Masters Thesis Proposal

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Introduction

Universal Health Care is important because it addresses two issues in medicine. Access to universal care addresses the issue of equity and helps bridge the gap between marginalized and privileged groups with regards to healthcare outcomes. Additionally, universal health care programs in general focus on cost-effectiveness of care, leading to more efficient use of resources. Universal health care would likely benefit America if implemented. However, there is a significant lack of support for Universal Health Care. Thus, improving likelihood of implementation by improving support for UHC is valuable.

Opposition of UHC in the U.S. hinges on several issues. The first is that it is impossible to quantify improved support for UHC without consensus as to what UHC is. To give an example, it would be reasonable to assume medical students understand health care and its distribution. Surprisingly, this is not the case! These students struggle to answer questions regarding UHC due to divergent beliefs as to exactly what 'universal coverage' means (Huebner et al. 2006). Secondly, without a framework for what care is to be distributed through UHC, rationing of limited health resources is haphazard and arbitrary. Indeed, the main mechanism through which racial prejudice predicts decreased support for UHC in the U.S. is 'unfair' disbursement of resources to undeserving minorities (Shen and Labouff 2016).

Looking at successful UHC programs in other westernized first world countries (UK, Canada, etc.) we can address these issues with an 'explicit health benefit plan' (HBP). An explicit health benefit plan is best defined as "a set of services that can be feasibly financed and provided under the actual circumstances in which a given country finds itself" (Glassman et al. 2016). While reaching consensus on the exact terms of the HBP is not a small process, definitionally, an explicit HBP ensures that there is little room for confusion regarding what is covered. Additionally, guaranteed parameters are clearly set for what care the government can subsidize. In doing so, concerns regarding fairness are strongly mitigated. In addition to solving these two problems, studies have shown that an explicit HBP can also improve efficiency in resource allocation, create explicit entitlements for patients which help prevent marginalized individuals from being excluded from care, and reduces arbitrary restrictions on access and services (Glassman et al. 2016). Despite this evidence, there has been no research examining if support for UHC is increased by implementation of an explicit HBP.

Additionally, it is important to explore what is the best way of exposing participants to an HBP. Previous research indicates that a simulated experience exercise can be more impactful than simply being told facts (Wegier and Shaffer 2018). Additionally, we are interested in building upon our recently concluded pilot study on support for UHC. Replacing our previous 'dummy exercise' control condition with a control condition reflecting 'standard' messaging in UHC adds additional external validity. Furthermore, our new 'standard informational intervention' hews more closely to the methodology for a control presented by Wegier et al. (2018).

Review of Literature

Inadequacies with our current system

Health care in the United States, as it is now, is very broken. The purpose of health care is to improve the well-being of those treated. However, until the passing of the 2010 Affordable Care Act, medical expenses were the most common cause of bankruptcy in the United States (Galvani et al. 2017). Indeed, there are several conceptual problems with a 'competitive marketplace' of multiple insurers. Galvani et al. (2017) notes, it is hard for a private insurance company to justify preventative care, as "future benefits could accrue to another insurance provider. The result is a systematic undervaluation of preventative measures". In fact, looking at our closest analogue for a broad public health option, Medicare and Medicaid, we find that billing rates and expenses for private insurance are up to six times more expensive! Simply put, medical care is unaffordable in the United States for many individuals.

Perhaps another way of looking at the issue is to consider health outcomes, instead of cost for health. However, even looking at the United States from this perspective, Galvani et al. (2017) finds that our life expectancy has been reversing since 2014, even as money spent on health has increased by 130%! Delving deeper, we see that even the care we deign to deliver is problematic. Manchikanti, Falco, and Boswell (2010) find that "almost 50% of our care is not evidence based" and "as much as 30% of our spending reflects care of uncertain or questionable value". It is thus trivial to conclude that our current system is broken. Fortunately for the United States, Universal Health Care cleanly answers these issues and has been put into practice for decades in many other first world countries.

Benefits of Universal Health Care

Before delving into the proven benefits of UHC in other contexts, it is important to define exactly what we mean by saying "Universal Health Care". A resolution adopted by the UN General Assembly states that UHC is "access to key promotive, preventive, curative, and rehabilitative health interventions for all at an affordable cost" (Assembly 1991).

One significant benefit of UHC is that it ensures continuous enrollment in a health care plan. Galvani et al. (2017) finds that uninsured individuals have a 40% elevated risk of mortality. Additionally, for individuals who have chronic conditions, significant barriers to re-engagement exist under 'traditional' insurance plans. Improvement in coverage is so great, that a study done by Panpiemras et al. (2011) found that within one year of the implementation of UHC in Thailand, the percentage of the population insured surged from 40% to 97%. It is likely that implementation would indeed lead to a significant reduction of un/underinsured Americans.

Merely improving quality of health would be extremely exciting, but UHC also is effective at reducing waste and cost in the health system. Compared to a similar country, Canada, we find that 25% of our total medical cost is administrative, more than twice what the percentage is under Canadian UHC (Galvani et al. 2017)! By transferring to a single payer option, Manchikanti et al. (2009) note that UHC results in savings "large enough to pay for most of the additional utilization by those previously uninsured". To look at another example, we can consider Jamaica. Their UHC program reduced sick days by 34%, leading to productivity gains that dwarfed the additional cost in healthcare, essentially producing pure value (Galvani et al. 2017). Another thing to note is that the collective bargaining power that comes from a UHC system cannot be downplayed. Manchikanti et al.(2009) finds that while we use 10% fewer drugs per capita than other OECD countries, our prices are somehow 50% higher for equivalent drugs! An extreme example can be found when looking at the recent price spikes for toxoplasmosis drugs, a 5500% increase, and EpiPens, a 791% increase, which has not occurred in Europe or Canada. This is due to both countries able to collectively bargain for drug prices due to UHC (Galvani et al. 2017). We can clearly see that UHC both improves health outcomes and is cheaper to implement than our current system. Yet, as UHC has not been implemented in the U.S., we must look at why there is opposition.

Opposition and Support to Universal Health Care

Looking at the subset of literature detailing support for Universal Health Care in the United States specifically, we find two main aspects that explain opposition to UHC. Huebner et al.(2006) examined how US medical students feelings towards UHC change from their first to their fourth year. Surprisingly, the researchers found significant confusion when designing the questionnaire. Medical student focus groups struggled to come to consensus on terms related to UHC such as "fee for service", "managed care", "single-payer", "multi-payer", and "universal health care". Furthermore, the authors note that 'complex policy terms' were not able to be defined in the questionnaire, which indicates a need to explain the concepts of UHC without necessarily using an informational intervention. Without a clear understanding of what exactly these terms mean, and what is being offered in a UHC program, it is impossible to accurately gauge support or opposition. Additionally, given that medical students would be assumed to have a greater understanding of these medical-adjacent terms, it stands to reason that the confusion would be even greater for members of the general populace.

Shen et al. (2016) chose to look at the issue of opposition to UHC from another aspect, whether racism describes why there is a lack of support for UHC. The authors hypothesized that Whites oppose government programs designed to eliminate racial inequity because it "represents 'unfair government assistance', such as welfare or 'free' busing". This is additionally relevant as the historically disadvantaged groups that tend to benefit from government aid have high uninsured rates compared to whites (11.7% for whites, 20.8% for blacks, 30.7% for Hispanics). Furthermore, while UHC does not directly aim at benefiting blacks, "those high in racial prejudice may assume so". Importantly, when looking to see if racism predicts opposition to UHC, Shen et al. (2016) found the surprising result that it did not predict opposition to UHC. In fact, it was the saliency of whether the individual purported to benefit from UHC was a 'free-rider', or someone who was unfairly benefitting from UHC. This was unrelated to race. This shows that concerns with equality, equity, and fairness are most important with regards to changing attitudes towards UHC. Determining how to easily address this, as well as confusion regarding the definition of UHC at the same time is a challenge.

Addressing These Issues with a Health Benefit Package

The concept of a Health Benefit Package, as studied by Glassman et al. (2016) neatly addresses the previously mentioned issues with opposition to UHC in America. Definitionally, what makes a HBP a HBP is three factors. First, HBPs are a portfolio of multiple services, as compared to single services or a category of care; this allows direct assessment of effectiveness across each category. Second, HBPs are costed using actuarially informed estimates of supply and demand. Third, HBPs constrain the services made available through the public health system, but in doing so, guarantee that at least certain services will be made available. Through these three mechanics, Glassman et al. (2016) finds that there are clear benefits in countries that adopt a HBP for their UHC. As the system creates explicit entitlements for patients, it reduces confusion as to what is being offered and ensures fairness and equity, by preventing discretionary variation in access to care that would otherwise be largely determined by clinical professionals. Since the categories are costed and explicitly budgeted for, an HBP facilitates adherence to budget limits, "which might otherwise only be attained through arbitrary restrictions on access and services", which clearly speaks to the issue of fairness and equity. Furthermore, setting transparent criteria on what services are to be offered with the resources available allows a proper debate to take place regarding the objectives of the health system, what should be prioritized, and how good performance should be determined. This improves perceptions of fairness and equity within the medical system.

While HBPs address issues that would lead to opposition to UHC in the US, HBPs have furthermore been shown to be a key factor for success of UHC in other countries as well. An economists' declaration published in the Lancet states a belief that UHC means "ensuring that everyone can obtain essential health services at high quality without suffering financial hardship" (Summers 2015). Yet the economists themselves realize that "resource constraints require individual countries to determine their own definition of 'essential' ". This speaks directly to the practical issue of universal health needing limits to be effective. In fact, looking at countries that have UHC without an HBP linked to cost, such as Ghana, Uganda, and Peru, we find significant fiscal imbalances and implicit rationing, reducing overall quality of healthcare outcomes (Glassman et al. 2016). Looking at a parallel situation of how cancer care is managed in the U.S., Chalkidou, Marquez, and Dhillon et al. (2014) find that a HBP like framework is essential, as evidence or guidelines towards care (an UHC

without an HBP) are unlikely to improve efficiency and quality of care without "the support of institutional, and legal frameworks" (UHC with an HBP). Given that we have shown that our issues with UHC in the U.S. can be addressed by an HBP, it then stands to reason that we must determine the best methodology for exposing our population to an HBP.

Communicating the Health Benefit Plan

When communicating the essence of an HBP, it is important to ensure that what is being presented is clear and easy to understand, as well as emphasizing the necessary nature of tradeoffs or compromises in medical care. Developed by Goold et al. (2005), the Choosing Healthplans All Together exercise exhibits these traits perfectly. The central tenet of the CHAT exercise is to use a 'gamification' of what actually occurs when deciding insurance spending; Participants chose components for their own health plan, by selecting categories of services at various levels of 'rationing' (e.g. generics instead of name-brand drugs, copayments, etc.). The purpose of the exercise was initially to help explain how trade-offs in medicine are necessary, given limited resources. Conveniently, the final chosen plan is clear and explicit in what care is offered and at what level, neatly answering the issue of consumer confusion at the specifics. Another factor is that CHAT is understandable, with a stunning 97% of participants finding the task easy to do (Danis, Biddle, and Dorr Goold 2002). Furthermore, the CHAT exercise has been adapted twice to the specific scenario of a government funded health plan. The first, by Danis et al. (2004), was letting Medicare enrollees come to a consensus on what services they prioritize, under the financial restraints of government funded Medicare. While a sizeable portion of participants felt that what was chosen was different than what they would have chosen for themselves (41%) surprisingly, 86% were still satisfied with the plan they got. The second adaptation, by Hurst, Schindler, and Goold (2018), was looking at what types of care that Swiss citizens' citizens would prioritize in their already extant HBP. The participants had no trouble using the exercise to improve their understanding of the Swiss HBP, were easily able to make trade-offs and set priorities, and found "the degree of consensus despite differing opinions surprising and valuable". Lastly, the CHAT exercise is particularly valuable in that it is a hands-on exercise as compared to a simple informational intervention. Work by Wegier et al. (2018) found that a simulated experience lead to more accurate understanding of information as compared to simply being given explicitly described statistics. Thus, it will likely be even more effective than a simple 'fact sheet' for an HBP that would otherwise be presented to the public.

Pilot Study

We initially ran a pilot with a more complex experimental condition, and a less generalizable control. Our first hypothesis was that exposure to an explicit health benefit package will improve support for UHC as compared to a control. Our second hypothesis was that the impact of exposure to an HBP on support for UHC would be moderated by whether the exposure was informational or experiential. The purpose of our pilot study was to test our experimental materials, to replicate past research on the usability of the CHAT paradigm, and find preliminary data supporting our hypothesis.

Pilot Method

Participants

Our participants were students enrolled in the Psychology 1000 course at a large midwestern university. The study fulfilled 1 credit requirement for students in the course, of which students were required to obtain 7 credit hours. In total, there were approximately 20,000 student hours available for the 2019 fall semester this data was collected in. Participants were not given any other incentive for participation in the study. Participants were randomized into different conditions within the online survey software used to administer the pre and post test measures. Our total number of participants was 189. This study was advertised on the university credit hours tracking software alongside other qualifying studies, but received no other advertisement.

Materials

Each participant began by being seated at a computer cubicle with running the online survey software "Qualtrics", which was used to deliver the pre and post test measures, as well as instructions on how to complete the measures as well as the condition exercise. Our only pre-test measure was a single measure of support for universal health care (UHC). This is a 4 item measure of support for UHC, adapted from Shen & Labouff (2013) that is taken as a simple average, with the third item reverse scored. The measures themselves are 7 item likert scales, ranging from 1 (strongly disagree) to 7 (strongly agree).

Next, each participant was given a packet of exercises adapted from the Choosing Healthplans All Together (CHAT) paradigm developed by Danis, Biddle & Goold (2002). This exercise consists of participants 'filling out' a game board by using 49 'points' to fill in 79 empty spaces. Several groups of medical care are represented by costing different amounts of markers, with some groups having up to two greater levels of intensity offered for correspondingly higher amounts of markers. The core of the exercise consists of the trading off of limited funds in order to determine priorities for the health care system and considering how the specifics of a given plan would affect individual health outcomes. For the pilot study, this version of the exercise has been adapted in three ways for our three experimental conditions. Our control condition replaces mentions of health care with pizza meal packages instead, as a similar length and intensity but ultimately 'filler' exercise. For both our control and our active condition, subjects were given pencil, paper, and calculators (for tracking 'what number they were at') to complete the exercise. Our 'passive' condition, instead of having the subject fill out a gameboard, has instead the subjects being given a completed gameboard filled out according to the consensus options in the initial deployment of the CHAT exercise by Danis et al. (2002). The subjects are then asked to examine this sheet in detail and consider how the health benefits guaranteed would affect their own lives.

Lastly, our participants received a post-test measure, that consisted of two main items. The first is a post-test measure of support for UHC, using the Shen et al. measurement tool. The second item was demographic information, including sex, age, and current year of schooling.

Design

The design of this experiment is best described by a multi-level model. Our multi level structure consisted of UHC measures (either pre or post intervention), nested within each subject. The experiment was thus a 2x3 between subjects design. While our time variable (pre or post intervention) is 'within' our subjects, any given subject will only be exposed to one of the experimental conditions, thus it is 'between' subjects. The '2' is our independent variables of time of measurement (pre or post intervention), the '3' is our three experimental conditions, namely, our control, our active intervention, and our passive intervention. Our dependent variable was support for UHC. I believe that there should be no extraneous variables that might influence our results.

Procedure

The study begins by our administrator requesting that all subjects turn off personal electronic devices, in order to minimize distraction and disruption. Next, the subjects are lead by the administrator into the room, and are briefly told that the study will consist of a computer survey, with a pencil and paper activity during the middle of the survey. Each subject was then brought to a single-occupant cubicle with a computer running our Qualtrics survey. At this point, participants were told to read the instructions carefully, and notify the administrator once the survey assigned them to an experimental condition. Our subjects at this point completed the first half of the survey, consisting of our pre-test measure. After this was completed, the Qualtrics software randomly assigned the survey participant to one of three experimental conditions, with instructions on how to complete the pencil and paper exercise displayed upon the screen. Once this occurred, the administrator brought the subject a packet of papers representing whichever experimental condition the subject was assigned to, and the subject completed the exercise after a brief verbal reminder of the task they were to be working on. After the experimental condition was completed, the subject returned to their computer cubicle and completed our post-test measures. Lastly, the subject read a one page paper debriefing them of the purpose and theory behind the research, and was then granted 1 credit in the Psych 1000 system. This entire process takes 20-25 minutes on average.

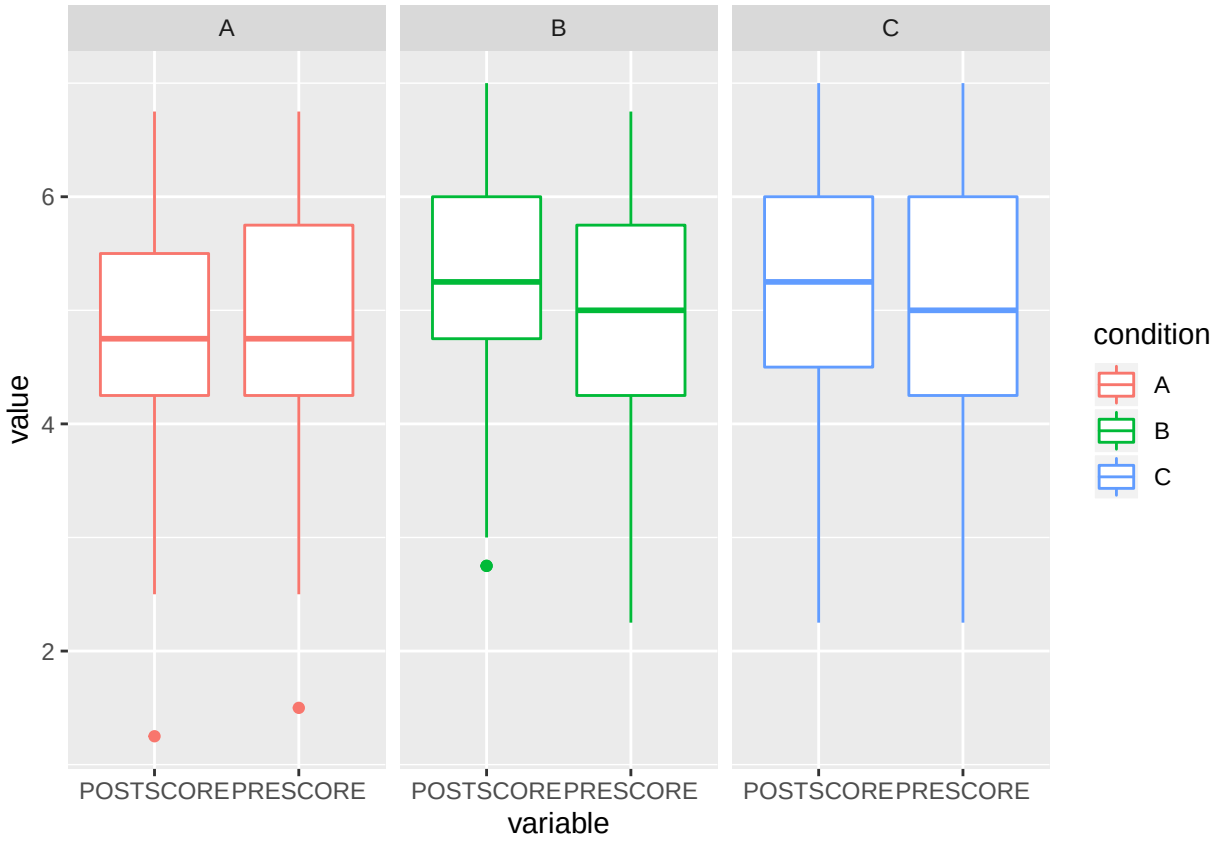
Results

Frequentist Methods

```
summary(m3)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: value ~ condition * variable + (1 | SUBJECT)
##    Data: UHC_final
##
## REML criterion at convergence: 815
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.2695 -0.3540  0.0051  0.3348  2.9905
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  SUBJECT  (Intercept) 1.1230   1.0597
##  Residual             0.1144   0.3382
## Number of obs: 368, groups:  SUBJECT, 184
##
## Fixed effects:
##                              Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)                   4.84836    0.14242 198.49949  34.042   <2e-16 ***
## conditionB                    0.34426    0.20142 198.49949   1.709   0.0890 .
## conditionC                    0.35325    0.20060 198.49949   1.761   0.0798 .
## variablePRESCORE             -0.06148    0.06124 181.00008  -1.004   0.3168
## conditionB:variablePRESCORE  -0.09836    0.08660 181.00008  -1.136   0.2575
## conditionC:variablePRESCORE  -0.14417    0.08625 181.00008  -1.672   0.0963 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) cndtnB cndtnC vPRESC cB:PRE
## conditionB  -0.707
## conditionC  -0.710  0.502
## vrbPRESCORE -0.215  0.152  0.153
## cB:PRESCORE  0.152 -0.215 -0.108 -0.707
## cC:PRESCORE  0.153 -0.108 -0.215 -0.710  0.502
```

```
plot3<-ggplot(UHC_final, aes(x=variable, y=value, shape=condition, color=condition)) +
  geom_boxplot()
plot3 + facet_wrap(~ condition)
```



Descriptive statistics are summarized in table 1 above. Our data was analyzed using a 2x3 ANOVA with one within subjects factor (time of measurement, pre or post intervention) and one between subjects factor (experimental intervention type). Our main effect for our 'passive' intervention was not significant ($p > .05$) with our estimate being that participants in the passive intervention having greater support for UHC than those in the control condition. Our main effect for our 'active' intervention was also not significant ($p > .05$) with our estimate being that participants in the active intervention having greater support for UHC than those in the control condition as well.

There was a significant interaction for the effect of time and our intervention. Participants only had an increase in support for UHC from pre to post measure when they were assigned to one of the two intervention conditions, specifically the interaction between being assigned to our passive intervention (condition C), and the post-intervention measure of support for UHC ($p = 0.095$).

Looking at our graph, we see in our box and whisker plot, that there does seem to be a trend towards increased scores on support for UHC from the pre to the post for our two experimental interventions. Just as importantly, we also see a strong lack of change from pre to post intervention support for UHC in our control condition.

Bayesian Methods

```
summary(m8)
```

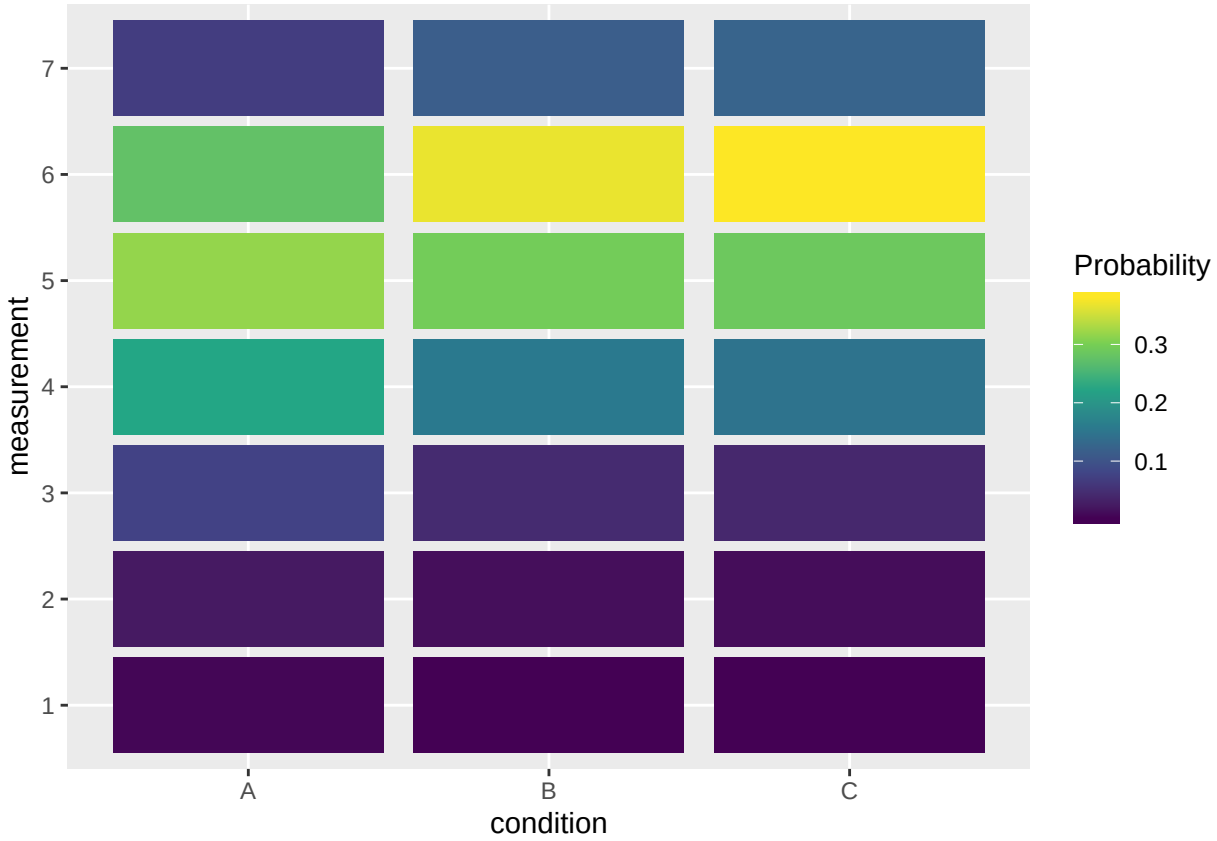
```
##  Family: cumulative
##   Links: mu = logit; disc = identity
## Formula: measurement ~ condition * time + (1 | SUBJECT)
##    Data: UHC_final_long (Number of observations: 1472)
## Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
```

```
##          total post-warmup samples = 4000
##
## Group-Level Effects:
## ~SUBJECT (Number of levels: 184)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     1.84      0.12     1.61     2.09 1.00     1152     1965
##
## Population-Level Effects:
##                    Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept[1]          -4.93      0.34    -5.63    -4.29 1.00     1237     2184
## Intercept[2]          -3.42      0.29    -4.01    -2.87 1.00     1025     1745
## Intercept[3]          -2.12      0.27    -2.68    -1.61 1.00      957     1773
## Intercept[4]          -0.70      0.27    -1.24    -0.18 1.00      900     1632
## Intercept[5]           0.64      0.27     0.10     1.15 1.00      901     1535
## Intercept[6]           2.60      0.28     2.07     3.13 1.00      944     1639
## conditionB             0.57      0.38    -0.18     1.28 1.00      854     1401
## conditionC             0.66      0.39    -0.09     1.42 1.00      918     1464
## timepre               -0.15      0.16    -0.47     0.17 1.00     3236     3217
## conditionB:timepre    -0.13      0.23    -0.58     0.32 1.00     3872     3481
## conditionC:timepre    -0.22      0.24    -0.69     0.25 1.00     3702     3276
##
## Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```
marginal_effects(m8, "condition", ordinal = TRUE)
```

```
## Warning: Method 'marginal_effects' is deprecated. Please use
## 'conditional_effects' instead.
```

```
## Warning: Argument 'ordinal' is deprecated. Please use 'categorical' instead.
```



Descriptive statistics are summarized in table 2 above. Our data was analyzed using a 2x3 ANOVA with one within subjects factor (time of measurement, pre or post intervention) and one between subjects factor (experimental intervention type). Being in condition B vs A has a 71.6% increase in the odds of seeing support for UHC increase by a point. Being in condition B vs A increases probability of improving support for UHC by a point by a maximum of 13.5%. Being in condition C vs A has a 95.4% increase in the odds of seeing support for UHC increase by a point. Being in condition C vs A increases probability of improving support for UHC by a point by a maximum of 16.75%. Looking at the variable that represents Pre scores for all conditions, the estimates for all the values are all negative, and roughly the same. Thus, I would consider all pre-test values to have lower scores than all post test values. There seems to be a moderate amount of uncertainty for the odds ratios of all our conclusions, excepting our interaction between condition C and postscore, which has a small amount of uncertainty.

Looking at our graph, we see in our "heatmap", that there does seem to be a trend towards increased scores on support for UHC from the pre to the post for our two experimental interventions. We can see this by looking at the increased probability of higher scores in the two intervention categories.

Pilot Conclusion

Summary of Pilot Study Results

The initial problem we were examining was how we could improve support for Universal Health Care. The method we landed on was exposing participants to an explicit health benefit package through either an informational intervention, or an experiential intervention. Our first hypothesis was that exposure to an explicit health benefit package will improve support for UHC as compared to a control. Our second hypothesis was that the impact of exposure to an HBP on support for UHC would be moderated by whether the exposure was informational or experiential. From our frequentist methods, we found no statistically evidence at an

alpha of 0.05 confirming either of our hypothesis. There was an interaction that trended towards statistical significance between our time measure and our intervention condition, which provides some support for our first hypothesis. Looking at our data using Bayesian modeling, we find that there is weak evidence supporting our first hypothesis, with a significant amount of uncertainty with our point estimate. Lastly, our simple two-sample t-test found no difference between our two intervention conditions, B and C, when seeing which group would accept/reject the proposed health benefit plan for themselves.

One concern that arose while running our experiment was that our control condition did not contribute any external validity. Because of this, we chose to change our 'control' condition in our planned study to more closely reflect 'standard' UHC messaging that subjects would see in the world around them, instead of a filler 'dummy' exercise.

Additionally, in the qualitative response section, we found that participants occasionally had difficulty understanding the instructions. Several occasions occurred where the participant asked the administrator how to complete the exercise, after being exposed to the instructions. Taken all together, we found that improving our instructions and potentially clarifying or simplifying the task was important before implementation of our actual study. For these purposes, we chose to then adapt the pencil and paper exercise into a web-form for ease of use.

Proposed Method

Participants

Our participants will be students enrolled in the Psychology 1000 course at a large midwestern university. The study fulfills 1 credit requirement for students in the course, of which students were required to obtain 7 credit hours. Participants are not given any other incentive for participation in the study. Participants are randomized into different conditions within the online survey software used to administer the pre and post test measures. We hope to have a total number of participants around 200. This study will be advertised on the university credit hours tracking software alongside other qualifying studies, but will receive no other advertisement.

Materials

Each participant begins by being seated at a computer cubicle with running the online survey software "Qualtrics", which is used to deliver the pre and post test measures, instructions on how to complete the measures, as well as the condition exercise. Our only pre-test measure will be a single measure of support for universal health care (UHC). This is a 4 item measure of support for UHC, adapted from Shen & Labouff (2013) that is taken as a simple average, with the third item reverse scored. Compared to our pilot study, each item was selected using a sliding scale that went from 0 (strongly disagree) to 100 (strongly agree).

Next, participants in our intervention condition will be directed to a web-exercise adapted from the Choosing Healthplans All Together (CHAT) paradigm developed by Danis, Biddle & Goold (2002). This exercise consists of participants 'filling out' a game board by spending up to 49 'points' in a maximum of 79 spaces. Several groups of medical care are represented by costing different amounts of points, with some groups having up to two greater levels of intensity offered for correspondingly higher amounts of points. The core of the exercise consists of the trading off of limited funds in order to determine priorities for the health care system and considering how the specifics of a given plan would affect individual health outcomes. As compared to the pilot study, the web-exercise for our intervention condition requires no mathematical calculation and is much simpler to administer. Our control condition replaces the 'hands on' task of the web-exercise with exposure to 'traditional' messaging on the benefits of UHC, as presented from trusted sources such as the World Bank and the World Health Organization. For either condition, the subjects are asked to consider how the universal health care would affect their own lives.

Lastly, our participants will receive a post-test measure, that consists of two main items. The first is a post-test measure of support for UHC, using the Shen et al. (2013) measurement tool. The second item is demographic information, including sex, age, and current year of schooling.

Design

The design of this experiment is best described by a multi-level model. Our multi level structure consisted of UHC measures (either pre or post intervention), nested within each subject. The experiment was thus a 2x2 between subjects design. While our time variable (pre or post intervention) is 'within' our subjects, any given subject will only be exposed to one of the experimental conditions, thus it is 'between' subjects. The first '2' is our independent variables of time of measurement (pre or post intervention), the second '2' is our two experimental conditions, the control and the intervention. Our dependent variable was support for UHC. I believe that there should be no extraneous variables that might influence our results.

Procedure

The study begins by our administrator requesting that all subjects turn off personal electronic devices, in order to minimize distraction and disruption. Next, the subjects are lead by the administrator into the room, and are briefly told that the study will consist of a computer survey, with a computer activity during the middle of the survey. Each subject is then brought to a single-occupant cubicle with a computer running our Qualtrics survey. At this point, participants are told to read the instructions carefully, and notify the administrator once the survey assigned them to an experimental condition. Our subjects at this point complete the first half of the survey, consisting of our pre-test measure. After this is completed, the Qualtrics software randomly assigns the survey participant to one of two experimental conditions, with instructions on how to complete the computer exercise displayed upon the screen. Once this occurs, the administrator brings reference materials to our intervention condition, and both groups of subjects will complete the exercise after a brief verbal reminder of the task they were to be working on. After the task is complete, the subject responds to our post-test measures. Lastly, the subject reads a one page paper debriefing them of the purpose and theory behind the research, and is then granted 1 credit in the Psych 1000 system. This entire process should take 20-25 minutes on average, as evinced in our pilot study.

Modelling

I plan to employ two sets of models. One standard frequentist model, accounting for the multi-level nested nature of our repeated measures. Our other model will be a Bayesian model. A special model detail of importance is choosing a prior for our cumulative multinomial regression, of a normal distribution with a mean of zero, and a variance of 4. This was chosen so as to mimic the nature of our log-odds being akin to a z-score, with ranges outside of 4 not having much meaning than one at 2.5. Our main results that we will attend to will be seeing if the variables that we have hypothesized having an effect on support for UHC are statistically sigificant, and from the Bayesian perspective, seeing how much uncertainty we see in our estimates.

Discussion

Relate Results to Past Research

Looking at our pilot study. our expectation was that there would be a strong effect confirming our hypothesis as our work related strongly to previous research in the field. We did find a slight effect when exposing individuals to HBP, but there was significant uncertainty regarding our result. Keeping in track with previous research, we did find that overall there was a reasonable level of support for UHC as the majority of our participants found the plan acceptable. We also replicated the generally positive level of support found by Huebner et al. (2006), but in a non-medical student population. With regards to likelihood of wanting the referenced plans for themselves, the slight positive result we obtained cleanly replicates the findings of Danis, Biddle & Goold, 2002. The majority individuals exposed to a health benefit package would be willing to use the health package for themselves. Lastly, our results were different from Weiger, Armstrong & Shaffer, 2019. According to Weiger et al. we should have expected a stronger effect with the experiential intervention as compared to the informational intervention. We neither saw a difference in support between our two interventions (as compared to each other, not the control), as well as no difference in likelihood to accept the

proposed HBP for self use. However, we may find different results with an informational intervention that reflects commonly shared information about UHC, as with our currently proposed study, as compared to the informational intervention we used in our pilot. Lastly, since there was a lack of conclusiveness, there is the possibility that the mechanism underlying opposition to UHC could be different than the initial two we hypothesized. While an HBP solves very neatly the issue of 'fairness' and 'lack of explicit definition' for the program, if opposition to UHC is due to another issue, it may not ameliorate the problem. Due to this lack of conclusiveness, there is significant value in the partial replication we are proposing.

Limitations

Both our pilot study and planned study recruited or will recruit participants from a large midwestern university located in a medium sized midwestern city. This is not necessarily reflective of the majority of the insurance buying population, or those individuals able to effect change on UHC. In addition, our methodology, specifically the process of instructing our participants how to complete the pencil and paper exercise in the pilot study, was imperfect. In the free response portion of the exit survey as well as when administering the experiment, participants often had trouble understanding the instructions. Furthermore, our control condition in our pilot was a 'dummy exercise', and we never presented supporting information for UHC using the 'standard' format or content that health organizations would use, reducing our external validity.

Appendix

Pilot Study Code for Frequentist MLM - treating ordinal values as continuous

The goal of this analysis is to examine my Universal Health Care benefit package data with an eye towards considering it as a multilevel model. The multilevel structure in this study is that each subject has two support for UHC measurements, one done as a pre-test measure, and one done as a post-test measure. Thus, our two trial times are nested within subjects. Our main level two predictor variable is which condition out of three our subjects were assigned to. We chose the first model assuming that we would best predict UHC support through a specific subject, and which condition they were assigned. This model failed to converge. We next moved to a model that predicted UHC support from just condition, and it was able to converge. We then wished to examine our interaction between time, and condition, as that was part of our hypothesis originally. The model for this also converged. We lastly tried a more complex model that allowed the intercept to vary by time, but the model did not converge, thus we returned to analyzing the results of model 3.

First model, predicting UHC support by subject, and condition, letting intercepts vary by subject.

m1<-lmer(value ~ SUBJECT + condition + (1|SUBJECT), data = UHC_final)

We move to this model, as the previous one registered errors.

m2<-lmer(value ~ condition + (1|SUBJECT), data = UHC_final)

We lastly use this model, as we wish to consider the effect of time as well as condition.

m3<-lmer(value ~ condition*variable + (1|SUBJECT), data = UHC_final)

We try both this more complex model, but we failure to converge, so we return to using m3.

m5<-lmer(value ~ condition*variable + (1|SUBJECT) + (1|variable), data = UHC_final)

Pilot Study Code for Bayesian MLM - Treating ordinal values as ordinal

To analyze the data in a different way, I have chosen to look at the per-item scores in the aggregated measure of support for UHC. Treating these values as ordinal, I reshaped my data from wide to tall, with each pre

and post test question recieving it's own row. I chose to set my prior based on the understanding that the variance range should roughly mimic z-scores, with values of +- 2.5 being near the edge of the range.

I started with a simple model, and added more complexity as I desired to test my hypothesis. The first model was a simple affect of condition, time, and question. After finding that the question parameter did not make much of an impact, I chose to look at the interaction between condition and time, something I presupposed would have an effect. The last model I examined had a random intercept by subject, but also allowed the slope for 'condition' to vary by subject. Sadly, this model refused to converge and thus I decided to use my m8 model.

Create a prior based on our understanding of likely ranges in a Z-score.

myprior<-prior(normal(0,2.5), class ="Intercept")

Simplest form of our model.

m7<-brm(measurement ~ condition + time + question + (1|SUBJECT), data = UHC_final_long, family = cumulative("logit"), prior = myprior)

Simplest form testing our base hypothesis.

m8<-brm(measurement ~ condition*time + (1|SUBJECT), data = UHC_final_long, family = cumulative("logit"), prior = myprior)

Model that did not converge

m9<-brm(measurement ~ condition*time + (condition|SUBJECT), data = UHC_final_long, family = cumulative("logit"), prior = myprior)

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