Final Project Report

The Effect of Survey Methodology on The Collection of Attitudinal Data

Prepared for **Teaching Old Models New Tricks (TOMNET) Transportation Center**

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16. Abstract

Surveys continue to be critical sources of data for making informed decisions about transportation plans and policies and understanding the evolutionary dynamics of the population. However, challenges associated with deploying surveys and obtaining representative survey data suggest that respondent samples are likely to differ from the general population not only on observables (socio-economic and demographic characteristics), but also on many unobservables (mobility choices, attitudes, values, preferences, and perceptions) for which census data is not available and does not exist. This study relies on two recent surveys conducted in the United States to examine sample representativeness. One survey, conducted in 2019, gathered data about people's lifestyle preferences as well as attitudes, values, and perceptions of emerging transportation technologies. The second survey, conducted in 2020, gathered data about people's lifestyle preferences and activity-travel responses to (and attitudes towards) COVID-19. The survey samples have been weighted to match population-wide census distributions along several socio-economic and demographic dimensions. Results show that descriptive statistics (means, standard deviations, median values) of attitudes and values for weighted survey samples are likely to be of limited value in drawing population-wide inferences necessary for designing transportation plans and policies.

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INTRODUCTION

The transportation profession continues to rely on surveys to collect data on traveler behavior and values, socio-economic and demographic characteristics, and mobility choices and patterns. Surveys continue to be critical sources of data for estimating and calibrating travel demand forecasting models, making informed decisions about transportation plans and policies, and understanding the evolutionary dynamics of the population of a region in terms of travel patterns and socio-economic and demographic characteristics. Despite the rise of big data streams, largely collected through passive means (such as cell phone traces and location-based service or LBS data), surveys have continued to play a critical role in transportation planning and policy analysis.

In recent years, with the increasing recognition that attitudes, values, preferences, perceptions, and opinions play an important role in shaping mobility choices (Jeremias, Narelle, Diaz-Lazaro, Poó, & Ledesma, 2021; Sunkanapalli, Pendyala, & Kuppam, 2000; Sangho & Mokhtarian, 2004) and vice-versa, transportation researchers and practitioners have been relying on surveys to provide insights into information about people's proclivities, particularly in the context of a rapidly evolving transportation landscape characterized by new mobility services and emerging transportation technologies (Circella, Alemi, Tiedeman, Handy, & Mokhtarian, 2018; Gkartzonikas & Gkritza, 2019). Surveys include a battery of questions requesting respondents to indicate their level of agreement with various statements, their preferences for different futuristic alternatives, and their opinions about or level of support for a new technology, policy, or pricing scheme (Richardson, Ampt, & Meyburg, 1995; Circella, Alemi, Tiedeman, Handy, & Mokhtarian, 2018; Loo, 2002; Hunt, 2001; Chana, Ishaq, & Shiftan, 2017). These surveys provide the data necessary to measure the "pulse" of the population, and assess people's priorities and preferences, perceptions of new technologies and policies, and levels of satisfaction with various elements of the transportation system.

There has been a growing interest in collecting increasing amounts of behavioral and attitudinal data, but the conduct of surveys itself has become increasingly challenging. Response rates are dismally low (particularly in the United States, but true in many contexts) and respondent samples are rarely, if ever, representative of the population from which they are drawn (Czajka & Beyler, 2016; Cornesse & Bosnjak, 2018). Surveys are increasingly administered online, raising concerns that respondent samples may be biased in favor of those who have ready access to the internet and are comfortable using technology to answer surveys (Sax, Gilmartin, & Bryant, 2003; Keusch, 2015). Because of the extremely poor response rates being experienced through traditional sampling means, surveys are now being deployed to paid panels (professional survey takers) maintained by commercial survey research firms and rely on convenience samples that are drawn through social networks and social media channels (Coppock & McClellan, 2019; Miller, Guidry, Dahman, & Thomson, 2020; Bennetts, et al., 2019).

All of the challenges associated with deploying surveys and obtaining representative survey data suggest that respondent samples are likely to differ from the general population not only on observables (socio-economic and demographic characteristics), but also on many unobservables (mobility choices, attitudes, values, preferences, and perceptions) for which census data is not available and does not exist. In other words, the likely presence of self-selection in survey response processes will lead to respondent samples deviating from general population characteristics on *both* observed socio-economic and demographic characteristics as well as unobserved mobility and attitudinal characteristics.

To adjust for biases in socio-economic and demographic characteristics, it is possible to weight survey data using readily available census data so that the weighted survey sample replicates the general population with respect to (joint) distributions on a number of socio-economic variables of interest in transportation planning and modeling. This survey weighting procedure can be done at different geographic levels to enhance the representativeness of the weighted sample, with weighting at a smaller geographic resolution generally preferred – as long as there is census data and sufficient survey sample size to support weighting at fine geographic resolutions (MARG, 2016). Alternative survey weighting schemes exist (Kalton & Flores-Cervantes, 2003; Franco, Malhotra, Simonovits, & Zigerell, 2017), but the basic objective remains the same – i.e., weight the respondent sample so that it replicates the population on key socio-economic and demographic variables for which census distributions are available.

Once a survey data set is weighted to be representative of the population on observables, the weighted survey statistics are often considered to be reflective of population characteristics. Mobility variables such as activity/trip frequencies, mode shares, trip length distributions, time of day distributions, trip chaining patterns, vehicle ownership patterns, and time use expenditures are assumed to be reflective of true population characteristics. The same goes with variables about attitudes, preferences, perceptions, and values. However, there is no census data upon which to stake this claim. Just because a survey data set has been weighted to be representative of the population on socio-economic and demographic characteristics, there is no guarantee that the weighted respondent sample is representative of the population when it comes to mobility choices, traveler behaviors, and attitudes and values. In the absence of such a guarantee, how is it possible to know for sure whether population mobility, attitudes, and values are being truly captured through the survey effort?

To answer this question, this study relies on experiences from two recent surveys conducted in the United States. One survey, conducted in 2019, gathered data about people's lifestyle preferences as well as attitudes, values, and perceptions of emerging transportation technologies (besides the usual battery of socio-economic, demographic, and travel characteristics) (TOMNET UTC, 2020). The second survey, conducted in 2020, gathered data about people's lifestyle preferences and activity-travel responses to (and attitudes towards) COVID-19 (COVID Future, 2020). The first survey was administered via different means - online and paper (mail). The second survey adopted a multi-pronged approach to sampling; the survey was deployed to a random set of email addresses, to a paid panel of professional survey takers, and a convenience sample of friends and colleagues through email and social media. Thus, both surveys offer distinct subsamples - the first survey offers subsamples based on survey administration (instrument) method while the second survey offers subsamples based on sampling scheme. For both surveys, the respective subsamples are weighted using well-established survey weighting methods to ensure that each subsample (regardless of administration method or sampling scheme) is representative of the general population from which it is drawn. Thus, at the end of the weighting process, the respective *weighted* subsamples in each survey will be identical to one another with respect to the socio-economic and demographic variables used as control distributions in the weighting process.

However, to what extent do the respective weighted subsamples match one another with respect to attitudes, behaviors, perceptions, and preferences? If the weighting process is intended to make each subsample representative of the population (and hence converge to an identical set of population-wide socio-economic/demographic characteristics), then it may be hypothesized that all subsamples should likewise converge to an identical set of measures on attitudes, perceptions, and preferences (and thereby reflect population-wide attitudes and opinions). It is this hypothesis that this study intends to test and address. It should be noted that mere convergence to an identical set of values does not necessarily guarantee population representativeness on attitudes and travel measures; the subsamples may have simply converged upon a set of measures that reflect a self-selected segment of the population rather than the population as a whole. Nevertheless, if there is convergence to an identical set of attitudinal and travel measures, two potential positives may be realized: first, if self-selection is not substantial, then the weighted measures may be quite close to being representative of the population as a whole; and second, concerns about biases arising from selection of a specific survey administration method or sampling scheme may be ameliorated (because an identical set of weighted attitudinal and travel measures is being obtained regardless of the survey administration method and/or sampling scheme). This study aims to document the extent to which weighting methods result in convergence of different subsamples to a similar set of attitudinal and travel measures and determine whether these two positives can be realized through typical survey weighting processes.

The remainder of this report is organized as follows. In the next section, the two surveys are described in detail. The third section presents the weighting methods that were implemented for the two surveys. The fourth section presents a detailed analysis of unweighted and weighted distributions on socio-economic, demographic, and attitudinal variables across subsamples in the respective surveys. The fifth section presents a discussion of the implications together with concluding thoughts and directions for future research.

DESCRIPTIONS OF SURVEYS

This section presents an overview of the two surveys used to assess the ability of weighting methods to bring convergence in measures of attitudes, values, and perceptions across survey subsamples that may have been recruited (sampled) differently or administered the same survey through different means.

Transformative Technologies Survey Pilot

In the Fall of 2019, the TOMNET and D-STOP University Transportation Centers, sponsored by the US Department of Transportation, conducted a comprehensive survey of attitudes, perceptions, and values related to new and emerging transportation technologies such as ridehailing services, micromobility, and autonomous vehicles (AVs). The survey is called the TOMNET - D-STOP Transformative Technologies in Transportation (T4) survey. This survey was administered in four metropolitan areas, namely, Phoenix, Austin, Atlanta, and Tampa. A total of 3,465 survey responses were collected from across the four regions in the main survey effort. Complete details about this survey effort are available elsewhere (TOMNET UTC, 2020). The main survey was conducted completely online with respondents recruited almost entirely via e-mail invitations.

Before the main survey, the study team conducted a small-scale pilot survey in the Phoenix area alone to test the efficacy of collecting survey data via different administration methods. The pilot survey was conducted in Fall 2018 and fielded the same questionnaire (a few minor updates were made for the full deployment of the survey in Fall 2019). The pilot survey was administered only in Maricopa County (the Greater Phoenix metropolitan area) and tested two different survey administration methods, namely a paper survey that was physically mailed to home addresses and an online questionnaire that was administered via e-mail invitation. A random address-based sample was purchased from a commercial marketing company for deploying the pilot survey. For the mail recruitment, 2,500 invitations were mailed out. It should be noted that an individual receiving the survey through the mail could opt to respond online rather than through the mail. Among the 2,500 people who received the survey through the postal mail, 126 individuals chose to mail back the survey booklet while 49 respondents completed the survey online. The overall response rate for this method was 7.1 percent.

At the same time, 3,500 invitations were sent via e-mail to a random database of e-mail addresses purchased from the same marketing company. A total of 87 respondents submitted a survey response online in response to the e-mail invitation. All recipients of the survey invitation (whether recruited via mail or e-mail) were informed that the first 100 respondents would receive a $10 gift card; appropriate care was exercised to ensure that mail respondents were not disadvantaged in qualifying for the gift card. Because this was a pilot survey, the sample size is small. This presented some challenges that are discussed later in the report; however, it afforded the ability to compare subsamples that responded online versus paper.

COVID Future Survey

In March of 2020, most of the world was coming to grips with the severity of the COVID-19 pandemic and changing the way in which people conducted business and led their lives. To measure and track changes in behaviors over time, a COVID Future survey project was launched in April of 2020. Complete information about the COVID Future survey project may be found at https://covidfuture.org/. The first phase of the data collection is referred to as Wave 1A of the COVID Future project. The survey included questions about work from home, travel and mode use patterns, school from home, shopping and dining, online orders and deliveries, attitudes and perceptions towards the virus and control measures as well as broader lifestyle attributes, and socio-economic and demographic characteristics. In addition, respondents were asked to answer questions on how they expect to conduct business, travel, engage in work and school activities, and shop and dine in a post-pandemic future when the virus is no longer deemed a threat.

Wave 1A of the survey was administered in April 2020. Respondents were largely recruited via a network of contacts, e-mail announcements to professional and social networks, and social media. Thus, the Wave 1A sample may largely be considered a convenience sample. A total of 1,110 responses were collected in Wave 1A. As the survey effort evolved and the pandemic appeared to linger for an extended period, the project team launched into Wave 1B of the survey. The survey instrument was enhanced based on analysis of the Wave 1A data, although care was exercised in updating the survey instrument to ensure that data from Wave 1A and Wave 1B could be pooled. To render the sample from Wave 1B more representative than the sample from Wave 1A, the project invested in two main sampling methods for Wave 1B, even though convenience sample responses were still collected during Wave 1B (yielding a final convenience sample of 1,575 responses). First, a random e-mail address-based invitation was sent to hundreds of thousands of e-mail addresses purchased from a commercial marketing company. Second, the project utilized the services of an online survey panel maintained by a professional online survey platform. The survey company was provided quotas with respect to meeting numbers for key attributes of interest, including age, race, geography, and income.

The first release of Wave 1B data covers responses received between June 19 and October 14, 2020. In this period, Wave 1B yielded 7,613 responses. The full sample of the first wave of the COVID Future survey project comprises both Waves 1A and 1B and represents a combination of subsamples obtained through three distinct sampling and recruitment methods: convenience sample (Wave 1A and Wave 1B), e-mail invitation sample (Wave 1B), and professional online panel (Wave 1B). Figure 1 shows the composition of the Wave 1 (A and B) sample of the COVID Future survey (Chauhan, et al., 2021). There are 8,723 complete records between Waves 1A and 1B. The survey implemented robust reminder protocols and a modest completion incentive (every 20th respondent among the first 4,000 respondents received a $10 gift card) to boost response rates.

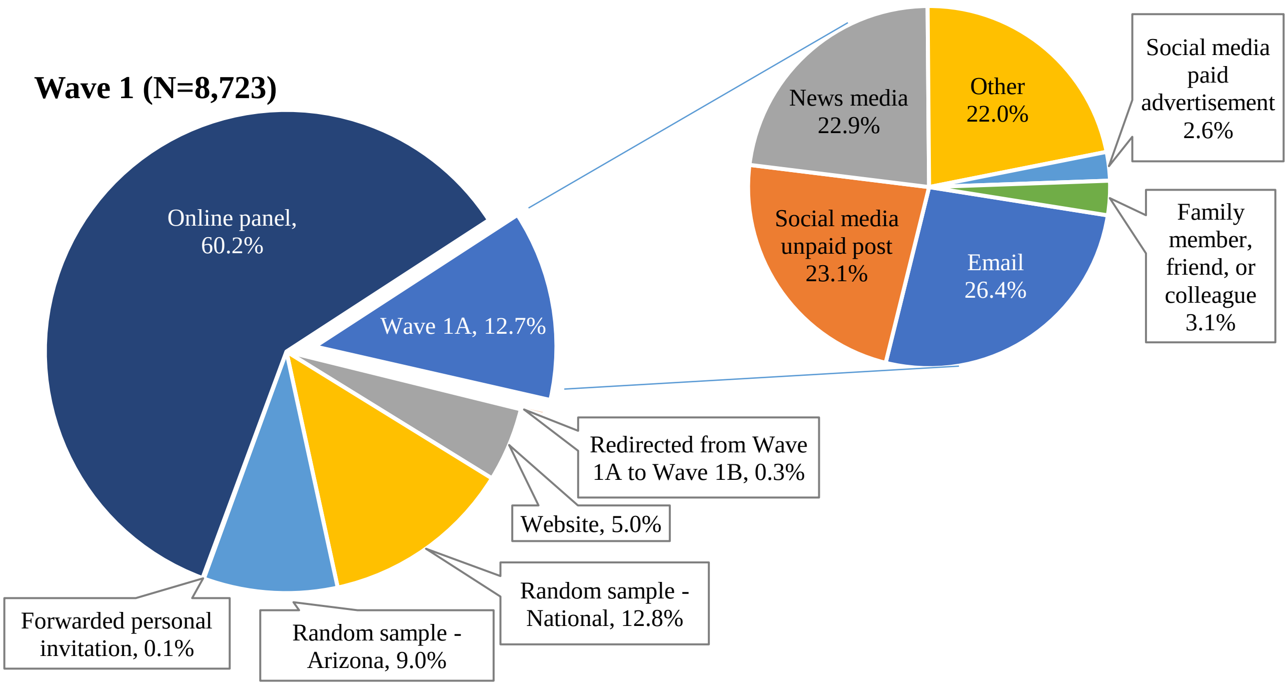

Figure 1 Record Source Distribution for Wave 1 of the COVID Future Panel Study (Chauhan, et al., 2021)

METHODOLOGY TO WEIGHT SURVEY SUBSAMPLES

This section presents the methodologies employed to weight the subsamples in the respective surveys to be representative of the population from which they are drawn. The T4 survey pilot includes two subsamples corresponding to two different administration methods - paper and online. The Wave 1 COVID Future survey sample consists of three subsamples based on sampling/recruitment method - convenience sample, professional online panel, and direct e-mail recruited sample.

Naive Weighting Methodology for Transformative Technologies Survey Pilot

The T4 survey pilot was a small-scale survey effort that yielded a modest sample in the Greater Phoenix metropolitan area. The paper survey subsample included 126 individuals while the online respondent subsample comprised 136 individuals. Thus the total size of the T4 survey pilot respondent sample was only 262 respondents. For comparing weighted subsamples, each subsample needs to be weighted separately and independently to be representative of the population. With respondent subsample sizes of 136 and 126 individuals, it is extremely difficult to implement traditional weighting schemes that employ iterative proportional fitting (IPF) methods.

To overcome the limitation of a small pilot with even smaller subsamples (defined by survey instrument type), this study employed a naive iterative weighting method for developing weights for the T4 Survey pilot. This naive approach essentially cycles through a multitude of control variables one-by-one in a sequential manner, adjusting the weights on records through a series of steps. This naive procedure is not as robust as a full-fledged iterative proportional fitting (IPF) algorithm, but nevertheless returns weights that result in a weighted sample that replicates the census along the control variables of interest fairly well. In the interest of efficiency, only 100 full iterations of the naïve weighting scheme were conducted for the T4 pilot survey sample.

Iterative Proportional Weighting Methodology for COVID Future Survey

The COVID Future survey sample (subsamples) were weighted using more traditional robust statistical methods founded upon the principles of iterative proportional fitting (IPF). Over the past decade, Ye et al. (2009) and Konduri et al. (2016) have developed an enhanced weighting procedure with a view to generate robust synthetic populations for activity based modeling such that the synthetic populations match census distributions with respect to *both* household and person level control variables. The procedures have been formalized in a software package called PopGen. This package computes weights for sample records such that the weighted sample distributions replicate population-wide census distributions at the level of geographic resolution desired (as small as a block group or traffic analysis zone, for example). The procedure combines the traditional IPF step with a subsequent step called IPU (iterative proportional updating). The IPF step is used to compute cell constraints (in the joint multidimensional matrix) that need to be matched by the weighted sample. The IPF procedure is applied to household-level control variables and person-level control variables, thus generating a set of household-level constraints and a set of person-level constraints. The IPF step is followed by the IPU procedure in which household weights are computed such that IPF-generated constraints are satisfied. The procedure is efficient and thousands of iterations can be run in a very short time. The procedure is found to return a robust set of weights for all sample records such that weighted samples closely replicate census distributions.

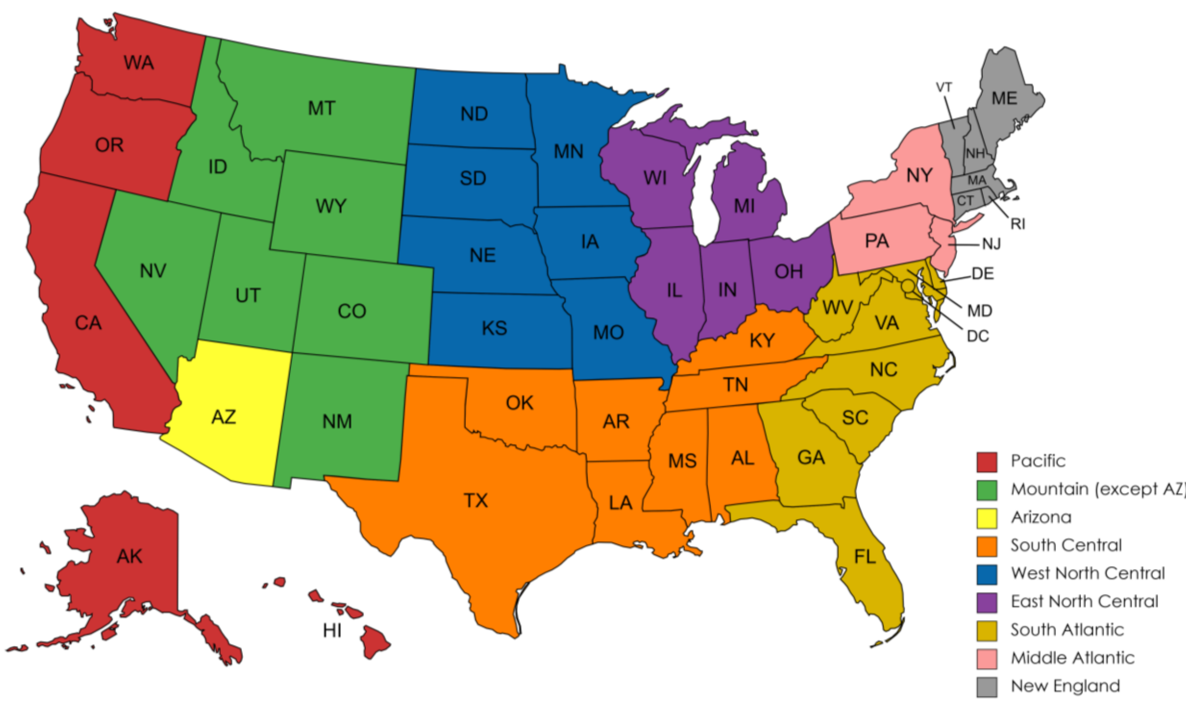

Figure 2 Modified Census Divisions Used for COVID Future Survey Weighting

The COVID Future survey sample is rather large and hence enabled the execution of PopGen for computing weights. Given the national profile of the COVID Future survey sample, weighting of the online panel was done to control for census distributions at the census division level (with some modifications). Figure 2 shows the geographic resolution of the weighting scheme employed for the online panel of Wave 1 of the COVID Future survey. The skewed nature of the convenience sample and the email deployment sample did not allow for such a disaggregated weighting scheme; so those sub-samples were weighted at the census region level (Northeast, Midwest, South, and West). By weighting sample records from various states to replicate population distributions in corresponding census regions and divisions, it was envisioned that the weighted sample as a whole would be able to accurately mirror census distributions for *both* individual regions/divisions as well as the nation.

COMPARISONS OF UNWEIGHTED AND WEIGHTED SAMPLE CHARACTERISTICS AND ATTITUDINAL MEASURES

This section presents the results of the analysis conducted using data sets derived from the two surveys. Because the surveys employed a multitude of survey administration (instrument) methods (in the case of the T4 Survey pilot) or a variety of sampling methods (in the case of the COVID Future survey), these two surveys have provided a powerful and unique opportunity to assess how weighting helps measure attitudes and values of the population of interest. Results are presented for the T4 Survey pilot first, while results for the COVID Future survey are presented second.

Transformative Technologies Survey Pilot - Survey Administration (Instrument) Method

Table 1 provides unweighted and weighted socio-economic and demographic characteristics of the pilot survey subsamples. As expected, paper and online samples differ considerably with respect to socio-economic and demographic variables prior to weighting. The subsample that responded via paper is skewed toward female and older respondents, as expected. Younger respondents, who tend to be more comfortable with technology, are represented to a greater degree in the online survey subsample. The paper respondent subsample also depicts a lower level of educational attainment, lower levels of employment (more retirees), and a greater proportion of Whites and individuals born in the US. Those responding via paper are also less likely to report having children and more likely to be of smaller household sizes. The income distribution shows that paper subsample has a higher representation of lower income individuals. The paper subsample also has a higher prevalence of individuals who own the home they occupy.

The weighting procedure applied to each subsample aims to adjust the subsample (compute weights for each record) such that the weighted subsamples depict sample level distributions that mirror the census distributions (rightmost column). Even the naive weighting methodology that was applied in view of the small sample sizes of the pilot survey was able to produce weighted subsamples that mirror the general population with respect to univariate distributions on socio-economic and demographic variables. For every socio-economic and demographic variable listed in the table, the weighted distributions in both subsamples are found to replicate those of Maricopa County. Thus, it can be said with confidence that the survey subsamples have been weighted successfully to be representative of the general population of the region, *and* the socio-economic and demographic distributions have essentially "converged" to be identical between the subsamples (this is a necessary condition for each subsample to be representative of the population).

Table 2 presents a comparison for attitudes and values in the dataset. The T4 survey included nearly 100 attitudinal statements, covering a variety of topical areas of interest. In the interest of brevity, only a random subset of attitudinal statements that would fit on one page are presented here (this is still a fairly large number of attitudinal measures). Each entry represents an average attitudinal metric. All statements were associated with a Likert scale that went from strongly disagree to strongly agree. These were numerically scored on a scale of -2 to +2 with neutral represented by zero. Average scores were computed for each subsample and compared using a t-statistic to determine whether the averages are significantly different from one another.

Table 1 Unweighted and Weighted Socio-economic and Demographic Characteristics of T4 Survey Subsamples

	Unweighted		Weighted		Maricopa County Census
	Paper (N=126)	Online (N=136)	Paper (N=90)	Online (N=106)	
Gender [a]					
Male	36.0%	44.8%	48.9%	48.6%	48.9%
Female	64.0%	55.2%	51.1%	51.4%	51.1%
Age [a] ***					
18 to 29 years	5.7%	13.6%	21.1%	22.2%	22.4%
30 to 44 years	18.9%	27.3%	26.7%	26.9%	26.8%
45 to 59 years	17.2%	27.3%	25.6%	25.0%	24.9%
60 years and over	58.2%	31.8%	26.7%	25.9%	25.9%
Education [a]					
High school graduate or less	18.3%	9.6%	36.7%	37.0%	37.2%
Some college or associate degree	24.6%	33.1%	34.4%	34.3%	34.2%
Bachelor's degree or higher	57.1%	57.4%	28.9%	28.7%	28.6%
Employment [a]					
Employed	58.3%	69.1%	61.1%	60.7%	60.5%
Not employed	41.7%	30.9%	38.9%	39.3%	39.5%
Place of birth [a]					
Born in the U.S.	90.5%	86.0%	85.6%	85.0%	85.2%
Not born in the U.S.	9.5%	14.0%	14.4%	15.0%	14.8%
Race [a] **					
White	89.7%	76.5%	77.8%	77.6%	77.6%
Non-white	10.3%	23.5%	22.2%	22.4%	22.4%
Hispanic status [a] **					
Hispanic	9.7%	19.4%	31.1%	30.8%	30.6%
Not Hispanic	90.3%	80.6%	68.9%	69.2%	69.4%
Household income [a]					
Low Income - Less than $49,999	38.8%	25.2%	34.4%	35.5%	35.1%
Medium Income - $50,000 to $99,999	32.2%	40.7%	33.3%	32.7%	32.8%
High Income - More than $100,000	28.9%	34.1%	32.2%	31.8%	32.1%
Presence of children in the household [a] **					
Not Present	78.6%	66.9%	62.2%	62.6%	62.4%
Present	21.4%	33.1%	37.8%	37.4%	37.6%
Household vehicles [a]					
No vehicles	4.8%	2.9%	4.4%	4.7%	4.6%
1 vehicle	27.8%	25.0%	26.4%	26.4%	26.5%
2 vehicles	38.9%	39.7%	40.7%	40.6%	40.6%
3 vehicles or more	28.6%	32.4%	28.6%	28.3%	28.3%
Household size [a] **					
Household Size 1	32.3%	20.5%	14.4%	15.0%	14.5%
Household Size 2	40.3%	34.6%	33.3%	32.7%	32.8%
Household Size 3	27.4%	44.9%	52.2%	52.3%	52.7%
Tenure [a] **					
Owner Occupied	85.7%	70.6%	62.2%	61.7%	61.7%
Not Owner Occupied	14.3%	29.4%	37.8%	38.3%	38.3%

Note. [a] Variable controlled in the weighting scheme.
p-value of Chi-Square test computed for the unweighted distributions *p<.05, **p<.01, ***p<.001

Table 2 Attitudes and Perceptions for Unweighted and Weighted Subsamples of T4 Survey

Category	Statement	Unweighted			Weighted		
		Paper (N=125)	Online (N=136)	t-stat	Paper (N=90)	Online (N=106)	t-stat
Activity engagement	I prefer to shop in a store in person rather than online.	0.67	0.24	3.429***	0.6	0.31	1.832
Environment	I am committed to using a less polluting means of transportation (e.g. walking, biking, and public transit) as much as possible.	0.01	0.25	-1.977*	-0.23	0.25	-3.279***
	I am committed to an environmentally friendly lifestyle.	0.86	0.9	-0.529	0.64	0.84	-2.035*
Privacy	I would be fine with renting out my car to people I don't know.	-1.59	-1.25	-3.241***	-1.49	-1	-3.298***
	I feel uncomfortable around people I do not know.	-0.33	-0.19	-1.146	-0.36	0.15	-3.495***
Residential location	I like the idea of having stores, restaurants, and offices mixed among homes in my neighborhood.	0.6	0.91	-2.402*	0.24	0.89	-4.3***
	I prefer to live in a spacious home, even if it is farther from public transportation or many places I go.	0.12	0.28	-1.259	0.52	0.45	0.459
	I prefer to live close to transit even if it means I'll have a smaller home and live in a more densely populated area.	-0.54	-0.53	-0.048	-1.12	-0.42	-4.891***
Technology	Learning how to use new technologies is often frustrating for me.	0.36	-0.6	7.134***	0.03	-0.83	5.384***
	I like to be among the first people to have the latest technology.	-0.22	0.43	-5.341***	-0.2	0.58	-5.645***
	Having internet connectivity everywhere I go is important to me.	0.41	0.88	-3.509***	0.22	1.04	-5.738***
	Sharing my personal information or location via internet-enabled devices concerns me a lot.	1.04	0.7	2.805**	1.01	0.78	1.651
Time-use	I try to make good use of the time I spend traveling.	0.77	1.1	-3.666***	0.93	1.04	-1.276
	I am too busy to do many of the things I like to do.	-0.14	0.1	-1.821	0.04	0.51	-3.212**
	I prefer to do one thing at a time.	0.06	-0.11	1.319	0.33	-0.18	3.844***
	Having to wait can be a useful pause in a busy day.	0.25	0.32	-0.607	0.2	0.21	-0.069
	The time I spend going to places provides a useful transition between activities.	0.36	0.33	0.258	0.57	0.53	0.313
Transportation	The functionality of a car is more important than its brand.	1.03	1.23	-1.887	1	1.03	-0.208

Note. *p<.05, **p<.01, ***p<.001

In comparing the unweighted subsamples, it is found that they significantly differ from one another for nine of the 18 attitudinal statements included in Table 2. There are two additional attitudinal statements for which t-statistics are -1.821 and -1.887. If those two are added to the list of attitudinal statements that significantly differ between the two survey subsamples, then 11 of the 18 statements essentially have statistically significant different average attitudinal ratings. The same comparison is done for the weighted subsamples, both of which are virtually identical to one another with respect to a complete host of socio-economic and demographic variables. Despite being weighted, it is found that the subsamples differ very substantially with respect to average ratings on attitudinal statements. In fact, the number of attitudinal statements for which average ratings are significantly different remains almost the same (although the set of 11 statements that differ for the weighted subsamples are not exactly identical to those for the unweighted subsamples). In several instances, the average ratings for the weighted subsamples differ very substantially from the average ratings for the unweighted subsamples. This implies that weighting can strongly influence the attitudinal metrics (quantitative measures of central tendency) that an analyst derives from a dataset. In other words, the average behavioral and attitudinal metrics derived from a dataset are dependent on the weighting scheme and configuration (choice of control variables, for example). Even after weighting on several dimensions, virtually no improvement has been obtained in getting the different subsamples to reflect similar attitudinal profiles. In some cases, the average attitudinal ratings actually diverge (although there are a few instances where the attitudinal ratings do get closer together). In examining the set of attitudinal statements for which divergence in scores is observed (following the weighting process), it is found that there is no systematic discernible pattern by which this is happening. Future research efforts should strive to unravel the connection as that may help shed light on why weighted samples are not converging when it comes to attitudinal statements. The bottom line is that weighting to replicate socio-economic and demographic variable distributions in the population provides no benefit to capturing true population-wide attitudes.

COVID Future Survey - Sampling Methodology

Table 3 presents unweighted and weighted socio-economic and demographic characteristics for COVID Future survey subsamples - convenience, professional online survey panel, and direct e-mail. In addition, the table shows the distributions for the entire Wave 1 sample (which is a summation of the three individual subsamples). As expected, the unweighted subsamples differ from one another quite substantially in terms of socio-economic and demographic characteristics. For example, the convenience sample exhibits a higher level of educational attainment relative to the direct e-mail and online survey panel. Those responding to the direct e-mail invitation tend to be considerably older than those in the convenience sample and the online survey panel. For the most part, none of the subsamples replicates the population distributions; the same applies to the overall Wave 1 sample as well.

Due to certain sample size and data constraints, the weighting process could not control for all variables shown in the table. While the weighting process did control for a host of socio-economic and demographic variables, it did not control for employment status, race, household size, and home ownership. As a result, the weighted statistics match population distributions very closely on all of the controlled variables, but not necessarily all that well on the uncontrolled variables. In fact, for all four uncontrolled variables, the weighted distributions differ across the survey subsamples and do not mirror national statistics as closely as one would typically like to see in a weighted sample.

Table 3 Unweighted and Weighted Socio-economic and Demographic Characteristics of COVID Future Survey Subsamples

	Unweighted				Weighted				
	Convenience sample (N=1,575)	Direct Email (N=1,898)	Online Panel (N=5,250)	Wave 1 (N=8,723)	Convenience sample (N=1,575)	Direct Email (N=1,898)	Online Panel (N=5,250)	Wave 1 (N=8,723)	Adults in the United States 2019 ACS
Gender [a]									
Male	40.2%	42.1%	34.9%	37.5%	48.7%	48.7%	48.7%	48.7%	48.7%
Female	59.8%	57.9%	65.1%	62.5%	51.3%	51.3%	51.3%	51.3%	51.3%
Age [a] *(convenience vs email vs panel* $\chi 2 = 7.347$, $p = 0.299$*)* [c]									
18-29	17.0%	3.6%	20.9%	16.4%	24.1%	20.9%	21.0%	21.5%	21.0%
30-44	35.3%	12.3%	28.8%	26.4%	24.3%	25.3%	25.2%	25.1%	25.2%
45-59	29.7%	27.3%	21.7%	24.4%	23.3%	24.4%	24.4%	24.2%	24.4%
60 years and above	18.0%	56.7%	28.6%	32.8%	28.3%	29.4%	29.4%	29.2%	29.4%
Education [a]									
High school or less	1.3%	7.3%	23.9%	16.2%	38.9%	39.0%	39.0%	39.0%	39.0%
Some college	10.7%	29.7%	34.6%	29.2%	30.4%	30.4%	30.4%	30.4%	30.4%
Bachelor or higher	87.9%	63.0%	41.5%	54.5%	30.7%	30.6%	30.6%	30.7%	30.6%
Employment (convenience vs email vs panel $\chi 2 = 148.033$, $p = 0.000$*)* [c]									
Employed	89.1%	55.5%	57.2%	62.6%	75.9%	63.3%	59.0%	63.0%	62.0%
Non-employed	10.9%	44.5%	42.8%	37.4%	24.1%	36.7%	41.0%	37.0%	38.0%
Race (convenience vs email vs panel $\chi 2 = 46.494$, $p = 0.000$*)* [c]									
White	86.9%	88.6%	77.0%	81.3%	81.5%	84.6%	77.5%	79.8%	73.6%
Non-white	13.1%	11.4%	23.0%	18.7%	18.5%	15.4%	22.5%	20.2%	26.4%
Hispanic status [a]									
Hispanic	6.5%	7.5%	12.7%	10.4%	16.4%	16.4%	16.4%	16.4%	16.4%
Non-Hispanic	93.5%	92.5%	87.3%	89.6%	83.6%	83.6%	83.6%	83.6%	83.6%
Household income [a]									
Less than $35,000	7.6%	13.1%	33.1%	24.1%	18.8%	18.9%	18.9%	18.9%	18.9%
$35,000 to $99,999	31.8%	43.1%	45.4%	42.5%	41.1%	41.1%	41.1%	41.1%	41.1%
$100,000 or more	60.6%	43.8%	21.5%	33.4%	40.1%	40.0%	40.0%	40.0%	40.0%
Presence of children in the household [a]									
Not present	73.9%	79.0%	70.0%	72.7%	67.1%	67.1%	67.1%	67.1%	67.1%
Present	26.1%	21.0%	30.0%	27.3%	32.9%	32.9%	32.9%	32.9%	32.9%
Household vehicles [a]									
No vehicles	8.4%	1.6%	8.6%	7.0%	9.3%	9.3%	9.3%	9.3%	9.3%
1 vehicle	31.4%	25.9%	43.0%	37.2%	22.6%	22.6%	22.6%	22.6%	22.6%
2 vehicles	42.2%	44.7%	34.9%	38.3%	37.4%	37.4%	37.4%	37.4%	37.4%
3 vehicles or more	18.1%	27.8%	13.5%	17.5%	30.7%	30.7%	30.7%	30.7%	30.7%
Disability [b]									
No disability	n/a	81.5%	74.9%	n/a	n/a	85.0%	85.0%	n/a	85.0%
At least one disability	n/a	18.5%	25.1%	n/a	n/a	15.0%	15.0%	n/a	15.0%
Household size (convenience vs email vs panel $\chi 2 = 128.24$, $p = 0.000$*)* [c]									
Household 1	19.4%	17.8%	18.8%	18.7%	15.7%	10.7%	10.9%	11.7%	16.7%
Household 2	43.4%	46.4%	33.8%	38.3%	39.7%	38.6%	31.3%	34.4%	32.9%
Household 3	14.3%	14.5%	19.9%	17.7%	13.0%	18.5%	22.3%	19.8%	18.7%
Household 4+	22.8%	21.3%	27.5%	25.3%	31.6%	32.2%	35.5%	34.1%	31.7%
Tenure (convenience vs email vs panel $\chi 2 = 2.311$, $p = 0.315$*)* [c]									
Owner occupied	62.1%	82.9%	57.4%	63.8%	63.8%	63.3%	65.1%	64.5%	65.7%
Not owner occupied	37.9%	17.1%	42.6%	36.2%	36.2%	36.7%	34.9%	35.5%	34.3%

Note. [a] Variable controlled in the weighting scheme of all samples. [b] Variable was used as a control variable for the direct email and online panel samples only. [c] ANOVA results for the weighted samples.

Table 4 presents the comparison of unweighted and weighted subsamples with respect to average attitudinal ratings. A total of 20 attitudinal statements are presented in the table (there are more attitudinal statements in the survey dataset, but only 20 are presented here for the sake of brevity and in the interest of fitting the table on one page). As expected, the unweighted survey subsamples differ from one another with respect to average attitudinal ratings. In fact, a one-way analysis of variance shows that the unweighted subsamples differ from one another on all 20 of the attitudinal variables. The F-statistic provided in the last column of each section of the table serves as a measure of statistical significance of the difference between average attitudinal ratings across survey subsamples.

Similar to the case of the T4 Survey pilot, weighting the samples to replicate census distributions on a host of socio-economic and demographic variables does little to bring about consistency in average attitudinal metrics. Only two of the 20 attitudinal statements now show an F-statistic that is statistically insignificant at the 0.05 level (both are marked). One noteworthy finding, however, is that the magnitude of the F-statistic diminishes in value for virtually all attitudinal statements (except for one). For 17 of the 20 statements, it is found that the F-statistic becomes smaller in magnitude. From a qualitative standpoint, this finding appears to suggest that the attitudinal measures did come closer to each other thanks to the weighting process. Thus, in the case of the COVID Future survey, it can be said (qualitatively) that the weighting process helped to some degree; however, significant differences remain - and obtaining true population-wide metrics for the attitudinal statements in the survey proves to be elusive even after the application of a rigorous state-of-the-art survey weighting methodology. The findings suggest that measuring attitudes may be an exercise in futility; despite a very comprehensive survey design, the adoption of multiple survey administration and sampling methods, and the application of a rigorous weighting process, the analyst is only very modestly closer to understanding the true population-wide attitudinal profile.

Table 4 Measures of Attitudes and Perceptions for Unweighted and Weighted Subsamples of COVID Future Survey

Category	Statement	Unweighted				Weighted			
		Convenience Sample	Direct email	Online panel	F statistic	Convenience sample	Direct email	Online panel	F statistic
Covid-related Attitudes	I am generally satisfied with my life.	1.08	0.91	0.67	99.50	0.77	0.75	0.8	1.42†
	If I catch the coronavirus, I am concerned that I will have a severe reaction.	0.43	0.58	0.61	12.21	0.22	0.52	0.52	33.55
	I am concerned that friends or family members will have a severe reaction to the coronavirus if they catch it.	1.26	0.9	0.97	60.43	1.11	0.94	0.93	16.78
	I feel that my community is well prepared for disasters.	-0.28	-0.16	-0.02	37.56	-0.02	-0.26	0.08	61.00
	Everyone should just stay home as much as possible until the coronavirus has subsided.	1.31	0.79	1.06	100.23	0.96	0.69	1.03	53.26
	Society is overreacting to the coronavirus.	-1.31	-0.74	-0.72	127.76	-0.77	-0.58	-0.67	7.51
	Shutting down businesses to prevent the spread of coronavirus is not worth the economic damage that will result.	-1.06	-0.33	-0.39	176.34	-0.58	-0.25	-0.32	26.84
	My friends and family expect me to stay at home until the coronavirus subsides.	0.91	0.22	0.39	167.74	0.58	0.19	0.36	40.00
Shopping and Dining	Even if I do not end up buying anything, I still enjoy going to stores and browsing.	0.07	0.25	0.58	122.94	0.22	0.44	0.59	54.85
	In-person shopping is usually a chore for me.	0.07	-0.06	-0.09	9.80	-0.03	-0.03	-0.15	7.89
Working from Home	I enjoy the social interaction found at a conventional workplace.	0.91	0.84	0.57	100.27	0.81	0.92	0.61	80.07
	It is hard to get motivated to work away from the main office.	-0.31	-0.2	-0.19	7.59	-0.1	-0.02	-0.17	10.59
	I like working from home.	0.84	0.45	0.53	64.31	0.48	0.33	0.44	8.09
Attitudes towards Technology	Learning how to use new technologies is often frustrating.	-0.55	0.02	-0.09	110.58	-0.16	-0.15	-0.15	0.06†
	Video calling is a good alternative to in-person business meetings.	0.81	0.65	0.87	37.69	0.83	0.72	0.87	15.63
	Video calling is a good alternative to visiting friends and family.	-0.36	-0.02	0.45	296.86	-0.26	0.04	0.42	178.01
	Online learning is a good alternative to high school- and college-level classroom instruction.	-0.34	-0.21	0.37	291.53	-0.31	-0.09	0.28	152.01
Residential Preferences	Apartment living doesn't provide enough privacy	0.31	0.6	0.52	32.67	0.55	0.63	0.51	6.41
	Having shops and services within walking distance of my home is important to me.	0.99	0.28	0.63	184.14	0.56	0.42	0.59	14.65
	I like to have a yard at home.	1.19	1.44	1.22	48.43	1.4	1.24	1.27	13.55

Note. † difference is not statistically significant.

CONCLUSIONS AND POLICY IMPLICATIONS

Surveys remain a major source of behavioral information for the transportation planning community. Traditional travel surveys are now being enhanced to include several attitudinal statements or questions to obtain more insights into human decision processes that may be affected by such attributes. As the transportation industry experiences disruptions due to rapidly evolving technology and the advent of new mobility services and options, the level of interest in understanding attitudes, values, perceptions, and preferences is only growing in intensity.

Survey samples are typically weighted to match population-wide census distributions along a number of socio-economic and demographic dimensions to ensure that the weighted samples are representative of the population of interest. The weighted sample characteristics are then used to understand behaviors, measure attitudes and perceptions, and draw inferences about people's preferences and proclivities. However, to what extent does weighting for socio-economic and demographic variables also correct for non-representativeness in attitudes and values? Just because socio-economic and demographic characteristics match census figures, does that imply that the attitudinal measures are also representative of the population? An issue that arises in the context of surveys is the choice of sampling method and administration (survey instrument) method. If a survey adopts one modality or sampling strategy versus another, is it possible to overcome the limitations of a specific survey methodology through survey weighting methods? Does survey weighting compensate for limitations arising from non-response, sampling deficiencies, and lack of multiple survey administration channels?

To answer these questions, this study utilizes two surveys conducted in the very recent past. One survey offers the ability to assess a paper-based instrument versus an online survey instrument. The second survey offers the ability to assess and compare a convenience sample, a professional online survey panel, and an e-mail-based respondent sample. Each subsample is weighted to be representative of the population on a host of socio-economic and demographic variables. The analysis in this study then turns to comparing attitudinal measures across survey subsamples. It is found that, even after weighting subsamples to replicate population distributions (and hence, each other) on socio-economic characteristics, the weighted subsamples do not resemble one another with respect to attitudinal measures. This finding holds true for both surveys, regardless of whether the comparison is based on survey administration method or survey sampling method. In the case of the survey with subsamples defined by sampling method, the attitudinal variables do get closer to one another after weighting the subsamples (from a qualitative standpoint), but remain significantly different from one another. In the case of the survey with subsamples defined by survey instrument type, the attitudinal metrics do not converge to identical values; in fact, differences for several attitudinal variables are amplified across survey subsamples following the weighting process.

The bottom line is that, based on the findings of this study, it appears that the measurement of true population attitudes and values is an exercise in futility. There is no census data on attitudes and values, and hence it is impossible to control for such variables in survey weighting processes. Survey samples can only be weighted based on a host of socio-economic and demographic variables. But individual attitudes, values, and perceptions tend to be so random, idiosyncratic, and individual-specific that merely correcting for biases on socio-economic dimensions do not sufficiently account for biases and variations in personal attitudes and values that may arise by virtue of the survey methodology (instrument type or sampling approach) adopted. Individuals who respond to travel surveys are likely to be a self-selected group to begin with. Even in the case of professional online survey panels, they are likely to be a self-selected group of professional survey takers. And the adoption of a specific survey instrument modality or sampling strategy will further introduce biases as any specific survey approach is likely to favor or be more compatible with the proclivities of specific subgroups of the population.

The results of this research lead to the following conclusions and recommendations. First, using descriptive statistics (means, standard deviations, median values) of attitudes and values for weighted survey samples is likely to be of limited value in drawing population-wide inferences about attitudes and behaviors (which are critical to formulating plans and policies). Second, to facilitate the weighting of survey samples so that there is any hope of obtaining inferences about attitudes and values that are potentially reflective of actual population characteristics, it would be helpful for very large-scale surveys (e.g., American Time Use Survey) or even the decennial census or American Community Survey to incorporate a host of attitudinal questions. Third, it is best to draw inferences about attitudes and their effects on behaviors through rigorous statistical and econometric modeling efforts. As sample biases are of little consequence in the estimation of model coefficients, it is entirely appropriate to draw inferences based on estimations of statistical and econometric models that explicitly incorporate attitudinal variables. In summary, it is not recommended to trust descriptive measures of attitudes, opinions, and perceptions in decision-making.

Future research efforts should aim to explore the impacts of alternative weighting schemes, conduct similar analyses for other survey data sets, and further assess whether the decrease in F-statistics found in the case of the COVID Future survey may offer promising directions for measuring attitudes, behaviors, and values through weighting processes.

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