Patterns of COVID-19 Testing Preferences in Rural Underserved Populations

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Table of Contents

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Abstract

Background: A particular challenge during the Covid-19 pandemic was to provide testing and treatment for already disadvantaged and vulnerable populations. Media reports suggested socioeconomic and racial disparities in access to testing. Many states implemented testing in a sporadic and disorganized way and it is unclear to what extent this disproportionally affected populations experienced barriers to accessing care. It is also unclear that if potential barriers to testing were due to systemic challenges or whether there were underlying individuals motivations for not getting tested.

Objective: The objective of this study was to understand the trade-offs individuals in rural and vulnerable populations make between attributes of individual diagnostic testing and how preferences and trade-offs vary across individuals.

Methods: We used a mixed methods approach, first conducting focus groups to identify barriers to COVID-19 testing and then identifying optimal strategies to increase testing using hypothetical scenarios by developing a Discrete Choice Experiment. We analyzed the data using a conditional logit model (CL) and using latent class analysis (LC).

Results: We found that respondents cared about select structural factors, but that these were not the primary drivers of choice for testing. We also found that the attributes of testing were all significant in the CL model, apart from home visit and walk in, and had the expected signs. However, when taking a closer look at preference heterogeneity and unobserved preferences, we concluded that some important covariates were driving preferences, including: age, gender, medical vulnerability, insurance status, trust in government organizations, and previous flu vaccination -which may be a proxy for compliance. In sum, these covariates helped explain the observed preference heterogeneity. Contrary to our hypotheses, rurality did not significantly impact preferences for testing.

Conclusions: The results suggest that important social, behavioral and even policy factors affect choice for testing. Contrary to our hypotheses, rurality did not significantly impact preferences for testing, but attitudes towards government and other beliefs did. Health care interventions intended to reduce rural health disparities that do not reflect the underlying values of individuals in those subpopulations are unlikely to be successful.?

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Preferences for Attributes of Diagnostic Testing Locations in Rural Areas: Lessons from Covid-19 for Individual and Surveillance Testing

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Conclusions

The results suggest that important social, behavioral and even policy factors affect choice for testing. Contrary to our hypotheses, rurality did not significantly impact preferences for testing, but attitudes towards government and other beliefs did. Health care interventions intended to reduce rural health disparities that do not reflect the underlying values of individuals in those subpopulations are unlikely to be successful.

Introduction

The COVID-19 pandemic created unprecedented challenges for the healthcare and public health systems. Healthcare providers have had to grapple with sudden changes in care delivery, ranging from potential inpatient bed capacity constraints, to delays in care, and the need to remotely manage medically and socially complex patients. Public health agencies have had to quickly ramp up testing at an unparalleled scale; additionally, infrastructure and processes to report these results to the public and their healthcare providers was urgently needed.

A particular challenge has been to provide COVID-19 testing and treatment for already disadvantaged and vulnerable populations[1-3]. Media reports suggested socioeconomic and racial disparities in access to COVID-19 testing[2,4-5]. Many states implemented COVID-19 testing in a sporadic and disorganized way, partly because the Centers for Disease Control and Prevention (CDC) guidelines changed several times over a short time span[6]. It is unclear to what extent disproportionally affected populations experienced barriers to accessing care. Even if we find that historically underserved populations received fewer COVID-19 tests, the question remains whether this was due to systemic challenges or whether there were underlying individuals motivations for not getting tested.

The objective of this study was to understand the trade-offs individuals in rural and vulnerable populations make between attributes of COVID-19 tests and how these vary across individuals. The study was done as part of the RADx-UP, a consortium of more than 125 research projects studying COVID-19 testing patterns in communities across the United States and its territories as well as Tribal Nations. The goal of RADx-UP is to “speed innovation in the development, commercialization, and implementation of technologies for COVID-19 testing”.

The study was focused on identifying structural, social, behavioral, and policy factors that could be sources of COVID-19 testing disparities. Structural factors generally refer to the broader conditions that either increase or decrease an individual's likelihood of getting testing. In this study, the primary structural factor is access to testing, defined in terms of travel time, which has been found to be a strong predictor of satisfaction with access to care[7]. Other than travel time, costs and wait times can also be structural factors[8].

Our main hypothesis was that preferences for attributes of COVID-19 testing vary between and within subpopulations, particularly vulnerable rural populations. We hypothesized that individuals were less likely to get tested if they face longer travel and/or wait times, more discomfort with testing, higher costs or longer wait time to hear of test results. We also hypothesize that rurality is an important factor affecting preferences for testing, influencing the travel time/distance to the nearest testing center. We used the four-level classification scheme (Urban, Large Rural, Small Rural, and Isolated Small Rural-Categorization A) for the Rural-Urban Commuting Area (RUCA) codes which is a census tract-based classification that uses standard census measures of population density, levels of urbanization and journey-to-work commuting to characterize all U.S. census tracts with respect to their rural/urban status and commuting relationships to other census tracts[1].[9]

Previous research has illustrated that many other factors affect the formation of new habitual behavior such as seeking a COVID-19 test. Recent data from a discrete choice experiment (DCE) suggested that the attribute of highest relative importance was test result turnaround time, followed by the type of test, specimen and venue. A DCE provides the opportunity to estimate pair-wise choices and analyze marginal values or the total value of a health service or good. In simulations by Zimba et al, immediate or same-day test results, both PCR and serology, or oral specimens

[1] https://familymedicine.uw.edu/rhrc/ruca/

substantially increased testing uptake over the current typical testing option[8]. Simulated uptake of a hypothetical testing scenario of PCR and serology via a saliva sample at a pharmacy with same-day results was 97.7% in this study, compared to 1.8% opting not to test. This study was performed in 2020 when at home tests were not on the market yet. Thus, the study did not take preference heterogeneity into account.

It remains unclear what factors encourage behavior change and incentivize people to seek testing. A review of approaches across different fields reveals several shortcomings in public health policy: most importantly that public health interventions do not take into account various psychological and behavioral factors[10]. Five blocks of factors have been identified with regard to the new (health) behavior in the literature: risk, attitudinal, normative, ability, and self-regulation factors [10]. This aligns with the health belief model which postulates that a person's belief in a personal threat of an illness or disease together with a person's belief in the effectiveness of the recommended health behavior or action, such as COVID-19 testing, will predict the likelihood the person will adopt the behavior[11-13].

Methods

For this study, we used a mixed methods approach. To understand which aspects or attributes of testing were important to people, we first conducted a series of focus groups throughout the Northern New England region to identify barriers to COVID-19 among medically and socially vulnerable rural adult populations. We then identified optimal strategies to increase testing using hypothetical scenarios fielded within a representative sample of the rural U.S. population, by developing a Discrete Choice Experiment[14-15]. The unique contribution of a DCE is that it allows researchers to analyze the trade-offs that patients are willing to make including options that may not exist but could in the future. DCEs are preferred to surveys because instead of simply asking “Would you get a COVID-19 test?”, this approach asks: “You have the choice between two tests, A and B; they differ in the following ways […]. Which would you prefer?" The set of direct, discrete choice options systematically varies and facilitates identifying and prioritizing the set of attributes that decision makers care most about (e.g., travel time versus swab testing method).

In this study's DCE, testing is described by its attributes, and the options presented vary by the levels of those attributes. The DCE included 15 choice questions each with three different testing options and an option not to test. Respondents were introduced to a set of hypothetical choices (see Appendix) and asked to select which testing option they would prefer most.

The marginal values of the testing attributes were estimated based on analyzing the set of pairwise choices[16]. Thus, the DCE facilitated analyzing trade-offs people were willing to make, including testing options that may not currently exist in the respondents' local environments but could in the future.

Qualitative Research

To design the hypothetical choice questions and understand which aspects or attributes of testing were important to people, we first conducted a series of focus groups throughout the Northern New England region to identify barriers to COVID-19 among medically and socially vulnerable rural adult populations: older adults in congregate housing, parents of school-aged children, and other community members. Focus groups transcripts were coded independently using NVivo v14.23.0 software and analyzed systematically using both deductive and inductive thematic analysis techniques.

The focus group questions addressed topics such as: reasons for seeking COVID-19 testing; testing barriers; feelings about getting tested; history of vaccination hesitancy; and social distancing behaviors during the pandemic. We also asked about sources of information that influenced their decision-making process. Focus group discussions also explored region-specific testing logistics, common barriers, swapping methods available, trusted sources of health information, public health campaigns to increase testing, and resources facilitating access to testing.

Experimental Design

The data from the focus groups identified distinct DCE terms and wording for conceptual attribute development[17]. Understanding how people made decisions about getting testing, and what sources of information informed their decisions, ensured the DCE accurately represented a realistic choice scenario. DCEs follow a general pattern of describing a COVID-19 scenario, followed by questions to elicit underlying preferences. Based on the qualitative research, we included eight testing attributes: cost, travel time, wait time to results, test accuracy, testing venue, testing methods and testing discomfort (see the Appendix for details).

We used a DCE in which we collected demographic data, data on housing and employment, vaccination acceptance, testing attitudes, risk taking behaviors (using the GRiPS score, a validated general risk propensity scale[18]), conspirational thinking and anti-expert sentiment[19], trust in public health authorities[20-22], political preference and religion.

The experimental design of the DCE was based on a-priori estimates of the values respondents would give for different attributes of the choice. These numbers were based on pilot data and estimates from the literature[8]. This way we did not have to portray the full factorial design of all the options for attribute levels, but an “efficient” design that would optimize our information with just 15 combinations of attributes and levels. *Figure 1* shows the attributes of a choice set and an example of a DCE choice set. The attributes and levels that differed by testing option were explained to participants prior to answering the survey questions with the vignette in Figure 1.

Data

Our data were sampled from an online Centiment panel[2] between April 29, 2023 through May 5, 2023. Out of 982 respondents; 184 were timed out before survey completion, leaving 798 completed surveys. Of the 798 respondents, 13 did not complete all the choice tasks, and 5 were likely robots based on our checks, leaving 780 completed responses. Of those 780 with good data, the mean survey duration was 28.25 minutes (median 20.52).

Centiment oversampled rural populations and used quota sampling for age, gender, household income (HHI) and race: 50 percent of household incomes were above and below the median rural income of $52k per year[23], and the maximum number of white, non-Hispanic respondents was 615. The study population included people who were medically and/or historically underserved: older adults in congregate housing, parents, and individuals living within Large Rural, Small Rural, and Isolated Small Rural areas nationally. The sample therefore included diverse and higher levels of social vulnerability and were nationally representative of rural populations. The online SurveyEngine platform was used to collect data (SurveyEngine GmbH, Berlin Germany, 2023).

Analytic Approach

We analyzed the data using a conditional logit model (CL) and using latent class analysis (LC). The conditional logit, developed by Daniel MacFadden[24], models the expected utilities in terms of characteristics of the alternatives rather than attributes of the individuals. The data from our repeated choice tasks can be treated as panel data in a conditional fixed effects logit model[25]. With this model, we used the respondents as their own controls and control for "stable" characteristics that do not change over time even if these were not measured. It is similar to an experiment with random assignment, controlling for omitted variables. With this model we focused on the estimation of

[2] https://www.centiment.co/

within-individual differences in preferences.

The latent class model is based on the assumption that individual preferences have a discrete distribution[26-27]. In the latter we used a weighted probability of class membership and multiplied that with the probability of choosing a particular choice option. LC accounts for serial correlation which means we model the probability of observing a sequence of choices. This way, we were able to predict the probability of the sequence of choices respondents made.

LC models are based on maximum likelihood estimation adding information about the preference heterogeneity within our study population. For example, the LC model does not assume that everyone has the same preference for the no choice option; rather, we analyzed whether some people were more likely to choose a no choice option. Subgroup analysis can be used to identify heterogeneous treatment effects. Latent class analysis (LCA) structure uses a class allocation model where probabilities vary across individual decision-makers as a function of their observed characteristics. Crucially, we analyzed if membership in a subgroup may differ by health disparities, socioeconomic status and different beliefs and attitudes, by entering vulnerability, rural location, comorbidities, income, race and other indicator variables in the class membership function.

We used the consistent Akaike Information Criterion (CAIC) and Bayesian Information Criterion (BIC) to determine the number of classes for the LCA[28]. Often the CAIC and BIC are used to determine the optimal number of classes, but with LC we cannot directly compare the likelihood functions, as models with more parameters will generally produce better results, even though the model is not statistically considered better[29]. We used Stata 18.0 for the statistical analysis which uses the expectation-maximization (EM) algorithm for fitting a discrete-mixture logit model (StataCorp, College Station, Tx, 2024).

Results

Sample Characteristics

As described, the data were gathered using a quota sampling approach for age, gender, household income and race. We compared the sample characteristics of those who had previous COVID-19 tests to those who did not, to see what the predicted uptake of testing would be, based on differences in attitudes and beliefs. Some studies have shown that previous choices may affect current choices, both in general terms[30] and in health choices specifically[31]. Within the descriptive analyses, we used chi square tests to detect statistically significant differences between the two groups. Table 1 shows that those who had a previous COVID-19 test had a significantly higher GRiPS score, and were somewhat more leaning towards politically liberal.

Respondents who had a previous COVID-19 test also had more trust in public health organizations and governmental institutions, were more religious, and less spiritual than respondents who did not have a previous COVID-19 test. We did not find a statistical difference for conspirational thinking and anti-expert sentiment scores between people who had already gone for testing and those who did not.

Conditional Logit

The results of the choice models can be found in Table 2. In the CL model, the dependent variable was “choice for test location” defined by the attributes in the choice task. Every coefficient shows the probability of picking a particular option versus not picking that option. We found that the attributes were almost all significant and had the expected signs. As hypothesized, respondents were less likely to choose a test location that had a higher wait time (coefficient -0.183, standard error 0.006); more travel time to get tested (-1.129, 0.054); that was more costly (-0.020, 0.000); where someone else would collect the sample (-0.230, 0.036); where it would take more time to receive results (-0.032, 0.006); and where tests would have more discomfort (-0.125, 0.007). They were more likely to choose a mail order option (0.494, 0.075) and options that had higher test accuracy (0.026, 0.001).

Latent Class analysis

After identifying preferences for attributes of testing for the sample population, we addressed the issue of unobserved preferences of respondents by probabilistically segmenting the sample population into different groups or "classes" based on a latent variable. Class membership was first defined by a membership function including the indicator variables, after which the utility functions of different classes were estimated through maximum likelihood estimation. First, we determined the number of latent classes. We considered theoretical interpretability and compared the statistical tests of model fit using models for one to five possible latent classes. The CAIC of the 5-class model was lowest, suggesting the 5-class model provides the optimal balance between model fit and model complexity. However, the difference in model fit between the 3, 4 and 5-class models was not large, and the interpretability of the 3-class model is more straightforward. We therefore report the results of the 3-class model in Table 3.

The covariates we used for the class membership model included gender (female), education, income, age, race (white), currently insured, currently employed, self-assessed health rating, vulnerability, the number of previous tests, rurality, flu vaccination history, risk-taking score (GRiPS), conspirational thinking and anti-expert sentiment scales, trust in public health and government organizations, self-rated religiosity, and whether they were politically republican leaning.

Looking at the coefficients for the attributes of the choice for test location, three groups can be identified: testing method does not matter/drive-through locations are preferred, strong preference for at home test and mail order options, and prefers self-administering the test. We call the first class the “Compliant” class, since these respondents are more likely to get tested but they do not care about the type of venue as long as they can take the test themselves. We call Class 2 the “Evaluative / less-compliant” since they seem to care most about the ease of testing, not requiring time or travel, they do not care about the test method or how long it takes to get results back. The results implied that members of Class 2 would get tested because they had to or to be compliant, but not because they thought it was important. This suggests they only go for testing if they have to. Members of class 3 want to drive somewhere for testing, but close to their homes. We call this class “Convenience”.

We found that age (-0.709, $p<0.01$), being insured (1.742, $p<0.01$), previous flu vaccination (0.580, $p=0.05$), and trust in various institutions (0.510, $p=0.02$) all significantly predicted membership of Class 1. For example, with every additional point increase on the Likert scale for trust, respondents would be more likely to be in Class 1 versus Class 3 which was the reference. We also found that gender (-2.610, $p=0.06$), vulnerability (0.803, $p=0.030$, previous flu vaccination (-0.921, $p<0.01$) and trust in government institutions (-0.687, $p=0.04$) also explained membership of Class 2. For example, females were far less likely than men to be in Class 2 compared to Class 3. Previous flu vaccination, which could be considered a proxy for “compliance”, defined class 1 membership, but those who were vaccinated were less likely to be in class 2. Where higher levels of trust in government institutions predicted Class 1 membership, these respondents were less likely to be in Class 2.

We found that 43.4 percent of the respondents in our study fall in Class 1 which is the group that cares significantly about being able to perform the test themselves. The coefficient ($\beta=-0.275$) is negative and twice as large as for the other two groups, meaning that they would be less likely to pick a test location where someone else would collect the sample.

Class 2 includes 15.9 percent of respondents, and they seem to care the most about convenience, as they have a significant and positive coefficient for mail order (β=0.871). This seems to be more about not wanting to travel, since they do not feel strongly about who administers the test (β=0.152). Indeed, the coefficient for travel time to test center is large (β=-1.448) and negative, suggesting that with every additional hour of drive time, respondents are less likely to pick that testing option.

Class 3 has a strong preference for drive-through testing options. All the other venue options have a negative sign, meaning they are less likely to pick an option that involves walk-in (-0.213), home visit (-0.536), and mail order (-0.567). The coefficient for travel time to test is large and negative (-1.965), meaning that with every one hour increase of travel time, respondents are disproportionally less likely to pick that testing option.

Marginal rates of substitution

Table 3 shows an analysis of the trade-offs respondents were willing to make, known as the marginal rates of substitutionv. First, we looked at their willingness to pay for different attributes of testing. Members of all three classes were willing to pay significantly to decrease travel time. Class 1 members would pay $30 more to decrease travel time within one hour; this was $131 for members in Class 2 and $57 in Class 3. Members of the different classes were willing to pay for different venues but varied widely. For example, members of Class 2 were willing to pay $18 more for a walk-in testing option than drive-through, where they would be willing to pay $33 for at-home testing option and $79 for mail-order. Members of Class 1 would only pay more ($11) for a mail-order option, while members of Class 3 would not pay for any of these options when compared to drive through. Members of Class 2 would also pay $11 more to receive a test with less discomfort, where this was only $2 for Class 1 and $4 for Class 3.

In terms of test accuracy and results, only members of Class 1 and 3 appeared to be willing to trade-off wait time, travel time and even discomfort to get a test that was more accurate. They were not willing to pay significantly more for a more accurate test, however. Members of Class 2 did not care about accuracy of the test at all. This was consistent with findings for time to results: members of Class 2 would not trade off travel time, wait time, cost, or discomfort to get results more quickly. This also seems consistent with the covariates predicting class membership: these were respondents who had lower trust in government institutions and fewer of them had previous flu vaccination.

Discussion

This study used data from a DCE to understand what trade-offs individuals in rural and vulnerable populations make between attributes of COVID-19, and how these vary by different individuals. The study was focused on identifying structural, social, behavioral, and policy factors that could be sources of COVID-19 testing disparities. We found that respondents cared about select structural factors, but that these were not the primary drivers of choice for testing. We found that the attributes of testing were all significant in the CL model, apart from home visit and walk in, and had the expected signs. However, when taking a closer look at preference heterogeneity and unobserved preferences, we concluded that some important covariates were driving preferences, including: age, gender, medical vulnerability, insurance status, trust in government organizations, and previous flu vaccination -which may be a proxy for compliance. In sum, these covariates helped explain the observed preference heterogeneity. This suggests that important social, behavioral and even policy factors affect choice for testing. Contrary to our hypotheses, rurality did not significantly impact preferences for testing.

It is important to note from the results of the LCA that decision-makers looking to optimize testing strategies, while incorporating patient preferences for attributes of testing, should differentiate between the different sub-populations they are serving. This requires careful consideration of individual characteristics as well as preferences. Overall, we found in this study that subpopulations are characterized by being either primarily compliant, evaluative to some extent non-compliant, or they were driven solely by convenience.

Public Health Implications

This study provides a clear message to public health and surveillance systems seeking to increase testing rates during a pandemic like COVID-19. Consistent with findings from previous and related work[32], we conclude that health care interventions intended to reduce rural health disparities that do not reflect the underlying values of individuals in those subpopulations are unlikely to be successful.

Another concrete public health implication from this study is that adding a consistent and “easy” mail-order testing option in a future pandemic may significantly increase testing rates. Both the total sample population in the CL model and the different classes identified in the LCA, while having different underlying tastes and unobserved preferences, have a significant, positive and relatively large effect size for adding this hypothetical mail order option. Members of two or three classes, adding up to 84 percent of all respondents, also had a strong preference for self-administering the test. Compared to other attributes of testing, such as travel time or wait time, mail-order and self-administering are significantly more important aspects of testing for most people.

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Figure 1: Choice Attributes and example of a Choice Task

Attribute	Scenario	Levels
“For the purpose of this study, imagine there is a new variant of the COVID-19 virus spreading, and you think you would like to get tested for it. Recently, many people have been testing using freely available "rapid test" kits, such as BinaxNOW, iHealth, or QuickVue. Though they have been free for most people, they are also available for purchase. In this scenario, you will be asked to choose between tests that may resemble the "rapid tests" you are familiar with, but they may be paid, or free, and they will not be labelled as "rapid tests." Instead, you will be shown different tests, with varying features, and are asked to choose among them. You will have three options of tests you can take, or you can choose not to get a test.”		
1. Cost	“This is the amount of money you would need to pay out of pocket to get the test. When purchasing a rapid test kit, two tests will come in the box-- for all options you see, the price shown is for one test.”	$0, $19, $120 which were based on reference levels for free tests; rapid test kits and PCR tests.
2. Travel Time	“This would be the maximum time you would need to get to the location for your test.”	0 minutes (which meant they would not have to leave their home to get the test), 30 minutes, 60 minutes, 90 minutes (regardless of the type of transportation)
3. Wait Time to Results	“This means how long you would have to wait to find out if you have the disease or not, starting from when you got the test.”	Immediate (within 15 minutes), same day, 48 hours, 5 days, more than one week.
4. Wait Time to Test	“Often, a testing appointment is not available right away, or if you have ordered a test online, it may take some time to ship. This means how long you will need to wait to take the test once you have ordered or scheduled it.”	Same day, 2 days, 4 days, 8 days.
5. Test Accuracy	“No test is perfect, and sometimes when a test tells you that you don't have the virus, the test is wrong. This is not common, but it happens to some people, and can result in someone accidentally exposing others to the virus.”	99% (meaning that out of 100 people who test negative for the disease using this test, one of them actually has the disease, and 99 do not), 90%, 82%.
6. Testing venue	“The location where the respondent would have to go to get the test.”	Walk-In, Drive-Through, Mail-Order,Home Visit
7. Testing Method	“How the sample would be collected.”	Somebody else collecting the sample or they would do it themselves.
8. Testing Discomfort	“Sometimes getting a test can be uncomfortable, for example a swab may be briefly put deep into your nose to collect a sample.”	Discomfort was rated mild (2), moderate (4), severe (6).

You think you would like to get tested for the pandemic virus. You have three options of tests you can take, or you can choose not to get a test. Please select which option you would **most prefer**.

	Test A	Test B	Test C	No Test
Wait Time to Test	Same Day	4 Days	Same Day	
Travel Time	30 minutes	60 minutes	30 minutes	
Cost	$0	$19 per test	$19 per test	
Testing Venue	Walk-In	Drive-Through	Drive-Through	
Testing Method	Somebody else collects sample	I collect the sample	I collect the sample	
Results Time	More than one week	48 hours	Immediate (within 15 minutes)	
Test Accuracy	98%	90%	98%	
Testing Discomfort	None (0)	Mild (2)	Severe (6)	
Which would you choose?	Test A	Test B	Test C	No Test

Table 1: Attitudes of Respondents

	Previous COVID-19 Test			
	No (%)		Yes (%)	
Conspirational Thinking Score	16.2	(6.3)	16.3	(6.3)
GRiPS Risk Score **	17.1	(7.8)	17.7	(7.8)
Political Leaning: Conservative (1) to Liberal (7)**	3.2	(1.9)	3.7	(2.0)
Trust (0-100%, mean)				
State's Government **	39.3	(32.4)	45.3	(30.9)
City/Town Government **	41.9	(32.6)	47.4	(30.4)
Police **	45.7	(34.0)	49.3	(33.7)
State Health Department **	49.0	(33.8)	56.8	(31.0)
Public Health Experts (CDC) **	48.3	(37.1)	55.8	(35.0)
Red Cross **	50.4	(34.6)	55.2	(33.1)
Healthcare System **	58.6	(32.8)	65.7	(30.7)
WHO **	41.4	(36.3)	48.7	(35.5)
Federal Government **	31.5	(33.6)	37.9	(32.9)
Scientific Researchers **	50.3	(35.1)	54.4	(34.4)
Governmental Effort **	33.1	(31.9)	39.2	(32.1)
Religiosity				
Atheistic/Agnostic **	5.8	12	9.7	53
Organized Religion **	49.5	102	51.6	282
Spiritual / Non-Organized / Other **	44.7	92	38.6	211

Table 2: Mixed Logit and LCA Results

	Conditional Logit model β	Latent Class 1 "Compliant"	Latent Class 2 "Evaluative/less-compliant"	Latent Class 3 "Convenience"
Class share (%)		0.434	0.159	0.407
Wait time to test (days)	-0.183*** (0.006)	-0.112*** (0.008)	-0.114*** (0.043)	-0.198*** (0.012)
Travel time to test (hrs)	-1.129*** (0.054)	-0.452*** (0.069)	-1.448*** (0.442)	-1.965*** (0.127)
Test Cost ($)	-0.020*** (0.000)	-0.015*** (0.001)	-0.011*** (0.003)	-0.034*** (0.001)
Venue (ref: drive-through)				
Venue: Walk-In	0.043 (0.040)	-0.079 (0.052)	0.205 (0.305)	-0.213*** (0.069)
Venue: Home Visit	0.061 (0.069)	-0.175 (0.131)	0.373 (0.457)	-0.536*** (0.159)
Venue: Mail Order	0.494*** (0.075)	0.179* (0.108)	0.871** (0.443)	-0.567*** (0.134)
Test Method	-0.230*** (0.036)	-0.275*** (0.047)	0.152 (0.254)	-0.130** (0.061)
Time to Results (days)	-0.032*** (0.006)	-0.021*** (0.008)	-0.030 (0.037)	-0.036*** (0.011)
Test Accuracy (%)	0.026*** (0.001)	0.044*** (0.002)	0.024*** (0.005)	0.028*** (0.001)
Test Discomfort	-0.125*** (0.007)	-0.030*** (0.009)	-0.131*** (0.046)	-0.163*** (0.021)

*** p<.01, ** p<.05, * p<.10

Table 3: Marginal Rates of Substitution

	WTP Class 1	WTP Class 2	WTP Class 3	Accuracy Class 1	Accuracy Class 2	Accuracy Class 3	Time Results Class 1	Time Results Class 2	Time Results Class 3
Wait time to appointment	-7.445	-10.367	-5.822	2.530	-4.703	7.123	5.213	-3.786	-5.557
Travel time	-30.065	-131.631	-57.648	10.217	-59.715	70.537	21.050	-48.073	-55.033
Cost				0.340	-0.454	1.224	0.700	-0.365	-0.955
Venue_walk	-5.251	18.655	-6.250	1.785	8.463	7.647	3.677	6.813	-5.966
Venue_home	-11.639	33.933	-15.733	3.955	15.394	19.250	8.149	12.393	-15.019
Venue_mail	11.913	79.194	-16.631	-4.049	35.927	20.350	-98.341	28.923	-15.877
Method	-18.320	13.845	-3.826	6.226	6.281	4.682	12.826	5.056	-3.653
Time to results	1.428	-2.738	-1.048	-0.485	-1.242	1.282			
Accuracy	2.943	-2.204	0.817				-2.060	-0.805	0.780
Discomfort	-2.014	-11.873	-4.788	0.685	-5.386	5.858	1.410	-4.336	-4.570

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Supplementary Files