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# A behavioral approach to personalizing public health

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**Abstract:** Behavioral policies are increasingly popular in a number of health care contexts. However, evidence of their effectiveness, specifically in low-income and highly disadvantaged populations, is limited. Some positive effects have been found for adaptive interventions, which merge more personalized approaches with advances in data collection and modern analytical methods. These approaches have only recently become feasible, as their implementation requires a confluence of large-scale datasets, contemporary machine learning, and validated behavioral insights. Such methods have considerable potential to improve outcomes without requiring substantial increases in effort on the part of individuals. Using examples from health insurance choice, clinical attendance rates, and prescription of medicines, we present an argument for how adaptive approaches, especially those considering disadvantaged populations explicitly, offer an opportunity to generate equity in public health.

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## Introduction

The trend of applying behavioral insights to clinical settings and population health (King *et al.*, 2013) is not likely to fade anytime soon (Patel *et al.*, 2018). Nor should it, given the impacts shown to date and possibilities for future initiatives (King *et al.*, 2013; Patel *et al.*, 2018). While nudges that seek to implement small changes in the choice architecture are certainly the most popular tool (Hertwig & Grüne-Yanoff, 2017), other behavioral tools are increasingly relevant in public health. Boosts, another popular tool, are interventions that aid individuals in understanding the consequences of their choices, particularly when there is no evident or universal optimal decision or preference (Hertwig & Grüne-Yanoff, 2017). Boosts such as providing simple calculators for investment decisions (Kuhnen, 2015) or for choosing optimal insurance plans encourage deliberation to enhance competency and resilience to deal with future decisions (Franklin *et al.*, 2019). When effective, such interventions as nudges and boosts generally come at low implementation costs (Chaiyachati *et al.*, 2018), making them appealing to attempt in low-resource settings.

Evidence on nudges and boosts is compelling in a general population (Kuhnen 2015; Franklin *et al.*, 2019), yet their effectiveness for improving health outcomes in low-income populations is limited and the evidence is inconclusive (Chaiyachati *et al.*, 2018). This lack of conclusive results is caused both by the absence of evidence for behavioral interventions in low-income populations, as well as the occasional evidence of absence of the effectiveness of specific interventions that have been shown to work in other less vulnerable populations (Mullainathan & Shafir, 2013; Allmark & Tod, 2014). One way to correct this may be through the personalization of behavioral approaches that increase efficacy and efficiency. This increases uptake by implementing interventions that reach those individuals who stand to benefit the most. For example, Franklin *et al.* (2019) recently compared nudges and boosts in a series of controlled experiments, and concluded that interventions have different effects based on individual behavioral patterns and circumstances. As we describe later, similar conclusions have been reached in real-world settings, indicating opportunities to maximize impact, avoid past mistakes or target the most critical groups.

A personalized strategy is distinct in that classical population approaches apply evenly and can result in inequitable outcomes. Personalized strategies consider inequities at the outset, aiming for equitable results. Consider a standard recommendation for employees to save 20% of their salary every month – although it as an even recommendation, it produces uneven outcomes. These potentially produce negative impacts for individuals who could be in a better financial position by paying down debt faster (i.e., saving less in the near term) or for individuals who may have fewer remaining working years and should therefore increase savings while still able to generate income.

Alternatively, a personalized approach begins with calibration based on individual circumstances (e.g., age, income, living in an urban or rural area), seeking an equitable result in spite of initial inequities. Such approaches align well with widespread interest in 'personalized medicine' in health care. Personalized medicine involves treatment plans based on individual patient characteristics and stage of illness, instead of offering the same treatment to all (Alyass *et al.*, 2015). To illustrate the benefits of moving from standard to personalized approaches, we briefly summarize three cases of current issues in health care: no-show rates, suboptimal insurance choices, and the overprescription of medication. While these examples are set in the context of US health care, the underlying behavioral aspects apply widely. We then explain the practice of personalization and discuss features leading to implementation and why the time is right to expand this approach.

## *Reducing no-shows*

Missed appointments ('no-shows') in primary care represent a universal behavioral issue faced by health systems (Aggrawal *et al.*, 2016). Dantas *et al.* (2018) estimated that as many as 23.5% of all medical appointments in North America are missed. Among low-income populations in Federally Qualified Health Centers in the USA, the no-show rate becomes as high as 45% (Cruz *et al.*, 2018). Such rates strain community health centers with limited resources (Kangovi *et al.*, 2013).

Text message reminders represent a common intervention to encourage attendance, with one systematic review finding them responsible for a 29% reduction in no-shows (Hasvold & Wootton, 2011). This benefit does not seem to extend to disadvantaged groups (Bellucci *et al.*, 2017; Ruggeri *et al.*, 2020a), suggesting that forgetting, though a common cause of no-shows generally (Kaplan-Lewis & Perac-Loma, 2013), is not the main barrier that low-income individuals face. Another barrier to attendance for low-income populations is transportation, with 24–51% reporting this as a reason for no-shows (Chaiyachati *et al.*, 2018). This is a barrier across rural and urban settings, even when within close proximity to public transport (Chaiyachati *et al.*, 2018). Chaiyachati *et al.* (2018) attempted to address this by offering low-income patients in Philadelphia free transportation to and from appointments through a ride-sharing platform. While all of the pieces seemed to be in place, minimal utilization resulted in little to no actual effect of the intervention.

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### *Insurance choice*

Whereas attendance behaviors can vary over time, insurance choices are a periodic decision with medium-term implications for receiving care as well as long-term implications for health and well-being. However, insurance behaviors tend to propagate and exploit the effects of inertia (Handel, 2013): once enrolled in an insurance plan, individuals are often very unlikely to change it, even if that plan is not the optimal choice (Baicker *et al.*, 2012). Complexity of information, considerable uncertainty around health outcomes, severity of the risks involved, and the lag time between choice and outcome can all magnify this effect. This comes with private costs in terms of needlessly high premiums and collective costs as it leads to a less efficient insurance market.

Attempting to increase the uptake of optimal plans, Ericson *et al.* (2017) sent three different e-mails (control, generic, and personalized) to marketplace consumers in Colorado, excluding the most price-sensitive individuals enrolled in the lowest-cost plans. In spite of salient messaging about the savings that could be realized through better insurance choices, the intervention had only a minimal impact: participants were more likely to click on the link for the behaviorally designed emails, but there was no effect on actual change in plan selection.

### *Drug prescription*

Overprescription is a major threat to public health and the sustainability of health care systems (Sacarny *et al.*, 2016). As thorough investigations on prescription behavior are time-consuming and expensive to carry out (Sacarny *et al.*, 2016), low-cost alternatives, such as nudges and boosts, are increasingly being utilized. One intervention that has shown some promise in relation to antibiotics is the use of a descriptive social norm, which informs overprescribers of the (lower) base rate of prescription and how their own behavior deviates from it. However, when Sacarny *et al.* (2016) applied this to the top 0.2% of opioid prescribers, no significant impact was found. While targeting was used in terms of focusing on the population of high opioid prescribers, no immediate context was integrated into the letters.

## **Opportunities to adapt**

Not all behavioral interventions work (Sunstein, 2017), yet lessons from the unsuccessful trials as presented here are invaluable for improving the application of behavioral insights. The key take-away from these examples is the need to align behaviorally informed interventions with personal circumstances, needs, and the immediate environment (Chaiyachati *et al.*, 2018; Ruggeri

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*et al.*, 2020a). In other words, in order to optimize behavioral interventions, they may need to be personalized. This is an important development, given that policy has classically focused on either high-risk strategies (i.e., an emphasis on where issues exist or are likely) or population strategies (i.e., no specific target group).

Population-based interventions can be successful when the problem targeted affects everyone in the community where the policy is implemented, such as regulations that ensure drinking water quality (Rose, 2001), apply a sugar tax on soft drinks (Roberto *et al.*, 2019) or enforce noise thresholds near airports (Zafari *et al.*, 2018). These can have widespread benefits for health equity: whereas unhealthy individuals may benefit the most from cleaner drinking water, healthy individuals also benefit. However, even when generally successful, these interventions can backfire: not every home can insulate against noise, and some individuals can drive to another town to purchase soda at a lower cost. Similarly, a flat charge on plastic bags – or even an outright ban on single-use plastics – can drastically reduce the number of bags used while also creating uneven effects for those who genuinely need them for survival, or they can simply be offset by using another form of plastic (Taylor, 2019).

These hypothetical illustrations are intended to present extremes, though the most common outcome is the absence of any noteworthy impact, as indicated in the three case examples of no-shows, insurance choice, and drug prescription. Such null effects might be avoided by adopting and adapting more context-aware interventions. Consider features of insurance choices (Baicker *et al.*, 2012): each plan has a different form of coverage, deductibles, and co-payments that will eventually sum up as total household health care spending. There is considerable heterogeneity for each of those factors within a population. There is also temporal heterogeneity (i.e., individual circumstances can improve, worsen or remain the same, all at differing levels), as well as uncertainty regarding future health care needs. While choice algorithms offer major benefits for avoiding suboptimal choice (Sunstein, 2019), algorithms naive to individual circumstances lack the flexibility to incorporate all of the relevant variability (i.e., a measure such as body mass index, which applies population-level assumptions about the link between body mass and health, can be very misleading at the individual level).

Based on underwhelming findings for the intervention aimed at reducing unnecessary prescriptions, Sacarny *et al.* (2018) recommended a different approach. Rather than assume a single norm would have a common utility, they recommend targeting norms toward those who actually needed information, such as providers who had less training on opioids. Taking this approach, Sacarny *et al.* (2018) found an 11% decrease in prescriptions. Similarly, the authors of the Philadelphia trial for attendance noted that they could have more specifically focused on those who needed transportation, and then focused on effects at the margins (critical for many nudges), rather than at the means. By applying their approach to the full population, this limited the chance of showing an overall effect, given that the full population may not have missed their appointments due to transportation issues.

The state of Maine attempted to implement intelligent targeting techniques to assign dual-eligible Medicare–Medicaid individuals to optimal prescription drug insurance plans. This replaced assigning random defaults, which was done in a few states (Medicare Rights Center, 2006). In this trial, the default option assigned to each individual was designed to match their individual health care and medication needs. Through tailoring, this increased individual coverage of necessary medications to 90–100% across all plans in Maine (Medicare Rights Center, 2006). By contrast, in states that suggested random defaults, one in five dual-eligible individuals ended up with plans that did not cover one or more of their prescriptions and therefore discontinued medication (West *et al.*, 2007).

Effective personalization requires better understanding of the barriers and levers to changes in optimal behaviors. Drivers of behavior are multifaceted, involving individual factors such as dispositions, abilities, and preferences, as well as external factors that are more or less stable over time. For example, in the case of no-shows, the most frequently referenced factors involve miscommunication (Kaplan-Lewis & Perac-Lima, 2013), forgetting (Kaplan-Lewis & Perac-Lima, 2013), and logistic and financial barriers (such as transportation issues and childcare; Starbird *et al.*, 2019). These are also compounded by emotional barriers such as anxiety, depression, and fear (Cook *et al.*, 1999; DuMontier *et al.*, 2013). On top of this, a lack of perceived respect in primary care (DuMontier *et al.*, 2013) may play a part. The examples provided here, which largely rely on informational features, may be sensitive to individual differences in literacy and numeracy, as well as in state and trait variability in executive function. These create additional barriers for vulnerable people because of how the challenges they face increase their baseline cognitive load (Moffitt *et al.*, 2011; Marteau *et al.*, 2012). Any number of these factors may be present for a given case; knowing which to target is a key challenge, which is even more complex in a disadvantaged population (Bellucci, 2017).

## Combination is key

When it comes to complex behavioral problems, particularly among disadvantaged populations, the most effective interventions should combine population approaches that target general causes with personalization that targets individualized, context-dependent factors (Pence *et al.*, 2018). In many cases, this is in direct response to the rule that those doing best in a population are more similar and those at greatest risk are more varied (King *et al.*, 2013; Ruggeri *et al.*, 2020b). To be absolutely explicit, we do not make any argument that one approach should replace another. On the contrary: personalization in this context means to capitalize on the most effective aspects of each approach, but in a realistic way, with incremental improvements.

Consider interventions that influence choices about health insurance plans. First, there is substantial legislation in place, particularly regarding enrollment periods. Next, there are many forms of communication that encourage individuals and families to evaluate options and nudge them to assess whether their current or default plan is appropriate. These typically involve salient messages along with norms such as average costs or savings, combined with simplification and chunking features. Moving beyond such standardized approaches, there is the option to calculate direct costs and probabilities relative to income, residence, and employment. This is a form of boosting that is inherently personal and goes beyond a generic algorithm. At this stage, we have mandated some behavior with legislation, encouraged engagement in the process through nudging and enhanced context-specific deliberation with boosting, all without adding substantial effort on the part of the decision-maker. It would even be possible to incorporate a default at this stage, which might require opting out of an optimal plan to return to the current one.

But how 'smart' can policies be? Addressing this challenge requires three features: first, better data collection methods that can effectively gather information relating to the presence of barriers and levers for behavior; second, stronger analytic techniques that can effectively link each behavior profile with the intervention that is most likely to work for them; and third, and perhaps most challenging, an appropriate platform for implementation, as not every intervention has an available medium to reach its intended audience.

To illustrate, an adaptive, personalized intervention for no-shows fundamentally requires data beyond clinical attendance rates. Extensive information is necessary about the nature of each appointment (e.g., patient, provider, location, context, costs), barriers to attendance, and, ideally, information about previous no-shows (e.g., through surveys). This wealth of data provides a perfect use case for machine learning classification methods, as these methods have the potential to improve predictive accuracy given sufficiently large datasets. Rather than only looking at mean or modal behaviors (such as the most common patient groups to no-show), more intensive models consider combinations of factors that can be used to allocate individuals to interventions, as depicted in Figure 1. But this is also not an end point; as demonstrated, even ideally placed interventions can have limited or no effects.

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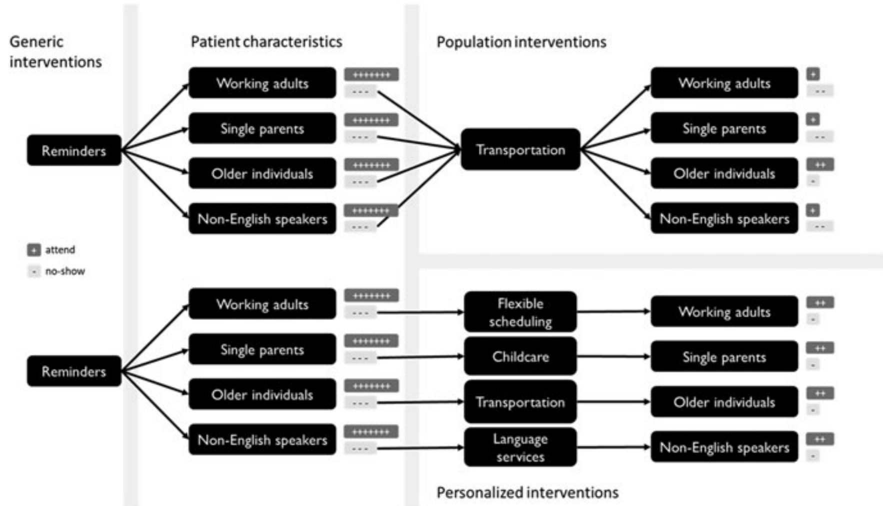


**Figure 1.** Personalizing nudges as a more efficient lever for behavior change. Top pathway: generic intervention (reminders) effective for the majority of individuals within and between groups. Further intervention (transportation) offered to those who did not attend, but minimal benefit is visible apart from one group (older individuals), for whom the method addresses a need or barrier. Bottom pathway: those who did not attend after the generic intervention receive personalized nudges, increasing efficacy within each group as well as in aggregate.
*Note:* The figure has been created by the authors of this article. It has been posted on a website introducing this research topic: https://datascience.columbia.edu/nudging-new-york-using-data-science-increase-healthcare-access-underserved-communities.

Machine learning methods can be applied to make interventions more adaptive: where seemingly optimal interventions fail, individuals can be reallocated to other interventions to test for greater effectiveness, improving model accuracy and utility over time. To consolidate, we recommend testing the value of personalized approaches using four discrete steps:

(1) Identify primary barriers for the desired behavior.
(2) Develop interventions targeting specific barriers.
(3) Stratify interventions and combinations of interventions by applying directly to those groups with relevant barriers.
(4) Where relevant, incorporate personalization features, such as calculators or algorithms that utilize user data.

The biggest challenge involves how and where to implement. For insurance choices, web portals where individuals make choices are natural platforms.

As is increasingly common, these can include multiple behaviorally informed features on the path from portal entry to final selection. Back-end, adaptive algorithms that incorporate various data entered by users are relatively simple to implement. Similar techniques can be applied in many financial contexts, given the prevalence of online banking.

Less obvious is how to implement adaptive attendance interventions at individual clinic levels, where it is impractical to allocate these functions to administrative staff on a perpetual basis. Such complex targeting schemes may primarily be relevant to larger institutions, where small increases in the preferred behavior offer a clear return on investment, as well as the resources that already include patient communication platforms. Smaller clinics or provider networks that lack capacity may find that their datasets are too small and that the cost of entry is too high, with too little return. For those providers, it may be more efficient to focus on generic interventions or to design special interventions for those patients at greatest risk of negative health outcomes.

Personalization in the extreme sense of customized interventions for each individual is not always feasible. Our argument is for a relative increase in personalization that increases the likelihood of benefit for disadvantaged populations, leading to greater impact of interventions that are continuously improved. This is possible in an era of low-cost computing power and massive self-generating datasets. Combined, these two factors have led to rapid decreases in the cost of effective intervention targeting and evaluation, to the point where it might now be cost-efficient for policymakers in most developed countries. Adding to this momentum is the fact that the political will currently exists to pilot these types of approaches.

Platforms that incorporate machine learning can enable stronger personalization while concurrently providing methods to learn more effectively from previous trials, generating a positive-feedback loop (e.g., the success of targeted health insurance defaults in Maine could be further amplified if outcomes from previous years would feed into future recommendations). This would allow for a direct assessment of the heavily speculated value of machine learning in public health.

Intelligent targeting should also offer equity in social challenges, as the examples used allude to how the most vulnerable individuals often do not benefit from generic or population-focused interventions. By ensuring intervention relevance for the majority as well as relevant subpopulations, greater effects can be seen across diverse communities. Ultimately, this facilitates behavioral interventions to make impacts in the margins as well as at the means. Doing so results in entire population shifts toward the positive end, which is the ultimate goal of policy.

In the context of health care, personalization would allow disadvantaged individuals to access a set of interventions that address each of their core barriers to entry, without necessitating resources being offered to everyone or reducing those in place more generally. In simpler terms, personalized approaches take nothing away from anyone, and only seek to offer policy equity to diverse populations.

## Limitations

Personalization is not always possible or appropriate. The extent to which the effectiveness of behavioral interventions generalizes differs widely between interventions. For example, electronically delivered nudges and boosts are much easier to personalize than interventions that require actions directly in a physical environment (e.g., recycling, wearing a facemask). In Table 1, we present a simple classification tool for when personalization may be more or less valuable or feasible for complementing behavioral interventions.

Recent taxonomies of behavioral interventions may help to determine when personalization is feasible and appropriate (Johnson *et al*., 2012; Münscher *et al*., 2016; Hollands *et al*., 2017). As the field has not yet converged on a common standard, these framework examples provide a promising starting point, and it may become worthwhile to explicitly include a dimension relating to the necessity and feasibility of personalization. In any case, personalization

**Table 1.** Differentiating interventions based on value and feasibility of personalization.

| | Useful | Not useful |
|---|---|---|
| Possible | Defaulting hospital employees into flu shot appointments that match the start of their first shift once vaccination is available | Severe weather guidelines based on personal circumstances. While weather warnings through alert systems could be personalized, threats from the most severe weather (i.e., flash floods, extreme temperatures) are uniform |
| Not possible | Adjusting choice architecture in grocery stores on an individual basis to encourage healthy eating. This can be done for online shopping, but adapting for budget, date, family size, recent purchases, etc., for each customer in a store cannot | Social distancing guidelines – the rules, benefits, risks, and impacts are uniform across the population, with only a few general subgroups (i.e., those at risk, caregivers), and therefore need to be consistently presented. Some adaptations may be possible locally, but not to a personal level |

should not be a class on its own, but rather a complementary tool, in the sense that the interventions are the actions and personalization is the adverb.

## Conclusion

There is sufficient evidence to support behaviorally informed interventions such as nudges and boosts as low-cost options for addressing a number of challenges. It is now critical to improve methods of implementation in the form of adaptive, personalized models, which may very well be the next frontier in behavioral research. This offers potential to go from isolated marginal effects to meaningful cumulative impacts by ensuring value directly to the individuals and communities that benefit most. By expanding the benefits to a wider number of individuals, this results in more substantial impacts on population health and well-being.

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