November 25, 2019

Dear Representatives Arrington, Davis, Sewell, and Wenstrup,

Please find below and attached our response to the Rural and Underserved Communities Health Task Force Request for Information. We are behavioral policy researchers based in the Department of Health Policy and Management of the Mailman School of Public Health at Columbia University, and have been advised by Ms Orriel Richardson, Esq, MPH, to submit this brief cover letter responding to the RFI along with a recently drafted manuscript relevant to the topic.

Our team works on a number of research questions pertaining to population-level behaviors in diverse populations, in the multidisciplinary field commonly referred to as behavioral economics. Specific topics we cover involve how short-term decision-making, particularly among disadvantaged groups, has long-term consequences in the context of financial and health outcomes. The largest of these studies focuses specifically on low attendance rates at Federally Qualified Health Centers, making use of large clinical and environmental datasets in order to design policies to increase attendance.

As this study is well underway and touches on a number of themes in the RFI, Ms Richardson advised us to provide a cover letter with responses to specifically relevant themes, and then attach the manuscript. We have done so in brief, covering only those that relate to our work. We appreciate the opportunity to provide input and hope this material, albeit unorthodox, is useful to the work of the Task Force.

1. The main health care-related factors that influence patient outcomes in the underserved urban communities where we work relate to the ability to attend appointments at Federally Qualified Health Centers. These barriers include a) transportation options, b) locations of clinics respective to work, residence, and transportation hubs, and c) access to *regular* primary care providers.

2. So far, the only successful models we have seen involve remote and flexible care options. Telemedicine, for example, appears to be promising. However, it raises concerns about sustainability and downstream effects. To avoid these downsides we instead suggest increasing access to empaneled PCPs (as opposed to random allocation) as well as more adaptive scheduling approaches.

4a. We have learned that a large number of patients go to emergency departments (as opposed to urgent care) immediately following periods when they missed a preventive care appointment. This is often for non-emergency care, such as blood pressure checks or chronic conditions. This indicates an under-utilization of FQHCs directly at their *raison d'être*.

5. We are exploring regional networks leveraging transport systems and telehealth/telemedicine. So far, it seems results for transportation have been inconclusive. We are testing a new approach of more targeted implementation and will hope to report back soon on findings (these results will only be from a small-scale pilot though). We anticipate making recommendations that aim to better target both transport and remote care options, possibly in combination.

8. The attached manuscript highlights our work aiming to increase access to care where gaps exist even when care is available for underserved communities.

9. In our work, the most critical data that would provide meaningful insight are non-clinical measures such as public transportation, workplace and employer information, and community support services (including local leadership).

10. The most critical changes we are exploring involve a) flexibility in care provision (e.g., appointment times, locations), b) more direct engagement with urgent care clinics to coordinate delivery of new programs, and c) encouraging primary care providers to connect with patients on a regular basis (i.e., preventive and other scheduled visits), as opposed to randomly allocating patients to providers based on availability.

We hope this material is useful for the Task Force and would be delighted to provide further details or clarification. Furthermore, as our work progresses, we would be happy to keep you informed of any relevant insights.

Best wishes,

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A behavioral approach to personalize 'public' health in disadvantaged populations

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Abstract

Behavioral policies are increasingly popular in a number of healthcare 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 require 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.

Key words: health policy, behavioral economics, personalization, adaptive methods, disadvantaged populations, machine learning

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, Volpp & Asch 2018). Nor should it, given the impacts shown to date and possibilities for future initiatives (King *et al.* 2013; Patel, Volpp & Asch 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 outcome (Hertwig & Grüne-Yanoff 2017). Boosts such as providing simple calculators for investment decisions (Kuhnen 2015) or choosing optimal insurance plans, encourage deliberation to enhance competency and resilience to deal with future decisions (Franklin, Folke & Ruggeri 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, Folke & Ruggeri 2019) yet their effectiveness for improving health outcomes in low-income populations is limited and inconclusive (Chaiyachati *et al.* 2018). 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, Folke & Ruggeri (2019) recently compared nudges and boosts in a series 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, which indicates 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 per cent of their salary every month (even recommendation with uneven outcomes). These potentially produce negative impacts (Sussman & O'Brien, 2016) for individuals that could be in a better financial position by paying down debt faster (i.e., saving less in the near-term), or for individuals that 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 extremely well with widespread interest in 'personalized medicine' in healthcare. Personalized medicine involves treatment plans based on individual patient characteristics and stage of illness, instead of offering the same treatment to all (Alyass, Turcotte & Mevre 2015). To illustrate the benefits of moving from standard to personalized approaches, we briefly summarize three cases of current issues in healthcare: no-show rates, sub-optimal insurance choices, and over-prescribing medication. While these examples are set in the context of US healthcare, the underlying behavioral aspects apply widely. We then explain the practice of personalization, 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 are a universal behavioral issue faced by health systems (Aggrawal, Davies & Sullivan 2016). Dantas *et al.* (2018) estimated that as many as 23.5 per cent of all medical appointments in North America are missed. Among low-income populations in Federally Qualified Health Centers in the United States, the non-attendance rate becomes as high as 45 per cent (Cruz *et al.* 2018). Such rates put strain on community health centers with limited resources (Kangovi *et al.* 2013).

Text message reminders are a common intervention to encourage attendance, with one systematic review finding them responsible for a 29 per cent reduction in no-shows (Hasvold & Wootton 2011). This benefit does not seem to extend to disadvantaged groups (Ruggeri et al. in submission; Bellucci *et al.* 2017), suggesting that forgetting, though a common cause of no-shows generally (Kaplan-Lewis & Perac-Loma 2013), is not the main barrier low-income individuals face. Another barrier to attendance for low-income populations is transportation, as 24 to 51 per cent reported this as a reason for no-shows (Chaiyachati *et al.* 2018). This is as 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 the pieces seemed to be in place, minimal utilization resulted in little to no actual effect for the intervention.

Insurance choice

Whereas attendance behaviors can vary over time, insurance choices are a periodic decision with medium-term implications for receiving care, and long-term implications for health and well-being. However, insurance behaviors tend to propagate and exploit the effects of inertia

(Handel 2013): once in a plan, individuals are often very unlikely to change, even if that plan is not the optimal choice (Baicker, Congdon & Mullainathan 2012). Complexity of information, considerable uncertainty around health outcomes, severity of risks involved, and lag time between choice and effect 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 uptake of optimal plans, Ericson *et al.* (2017) sent three different emails (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 savings through better 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

Over-prescription is a major threat to public health and the sustainability of healthcare 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 utilized. One intervention that has shown some promise in relation to antibiotics is to use a descriptive social norm, which informs over-prescribers 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 per cent of opioid prescribers, no significant impact was found. While there was targeting 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 insights from the unsuccessful trials as presented here are invaluable for improving the application of behavioral insights. The lesson from these examples is the need to align behaviorally-informed interventions with personal circumstances, needs, and immediate environment (Chaiyachati *et al.* 2018; Ruggeri *et al.* in submission). In other words, 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., 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). This 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 simply be offset by going to 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 adapting more context-aware interventions. Consider features of insurance choices (Baicker, Congdon & Mullainathan 2012): each plan has a different form of coverage, deductibles, and co-payments that will eventually sum up as total household healthcare 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 healthcare needs. While choice algorithms offer major benefits to avoid sub-optimal choice (Sunstein 2019), algorithms naïve to individual circumstances lack the flexibility to incorporate all relevant variability. I.e., a measure as BMI, which applies population-level assumptions about the link between body mass and health, can be very misleading on 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 that had less training on opioids. Taking this approach, Sacarny *et al.* (2018) found an eleven percent decrease in prescriptions. Similarly, the authors of the Philadelphia trial for attendance noted that they could have more specifically focused on who needed transportation, and then focused on effects at the margins (critical for many nudges), rather than at the means. By applying to the full population, this limited the chance of showing an overall effect, given the full population may not have missed their appointment due to transportation issues.

The state of Maine attempted 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 healthcare and medication needs. By tailoring, this increased individual coverage of necessary medications to 90 to 100 per cent across all plans in Maine (Medicare Rights Center 2006). By contrast, in states that suggested random defaults, 1 in 5 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 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. Eg., 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 child care) (Starbird *et al.* 2019). These are also compounded by emotional barriers such as anxiety, depression, and fear (DuMontier *et al.* 2013; Cook et al. 1999). On top of this, a lack of respect perceived in primary care (DuMontier *et al*. 2013) may play a part. 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 amongst 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.* forthcoming). To be absolutely explicit, though, 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 if 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. Last, 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 data sets. 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 which 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.

Figure 1: Personalizing nudges as a more efficient lever for behavior change
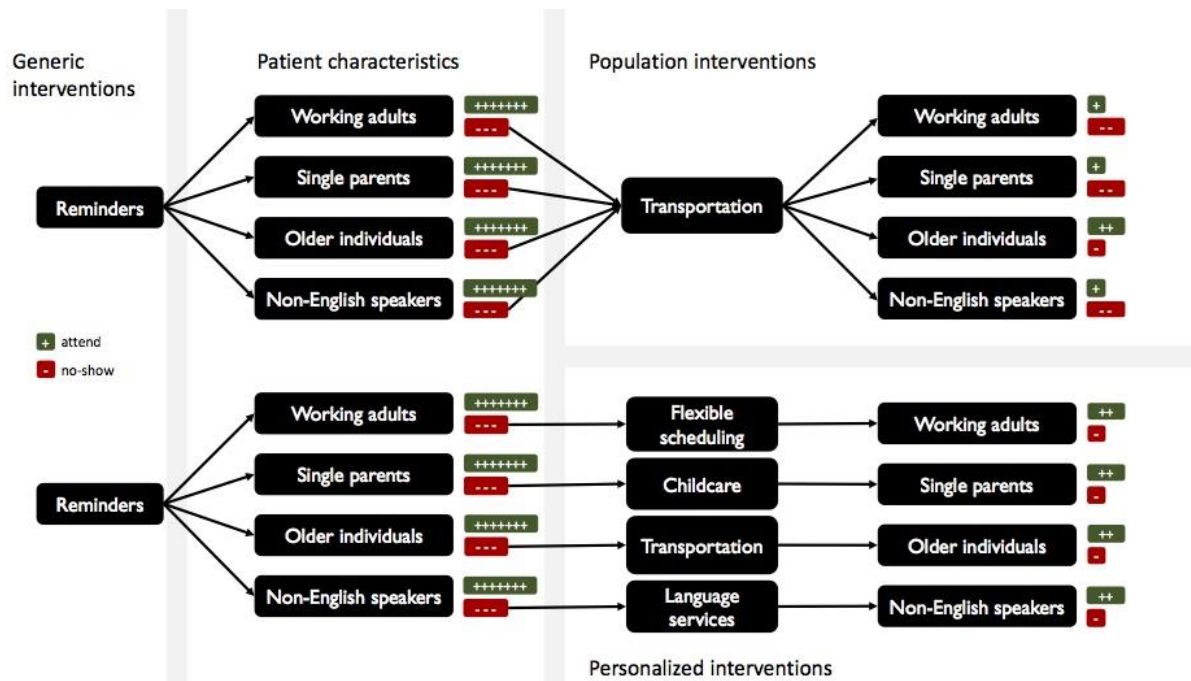
Top pathway: Generic intervention (reminders) effective for the majority of individuals within and between groups. Further intervention (transportation) offered to those who did not attend but minimal benefit is visible apart from one group (older individuals) where method addresses a need or barrier. Bottom pathway: Those who did not attend after the generic intervention receive personalized nudges, increasing efficacy within each group as well as in aggregate.

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 (elaborated in Figure 1):

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 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 policy makers in most developed countries. Adding to this momentum is the fact that there currently exist political will 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 on the heavily speculated value of machine learning in public health.

Intelligent targeting might 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 the means, and this is an ultimate goal of policy.

In the context of healthcare, personalization would allow disadvantaged individuals to access a set of interventions that address each of their core barriers to entry, without necessitating resources to offer 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.

Conclusion

There is sufficient evidence to support behaviorally-informed interventions such as nudges and boosts as low-cost options to address 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 marginal or moderate cumulative effects because it offers benefits to those in the community who may need it 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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