A Before-After Intervention Experiment and Survey

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16. Abstract

In this project, we first develop a strong theoretical model accompanied by data collection to test some of its aspects for behavioral change research. Data collection shifted from the originally planned public transportation intervention to the examination of COVID-19 impacts on the life of Los Angeles Metropolitan area residents. In terms of substantive findings, we verified that in this region as in other parts of the US people experienced loss of jobs, forced relocations, and major changes in working and studying. In terms of the attitude-behavior relationship, we also confirmed the existence of more diversity in attitudinal groups of people with respect to their position towards the private automobile and found that these attitudes are strongly correlated with the use of different modes. The survey design and conceptual model form the foundation for subsequent data collection and analysis based on the pilot examples of this project. A third pilot study within this project is the design of a smartphone application. Guidelines for survey design are provided in this report with a description of an ongoing research effort at UCSB that continues beyond the project reported here.

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Contents

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The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

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Disclosure

Acknowledgements

Abstract

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A Before-After Intervention Experiment and Survey

Executive Summary

In this project, we first develop a strong theoretical model accompanied by data collection to test some of its aspects for behavioral change research. The behavioral determinants in this conceptual formulation are extracted from research in social psychology and applications in travel behavior. These include behavioral intentions (underlined by attitudes, social factors, and affect), habit, and context/facilitating conditions. This model was then used to design a survey customized to the newly opening Crenshaw/LAX metro line that did not proceed as originally planned due to the upheaval and major disruption of COVID-19. This same conceptual model was then used for a COVID-19 customized survey to collect data about the impact of COVID-19 and to test strategically selected correlations between attitudes and mode choice using behavioral clusters.

The COVID-19 survey asks respondents about their work, school, and travel behavior before and during the COVID-19 restrictions. There are also a few questions about people's predictions for how their work behavior might change once restrictions are lifted. For employment, they are asked about employment status, number of workdays, how often they work from home, and how often they participate in online meetings. In travel behavior, respondents are asked what travel modes they use to commute, then they are asked to estimate the distance and time from their homes to work/school by each mode. Everyone, regardless of work/school status, is asked what means of transportation they use for all their trips. They are then asked how many trips they estimate making in a typical week by each of those modes. Respondents were asked to provide the city they live in, ZIP code, household income, gender, and age. A unique aspect of this survey is the questions about whether people moved because of COVID-19. Many people changed home locations during this pandemic, either temporarily or permanently. Some moved in with friends or family to get their social needs met, others were obligated to move to take care of family members, or to separate households when some members might be exposed to COVID-19. Data analysis of this survey and in terms of the attitude-behavior relationship, we also confirmed the existence of more diversity in attitudinal groups of people with respect to their position towards the private automobile and found that these attitudes are strongly correlated with the use of different modes. The survey design and conceptual model form the foundation for subsequent data collection and analysis based on the pilot examples of this project.

During this study a pilot experiment was also completed on the design of a smartphone application. Guidelines for survey design, survey contents, trade offs among different options, and coding options and testing. This pilots is part of an ongoing research effort at UCSB that continues beyond the project reported here to complement the survey described above and support data collection based on the conceptual behavioral model.

Introduction

The original aim of this project was to survey residents of a specific area of Los Angeles about their daily travel before and after the opening of the LA Metro Crenshaw rail line. However, COVID-19 and the change of plans by the public transportation agency caused a need to modify our original data collection and proposed analysis. As reviewers of the original proposal suggested, the project plan was modified to account for COVID-19. Throughout the period of performance of this project, there was continuous uncertainty about how long the virus would disrupt normal operations, so the plan adapted with time as explained below.

First adaptation: May 2020. To prepare for the potential of business establishments remaining closed through the duration of this project timeline, we designed a survey and collected data about the effects of COVID-19 on the life of people in the study area emphasizing commuting and going to school. We developed a repeated cross-sectional data collection plan. The first cross-section (Wave 1) with funding from this project and the second with UC Santa Barbara funding after the end of this project at approximately May 2022 (Wave 2). Wave 1 data was collected asking people to reflect on their travel behavior before the pandemic, and to report on their current travel behavior during the pandemic. During this time, a detailed theoretical framework was developed for the data collection and analysis according to the original plan. This theoretical framework still guides the final version of the project plan, although the entire conceptual model cannot be tested with the available data.

Second adaptation: Create a smartphone application to collect travel diary data after the Crenshaw line opening. The construction of the Crenshaw line was delayed again due to the virus. This portion of the work is ongoing and will continue beyond the end of this project.

Third adaptation: The Crenshaw line was further delayed. It became clear that the pandemic was not going to subside in time to collect travel diary data that would truly be comparable to data collected after the completion of the rail line because the virus disrupted normal travel patterns so severely. All of Los Angeles was still under restrictions. There would be no chance of collecting "after" data to follow up on the COVID survey during the project time, since restrictions are still in place. A different survey is planned for May 2022. It was decided for this report to conduct detailed analysis of the data collected in May 2020 and illustrate the data analysis methods.

As the world reeled from the effects of the COVID-19 pandemic, anyone who could work from home was doing so. In the wake of the crisis, employers set up systems to allow for easier telecommuting, including video chat software, secure remote computer access, and communication tools like Slack. Universities and K-12 schools set up systems to do all teaching remotely. All this raises questions about how these new systems are going to be utilized during and after the crisis recovery period. Will things just go back to business-as-usual, or will we see people continue to use these systems? Did people see benefits from working from home (e.g., not having to sit in daily commuter traffic, more time with family members, flexible work schedule, healthier work-life balance, etc.)? Moreover, would those benefits outweigh the disadvantages enough that people would continue to telecommute in the future? People may find that some work activities they have been doing face-to-face actually work better remotely. Companies and institutions may also change their internal procedures to allow telework, mobile work, and flexible work schedules. For example, surgeons may find that in many cases it is not necessary to ask recovering post-operation patients to drive to hospitals for a one-hour meeting. Instead, they offer medical support using

telemedicine meetings and decide during those if an in-person meeting would be beneficial. Health care suppliers are already moving to telehealth to enable major changes in the medical system with implications for travel.

The Wave 1 survey conducted examines changes in the following: modes of travel used, employment status, "essential worker" designation, job changes, typical work/school commute travel time and distance, non-commuting travel behavior, perceptions, attitudes, household structure, socio-economic status, and other traits. This includes a retrospective *before* section asking respondents to reflect on their behavior before the pandemic. The *during* section asks about travel behavior of people amid the pandemic, whether people's employment/school status changed, and if they work(ed) from home or took classes from home.

The research process has been documented in this GitHub repository. The data collected in this project are available for other researchers to use on GitHub (see also the data section in this report).

Theoretical Framework

This section reviews the literature informing the conceptual model underlying this project. First is a general discussion of behavioral research and travel behavior research. Then, the conceptual model that forms the framework of this report is presented. The conceptual behavioral model was developed with the intention of testing its effectiveness using the originally planned data collection. The complete descriptions of the validated instruments under consideration to measure each of the constructs in the conceptual model can be found in the Appendix. In the final adaptation of this project plan, a portion of the conceptual model is investigated: Attitudes and Travel Behavior Clusters.

Past Research in Behavior

The behavioral research that underlies the data collection and analysis here is based on past research about theoretical and empirical relationships between attitudes and behavior. There are a few important models on this discussed in detail in the following subsections. Behavior here means the amount of travel a person does in a day, the selection of modes for this travel, and any time and money allocation for travel. There are a few fundamental conceptual models that support other more popular conceptual models, and they are presented first below.

The Knowledge-Attitude-Behavior model suggests that increased knowledge will lead to favorable attitudes, which will in turn lead to favorable changes in behavior (*1*, *2*). Evidence shows there is a moderate relationship between attitudes and behavior, and that the relationship between the two is mediated and moderated by several other variables. Also, it shows that the Attitude-Behavior relationship is not uniformly the same. It varies depending on the type of attitude, characteristics of the attitude (e.g., how long people hold an attitude and how consistent it is over time), and the way of measuring the attitude (*3*).

The Norm Activation Model theorizes that behavior will correspond to personal norms to the extent that someone is aware of the consequences of their behavior and feels some responsibility for those consequences (*4*)

Value-Belief-Norm (VBN) theory states that morality is the basis for intent to perform pro-environmental behavior, however, intent to perform behavior is not the same as actually performing it (*5*). There is validity in this, and the VBN theory is integrated into the conceptual model.

The Theory of Planned Behavior

The Theory of Planned Behavior (TPB) states that people's behavioral **intentions** are what immediately determine their behavioral choices (*6*). These intentions are built from attitudes, subjective norms, and perceived behavioral control. In the TPB, **attitudes** are the internal, personal influences on behavioral intentions. **Subjective norms** are the external influences on intentions from societal expectations, social roles, et cetera. **Perceived behavioral contro**l is an individual's perception of how much control they have over performance of an action. This includes perceptions of the availability of resources and opportunities necessary to perform a given behavior. This is to account for the fact that although someone may have the intention to perform a certain behavior, they may not be able to perform it due to external forces, whether or not those external forces are objectively present. For example, someone might prefer to commute by bus, but the bus line does not stop near their home so they must commute by other means. Perceived behavioral control has an indirect effect on behavior through the behavioral intentions as well as a direct effect on behavior. The indirect effect is present because it is assumed that these perceptions will influence motivation. To reference the previous example, if someone feels that it would be exceedingly difficult to use transit to get to work, then their motivation to do so would diminish. The direct effect represents the actual control someone has over a behavior. In our example, the actual access to a viable bus line would directly affect whether a person can take the bus to work. When measuring perceived behavioral controls, this direct effect will only be significant if an individuals' perceptions of control align accurately with the reality.

Madden *et al.* (*6*) say that the direct effect will only be significant if there are actual things out of a person's control that change the choices available to them, and this assumes that there is some measurement of objective reality as a model input. However, if a person is unaware of available options, then these options will not factor into their choice making process. Whatever objective reality might be, in terms of decision making, someone's understanding of reality is what matters. Including objective reality in the model regardless of an individual's awareness of it will not properly model the decision-making process. To reference the example one final time, if someone is unaware of a viable bus line that stops near their house, then they will perceive this as having no option to commute by bus, so they will not do so.

From the TPB, the project model pulls the concept of "intention" as an influence on behavior, and the concept that attitudes and subjective norms make up intention. There is also influence of the perceived behavioral control, but this influence is modified and updated in a comparable way to what is seen in the modifications made in the Theory of Interpersonal Behavior discussed next.

The Theory of Interpersonal Behavior

The Theory of Interpersonal Behavior (TIB) was originally developed by Charalambos (Harry) Triandis (*7*). It builds upon the TPB, and thus shares many similarities with it. Under both theories, intention is a primary driver of behavior, and both include attitude and social factors as building blocks of intention. In the TIB, attitude is built from beliefs about outcomes and evaluation of outcomes. This is an evaluation of the consequences of actions, which are weighed when considering the intention to perform a given action. The TIB also includes affect as an influence on intention (*8*). Here, **affect** refers to the emotional disposition someone has about the behavior in question (*8*). The concept of the subjective norm from the

TPB is modified in the TIB and called "social factors." **Social factors** consist of social norms, roles, and self-concept. Another important addition made by the TIB is the inclusion of habit as an influence on behavior (*4*). **Habit** refers to repeated behaviors that become increasingly unconscious as they are performed more frequently. The TIB modifies the concept of perceived behavioral control, instead including what they call facilitating conditions as a moderator to behavior. These **facilitating conditions** are conditions that compel or hinder a behavior. They can be external or internal, including conditions like the surrounding environment or difficulty to perform an action.

From the TIB, the conceptual model takes the concepts of habit and affect as direct influence on behavior. It uses the framework of social factors exemplified in the TIB (being built from social norms, roles, and self-concept), and it adds facilitating conditions as a moderator between behavior and the direct influences of intention and habit.
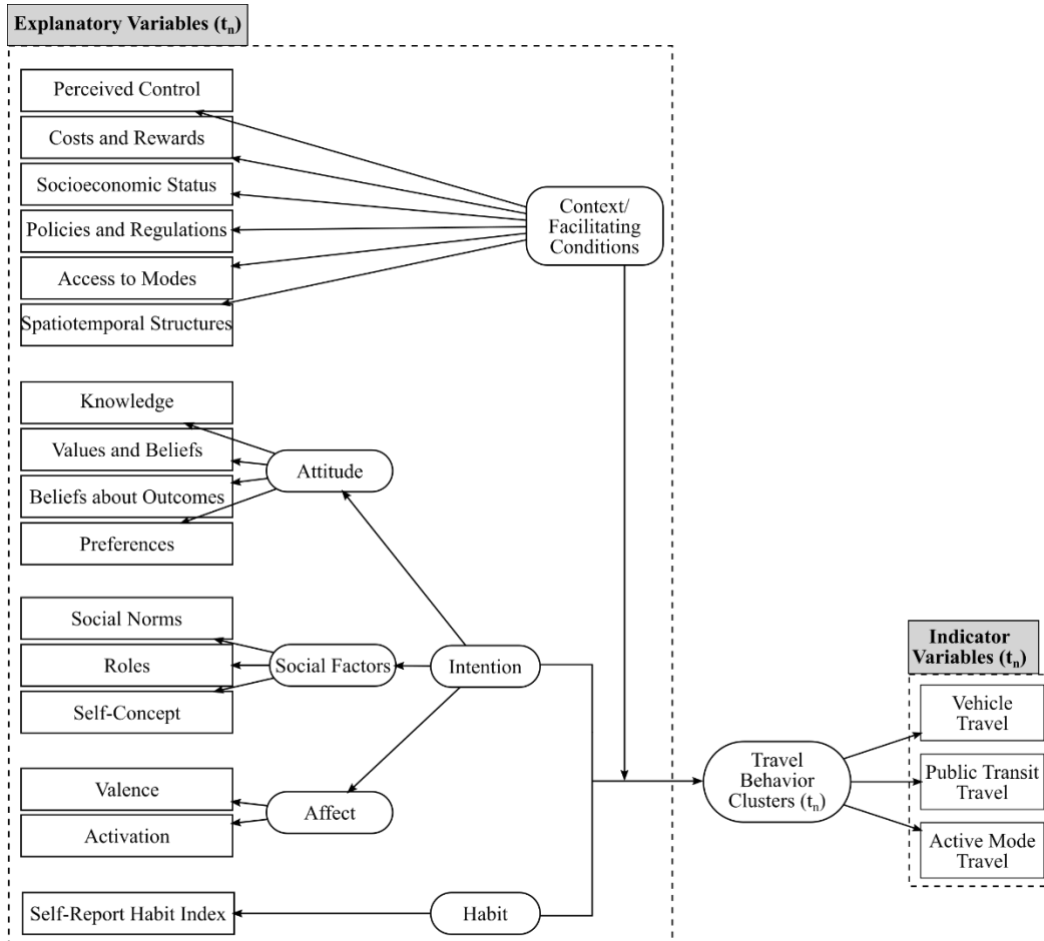
The Attitude-Behavior-Context Model

The Attitude-Behavior-Context (ABC) model theorizes that attitudes are the drivers of behavior, but their influence on behavior is limited by contextual factors (*5*, *9*). As contextual forces become stronger, their influence over behavior increasingly overpower the influence of attitudes. These contextual factors can be inhibitors or compellers, including things like the amount of effort an action takes or the temporal or monetary costs of an action. Stern (*5*) expands upon the ABC model by discussing specific causal variables divided into the categories of habit/routine, attitudinal, personal capabilities, and contextual factors.

The concept of contextual factors is similar to the TIB concept of facilitating conditions, so in this dissertation, the two concepts are combined into one and used as a moderator on the direct influences on behavior. Two variables discussed in Stern (*5*) are added as contextual factors: costs/rewards and policies/regulations.

Conceptual Model Used in this Project

All the theories outlined above are integrated into a conceptual model (Figure 1) for what makes up travel behavior and how attitudes and many other factors combine to lead to specific behaviors. In Figure 1, the rectangular boxes are responses to questions and the rounded rectangles are latent variables (called factors in factor analysis) that are used to explain the variation in responses to the items listed in the rectangles. The factors can be a continuous variable or a discrete variable. For example, the latent item "Travel Behavior Clusters" is a discrete variable with categories that represent different behaviors.

Figure 1 Conceptual model

Intention

As discussed in detail earlier, intention is the concept that people have an internal plan to perform certain actions. In this project, intention is built from three latent items: attitudes, social norms, and affect.

Attitude. Attitude is a person's worldview, and it is built from knowledge, values and beliefs, and preferences. Knowledge is a person's understanding of a situation, and it is a part of attitudes because evidence shows that knowing more about something can affect one's attitude about it (*1*, *2*). Values and beliefs are the core morals of a person. They can include political alignment, religious beliefs, and more general principles someone aligns with like altruism. Preferences are a person's likes and dislikes (i.e., "I hate the bus" or "I love riding my bicycle").

Knowledge. With knowledge, we measure how much people know about the options available to them. As described above, the assumption is that a person's knowledge about the choices they are making will sway their attitude about those choices (*1*, *2*).

Values and beliefs. Travel behavior intention is likely influenced by similar values to those discussed in general pro-environmental value literature. As described by de Groot and Steg (*10*), pro-environmental behavior is generally assumed to be influenced by egoistic, altruistic, and biospheric values. These values influence beliefs, which in turn influence intentions. People with strong egoistic values will primarily consider the personal costs and benefits of pro-environmental behavior. People with strong altruistic values will primarily consider the costs and benefits to other people. People with strong biospheric values will primarily consider the costs and benefits for the planet.

Beliefs about outcomes. This comes from the Theory of Interpersonal Behavior (TIB). It is a person's evaluation of the potential outcomes of their decision. This includes perceptions of safety and convenience. For example, a belief that traveling by bicycle is unsafe, or that traveling by car is comfortable.

Preferences. Preferences are based on what people like and dislike, which should influence attitude. The challenge of measuring preferences is that they will be influenced by the other building blocks of intention (beliefs about outcomes, values, and lack of knowledge about the other options). In Random Utility Models (RUM) preferences are considered to be "revealed" from the choices people make and when some options are not available and hypothetical option data are generated and RUMs estimated based on them called "stated preferences" (*11*–*13*).

Social Factors. Social factors are the external influences on intention. They include the social norms, roles, and self-concept. Social norms are the standard behavioral expectations of the society a person lives in. Roles are the positions a person holds in society and/or the household. A person's behavior will be shaped by the responsibilities and expectations that come with those roles. Self-concept is the way a person sees him or herself. This can be aligned with roles and social norms, but also includes personal views about oneself. For example, someone seeing themselves as an environmentally friendly person, or a moral person.

Affect. Affect is the emotional state of an individual when thinking about a given behavior. This is separate from attitudes, which are built from cognitive processes. Affect toward a behavior could include joy, pleasure, excitement, fear, anger, or anything in between. Russel and Barrett (*14*) define "core affect" as occurring on two dimensions called "valence" and "activation." Valence is described as the spectrum of

pleasure to displeasure or good to bad mood. Activation is a person's sense of their energy level: from sleepy to hyperactive.

Related to affect are also ideas about Quality of Life (QoL) and subjective well-being that received considerable attention in travel behavior research (*15*). We can divide QoL into "objective" measures (e.g., educational attainment, household income, household wealth, and life expectancy) and in subjective well-being. Subjective well-being has three separable components as identified by Diener (2000): life satisfaction (global judgments of one's life), satisfaction with important domains (e.g., work and marital satisfaction), and experiencing positive and negative effects of emotions and moods (e.g., mental health). The COVID-19 pandemic impacted all dimensions of QoL. From past research on the long-run impact of financial crises such as a recession show inhibition of educational attainment, decrease of household income, and lower life expectancy. COVID-19 had the same direct and immediate impacts on QoL with amplified impacts on some segments of population with major differences across cohorts (generations), geographic regions, and groups.

Habit

Habit is an influence on behavior that is separate from intention. A habit is a pattern of behavior characterized by frequent occurrence, a low level of control over the choice of whether to perform the behavior, and a lack of awareness while performing the behavior. Inclusion of habit in the model comes from the TIB. Habits are repeated behaviors that, with time, become increasingly automatic and take up less mental energy to do. Because of the low cognitive load of choosing the habitual behavior, it can be difficult to choose a different behavior that will take more conscious effort, even if the intention to do so is there. According to Triandis (*7*) and Robinson (*8*), the strength of the influence of habit on behavior is determined by the novelty of a behavior, frequency of a behavior being performed, how well the conditions reflect the conditions when a behavior was performed in the past, and state of arousal (heightened state of arousal leads to more dependence on habit).

Context/Facilitating Conditions

The inclusion of context/facilitating conditions as a moderator for habit and intention is influenced by both the ABC model and the TIB. As explained in the descriptions of the ABC model and the TIB, these are conditions that can either hinder or compel behaviors. Stern (*5*) says "Interventions do little or nothing until one of them removes an important barrier to change" (p. 419). These items range from structural conditions (e.g., proximity of a bus stop) to personal conditions (e.g., socioeconomic status). In the model, internal contextual factors include perceived control, costs and rewards, and socioeconomic status. External contextual factors include policies and regulations, access to modes, and spatiotemporal structures. All these conditions mediate whether a person can act in the way that they intend to or are habituated to. The TPB includes restricting factors as perceptions of the individual, while the TIB includes them as objective. Perceptions are important, but there are concrete things like spatiotemporal structure that are objectively present and influential on behavior. However, perceptions about those concrete things are also important (if not more important) than the objective facts.

Spatiotemporal structures are the temporal and spatial constraints to movement in a person's day. These constraints are determined by a person's schedule, which adds certain requirements to a person's day that will limit where they can go and for how long they can do activities. Following Hägerstrand's (*16*) seminal keynote speech that has been the foundation of time geography, constraints are characterized as physical (e.g., speed of movement and maximum distance that can be reached), institutional (e.g.,

opening and closing hours of stores), and coupling (e.g., the need to be contemporaneously at the same place at the same time). These constraints are included in the box of spatiotemporal structures of Figure 1.

In this report, a mixture model for identifying latent classes of attitudes and a similar model for identifying latent classes of travel behavior are developed. To further investigate the efficacy of the conceptual model, the relationship between the two classifications is studied.

Survey Design and Data Collection

Responses to this survey were collected from residents of the Greater Los Angeles Metropolitan area in May 2020. SurveyMonkey's proprietary panel was used to recruit 1002 respondents for this survey. This survey asks respondents about their work, school, and travel behavior before and during the COVID-19 restrictions. There are also a few questions about people's predictions for how their work behavior might change once restrictions are lifted. For employment, they are asked about employment status, number of workdays, how often they work from home, and how often they participate in online meetings. For schooling, they are asked whether they are in school, what level of school they are in, and how their schooling has been affected by COVID-19 (e.g., have classes been cancelled or moved online, etc.). For travel behavior questions, if respondents work and/or go to school, they are asked what travel modes they use to commute, then they are asked to estimate the distance and time from their homes to work/school by each mode. Everyone, regardless of work/school status, is asked what means of transportation they use for all their trips. They are then asked how many trips they estimate making in a typical week by each of those modes. Respondents were asked to provide the city they live in, ZIP code, household income, gender, and age.

A unique aspect of this survey is the questions about whether people moved because of COVID-19. Many people changed home locations during this pandemic, either temporarily or permanently. Some moved in with friends or family to get their social needs met, others were obligated to move to take care of family members, or to separate households when some members might be exposed to COVID-19. As shown in Table 1, about half of respondents who moved plan to move back to their previous residence, while the other half have permanently moved out of that residence.

Table 1 Responses from People who Moved

Characteristic	N = 54
Have you moved permanently to the residence you are/were residing in during the Stay at Home order?	
No - but I am not going back to my previous residence	7
No - I plan to move back to my previous residence once the order is lifted	23
Yes - I have permanently moved to this residence	24
What influenced your decision to change residences?	
Assist family or friends	14
Protect family or friends	14
Social needs	14
Comfort, access to resources	13
Eviction	8
Necessity (was already moving)	11

Data Cleaning

The data collected required extensive cleaning. All the cleaning was done in R, some using the package "janitor" to identify duplicates, and some using criteria based on the feasibility of travel behaviors. The data started with 1002 cases, and by the time all cleaning was complete, 202 cases were removed. For this reason, we do not recommend the SurveyMonkey proprietary paid panel for data collection in the future unless proper quality assurance procedures are created and warranties are provided by the vendor to increase data quality.

A large number of people who responded multiple times to the survey, giving the exact same answers to almost all of the questions, including key questions that made it clear they could only be coming from the same person. Presumably, this is because the panel is paid per survey completed, and some people abuse the system to respond multiple times. It is assumed that SurveyMonkey would have security measures in place to prevent this, but it appears that people are able to get around them. In total, 34 duplicate records were flagged in the data for removal. The survey was only of people aged 18 and older, which was a specification given to SurveyMonkey. 39 people reported that they were under 18 in a survey question. About 12 persons gave "nonsense" responses to at least one important text response question, so their other responses were untrustworthy and had to be removed. 143 people were flagged to remove based on criteria to do with poor (or impossible) responses to travel behavior questions. People whose reported time to get to work or school was greater than 3 hours were also removed. If respondents' average travel speed was over 80 miles per hour (calculated by dividing reported distance by reported time) they were also removed. This cutoff was chosen because even if people were driving 80 miles per hour (mph) the entire time they were on the freeway, they still would need to get on and off the freeway using side streets

with lower speed limits. They were also removed if their walking speed was greater than 6 mph or their biking speed was greater than 30 mph. The walking speed cutoff was based on a study of walking speed for which the maximum was 3.2 miles per hour (*17*). 6 mph was decided as the cutoff point to give some leeway for estimation error from respondents. The biking speed cutoff point was decided based on a study showing that the typical cycling speed in three different municipalities in Sweden was between 7 and 16.5 miles per hour (*18*). Leeway was given again for this cutoff. 7 respondents were manually removed based on visual inspection that clearly showed the respondents were not answering truthfully. In total, these add up to 235, which is more than the 202 cases removed because some people ended up flagged in more than one removal category.

Data Collected

A summary of the characteristics of the final sample of respondents is shown in Table 2. Some comparisons can be made of changes experienced because of the pandemic. 341 respondents reported that they were not working before the pandemic. This jumped up by 112 people to 453 as of May 2020, as shown by the summary question "How many days per week do you typically work now?". In May 2020, only essential businesses were open in Los Angeles, and the data reflects the impact this had on people's ability to work. Comparing how many days per week respondents worked from home before versus during the lockdown, the percentage who said they never work from home went from 67% to 39%. This jump in people working from home also corresponds with the effects of the lockdown.

Table 2 Summary Statistics

Characteristic	N = 800[1]
In a typical work week (before COVID-19 restrictions) I worked on a...	
...fixed schedule defined by me (start in the morning and end of afternoon/evening)	120 (25%)
...fixed schedule defined by my employer (start in the morning and end of afternoon/evening)	172 (36%)
...flexible schedule defined by me	83 (17%)
...flexible schedule defined by my employer	31 (6.4%)
...shift schedule defined by me	22 (4.6%)
...shift schedule defined by my employer	54 (11%)
Not Working	318
In a typical work week (before COVID-19 restrictions) …	
I just worked from home	26 (5.4%)
I went to work at multiple places designated by others, excluding home (employers, customers, etc.)	49 (10%)
I went to work at multiple places of my own choosing, excluding home	38 (7.9%)
I went to work at the same place every day, excluding home	314 (65%)
I worked from home and other places designated by others	16 (3.3%)
I worked from home and other places of my own choosing	39 (8.1%)
Not Working	318
Before the COVID-19 restrictions how many days did you work from home in a typical week?	
0	304 (67%)
1	25 (5.5%)
2	32 (7.0%)
3	15 (3.3%)
4	15 (3.3%)
5	48 (11%)
6	6 (1.3%)
7	12 (2.6%)
Not Working	343

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Table 3 Summary Statistics (continued)

How many days do you work from home now?	
0	133 (39%)
1	16 (4.7%)
2	24 (7.0%)
3	25 (7.3%)
4	17 (5.0%)
5	101 (30%)
6	14 (4.1%)
7	11 (3.2%)
Not Working	459
Are you a student?	
No	713 (89%)
Yes, full-time	58 (7.2%)
Yes, part-time	29 (3.6%)
What school grade or level do you attend?	
2-year college (community college)	26 (30%)
4-year college or university	30 (34%)
Grade 9 to 12	4 (4.6%)
Graduate school/professional	19 (22%)
Other (please specify)	1 (1.1%)
Technical/vocational school	7 (8.0%)
Not in School	713
Did you move residences during the COVID-19 restrictions, even temporarily?	54 (6.8%)
Do you have a valid driver's license?	697 (87%)
What best describes your gender?	
Female	421 (53%)
Male	379 (47%)
Age	
18-29	169 (21%)
30-44	159 (20%)
45-60	226 (28%)
> 60	246 (31%)

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Analysis

The analysis in this section explores strategically selected aspects of the conceptual model in **Error! Reference source not found.**. This analysis contains two mixture models: a latent class analysis (LCA) to find groups of individuals with similar travel behavior and a latent profile analysis (LPA) to find groups of individuals with similar attitudes about driving cars. The resulting classes from these two analyses are cross-classified and tested with a Pearson's chi-squared.

LCA uses categorical variables to identify underlying unmeasured classes. Grouping people using mixture models like LCA is different from simply using cutoff scores because, unlike cutoff scores, mixture modeling assumes that the class groupings are unknown. It uses probabilities of group membership, where the class with the highest probability is the class that an individual is placed in. Indicator sensitivity is considered, so LCA can look at which indicators are best for differentiating the classes. It also allows for measurement error.

Latent Class Analysis: Mode Choice for Commuting

In this LCA, we find the clusters of modes used for commuting to work and/or school based on travel done BEFORE the coronavirus restrictions. Respondents who reported that they were going to neither work nor school were not included in the LCA and are consolidated into a sixth category. This category will be referred to as *Not in School or Working.*

The LCA was conducted using Mplus 8.6 (*19*). The order of operations for performing an LCA are as follows: A one-class model is fit, followed by a two-class, *et cetera* until a model is run that is not well-identified (*20–22*). Determining whether a model is well-identified involves inspection of a set of fit statistics which are recorded for each model. These are presented in Table 4. Depending on the purpose of the LCA, different fit statistics have greater priority to consider. For a model such as this one that is going to be used in further analysis, "within-class homogeneity and across-class separation" are important to consider, which means a greater emphasis placed on high entropy (*20*).

Table 4 Fit Statistics: Travel Modes Used

Classes	Log likelihood	BIC	ABIC	p-value of BLRT	p-value of VLMRT	Entropy	BF
1	-1322.964	2695.757	2670.364	-	-	-	0.000
2	-1212.456	2530.796	2476.836	< 0.001	< 0.001	0.712	0.000
3	-1142.398	2446.737	2364.210	< 0.001	< 0.001	0.849	> 15.000
4	-1125.058	2468.115	2357.021	< 0.001	0.003	0.887	> 15.000
5	-1107.970	2489.995	2350.334	< 0.001	0.032	0.899	> 15.000
6	-1099.065	2528.242	2360.013	0.092	0.295	0.965	-

Note. BIC is Bayesian Information Criterion. ABIC is adjusted Bayesian Information Criterion. BLRT is Bootstrap Likelihood Ratio Test. VLMRT is Vuong-Lo-Mendell-Rubin Likelihood Ratio Test. BF is Bayes Factor.
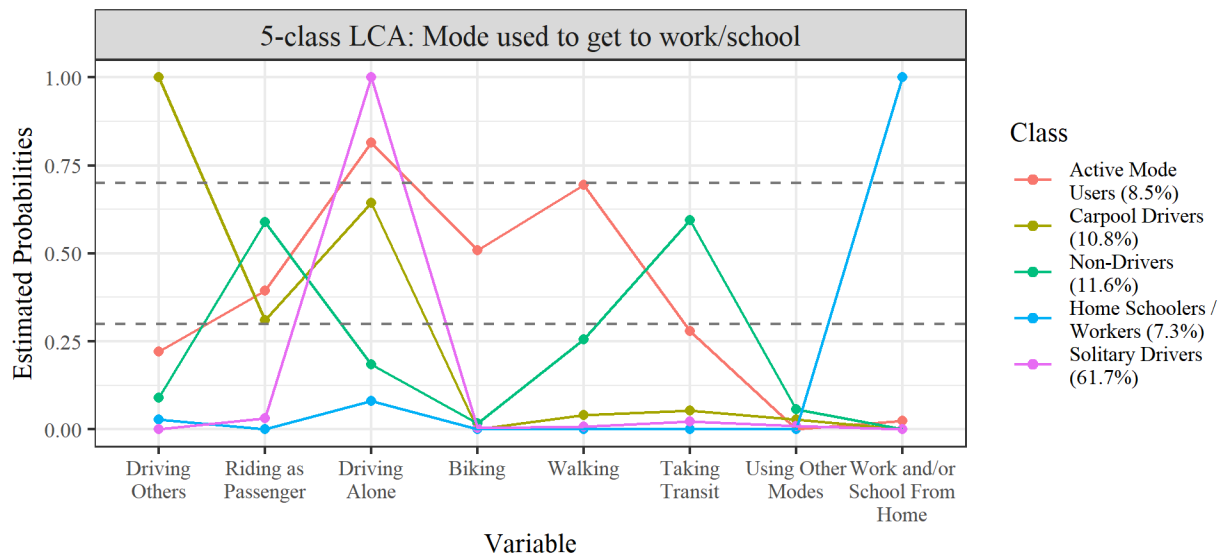
A non-significant *p*-value for either the Bootstrapped Likelihood Ratio Test (BLRT) or the Vuong-Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (VLMRT) indicate that there is not a statistically significant improvement in model fit in the *k* class model as compared to the *k-1* class model (*20–22*). As Table 4 shows, The VLMRT reached a non-significant *p*-value of 0.295 with the 6-class model.

Based on fit criteria, class sizes, and interpretability, the 5-class model was chosen. An entropy value approaching 1 indicates clear delineation of the classes. So, the entropy value of 0.899 for the 5-class model means the indicators discriminate well between the classes (*23*). Based on properties described in further detail below, the 5 classes will be referred to by the names *Actie Mode Users*, *Carpool Drivers, Non-Drivers, From-Home Workers,* and *Solitary Drivers*.

Figure 2 shows the class-specific propensities for respondents to use each mode to get to work and/or school. There are distinct differences in the mode choices between the classes. Note that the item "Using Other Modes" has low probabilities for all classes. This means it would be an item to consider eliminating if future models were to be run since it does not differentiate well between the classes. Since all classes have low propensity for this item, it will not be examined in the class-specific discussions ahead. All but two classes have a high propensity for driving alone to get to work/school. This is reflective of the "driving culture" of Los Angeles. This is also reflected in the *Solitary Drivers* class containing 61.7% of the sample who work or go to school.

Horizontal lines have been added at y intercepts 0.7 and 0.3. This is to aid in interpretation and class differentiation, as any probabilities above 0.7 or below 0.3 would be considered high or low propensity, respectively.

Figure 2 Class-specific item probability profile plot: 5-class LCA of modes used

The *Active Mode Users*, with an estimated proportion of 8.5%, have the highest probabilities of commuting using bicycles and walking of all the classes. This group of individuals has a low propensity for reporting driving others or working/schooling from home. Although the probability of using bicycles is only 0.50, it is significantly higher than the probability of biking in any other class. Class members have a high propensity for reporting walking to work/school, and although their probability of reporting using

transit is on the border of the "low" category, it is the second highest probability of any class. Even the class that could be considered the most "eco-friendly" are very unlikely to use transit to commute. They also have a high propensity for driving alone. This is a manifestation of travel culture in Los Angeles and the lack of viable public transit infrastructure. Options for using public transit are limited and slow, and people do not use it unless they must (as is the case for *Non-Drivers*).

The *Carpool Drivers* make up 10.8% of the analyzed sample. They have a 100% probability of choosing driving others as one of their modes of travel. When compared to the low propensities of all the other classes, the difference becomes starker. Basically, almost everyone who drives others to work has been put into this same class. Members of this class have a low propensity for any travel mode that is not in a car: biking, walking, and public transit. They also have a low probability of working from home.

The *Non-Drivers,* with an estimated proportion of 11.6%, are characterized by having a low propensity for driving alone and driving others. Unlike the other classes besides the Home Schoolers / Workers, this group of individuals does not have a high propensity for commuting by any mode that involves driving a car. This class does not have any modes for which the probability of using it is higher than 0.7. The highest propensities this group has are for riding as a passenger and taking transit, which are both around 0.6. This indicates that individuals in this group do not drive a car very often.

The *Home Schoolers/Workers* make up 7.3% of the analyzed sample. Members of this class have a 100% probability of responding that they worked or went to school from home before the pandemic. This is the only class for which people have a low propensity to have reported traveling by any mode to work or school. This means that most of the people in this class mainly work/school from home, and do not ever commute to a work or school location.

Members of the *Solitary Drivers* class are characterized by a high propensity for driving alone and a low propensity for using any other mode or for working/schooling from home. This is the largest class, making up 61.7% of the sample, meaning this is the most typical pattern that would be present in the population. This is accurate to the general travel behavior of Los Angeles residents.

Latent Profile Analysis: Attitudes

Latent profile analysis (LPA) is essentially the same as latent class analysis but using continuous instead of categorical variables. All the model interpretation methods described in the previous section still apply. Attitudes towards driving and other modes of transportation were measured using a shortened set of attitudinal questions originally used in the Puget Sound Transportation Panel (PSTP) (*24*). The full set of 23 questions was previously used by Lee and Goulias (*25*) in an LPA, where the Likert scale items were used as continuous variables as we do in this analysis. All members of the 800-person sample were used in this analysis. Respondents rated their agreement with the following statements on a scale of 1 to 5, from "Strongly Disagree" to "Strongly Agree":

- "I like the freedom of driving my own car"
- "I won't rely on another person to get to work on time"
- "My schedule is too erratic to be in a carpool"
- "Taking public transit doesn't fit my lifestyle"
- "Driving a car is a relaxing way to commute"
- "I enjoy driving my car even in heavy traffic"

Table 5 contains the fit statistics of different models estimated. Typically, for the likelihood ratio tests (VLMRT and BLRT) the *p*-value gradually increases with each increase in number of classes, indicating that the improvement in model fit gets less and less significant with each class increase. With this analysis, the 4-class model has a non-significant *p*-value, but the 5- and 6-class models both show highly significant improvements in model fit. In this type of analysis, it is uncommon for a model with fewer classes to have a less significant *p*-value than the models with more classes. Although according to the non-significant *p*-value of VLMRT for the 4-class model, the 3-class model would be the optimal choice, the 5- and 6-class models both show statistically significant improvements in model fit, and thus are viable candidates for model selection.

Table 5 Fit Statistics for LPA of Attitudes

Classes	Log likelihood	BIC	ABIC	*p*-value of BLRT	*p*-value of VLMRT	Entropy	BF
1	-7652.121	15384.457	15346.350	-	-	-	0.000
2	-7319.193	14765.394	14705.058	< 0.001	< 0.001	0.935	0.000
3	-7126.237	14426.274	14343.710	< 0.001	< 0.001	0.985	0.000
4	-6534.574	13289.740	13184.946	< 0.001	0.142	0.999	0.000
5	-6433.476	13134.336	13007.314	< 0.001	< 0.001	0.937	0.000
6	-6373.291	13060.759	12911.508	< 0.001	0.001	0.911	-

Note. BIC is Bayesian Information Criterion. ABIC is adjusted Bayesian Information Criterion. BLRT is Bootstrap Likelihood Ratio Test. VLMRT is Vuong-Lo-Mendell-Rubin Likelihood Ratio Test. BF is Bayes Factor.

Upon visual inspection of the 3- 4- and 5-class Item Probability Plots (Figure 3), it becomes clear why the 4-class model does not show significant improvement in fit over the 3-class model, but the 5-class model fits significantly better than the 4-class. While the 4-class model does not appear considerably different from the 3-class model, a unique class emerges in the 5-class model. This class will be referred to as the *Freedom Lovers* and will be described in more detail below. The 5-class model was chosen due to the good fit statistics, good separation of classes (Entropy = 0.937), clear distinctions in the qualities of each class, and parsimony over the 6-class model. The 5 classes will be referred to as *Cars Haters*, *Indifferent Respondents*, *Freedom Lovers*, *Car Users,* and *Car Lovers*.
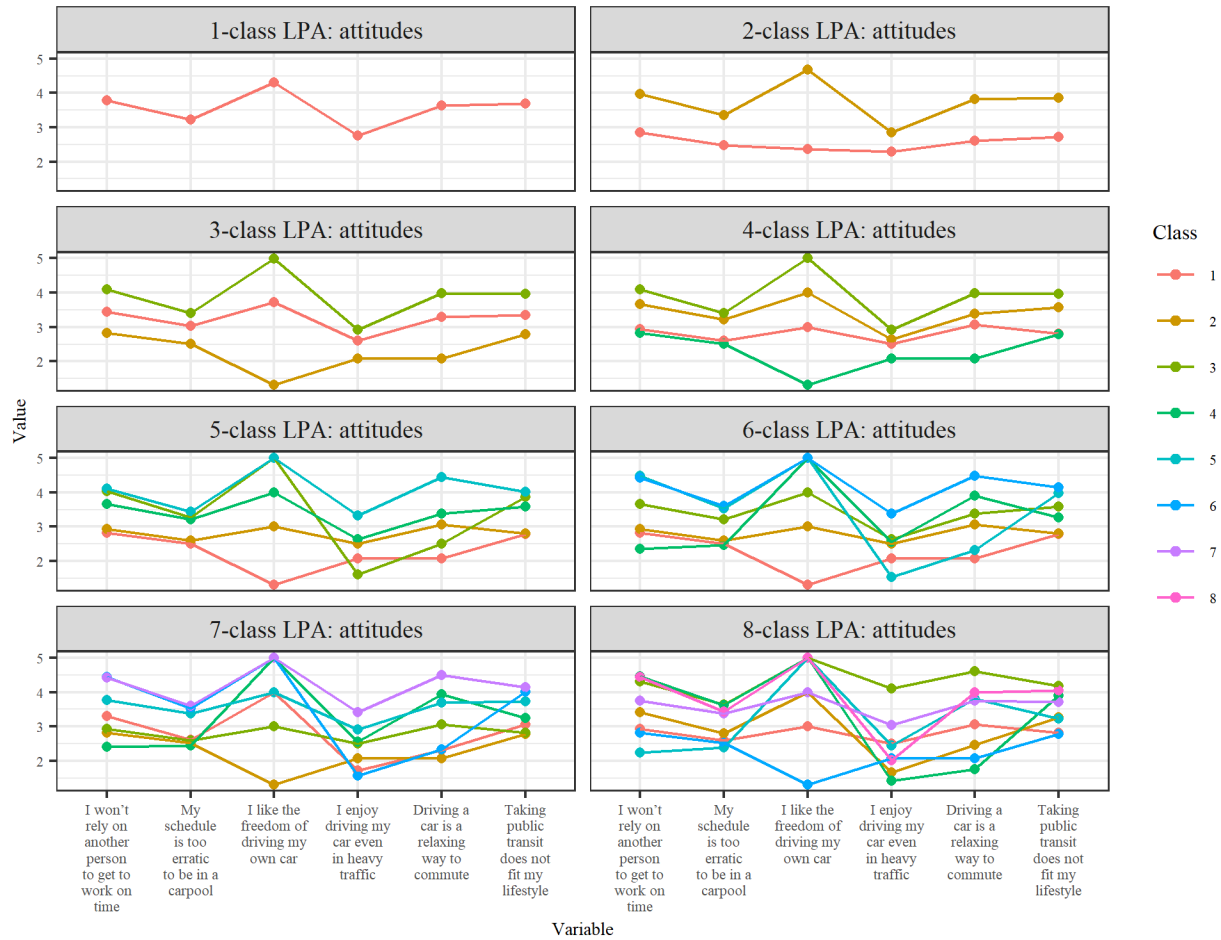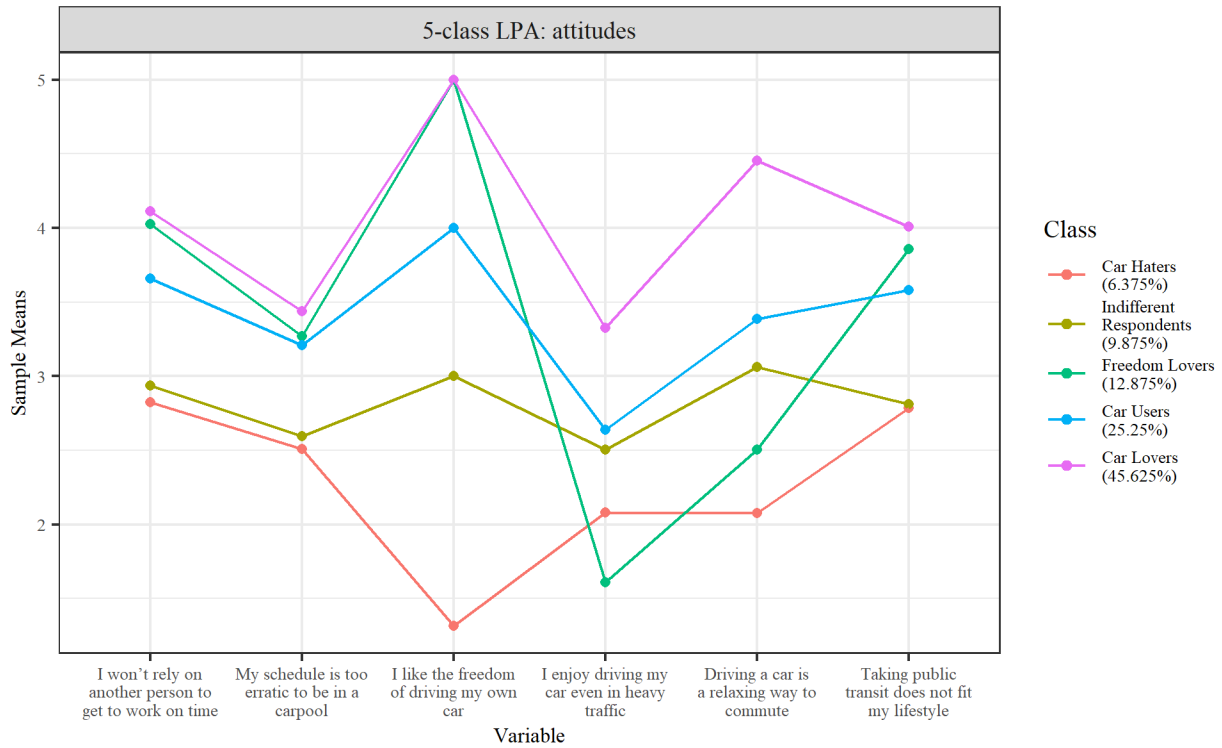
Figure 3 Item Probability Plots for Attitude LPA

Figure 4 shows a larger and more detailed IPP of the 5-class model. On the y-axis, 1 is "strongly disagree", 3 is "neither agree nor disagree", and 5 is "strongly agree". The *Cars Haters* group members, making up 6.4% of the sample, do not think of cars as providing freedom, and they do not like using cars to get around. Unlike any other class, this one has a strong negative response to the prompt "I like the freedom of driving my car." They also have negative responses to whether they enjoy driving their car in traffic and whether driving a car is a relaxing way to commute.

Figure 4 Item Probability Plot: 5-class LPA of Attitudes

Indifferent Respondents make up 9.9% of the sample. They have little opinion either way for most of the questions. The means of their responses to every question came out around the 3, which is "neither agree nor disagree". They have no notably strong opinions about any of the prompts given.

Freedom Lovers, making up of 12.9% of the sample, dislike congestion but love the freedom of driving in their car. They may enjoy driving for pleasure, but not commuting. They are characterized by their strong positive association towards the prompt "I like the freedom of driving my own car" coupled with strong negative association towards the prompt "I enjoy driving my car even in heavy traffic." They also positively endorse the statement that they will not rely on another person to get to work on time, and that public transit does not fit their lifestyle. These responses further emphasizing the importance of freedom of movement to this group.

Car Users make up 25.25% of the sample. Members of this group are fine with using their cars, but they do not feel passionately about it. They do not have extraordinarily strong opinions either way about any of the prompts, but on average they do respond moderately positively to the prompt about enjoying the freedom of driving a car.

Car Lovers make up 45.6% of the sample. Although this is a high percentage, it is not enough to call this the "normal" or "typical" attitude (*20*). On average, group members respond positively to prompts about driving their cars in all situations. Although they respond less positively to driving in heavy traffic, it is still a more positive response than any other group.

Cross Classification of Travel Mode and Attitude Classes

One way to consider the relationship between the LPA and the LCA model estimates is to use a cross classification of the latent classes extracted from the travel mode and attitude models (Table 6).

Table 6 Cross Classification of Mode and Attitude Models

		Attitudes					
		Car Haters	Indifferent Respondents	Freedom Lovers	Car Users	Car Lovers	Row Totals
Commute Modes	Active Mode Users	6	2	3	9	23	43
	Carpool Drivers	3	2	5	17	28	55
	Non-Drivers	6	17	7	18	11	59
	From-Home School / Worker	2	6	9	8	12	37
	Solitary Drivers	12	10	40	83	168	313
	Not in School or Working	22	42	39	67	123	293
Column Totals		51	79	103	202	365	800

Pearson's Chi-squared test
X-squared = 80.82, df = 20, p-value = 2.848e-09

For the Attitudes and Commute Modes model cross tabulation, Pearson's Chi-squared test resulted in a chi-squared value of 80.82. The *p*-value is less than the significance level of 0.05, so we reject the null hypothesis and conclude that the two variables are dependent/correlated. This means the observed relationship between the two is significantly better than chance (i.e., the membership of the categories on one set of groups is not uniformly distributed across the categories of the other set of groups). In other words, attitudes are correlated with behaviors in a systematic way as expected. For example, the *Solitary Drivers* are more likely to be *Car Lovers*. 14% of *Active Mode Users* are in the *Car Haters* group. In contrast, among the *Solitary Drivers*, only 3.8% are *Car Haters*. Among the *Not in School or Working* group, only 7.5% are *Car Haters*. But, among the *Active Mode Users* we have 13.95% *Car Haters*. Moreover, 53.67% of *Solitary Drivers* are also *Car Lovers*.

Even with a database on COVID-19, the theoretical model shows validity. This illustrates how one goes about testing hypotheses of the relationships between attitudes and behavior using responses in surveys. Adding other factors and testing relationships among factors is one way to study the significance of the relationships in the conceptual model (**Error! Reference source not found.**). We turn next to another objective of our study that is the design of a new and better data collection method that follows the footsteps of other smartphone enabled travel surveys.

Travel Diary Smartphone Application

We will refer to the type of travel behavior data collection done for this project as "reflection" data, which would involve asking respondents to reflect on their own behavior over an amount of time. This differs from the travel diary, which is a highly detailed form of data collection from respondents. In essence, the travel diary records every trip a person makes with the mode used, origin and destination, duration in time and distance, mode used and then adding other prompted questions depending on the purpose of the survey. Typically, a travel diary is collected by distributing a travel log, and asking respondents to carry this around with them for a day recording their trip details. Respondents must then return this diary to researchers for digitization.

Generally, there are pros and cons to both reflection and travel diary data, as shown in Figure 5. Although reflection surveys are typically faster to deploy, easier for respondents to fill out, and less work for researchers in terms of data cleanup and prep for analysis, they do not provide as accurate of information, nor as detailed. Respondents have unreliable memories for accurately reporting their activities and travel. The level of detail is also lower with reflection data. The travel diary provides a more accurate representation of a day in the life of a respondent, and it gives researchers a flexible dataset to use for future analysis, since it is at a high level of detail (every trip is recorded in detail for a day). However, a travel diary is typically much more labor-intensive for a respondent, labor-intensive for surveyor, prone to response errors because of the handwritten nature of the diary, labor-intensive for researchers in the digitizing stage, and prone to errors when digitizing these handwritten locations.

Figure 5 Comparing Reflection and Travel Diary Data

Reflection	Travel Diary

•Pros
  •Easy to collect from respondents
  •Faster to set up and deploy survey
  •Less work for respondents
  •Less data cleanup work
•Cons
  •Loss of accuracy
  •Unreliable memories
  •Prone to respondent errors
  •Less detailed information
	•Pros
	  •More accurate representation of a single day for the respondent
	  •Highly detailed information
	  •Less issue with memories
	  •Flexible for future analysis
	•Cons
	  •More invasive (privacy concerns)
	  •Labor-intensive for respondent
	  •Labor-intensive for surveyor
	  •Prone to respondent errors
	  •Prone to digitizing errors

If it were possible to lessen the downsides of the travel diary, then it would be the preferable option for data collection in most quantitative travel behavior research contexts. One solution to this is to use a smartphone application to collect the diary. Smartphone travel surveys became popular with travel behavior researchers because they decrease the burden of respondent diaries from whom we need to

have locations visited and the timing of all their trips in a day. The most attractive feature of smartphones is the accurate location capability and the more accurate recording of travel patterns provided strategic prompts are included in the smartphone app (*26*). Evidence is also starting to accumulate about the positive attitudes of survey participants when the apps are easy to use and are perceived to be useful by the respondents as useful while the perceived risk of loss of privacy does not appear a major issue (*27*).
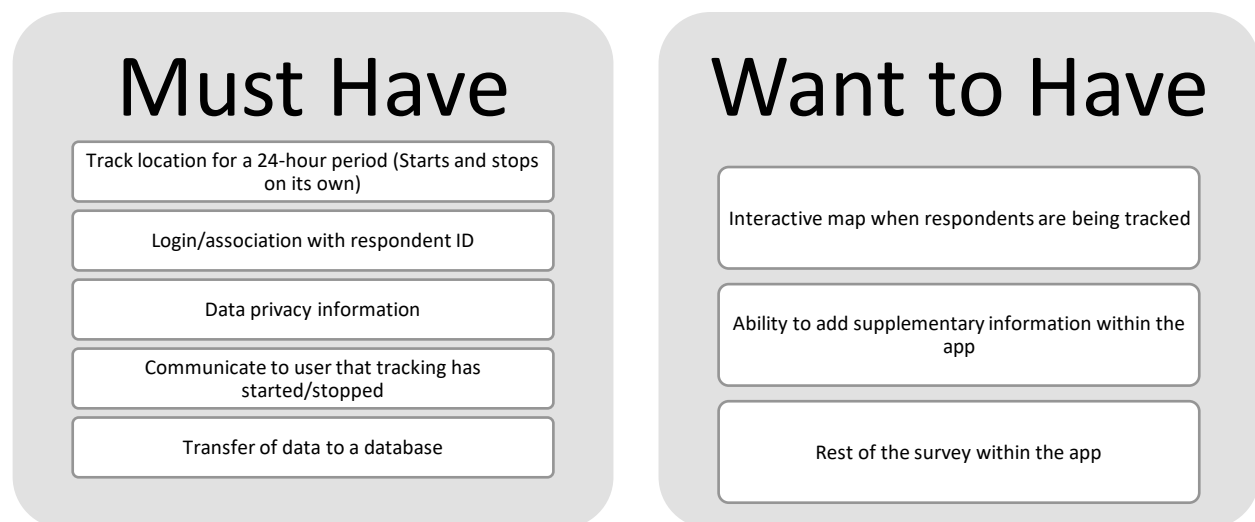
Most people already carry a smartphone around with them throughout the day, so respondents would not have to carry the physical diaries around and remember to write every trip down in them. They would not have to mail the diary to the researchers afterwards either. The smartphone app would just require them to allow location access and provide supplementary information about the trips recorded after the day is over. For researchers, they would no longer need to digitize the handwritten logs, get coordinates from addresses or business names. It would also reduce the need for error checking and data cleanup, and the data would automatically be set up in a database structure.

Although there are a few options available for smartphone applications, most are either proprietary or if they are open source they are no longer maintained and are very out of date. There is not a good option available for a modern, open-source smartphone application framework. We aim to create an app framework that future researchers can use for a low cost to reduce the typically large monetary barrier to collecting detailed data such as a travel diary. The app designed here would include an online survey as the survey described in this report for COVID-19 with the addition of the smartphone app for the travel diary portion of the overall survey.
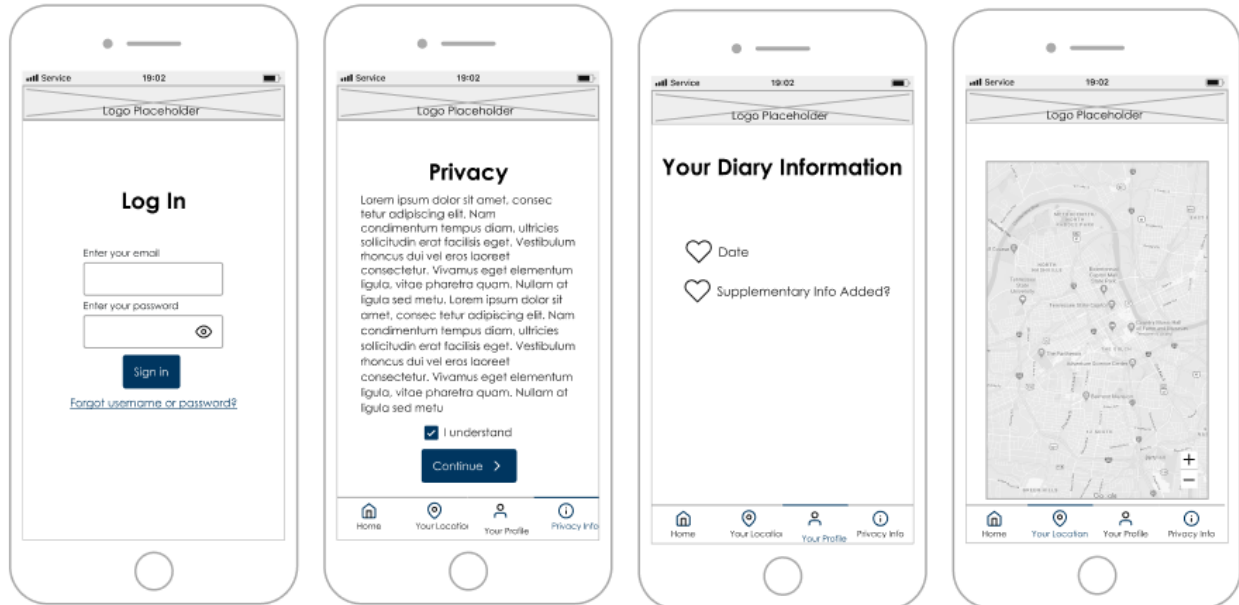
Designing the app

First, the application features must be identified. Then, they must be separated into those that are necessary features must be identified, and separated from the features that would be desirable, but not necessary. Figure 6 details these features and shows the division between the two categories.

Figure 6 Necessary and Desired Features

The next step is to create a "wireframe" for each page in the app, as shown in Figure 7. This provides a visual representation of the application to act as a set of guidelines for the coding process. The wireframe the features of the application and the way it functions, including the relationships between the screens and how navigating between screens will work.

Figure 7 Wireframe of Smartphone App

Coding the Application

There are two options for building an application for both iOS and Android phones. One option is to build the application separately for each platform, called building a "native" app. iOS uses the language Swift, and Android uses Java. However, maintenance of applications built in this way requires having someone available to bug-check and maintain the app in both languages. The other option is to write the application once for both platforms, called a "cross-platform" app. Some options for doing this include Flutter, Ionic, NativeScript, and ReactNative. We decided to use ReactNative, because it has a framework called Expo that makes application development faster and easier for those who have not done it before. ReactNative apps are written in JavaScript, then rendered in native code. Expo makes a simulated version of the app for the developer, where features like as button clicks and even location tracking will work as they would in the final product. It is possible to test the simulated app on both virtual phones that are emulated on a computer and physical phones by downloading the Expo Go app.

Publishing

Publishing the application will involve submitting it to both the Google Play Store and Apple App Store for review. Upon acceptance, the app will be publicly available for download. In the past year or so, the phone companies have been cracking down on background location tracking. Developers must provide a good explanation for why it is needed, and all the privacy measures and details of how the location tracking will work must be made clear to the app users. The justification for using background location in this

application is as follows. The locations collected are being used for research purposes, and they will never be sold or used for profit. Their information is kept in a secure database, and it will only be provided to researchers who have received Institutional Review Board (IRB) approval, meaning they have legally agreed to protect the rights, welfare, and privacy of participants. Tracking will permanently stop at the end of a specific, scheduled 24-hour period that participants have agreed to, so they will know exactly when their locations are being recorded. After the tracking period is over, respondents will also have a chance to review the information collected.

Progress

Thus far, the application can track locations with a "start" and "stop" button, and it sends those locations to an Amazon Web Services database. However, it is still not able to start and stop on its own based on a scheduled time. Aiming to have it start and stop on a schedule is a potential barrier, because it can cause some privacy issues that may be flagged by the application stores. The method of tracking the locations for a specific number of hours may need to be revised. Also, there is not yet an interface for respondents to add supplemental information and corrections after locations have been recorded. After these two steps have been completed, the application will be exported from the Expo simulation framework into a standalone application at which point it will be tested on multiple smartphones with different operating systems. Once it has cleared the testing phase, the application will be ready to submit to the app stores for approval. The application in its current state can be found in the GitHub repository linked here. [1]

Conclusions

In this project, a few strategic changes of direction have been employed to account for external changes to the project circumstances. The fundamental direction of developing a strong theoretical model accompanied by data collection to test some of its aspects stayed the same as the original intent of the project. In addition, data collection was done to examine COVID-19 impact on the life of Los Angeles Metropolitan area residents. In terms of substantive findings, we verified that in this region as in other parts of the US people experienced loss of jobs, forced relocations, and major changes in working and studying. In terms of the attitude-behavior relationship, we also confirmed the existence of more diversity in attitudinal groups of people with respect to their position towards the private automobile and found that these attitudes are strongly correlated with the use of different modes. The survey design and conceptual model form the foundation for subsequent data collection and analysis based on the pilot examples of this project. A third pilot study within this project is the design of a smartphone application, which is an ongoing effort at UCSB and will continue beyond the project reported here.

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[1] https://github.com/e-mcbride/travel-diary-app

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Appendix A: Survey Sample Questions for Public Transport Interventions

The following writeup contains initial sample questions and their reasoning consistent with the conceptual model of Figure 1 in this report (also reproduced as Figure B.1 here). These are the originally planned questions for the survey of residents living near the Los Angeles Crenshaw/LAX Metro Line. For reader convenience, we repeat part of the literature review here to make the appendix self-standing. Recall that the structure of this model is a hybrid of past theories of behavior, primarily influenced by the Theory of Planned Behavior (*28*), the Theory of Interpersonal Behavior (*7*), and the Attitude-Behavior-Context model (*5*, *9*). In the main body of this report, we provided a discussion on a shortened version adapted for COVID-19, and here we provide a literature review and survey question examples that are customized to possible behavioral change in favor of public transportation use.
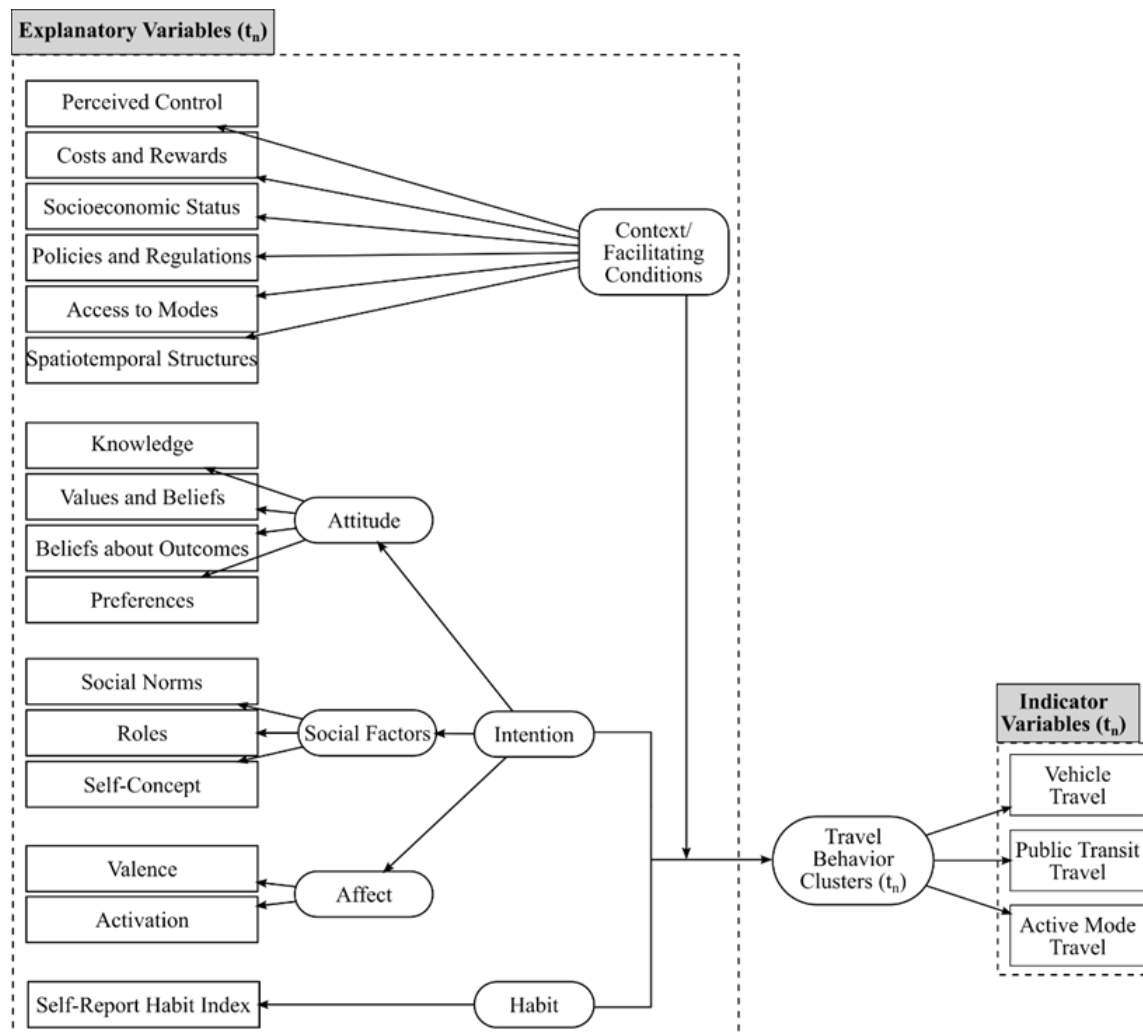

Figure Error! No text of specified style in document.**.1 (same as Figure 1 in report) Updated Conceptual Model of Travel Behavior**

In the model, the three primary influences on behavior are **intention**, **habit**, and **context/facilitating conditions**. Intention is the primarily conscious motivation to perform a certain behavior. It is shaped by a person's attitudes, social surroundings, and their feelings when they think about performing the action (called "affect"). Habit is a more unconscious driver of behavior. Habit is formed by the repetition of an action and maintained by the low cognitive load of choosing the habitual behavior over a non-habitual option. It can often be at odds with intention. Context/facilitating conditions are moderating conditions that can compel or hinder a behavior. As contextual forces become stronger, their influence over behavior increasingly overpowers the influence of habit and attitudes. Each of these primary constructs have sub-constructs that will be built by direct measurement of relevant variables in the survey. The following writeup discusses the measurement of these sub-constructs, including sample questions for public transportation use.

Intention

The concept of intention as a motivator of behavior originally comes from the Theory of Planned Behavior (TPB). It is also present in the Theory of Interpersonal Behavior (TIB), which built off the TPB. Intention is composed of three sub-constructs: Attitude, Social Factors, and Affect.

Attitude

In the dissertation model, the sub-construct Attitude is built by measuring four key concepts: values, beliefs about outcomes, knowledge about the subject, and preferences. Following is a discussion of each of these concepts with sample questions.

Values. There are two concepts within values that are relevant for measurement: general values and environmental values. Both may contribute to travel behavior intention, but since the Crenshaw/LAX survey will already be difficult to keep short, it is necessary to pare down. A discussion of measuring values in general is included here, including sample questions. However, there will likely only be space to include questions about environmental values, which are more relevant to travel behavior decision-making.

One possibility for measuring values in general is a shortened version of Schwartz's Portrait Value Questionnaire (PVQ), which measures values in ten dimensions: conformity, tradition, benevolence, universalism, self-direction, stimulation, hedonism, achievement, power, and security (*29*). Schwartz later developed and validated two shortened versions of the PVQ: a Twenty Item Value Inventory (TwIVI) and a Ten Item Value Inventory (TIVI) (*30*). The TIVI, although outperformed by the TwIVI, still meets the acceptable standards for validity and reliability (*30*).

Values (TIVI)

- Here we briefly describe some people. Please read each description and think about how much each person is or is not like you. Using a 6-point scale from "not like me at all" to "very much like me," choose how similar the person is to you.

6	5	4	3	2	1
very much	like me	somewhat	a little	not like	not like
me					
like me		like me	like me	me	at all

- **HOW MUCH LIKE YOU IS THIS PERSON?**

- _____ 1. S/he believes s/he should always show respect to his/her parents and to older people. It is important to him/her to be obedient.
- _____ 2. Religious belief is important to him/her. S/he tries hard to do what his/her religion requires.
- _____ 3. It's very important to him/her to help the people around him/her. S/he wants to care for their well-being.
- _____ 4. S/he thinks it is important that every person in the world be treated equally. S/he believes everyone should have equal opportunities in life.
- _____ 5. S/he thinks it's important to be interested in things. S/he likes to be curious and to try to understand all sorts of things.
- _____ 6. S/he likes to take risks. S/he is always looking for adventures.
- _____ 7. S/he seeks every chance s/he can to have fun. It is important to him/her to do things that give him/her pleasure.
- _____ 8. Being very successful is important to him/her. S/he likes to impress other people.
- _____ 9. It is important to him/her to be in charge and tell others what to do. S/he wants people to do what s/he says.
- _____ 10. It is important to him/her that things be organized and clean. S/he really does not like things to be a mess.

To measure environmental attitudes specifically, it may be difficult to find an instrument that is brief enough to include in full in this survey. All the validated instruments under this topic are too long for our purposes. This is because there are many dimensions to environmental attitudes and values. Most likely, it will be necessary to utilize concepts from these instruments in the creation of a short set of questions.

For specifically measuring environmental attitudes, the Environmental Attitudes Inventory (EAI) from Milfont and Duckitt (*31*) may be a good option. There are twelve dimensions measured: enjoyment of nature, support for interventionist conservation policies, environmental movement activism, conservation motivated by anthropocentric concern, confidence in science and technology, environmental threat, altering nature, personal conservation behavior, human dominance over nature, human utilization of nature, ecocentric concern, and support for population growth policies. They give two options: a longer 120-item measure and a shorter, 72-item measure. Both are far too long for the purposes of inclusion in this developing survey; however, it may be possible to utilize the concepts and validated question formatting to create a shortened version of this survey.

Another possibility for measuring this is the scale for measuring Multiple Motives toward Environmental Protection (MEPS) developed by Gkargkavouzi, Halkos, and Matsiori (*32*). This is the one in the sample

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questions. This measures six motives: normative, altruistic, biospheric, egoistic, gain, and hedonic. It also measures constraints to motives. This instrument may be a good option because it integrates some measurement of general values. The MEPS is a 28-item instrument, which is a more reasonable number, but still too large for this survey. This is something that will need to be considered. Perhaps a shortened version can be used without too many issues.

Multi-Motives to Environmental Protection Scale (MEPS)

- **Normative motives**
  - I feel a moral obligation to protect the environment.
  - Don't know; It is not my responsibility to treat nature with respect. (r)
  - The people I care about believe that one ought to protect the environment with his/her actions.
  - Most people who are important to me engage in pro-environmental practices.
- Altruistic motives
  - Good environmental conditions benefit the health of the community and its members.
  - It is urgent to safeguard natural resources for future generations.
  - Environmental degradation has adverse consequences on humanity.
  - Don't know; I am not concerned about the welfare of other people. (r)
- **Biospheric motives**
  - All living organisms have equal intrinsic value.
  - We need to preserve every scrap of biodiversity.
  - Environmental deterioration has adverse consequences on natural ecosystems.
  - Don't' know; I am not concerned about biodiversity loss. (r)
- **Egoistic motives**
  - Nature provides people with food and raw materials.
  - Ecosystems provide recreation and cultural services.
  - A healthy environment is strongly associated with my physical health.
  - Natural areas provide ecosystem services that clean the air and the water.
- **Gain motives**
  - I save money by using public transportation.
  - Government provides monetary subsidies for pro-environmental activities.
  - I gain tax and fees deduction by adopting eco-friendly behaviors.
  - By preserving water and energy, I pay lower utility bills at home.
- **Hedonic motives**
  - I derive pleasure and satisfaction when I engage in environmental behaviors.
  - Don't know; I do not feel any better by protecting the environment. (r)
  - Makes me happy to prevent natural scenery.
  - I enjoy spending time in nature.
- **Constraints to motives**
  - It is expensive to adopt environmental behaviors.
  - It is time-consuming.
  - Needed effort makes the engagement in environmental behaviors difficult. My lifestyle in terms of convenience would change for the worse.

Beliefs about outcomes. This comes from the Theory of Interpersonal Behavior (TIB). It is a person's evaluation of the potential outcomes of their decision. This includes perceptions of safety and convenience. This may be an instrument that need to be designed ex novo, since the measures will be specific to the type of policy we explore in the Crenshaw/LAX intervention.

> **Beliefs about Outcomes**
>
> •Traveling by MODE is safe
> •Traveling by MODE is comfortable
> •Traveling by MODE is convenient
> •Traveling by MODE is relaxing

Knowledge. Respondents' knowledge about the options available to them should influence their attitude about those choices. Inclusion of knowledge in this model comes from the Knowledge-Attitude-Behavior (K-A-B) model (*2*). The sample questions for this section are created by McBride and listed below.

Preferences. Preferences are based on what people like and dislike, which should influence attitude. The sample questions below were written by me to measure this. The challenge of measuring preferences is that they will be influenced by the other building blocks of intention (beliefs about outcomes, values, and lack of knowledge about the other options). Below, MODE consists of "driving my car," "taking the bus," "taking the subway," "riding my bicycle," etc. In the main report body, we also outline work done in choice modeling on this.

> **Knowledge**
>
> •Please rate your familiarity with the public transportation options accessible to you around your home.
> • Please rate your familiarity with the roads around your home.
> •Please rate your familiarity with the bicycle lane infrastructure around your home.

> **Preferences**
>
> •**Likes/Dislikes**
> •I prefer to use my car to get around.
> •I love MODE.
> •I hate MODE.
> •If it took a similar amount of time, I would use public transportation to get around.
> •I think MODE is a comfortable way to travel
> •**Safety** (this may belong in Perceptions within Context/facilitating conditions)
> •Driving my car is safe
> •Ridng my bicycle is safe
> •Taking public transportation is safe
> •**Independence**
> •I do not like to rely on schedules (independence), on others for my movement
> •I prefer the freedom of my own car.

Social Factors

These are the social influences on intention. In the TPB, this is called "subjective norms." They include the social norms, roles, and self-concept. Social norms are the standard behavioral expectations of the society

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a person lives in. Roles are the positions a person holds in society and/or the household. A person's behavior will be shaped by the responsibilities and expectations that come with those roles. Self-concept is the way a person sees him or herself. This can be aligned with roles and social norms, but also includes personal views about oneself. For example, someone seeing themselves as an environmentally friendly person, or a moral person. This is the construct that has to do with how people see themselves, and the influence of their image. One challenge in measuring these is to separate self-concept from the social norms and roles, especially since these are all going to be self-reported measures. Restructuring the Social Factors section by eliminating the self-image subtopic and integrating it into the remaining two subtopics is under consideration. These sample questions are written ex novo, as validated and succinct instruments to measure these items have not been identified.

Social Norms

- Green self-image as a social norm (Welsch & Kuhling, 2018)
  - The paper does not have the measures used.
- In my neighborhood, people mostly use MODE to get around.
- In my neighborhood, it is normal to use MODE to get around.
- It would be considered weird/odd/abnormal if I used MODE in my neighborhood.

Roles

- I think of myself as a leader in my community.
- I think of myself as a role model for people around me.
- I have people in my life who look up to me.
- There are certain **expectations** I need to live up to.
- I have **responsibilities** that I must maintain.

Self-Concept

- Green self-image (Welsch & Kuhling, 2018)
  - paper does not contain the instruments used
- I see myself as an environmentally-conscious person.

Affect

This is how someone's emotional response to a topic, or their affect, influences their intention. This comes from the Theory of Interpersonal Behavior (*7*). Russel and Barrett (*14*) define "core affect" as occurring on two dimensions called "valence" and "activation." Valence is described as the spectrum of pleasure to displeasure or good to bad mood. Activation is a person's sense of their energy level: from sleepy to hyperactive. After reviewing validated measures of affect, the Swedish Core Affect Scales (SCAS) (*33*) seems to be an appropriate measure of affect for the purposes of this model. In Västfjäll and Gärling's article validating the SCAS they created, the authors determine that this is a good measure to use for quick assessment of affect in longer surveys, which is perfect for use in a complex model such as this one (*34*).

Despite its brevity, the SCAS measures affect on two dimensions: valence (pleasant vs unpleasant affects) and activation (level of arousal). In the sample questions, TRAVELING BY MODE includes "driving your car," "riding in the bus," "riding a subway/rail line," "riding a bicycle," *et cetera*.

Valence

- Please rate your general feelings when you think about TRAVELING BY MODE (scale of 0 to 6 OR -3 to 3)
  - Displeased–Pleased
  - Sad–Glad
  - Depressed–Happy

Activation

- Please rate your general feelings when you think about TRAVELING BY MODE (scale of 0 to 6 OR -3 to 3).
  - Sleepy–Awake
  - Dull–Peppy
  - Passive–Active

Habit

Habit is an influence on behavior that is separate from intention. Inclusion of habit in the model comes from the TIB. Habits are repeated behaviors that, with time, become increasingly automatic and take up less mental energy to do. Because of the low cognitive load of choosing the habitual behavior, it can be difficult to choose a different behavior that will take more conscious effort, even if the intention to do so is there. To measure habit, the Self-Report Habit Index (SRHI) developed by Verplanken and Orbell (*35*) seems to be a good option. Their index measures habit based on four attributes: its repetition, lack of awareness and conscious intent, difficulty of avoiding the behavior, and mental efficiency (meaning it has a small cognitive load). Below, where the sample questions say "MODE," this can be replaced with different modes of travel, like "my vehicle," "public transit," or "my bicycle."

Self-Report Habit Index

- Taking **MODE** to get around is something...
  - I do frequently.
  - I do automatically.
  - I do without having to consciously remember.
  - That makes me feel weird if I do not do it.
  - I do without thinking.
  - That would require effort not to do it.
  - That belongs to my (daily, weekly, monthly) routine.
  - I start doing before I realize I'm doing it.
  - I would find hard not to do.
  - I have no need to think about doing.
  - That's typically "me."
  - I have been doing for a long time.

Context/Facilitating Conditions

The inclusion of context/facilitating conditions as a moderator for habit and intention is influenced by both the ABC model and the TIB. As described in the introduction, these are conditions that can either hinder or compel behaviors. These range from external/structural conditions like proximity of a bus stop or parking policies to personal conditions like socioeconomic status. Briefly, it is worth mentioning that "spatiotemporal structures" are the temporal and spatial constraints to movement in a person's day. This is a person's schedule, which adds certain requirements to a person's day that will limit where they can go and for how long they can do activities (*16*). See also the explanation in the main body of this report.

In terms of the question design, most of this section was modified and the content switched to COVID-19 issues. Many of the questions above do not require as much background research into validated instruments, as almost all these sub-topics are external/environmental conditions or more objective measures. The exception to this is perceived control over the options available, which comes from the TPB, where it is called "perceived behavioral control." This is people's perception of how much choice they have in their actions. There are a few examples in the literature of active transportation on perception and reality of options attributes (*36*, *37*) and public transportation quality of service (*38*).

Data Management Plan

Products of Research

Responses to this survey were collected from residents of the Greater Los Angeles Metropolitan area in May 2020. SurveyMonkey's proprietary panel was used to recruit 1002 respondents for this survey. This survey asks respondents about their work, school, and travel behavior before and during the COVID-19 restrictions. There are also a few questions about people's predictions for how their work behavior might change once restrictions are lifted. For employment, they are asked about employment status, number of workdays, how often they work from home, and how often they participate in online meetings. For schooling, they are asked whether they are in school, what level of school they are in, and how their schooling has been affected by COVID-19 (e.g., have classes been cancelled or moved online, etc.). For travel behavior questions, if respondents work and/or go to school, they are asked what travel modes they use to commute, then they are asked to estimate the distance and time from their homes to work/school by each mode. Everyone, regardless of work/school status, is asked what means of transportation they use for all their trips. They are then asked how many trips they estimate making in a typical week by each of those modes. Respondents were asked to provide the city they live in, ZIP code, household income, gender, and age.

Data Format and Content

This information will be provided after Elizabeth McBride's dissertation publication.

Data Access and Sharing

Data and Code available at https://github.com/e-mcbride/covid19.commuting. Additional information will be added after Elizabeth McBride's dissertation is published.

Reuse and Redistribution

There are no restrictions on the use of the data.