating an individual's past behaviors—specifically, their past adherence to nudging—into targeted nudging. For instance, financial institutions might send nudges to their customers about beginning to save for retirement at the start of each tax year. If some customers chose not to save last year, despite a personalized social norm nudge encouraging them to do so, in the coming year they may receive a personalized loss aversion nudge emphasizing the benefits they have lost. If that is not effective, the following year might involve a wholly different nudge. For instance, they might receive an adaptive default where the default option has been updated based on their past decisions.[1] Data about past decisions can be a powerful tool for personalizing interventions because they capture information about the relationship between a person and a nudge that may not be possible to observe beforehand.[17,57]

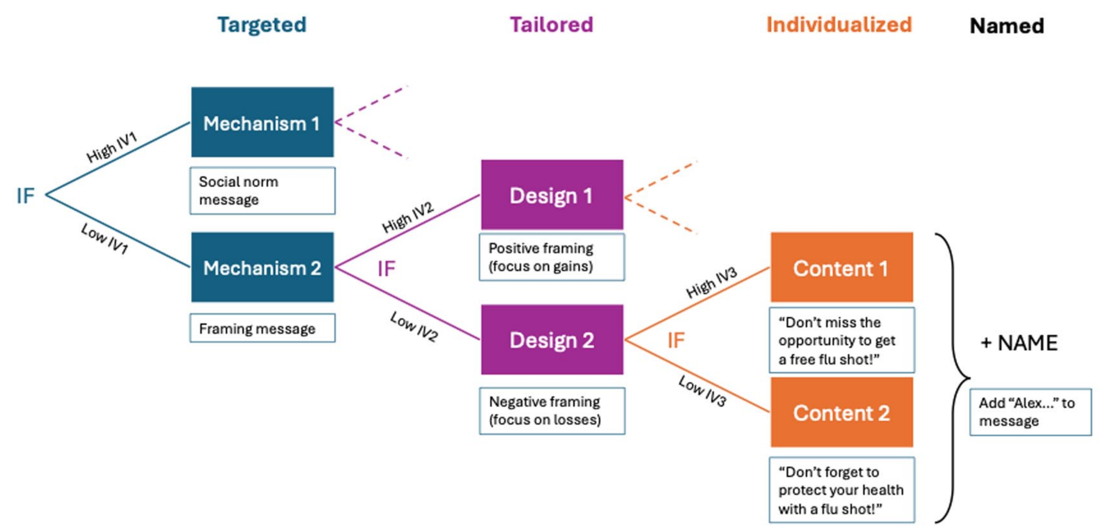
In many instances, adaptive personalization implies choice environments that are extremely malleable.[58] However, adaptive nudging may also be possible in less malleable settings. For instance, the concept of responsive regulation emphasizes how regulatory approaches adapt to individual actions. Debt holders might initially receive letters encouraging them to pay, followed by more threatening letters and phone calls as time goes on.[59]

Still, malleability is a key component of adaptive nudging.[24,36] For instance, demographics have been used to predict the most effective of four nudging mechanisms (framing, gamification, reminders, and social influence) to encourage physical activity, with interventions adapting to individuals using real-time physical activity data to capture adherence to the nudge.[17] In another example, adaptive nudging has been used to personalize messages given to diabetes patients to encourage adherence to their health care program. Messages are adapted in response to past patient behaviors.[60] In education, adaptive nudging has been used to predict and adapt lesson presentation and feedback messages to support student learning as they progress through online courses.[61] In each instance, choice environments must be sufficiently malleable to afford optimal adaptions of interventions.

Summary

The levels of personalization in the PeN framework reflect differences in the content, design, and mechanism of the nudge, given data and malleability constraints. Named nudges personalize a single piece of content to produce an indirect behavioral effect, while individualized nudges personalize substantive content for a direct effect. Tailored nudging personalizes design elements such as framing, presentation, and delivery, while targeted nudging also personalizes the psychological mechanism itself, based on the predicted response of groups and individuals. Adaptive nudging incorporates past adherence to nudge designs to adapt future nudges.

Figure 1. **Illustration of the personalized nudging (PeN) framework as a series of IF-THEN statements**



Note. IV = independent variable.

These levels are illustrated in Figure 1 and are summarized and exemplified in Table 1. Table 1 summarizes the different levels of the PeN framework and provides examples and descriptions for each level, including how each level differs in the personal data required to afford personalization, and the malleability of the choice architecture required to personalize the nudges at that level.

Figure 1 shows how each level uses some independent variable to personalize the nudge by changing its mechanism (targeted nudging), design (tailored nudging), or content (individualized and named nudges). This algorithm of IF-THEN statements can be repeated based on responses to different nudges to achieve the higher level of adaptive nudging.

Progressing from one level to another should not be considered as necessarily improving the personalization of the nudge, insofar as the effect size increases. Rather, each level simply emphasizes different ways of personalizing. The PeN framework can be considered a map of personalization. Just as a far-off island is no better than any other by virtue of being farther away, so too is one level of personalization no better than another by virtue of, say, using more data, possessing more complex technology, or demanding more malleability.

The framework also helps address the question of the appropriate control condition for PeN. Comparing a personalized nudge to a no-nudge control does not demonstrate that personalization has an effect beyond the nudge itself. Thus, the effects of different levels of PeN should be compared to the appropriate control conditions, which depend on the level of personalization. Specifically, while named and individualized nudges should be compared to impersonal messages, the case is different for tailored and targeted nudges. For tailored and targeted nudges, the control should include an assignment of the different nudges randomly, without considering individual differences. For example, a PeN condition in which risk-seeking individuals are assigned a positive framing nudge and risk-averse individuals receive a negative framing nudge should be compared to a condition in which participants receive either a positive or negative framing nudge randomly, without considering their risk preferences. In other words, to show the unique effect of personalization in PeN, researchers must design the study to contain as many control conditions as their personalization scheme. This also applies to targeted nudges (which use different mechanisms), as was done, for example, in a 2020 study by Peer et al.[7]

Similarly, adaptive nudging should be compared to delivering the set of nudges included in the study design but with random application rather than considering previous responses to nudges or any individual differences. This also

Table 1. Levels, design factors, & data & malleability requirements in the personalized nudging (PeN) framework

Level	Design factors			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, allowing for accurate matching of the nudge to the individual.	Named messages to increase fine payments[47]
Individualized 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, allowing for accurate matching of the nudge to the individual.	Home Energy Reports[49]
Tailored nudging	Framing risks versus 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 correlate or are predicted to correlate with susceptibility to different message framing	Broad adjustments to content are possible within the given design, facilitating accurate matching of the nudge to the individual.	Personalized persuasion messages to personality traits[18]
Targeted nudging	Social proof versus present bias	Message versus 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 correlate or are predicted to correlate with susceptibility to the different types of nudges	Comprehensive adjustments to content and design are possible, facilitating accurate matching of the nudge to the individual.	Reducing meat consumption by fitting interventions to stage of behavioral change;[54] personalized password nudges[7]
Adaptive nudging	Variable	Variable	Varies by type and level of nudge; that is, first send impersonal social norm nudge, if no effect, send another nudge (e.g., named or individualized), etc.	The above, plus data on past responses to nudges of different content, design, and mechanisms	Comprehensive, real-time adjustments to content and design are possible. Formatting is updated in real time. Mechanisms are organized into a hierarchy of most likely to affect behavior, which is updated in real-time. This approach results in hyperaccurate (near perfect) matching of the nudge to the individual.	Increasing medication adherence among diabetes patients using messages personalized based on responses to past messages[60]

Note. [a] Data examples given relate specifically to the examples given in the Content column. Different designs may require different data, and data may come from different sources.

suggests that a study design should include an additional no-nudge control condition, which facilitates comparing the effect of the nudge itself (unpersonalized) to the effect of the personalized nudge. Using this approach, Peer et al. showed how personalization increased the nudge's effect 10 times compared to no nudge and 4 times compared to a random nudge.[7] The PeN framework, by distinguishing between levels of personalization, thus also helps researchers choose the appropriate controls for their studies.

Discussion

By building on one rather ill-defined notion lacking conceptual clarity and possessing high methodological variability, the PeN framework offers a coherent structure for future research into PeN and policy application. The benefits for research include enabling clearer definitions of personalization that can be used when designing and implementing future studies. Specifically, the framework enables different researchers to talk about PeN in a common language, rather than having to traverse the confusing terrain of adjectives that is the present PeN landscape. By incorporating discussions of requisite data and malleability, the PeN framework also enhances understanding of the skills and resources necessary for undertaking research on personalized nudges, which should further support researchers.[12]

The framework also enhances emerging research practices in behavioral science, creating new avenues for investigation. For instance, megastudies have examined a large number of different nudges and other behavioral interventions across sizable and diverse samples.[62,63] Such studies increasingly incorporate individual-level data and offer insights into nuances of behavior at the individual level.[64] The megastudy approach is naturally disposed to testing and investigating various types of personalized nudges,[12] which the PeN framework now enables. Furthermore, by conceptualizing personalization in terms of levels, the framework shifts establish perspectives on personalization. Rather than nudges being personalized or impersonal, the levels approach should encourage more granular testing of personalization strategies. As the body of PeN studies grows, the levels approach could lead to meta-analyses in which the level of personalization is a key moderating variable.

The framework is also an important contribution to behavioral policymaking. Policymakers, as with researchers and practitioners, have been interested in PeN, with regulatory voices in particular placing greater scrutiny on such approaches following advances in AI.[65–67] For instance, concerns have been raised about the risk of personalized information and fraud tactics.[66] Broadly, the PeN framework should support efforts to develop effective regulatory positions on personalization.[13] Specifically, by connecting data, malleability, and nudge design features to personalization, the PeN framework signposts key capabilities—data, malleability, and nudge design features—that regulators can investigate, monitor, and sanction.

While this article has presented its descriptive contribution, it may serve to help practitioners and researchers use the PeN framework by briefly considering the prescriptive arguments for personalization. A key argument is the promise of increased effect sizes and thus welfare impacts from nudging.[6,8] Where personalization allows a person to find an outcome more readily, which leaves them better off,[68] personalized nudges can be expected to demonstrate larger effect sizes, compared to their impersonal counterparts. In turn, one should anticipate greater welfare returns from nudging.[69] These benefits may extend further if personalization techniques (such as data analysis and digital interfaces) are extended to the personalization of outcomes, as well as the personalization of designs.[26,27] We did not focus on personalized paternalism in this article, and it remains an area in need of further study.

Another area of prescriptive relevance is that of distributional effects. Impersonal nudges can have distributional effects when relevant. Yet when ignored, individual differences can lead to substantially different outcomes.[3] For instance, those who already exercise may be more attentive to the risk of being unhealthy than those who are already unhealthy. Such individual differences may impact people's "nudgeability," thus skewing the distributive benefits (and costs) of nudges.[70] For instance, healthy people may engage in even healthier behaviors, while those who are unhealthy (and so would benefit most from the nudge) do not. Thunström et al.[(16)] found a similar phenomenon in relation to spending behavior.

PeN emerges as a promising policy approach, as negative distributional effects may be reduced through integrating such differences.[3] This may, in turn, hold efficiency benefits from a policymaking perspective, with fewer resources being dedicated to those whose marginal benefit is likely to be quite small. Again, research into distributional effects is a nascent area of study, but given its close association with PeN, the PeN framework is likely to assist researchers in this area.

Conclusion

This article presented a framework that classifies and outlines different levels of PeN. Levels emerge through considering the different aspects of content, design, and mechanism being personalized and the constraining factors that influence personalization, namely data and malleability. By systematically considering how changes in nudges' aspects and constraining resources create new opportunities for personalization, various levels of personalized nudges emerge. These levels form the PeN framework.

The PeN framework supports future research agendas by offering a conceptually consistent language and organizing rationale for the study of PeN. The framework is also likely to support policymakers' and practitioners' efforts in this space by disentangling different perspectives on personalized nudges, allowing for more precise specification and evaluation of different personalization strategies. To this end, the PeN framework can promote future research and applications of PeN, thereby allowing people to receive optimal interventions that maximize individual and societal gains.

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References

1. Goldstein, D. G., Johnson, E. J., Herrmann, A., & Heitmann, M. (2008). Nudge your customers toward better choices. *Harvard Business Review*, *86*(12), 99–105.
2. Mills, S. (2021, March 15). The future of nudging will be personal. *Behavioral Scientist*. https://behavioralscientist.org/the-future-of-nudging-will-be-personal/
3. Sunstein, C. R. (2023). The distributional effects of nudges. *Nature Human Behaviour*, *6*, 9–10. https://doi.org/10.1038/s41562-021-01236-z
4. Tor, A. (2024). Personalized behavioral regulation is here: What lessons for "personalized law"? *Jerusalem Review of Legal Studies*, *29*(1), 48–64. https://doi.org/10.1093/jrls/jlae005
5. Bergram, K., Djokovic, M., Bezençon, V., & Holzer, A. (2022). The digital landscape of nudging: A systematic literature review of empirical research on digital nudges. In S. Barbosa, C. Lampe, C. Appert, D. A. Shamma, S. Drucker, J. Williamson, & K. Yatani (Eds.), *CHI'22: Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (Article 62). Association for Computing Machinery. https://doi.org/10.1145/3491102.3517638
6. Mills, S. (2022). Personalized nudging. *Behavioural Public Policy*, *6*(1), 150–159. https://doi.org/10.1017/bpp.2020.7
7. 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*, Article 106347. https://doi.org/10.1016/j.chb.2020.106347
8. Sunstein, C. R. (2013). The Storrs Lectures: Behavioral economics and paternalism. *The Yale Law Journal*, *122*(7), 1826–1899. https://www.yalelawjournal.org/pdf/1164_j5m12m5y.pdf
9. Maier, M., Bartoš, F., Stanley, T. D., Shanks, D. R., Harris, A. J. L., & Wagenmakers, E.-J. (2022). No evidence for nudging after adjusting for publication bias. *Proceedings of the National Academy of Science*, *119*(31), Article e2200300119. https://doi.org/10.1073/pnas.2200300119
10. Mrkva, K., Posner, N. A., Reeck, C., & Johnson, E. J. (2021). Do nudges reduce disparities? Choice architecture compensates for low consumer knowledge. *Journal of Marketing*, *85*(4), 67–84. https://doi.org/10.1177/0022242921993186
11. Benartzi, S. (with Lehrer, J.). (2017). *The smarter screen: Surprising ways to influence and improve online behaviour*. Portfolio/Penguin.
12. Mills, S., Costa, S., & Sunstein, C. R. (2023). AI, behavioural science, and consumer welfare. *Journal of Consumer Policy*, *46*(3) 387–400. https://doi.org/10.1007/s10603-023-09547-6
13. Mills, S., & Sætra, H. S. (2024). The autonomous choice architect. *AI & Society*, *39*(2), 583–595. https://doi.org/10.1007/s00146-022-01486-z
14. Karlsen, R., & Andersen, A. (2022). The impossible, the unlikely, and the probable nudges: A classification for the design of your next nudge. *Technologies*, *10*(6), Article 110. https://doi.org/10.3390/technologies10060110
15. 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*, *59*(2), 135–150. https://doi.org/10.1177/10949968231189505
16. 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 & Organization*, *153*, 267–282. https://doi.org/10.1016/j.jebo.2018.07.005
17. 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. https://arxiv.org/pdf/2401.10816.pdf
18. Hirsh, J. B., Kang, S. K., & Bodenhausen, G. V. (2012). Personalized persuasion: Tailoring persuasive appeals to recipients' personality traits. *Psychological Science*, *23*(6), 578–581. https://doi.org/10.1177/0956797611436349
19. Auer, M., & Griffiths, M. D. (2024). 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*, *40*, 1227–1244. https://doi.org/10.1007/s10899-023-10276-1
20. 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 & Organization*, *115*, 144–160. https://doi.org/10.1016/j.jebo.2014.12.008
21. 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. https://doi.org/10.1111/iere.12589
22. Smith, N. C., Goldstein, D. G., & Johnson, E. J. (2013). Choice without awareness: Ethical and policy implications of defaults. *Journal of Public Policy & Marketing*, *32*(2), 159–172. https://doi.org/10.1509/jppm.10.114
23. Goldstein, D. G., & Dinner, I. M. (2013). A fairly mechanical method for policy innovation. In H. C. M. van Trijp (Ed.), *Encouraging sustainable behavior* (pp. 55–68). Psychology Press.
24. Dalecke, S., & Karlsen, R. (2020). Designing dynamic and personalized nudges. In *WIMS 2020: Proceedings of the 10th International Conference on Web Intelligence, Mining and Semantics* (pp. 139–148). Association for Computing Machinery. https://doi.org/10.1145/3405962.3405975
25. 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), 686–710. https://doi.org/10.1177/0013916514553835
26. Johnson, E. (2021, October 18). How Netflix's choice engine drives its business. *Behavioral Scientist*. https://behavioralscientist.org/how-the-netflix-choice-engine-tries-to-maximize-happiness-per-dollar-spent_ux_ui/
27. Sunstein, C. R. (2023). Behavioral biases, choice engines, and paternalistic AI. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4539053

28. Thaler, R. H., & Tucker, W. (2013). Smarter information, smarter consumers. *Harvard Business Review*, *91*(1–2), 44.
29. Thaler, R. H., & Sunstein, C. R. (2003). Libertarian paternalism. *American Economic Review*, *93*(2), 175–179. https://doi.org/10.1257/000282803321947001
30. 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), 1594–1616. https://doi.org/10.1287/mnsc.2014.1961
31. 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 & Technology*, *131*, 151–163. https://doi.org/10.1016/j.tifs.2022.10.018
32. Ingendahl, M., Hummel, D., Maedche, A., & Vogel, T. (2021). Who can be nudged? Examining nudging effectiveness in the context of need for cognition and need for uniqueness. *Journal of Consumer Behaviour*, *20*(2), 324–336. https://doi.org/10.1002/cb.1861
33. Schöning, C., Matt, C., & Hess, T. (2019). Personalised nudging for more data disclosure? On the adaption of data usage policies design to cognitive styles. In *Proceedings of the 52nd Hawaii International Conference on System Sciences* (pp. 4395–4404). Association for Information Systems. https://doi.org/10.24251/hicss.2019.532
34. Moon, Y. (2002). Personalization and personality: Some effects of customizing message style based on consumer personality. *Journal of Consumer Psychology*, *12*(4), 313–325. https://doi.org/10.1016/S1057-7408(16)30083-3
35. Thaler, R. H., & Sunstein, C. R. (2021). *Nudge: The final edition*. Penguin Books.
36. Mills, S. (2022). Finding the 'nudge' in hypernudge. *Technology in Society*, *71*, Article 102117. https://doi.org/10.1016/j.techsoc.2022.102117
37. Yeung, K. (2017). Hypernudge: Big data as a mode of regulation by design. *Information, Communication & Society*, *20*(1), 118–136. https://doi.org/10.1080/1369118X.2016.1186713
38. 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*, 949–960. https://doi.org/10.1016/j.jbusres.2020.09.004
39. Sadeghian, A. H., & Otarkhani, A. (2023). Data-driven digital nudging: A systematic literature review and future agenda. *Behaviour & Information Technology*, *43*(14), 3834–3862. https://doi.org/10.1080/0144929X.2023.2286535
40. 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*, Article 105116. https://doi.org/10.1016/j.appet.2021.105116
41. Krpan, D., & Urbaník, M. (2021). From libertarian paternalism to liberalism: Behavioural science and policy in an age of new technology. *Behavioural Public Policy*, *8*(2), 300–326. https://doi.org/10.1017/bpp.2021.40
42. Ramirez, E. J., Elliot, M., & Milam, P.-E. (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*(3), 527–542. https://doi.org/10.1007/s10676-021-09594-y
43. Frischmann, B. (2021). Nudging humans. *Social Epistemology*, *36*(2), 129–152. https://doi.org/10.1080/02691728.2021.1979121
44. 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*, Article 102673. https://doi.org/10.1016/j.jhealeco.2022.102673
45. 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*(1), 74–85. https://doi.org/10.1080/15252019.2016.1161568
46. Pelham, B. W., Carvallo, M., & Jones, J. T. (2005). Implicit egotism. *Current Directions in Psychological Science*, *14*(2), 106–110. https://doi.org/10.1111/j.0963-7214.2005.00344.x
47. 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), 718–730. https://doi.org/10.1002/pam.21717
48. Esterl, M. (2014, September 25). 'Share a Coke' credited with a pop in sales. *The Wall Street Journal*. https://www.wsj.com/articles/share-a-coke-credited-with-a-pop-in-sales-1411661519
49. Allcott, H. (2011). Social norms and energy conservation. *Journal of Public Economics*, *95*(9–10), 1082–1095. https://doi.org/10.1016/j.jpubeco.2011.03.003
50. 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*, 72–87. https://doi.org/10.1016/j.obhdp.2021.06.005
51. Peer, E., Mazar, N., Feldman, Y., & Ariely, D. (2024). How pledges reduce dishonesty: The role of involvement and identification. *Journal of Experimental Social Psychology*, *113*, Article 104614. https://doi.org/10.1016/j.jesp.2024.104614
52. Ladhania, R., Spiess, J., Ungar, L., & Wu, W. (2023). *Personalized assignment to one of many treatment arms via regularized and clustered joint assignment forests.* arXiv. https://arxiv.org/abs/2311.00577
53. Veltri, G. A. (2023). Harnessing heterogeneity in behavioural research using computational social science. *Behavioural Public Policy*, 1–18. https://doi.org/10.1017/bpp.2023.35
54. Lacroix, K., & Gifford, R. (2020). Targeting interventions to distinct meat-eating groups reduces meat consumption. *Food Quality and Preference*, *86*, Article 103997. https://doi.org/10.1016/j.foodqual.2020.103997
55. 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*, Article e006237. https://doi.org/10.1136/bmjgh-2021-006237
56. Attwell, K., & Freeman, M. (2015). I immunise: An evaluation of a values-based campaign to change attitudes and beliefs. *Vaccine*, *33*(46), 6235–6240. https://doi.org/10.1016/j.vaccine.2015.09.092
57. Saponaro, M., Vemuri, A., Dominick, G., & Decker, K. (2021). Contextualization and individualization for just-in-time adaptive interventions to reduce sedentary behavior. In *CHIL '21: Proceedings of the 2021 Conference on Health, Inference, and Learning* (pp. 245–256). Association for Computing Machinery. https://doi.org/10.1145/3450439.3451874
58. Frischmann, B. M., & Selinger, E. (2018). *Re-engineering humanity*. Cambridge University Press.
59. Braithwaite, J. (2011). The essence of responsive regulation. *University of British Columbia Law Review*, *44*(3), 475–520.
60. Lauffenburger, J. C., Yom-Tov, E., Keller, P. A., McDonnell, M. E., Crum, K. L., Bhatkhande, G., Sears, E. S., Hanken, K., Bessette, L. G., Fontanet, C. P., Haff, N., Vine, S., & Choudhry, N. K. (2024). The impact of using reinforcement learning to personalize communication on medication adherence: Findings from the REINFORCE trial. *npj Digital Medicine*, *7*, Article 39. https://doi.org/10.1038/s41746-024-01028-5
61. Sayed, W. S., Noeman, A. M., Abdellatif, A., Abdelrazek, M., Badawy, M. G., Hamed, A., & El-Tantawy, S. (2022). AI-based adaptive personalized content presentation and exercises navigation for an effective and engaging E-learning platform. *Multimedia Tools and Applications*, *82*(3), 3303–3333. https://doi.org/10.1007/s11042-022-13076-8
62. Duckworth, A. L., & Milkman, K. L. (2022). A guide to megastudies. *PNAS Nexus*, *1*(5), Article pgac214. https://doi.org/10.1093/pnasnexus/pgac214
63. Milkman, K. L., Gromet, D., Ho, H., Kay, J. S., Lee, T. W., Pandiloski, P., Park, Y., Rai, A., Bazerman, M., Beshears, J., Bonacorsi, L., Camerer, C., Chang, E., Chapman, G., Cialdini, R., Dai, H., Eskreis-Winkler, L., Fishbach, A., Gross, J. J., . . . Duckworth, A. L. (2021).

Megastudies improve the impact of applied behavioural science. *Nature*, *600*(7889), 478–483. https://doi.org/10.1038/s41586-021-04128-4

64. 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 Sciences*, *120*(17), Article e2216115120. https://doi.org/10.1073/pnas.2216115120
65. Colback, L. (2024, February 1). Personalisation and the battle for customers' attention. *The Financial Times*. https://www.ft.com/content/eae952f8-5290-449b-9447-b17b395e3643
66. Competition & Markets Authority. (2024). *AI foundation models: Initial report*. https://assets.publishing.service.gov.uk/media/65081d3aa41cc300145612c0/Full_report_.pdf
67. 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*, Article 4692. https://doi.org/10.1038/s41598-024-53755-0
68. Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness*. Yale University Press.
69. Allcott, H., & Kessler, J. B. (2019). The welfare effects of nudges: A case study of energy use social comparisons. *American Economic Journal: Applied Economics*, *11*(1), 236–276. https://doi.org/10.1257/app.20170328
70. de Ridder, D., Kroese, F., & van Gestel, L. (2022). Nudgeability: Mapping conditions of susceptibility to nudge influence. *Perspectives on Psychological Science*, *17*(2), 346–359. https://doi.org/10.1177/1745691621995183