Collective Intelligence in Public Health Policy Making: Crowdsourcing Health Care Priorities Setting

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1. INTRODUCTION

Since the early academic studies that effectively used general-purpose crowdsourcing platforms for advancing scientific research (e.g. Kittur et al. 2008; Villarroel 2008), an array of scientific experiments in various academic fields of inquiry have been conducted (e.g. Paolacci et al 2010; Wiggins & Crowston 2011; Shapiro, Chandler & Mueller 2013). The fields of application continue to expand as more crowdsourcing platforms emerge that offer new possibilities for conducting online experiments requiring human intelligence. On the one hand, there is a growing body of evidence suggesting that crowd-contests can be effective to obtain solutions to "highly specialized" problems from one or a few highly talented individuals (e.g. Lakhani et al. 2013). On the other hand, our ability to systematically harness online collective human intelligence from large groups to address "big picture" complex problems such as devising public health policy has been little explored. This research reports a novel approach to unveil statistically reliable Health Care Priorities Settings (HCPS) -a focus area of public health policy- from N=1,194 concerned citizens within a country. The findings unveil an important gap that may be systematically missed by traditional policy making.

1.1 The Limits of Collective Intelligence

Evidence of the existence of collective human intelligence in groups, two to five persons in size, was first unveiled in a seminal study by Woolley et al. (2010). Evidence was set forth that (1) a collective intelligence factor c exists [with only 40 groups], and (2) it is a predictor of group performance, controlling for the (average and maximum) intelligence of the group's members [in a regression with N=40]. More recently, Engel et al. (2014) successfully extended this research to the online realm. However, Katzenbach would rather describe these deterministic groups of two to five members, interacting with one another in one physical location, as "teams" (Katzenbach, 1993). The increasing importance of mass communication technology raises the question about the 'new' collective intelligence available in groups of people orders of magnitude larger and diverse, such as those found on crowdsourcing platforms —to whom we refer here as 'crowds'. Firms are now able to extend their operations to work with crowds in useful and unprecedentedly efficient ways, referred to as 'online distributed organization' (Villarroel and Gorbatai, 2011; Villarroel, 2013). Yet, when it comes to elucidating sound collective intelligence solutions to "big picture" complex problems, such as defining public policy for a nation, there are few empirical examples. This research contributes in this sense.

1.2 The Limits of Public Health Policy Making

Scientific research in public health policy, as in most social-related sciences, needs to collect data from populations that are typically difficult to reach out to, facing significant structural impediments in reaching out to stakeholders. Research for public health policy making faces a more exacerbated problem as geographic barriers add to structural barriers when seeking access to the populations of interest, whom the policies should ultimately affect. As such, public health policy research is typically developed using heterogeneous data sources —over which the researcher has little control—, and conducting expensive and time-consuming field research —which is often travel and labor intensive, when it is properly supported financially. In this context, the literature on Health Care Priorities Setting (HCPS) shows that views vary much depending on the techniques used to unveil them, namely depending upon the sources used: government officials, policy analysts, health experts, etc. (Dolan et al, 1999; Mitton, Patten, Mullen & Spurgeon, 2000). An acknowledged problem with such otherwise authoritative sources is that they are inherently “closed”: only ‘authorities’ participate in the HCPS process, which makes it prone to suffer from bounded rationality (Simon, 1955). As such, they can be biased in ways that are unrelated to the real needs of the final beneficiaries of the policies that result from their decisions (Kapiriri, Norheim, & Martin, 2006, 2008).

2. THE COLLECTIVE INTELLIGENCE APPROACH TO PUBLIC HEALTH POLICY MAKING

The collective intelligence approach reported in this research responds to calls for “more formalized, workable and transparent approaches to priority setting” in the public health policy making literature (e.g. McDonald & Ollerenshaw, 2011). Consistent with ‘participatory action research’ in public health (Baum, McDougall, & Smith, 2006), this approach (described in sections 2.1 and 2.2) unveils public views directly from regular citizens, in an anonymous online setting where participating citizens are free to reveal their true preferences. The (collective intelligence) outcomes thus generated should provide a timely complement to the institutional (traditional) approaches, adding to an increasingly multidisciplinary system (Peacock, Mitton, Bate, McCoy, & Donaldson, 2009). In short, our research shows that the CI approach: (1) proves simple enough for layman citizens to understand and to use to provide useful insight, (2) yields statistically robust health care priorities settings from a population that can be used in econometric analysis, and (3) offers timely complementary insights to those derived from government and institutional sources, whose data typically lag a few years and are often disconnected from the actual needs of the final beneficiaries.

2.1 Antares Matrix of Health Care Priorities

A novel approach to Health Care Priorities Setting (HCPS), focusing on five strategic priority dimensions (discussed below), has been introduced by Bloom, Chu, and Smullin (2012) under the umbrella of the Project Antares research program at Harvard University. Their vision is that “high-impact interventions can be brought to the masses with permanence, continuous efficacy and sufficient continuous efficacy that allow a lasting social impact” (Chu and Bloom, 2011:1). The Antares Matrix offers a data-driven health care prioritization model that should ultimately help inform stakeholders’ decisions on public health care policies and interventions. At its core, the Antares Matrix relies on existing measures of mortality, morbidity, DALY, cost-effectiveness, household income, as well as medical and social externalities that may disproportionately affect women, children and the poor (Chu and Bloom, 2011). These data were combined to produce a list of top health care priorities (Chu and Bloom, 2011), of which five were strategically chosen for inclusion in a model known as the Antares Star (Bloom, Chu, and Smullin, 2012). The present study builds on an Adaptation of the Antares Star (AAS) five dimensions as they apply in India. The five strategic priority dimensions Dn in the Adapted Antares Star (AAS) are described in more detail in Villarroel (2014), and their measurement in Table 1 (section 2.2).

2.2 Measuring the Health Care Priorities Settings Dimensions

A survey was carefully designed and tested prior to use it to unveil the health care priorities of the population. Study participants were invited to think about “What do you think should be the priority of your government on treating diseases?”. To statistically address this question they were presented with eight random combinations of five questions (See Table 1). One question for each strategic HCPS dimension of the Antares Star (cf. section 2.1). For each randomly presented question combination, study participants were asked to distribute 100 points among the five (concurrent) options to indicate the treatment priorities they would like to see their government implement ("I think Government should prioritize the treatment as follows").

Table 1. The approach reported in this research unveiled a statistically robust measurement of the strategic dimensions D*n*. Each respondent was asked to assess 8 separate instances of the Antares Star. Each instance had one question (out of two) for each of the five dimensions. This was done to avoid measurement bias from any one given set of 5 questions.

DIMENSION MEASURED	Cronbach's Alpha
D1 Scale of disease: 1. Infectious diseases that are widespread, like an epidemic. 2. Diseases that are a main source of death.	0.84
D2 Household financial effects: 1. Diseases that cause a significant reduction in aggregate household income. 2. Diseases that represent an expense for the household over an extended period of time (years).	0.74
D3 Social equity: 1. Diseases that affect mainly children. 2. Diseases that affect mainly poor people.	0.81
D4 Cost effectiveness: 1. Diseases for which there are readily available treatments, but not currently given to the population. 2. Diseases for which the hospital network offers an effective mechanism to deploy treatment.	0.73
D5 Spillover effects: 1. Diseases that reduce the patient's productivity or ability to work. 2. Diseases that negatively affect the patient's social relationships with his/her community.	0.70

3. EMPIRICAL SCOPE AND POLICY IMPACT OF THE APPROACH

Full Model for All 5 HCPS Dimensions	D1	D2	D3	D4	D5
votedInLastElection	**-1.220***	**1.286*****	**-1.650*****	**0.704***	**0.893****
	(-0.672)	(-0.437)	(-0.597)	(-0.379)	(-0.385)
age	0.034	-0.011	**0.063*****	**-0.041****	**-0.044****
	(-0.030)	(-0.021)	(-0.024)	(-0.020)	(-0.020)
female	0.040	-0.114	-0.163	0.262	-0.006
	(-0.463)	(-0.317)	(-0.407)	(-0.297)	(-0.278)
education	**0.468****	**-0.329****	0.170	-0.242	-0.068
	(-0.206)	(-0.167)	(-0.224)	(-0.175)	(-0.143)
income	**0.354*****	**-0.165*****	0.101	**-0.161*****	**-0.132****
	(-0.091)	(-0.059)	(-0.080)	(-0.059)	(-0.054)
household size	-0.111	-0.027	0.082	-0.056	0.116
	(-0.127)	(-0.082)	(-0.121)	(-0.081)	(-0.092)
location dummies	[urban baseline]	[urban baseline]	[urban baseline]	[urban baseline]	[urban baseline]
sub-urban	**-0.832***	-0.138	0.643	-0.095	0.411
	(0.493)	(0.341)	(0.469)	(0.330)	(0.333)
rural	**-1.770*****	**0.856****	**-0.916***	0.349	**1.493*****
	(0.555)	(0.351)	(0.476)	(0.361)	(0.342)
_cons	23.284***	18.800***	22.734***	18.629***	16.536***
	(1.607)	(1.082)	(1.316)	(1.131)	(1.029)
N	1,194	1,194	1,194	1,194	1,194

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2. Regression analyses against the five HCPS dimensions measured in this study.

The scope of the data and related analysis discussed in this paper encompasses a sample of 1,194 study participants from India. Amazon Mechanical Turk offered an effective vehicle to reach out to this population. The analysis is derived from three kinds of data from the study participants: (1) geo-location data, (2) quantitative data on the five strategic dimensions of HCPS preferences for the community within which the participant lives, (3) demographic data. First, the five strategic HCPS dimensions D*n* were found to be statistically consistent across the different question combinations used to unveil them (See Table 1, Cronbach's alpha). The internal consistency for each strategic dimension D*n* is 0.70 or higher in all cases, which is considered good (Nunnally 1978). Second, we constructed a combined variable for each dimension, which was the average value of the eight individual measurements performed. Third, we demonstrate the applicability of our identified HCPS dimensions D*n*, by regressing them against a set of demographic and control variables (See Table 2, full model regressions for all D*n*). Among the most salient results, we found statistically significant differences in HCPS preferences between the sub-population who voted in the last elections and the sub-population who did *not* vote in the last elections, across all dimensions D*n* (reported in the first line of Table 2). 'Traditional' public health policy is decided by government representatives and their close entourage; therefore it is likely biased towards responding to the needs of those who did vote in the last elections. The systematic differences in views unveiled by this study suggests that this kind of collective intelligence approach to public health policy making can help governments (1) measure, (2) identify, and (3) address real differences in policy preferences held by the constituent population.

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