Emotional Agents: Modeling Travel Satisfaction, Affinity, and Travel Demand Using a Smartphone Travel Survey

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Abstract

This dissertation seeks to understand travel satisfaction, travel affinity, and other psychological factors in relation to travel demand, such as the desire for trip making, willingness to spend time traveling, and choice of travel mode. The research was based on the Mood State in Transport Environments survey of 247 Android users (about 6,000 completed trip surveys) in the Blacksburg-Roanoke, VA, Washington, DC, and Minneapolis, MN metropolitan areas from fall 2016 to spring 2018. Respondents answered an entry survey, tracked their travel for 7 days, and answered a trip survey associated with each trip. The dataset provides opportunities to examine travel and activities during travel at the within- and between-person levels.

Three studies in this dissertation examined three measures of the positive utility of travel and their relationship with travel behavior. I quantified (1) the desirability of trip making, (2) the ideal travel time related to different travel characteristics, and (3) the effect of satisfaction on commute mode choice. The first study examines the patterns of travel affinity with various travel modes, trip purposes, and activities during the trip. Travel affinity was measured by asking the willingness to forgo a trip when there is an opportunity to do so. I found that this is a valid and strong measure of the positive utility of travel. Travelers were more willing to make trips when they traveled on foot or bicycle, talked with someone during the trip, and took shorter trips. Additionally, commute trips were less likely to be enjoyed as compared to other, non-commute trips.

The second study focused on (1) testing the validity of the "ideal travel time" measurement and (2) measuring factors associated with the willingness to spend time traveling. I found that although ideal travel time was a strong measure of the positive utility of travel, it was very weakly associated with the desirability of trip making and satisfaction with trips. Although few people wanted zero commute time (3%), the number of trips that had zero ideal travel time was much higher (16%), indicating that the desired travel amount may vary across different trip and environmental characteristics and purpose. Ideal travel time was longer for active travel trips, leisure trips, when conducting activities during trips (e.g., talking, using the phone, looking at the landscape), when traveling with companions and during the weekend.

The third study investigated the role of travel satisfaction and attitude in mode choice behavior. This is one of the very few studies that have considered the role of these psychological factors in multimodal mode choice based on revealed preference data. I found that satisfaction and attitude toward modes and travel played a significant role in the choice model; it also modified the role of travel time in the models. However, the perception of travel time usefulness was insignificant in the model. Scenario analyses based on the model results showed that it is optimal to invest in active transportation and public transit at the same time in order to shift car drivers to these sustainable modes.

These studies contribute to the small but growing body of literature on the positive utility of travel and transrational decision making in transportation. It is the only study that employed a smartphone survey with a repeated measure of trips over the course of 1-2 weeks. The third study is among the earliest attempts to include satisfaction and attitude together into mode choice models.

This dissertation has several implications for research and practice. First, it calls for better measurements of well-being and satisfaction. Second, models with appropriate psychological factors would more realistically resemble actual travel behavior. Including satisfaction in the choice model changes the coefficient of travel time (and potentially cost), which modifies the value of travel time savings, a basis of most benefit-cost analyses in transportation planning and engineering. Better mode choice and trip generation models will generate more reliable predictions of future infrastructure use and investment. Third, studies of travel affinity (positive utility of travel) have implications for demand modeling and management practice. Practitioners should reevaluate the effectiveness of travel demand management strategies aimed at reducing travel time and trips, such as congestion pricing (e.g., tolls), online shopping, and telecommuting.

General Audience Abstract

People have various motivations to travel every day. For some, traveling is a means to an end to get from one place to another. Their main travel purpose is to perform some activities at destinations, such as grocery shopping, working, or visiting a friend. For others, traveling is a joy to get some fresh air, to be on one's own company, to enjoy driving or exercising (while walking or bicycling), in addition to conducting activities at destinations. This idea of traveling for fun is still unpopular in transportation research. This dissertation seeks to understand the patterns of travel and motivations: who are traveling for fun, and when? Whether this affinity and satisfaction for travel drive people's decision to choose a travel mode?

To answer these questions, I measured the affinity for travel in two ways: willingness to make trips (i.e., travel from one place to another) and desired amount of time spent on travel. I found that people were willing to travel more when they conducted certain activities during trips, such as talking to others, talking on the phone, or other activities. Commuting was less fun as compared to other travel purposes, such as socializing or leisure. Bicyclists and pedestrians liked their trips and wanted to travel more than car drivers and bus users. People who were satisfied with their commute trips made by one mode would be more likely to use that mode for commuting.

The affinity for travel is relevant to urban residents' mental well-being and demand for travel, which translate into health and congestion relief benefits. The results from my studies suggest that more attentions on traveling for fun and multitasking should be paid to account for future mobility options, such as ride hailing (e.g., Uber, Lyft) and autonomous vehicles. These modes have promised fun from activities during travel, the autonomy, and

convenience, and thus would generate more traffic on the road while providing less social and environmental benefits.

The results from this dissertation would inform city planners, engineers, and health practitioners on planning for sustainable cities by improving well-being for transportation users and accommodate sustainable modes of transport, such as bicycling, walking, and transit by providing users with safe and satisfactory travel environments. The results also imply potential pitfalls of the current planning practice such as overestimating the value of travel time savings, benefit-cost analyses, and the effectiveness of travel demand management strategies, such as telecommuting and using information and communications, in reducing travel.

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List of Abbreviations

ACS	American Community Survey
ATUS	American Time Use Survey
AV	Autonomous vehicle
CATI	Computer-assisted telephone interviewing
DTTS	Desired travel time savings
GPS	Global Positioning System
ICT	Information and communications technology
NHTS	National Household Travel Survey
PUT	Positive utility of travel
STS	Satisfaction with Travel Scale
SWB	Subjective well-being
TMS	Travel Mood Scale
TPB	Theory of Planned Behavior

Disclaimer

This dissertation consists of three studies (Chapters 4-6) that follow a journal article format and serve as stand-alone chapters. However, they share the same research theme (i.e., travel demand management) and use the same dataset from the Mood State in Transport Environments project. Therefore, some contents, such as methods, data cleaning, and discussion may overlap.

1 Introduction

1.1. Motivations

Most cities aim to promote sustainable transportation and improve environmental and health outcomes. This goal often includes reducing car travel (e.g., vehicle miles of travel), relieving congestion, and boosting the use of alternative modes, such as bicycling, walking, and transit (Handy, Boarnet, Ewing, & Killingsworth, 2002; Saelens, Sallis, & Frank, 2003). However, the percentage of trips made by transit, bicycle, and walking is small in most American cities while car driving is still a dominant mode for all trips (ACS, 2017; NHTS, 2017). A better understanding of how individuals make decisions about their travel (e.g., amount of time spent traveling, modes chosen) would allow researchers to improve the understanding of travel choices and achieve that goal.

Transportation research heavily relies (either implicitly or explicitly) on the rational choice theory—assuming individuals choose the mode of transport, travel time, or make trips by maximizing their utility. However, recent advancements in neuroscience and behavioral sciences have shown that affective and cognitive experiences (e.g., emotions, satisfaction) influence individual decision making (Damasio & Carvalho, 2013; George & Dane, 2016; Kahneman & Krueger, 2006; Oliver, 2014) and that human decisions often substantially deviate from the rational approach (Kahneman & Krueger, 2006). Only a few transportation studies incorporate these factors (e.g., satisfaction with the travel) in their choice models (Abou-Zeid & Ben-Akiva, 2012; De Vos, Schwanen, Van Acker, & Witlox, 2016; Le, Li, & Carrel, 2019; Singleton, 2017); in which only one addresses satisfaction as part of the multimodal choice model (Singleton, 2019).

It has been assumed that travel has negative utility and travelers look to minimize their amount of travel. This is not always the case, as found by Mokhtarian & Salomon (2001) who named this phenomenon "the positive utility of travel", which has been tested in a small but growing body of literature. The findings were consistent: travelers may enjoy their trips, wish to travel more by making unnecessary trips, travel longer routes, travel to unplanned destinations, be unwilling to forgo their travel, and other behavioral manifestations (Mokhtarian, 2005; Mokhtarian & Salomon, 2001; Singleton, 2017). However, more research is needed to quantify the amount of positive utility and how it can help to manage travel demand in a more sustainable manner (e.g., mode shift, reduce vehicle miles of travel, reduce unnecessary car trips).

At the same time, measurement is of concern in studying psychological factors. Satisfaction and well-being have not been considered in the transportation context until recently. This negligence is partly due to the lack of standardized, validated measurements for travel experience (e.g., satisfaction, emotions, cognition). Only two scales have been specifically developed for the purpose of transportation, namely the Satisfaction with Travel Scale (Ettema et al., 2011) and the Travel Mood Scale (Glasgow, Geller, Le, & Hankey, 2018). Another measurement issue is the lack of a real-time, repeated measure of emotion and satisfaction. Travel surveys typically employed a paper or web-based questionnaire asking respondents to recall information of the past day or past week from their memory—not allowing them to instantly report after each trip. Self-report questionnaires based on recalled information can be unreliable and biased. Studies have shown that travelers tend to underreport short trips

(especially walking) and under/over-estimate trip duration. This necessitates the use of objectively measured data such as GPS tracking (e.g., using GPS devices or smartphone GPS) to track travel and activities.

Another limitation of previous studies of travel experience and satisfaction is the lack of diversity in trip characteristics. These studies often surveyed travelers' experience of the most recent trip or typical experience with one type of trip, allowing for little or no variation in day-to-day trip characteristics, which can be influential to travel affect and satisfaction. Surveyed trips were usually limited to common trip purposes such as commute (Páez & Whalen, 2010; Redmond & Mokhtarian, 2001; Singleton, 2017; Smith, 2017) or leisure trips (Vos, Mokhtarian, Schwanen, Acker, & Witlox, 2015). Satisfaction with trips of other purposes, which account for a significant number of all daily and weekly trips, were not explored.

All in all, these issues inform this dissertation study to better measure psychological constructs, incorporate them into travel demand models, and quantify the effect of the positive utility of travel. Researchers can do so by moving beyond the rational choice approach and considering the intrinsic demand for travel, travel experience, and well-being. Such understanding would contribute to more effective policies to promote sustainable behaviors and improve subjective well-being of transport users.

1.2. Objectives

Overall, this dissertation aims to measure travel affinity and satisfaction in near real-time and quantify their effects on travel demand. It aims to demonstrate how researchers can employ a smartphone app to repeatedly measure mood and satisfaction with travel and activities (e.g., during travel and after travel) and compare it with the overall well-being. The first

study explores the factors associated with the willingness to make trips, such as socio-demographics, activities during travel, trip purpose, companionship, time of day, and other trip characteristics. The second study investigates the determinants of a willingness to spend time on travel. The third study models commute mode choice with the inclusion of travel attitude and satisfaction with travel.

1.3. Contributions

This dissertation contributes to the field of transportation planning in numerous ways. Overall, it advances data collection methods using smartphone surveys and provides further evidence of travel affinity, satisfaction, and the positive utility of travel. This knowledge in turn contributes to the research and practice of travel demand management.

First, this is one of the very few studies that explores travel experience and the positive utility of travel in a broader US geographical area and is the only study that employed a smartphone app for such a purpose. It is also among the few smartphone travel surveys applied for all modes of travel (e.g., walking, bicycling, public transit, car, and other modes) with a week of GPS tracking in the US. The smartphone app allowed an instantaneous report of satisfaction, emotions, and other psychological factors, which resulted in more accurate measures compared to retrospective methods such as paper-based and web-based surveys, including computer-assisted telephone interviewing (CATI).

This dissertation adds more evidence for the positive utility in daily travel. Unlike previous studies which are cross-sectional with single time-point measures, this study diversifies the literature on these topics by using repeated-measure data that include various travel modes and trip purposes. Additionally, this dissertation study is among the earliest studies to

include satisfaction and attitude in mode choice models (i.e., multimodal mode choice for commute trips).

Results from this dissertation imply various strategies for increasing satisfaction for sustainable modes and promoting physical activity. They also imply a potential pitfall in the current travel demand modeling practice where practitioners may underestimate demand for trip generation and vehicle miles of travel. It necessitates the need to reevaluate the value of travel time savings, benefit-cost analysis, and the effectiveness of travel demand management strategies to reduce travel and energy consumption. Finally, this dissertation offers a novel examination of psychological factors in travel behavior. It also calls for incorporating well-being into policy making.

1.4. Dissertation structure

This dissertation is structured as follows. The first chapter provides an overview of the dissertation study and its contributions to the literature in travel demand and travel survey methods. The second chapter introduces the key theories and literature that inform this dissertation.

Chapters 3–6 address the four objectives of this dissertation. The third chapter presents the research design and data collection for this dissertation study. The fourth chapter sketches a picture of the positive utility of travel with different measurements, and focuses on modeling the determinants of travel affinity, expressed through the willingness to make trips. The fifth chapter follows this line of research by presenting findings on the willingness to spend time traveling. The sixth chapter investigates the role of travel satisfaction in mode choice for commute trips. An overview of these studies is presented in Table 1.

Chapter 7 summarizes the key findings of this dissertation and implications for research and practice. It also highlights the major limitations and directions for future research to advance travel survey methods and travel demand modeling.

Table 1. Overview of this dissertation study

Research design	(Chapter 3) Entry survey and smartphone-based survey with GPS tracking over 1-2 weeks during Fall 2016-Spring 2018. N_1 = 247 people, N_2 = 5,748 trips.		
	⇩	⇩	⇩
Topic	What determined the desirability of trip making?	What determined the desired travel time?	How travel satisfaction and travel affinity influenced mode choice?
	Study 1 (Chapter 4)	**Study 2 (Chapter 5)**	**Study 3 (Chapter 6)**
Analytic methods	- Multilevel ordered logit models. - Compared different measurements of the positive utility of travel	- Random-effects (RE) Tobit models and RE ordered probit models.	- Obtained travel time, cost of all alternative for commute trips. - Imputed trip satisfaction - Took average of satisfaction with commute over the course of a week. - Logit model for multimodal mode choice.
Contributions	- Near-real-time psychological experiences after each trip. - Repeated-measure data that could account for various trip purposes, travel environments, and trip characteristics.		
	- Among few studies that empirically tested the positive utility of travel. - Focused on trip-based variations (within-person effects) as well as person-based variations (between-person effects).		- Among few studies that tested the effects of satisfaction on travel behavior (e.g., mode choice). - Imputation of psychological factor based on repeated measures of trips over a long tracking period.
Implications	- Travel demand modeling and management: trip and travel time reduction - Increase satisfaction of transport users in order to nudge travelers toward sustainable travel modes (e.g., walking, bicycling, transit)		
	- Willingness to replace actual travel with online shopping, telecommuting, online social interactions - Estimating the adoption rate of ridesharing, ride hailing, and autonomous vehicles.		- Potential pitfall in estimating the value of travel time savings in traditional choice models.

2 Literature review

This section provides an overview of major literature in travel behavior research that lays the foundation for this dissertation. This is not intended to be an exhaustive review of all literature in travel demand and psychological factors. Instead, I only focused on major theories behind the decision making process (e.g., rational and transrational decision making) and the utility of travel, as well as the advance in smartphone data collection methods. A more complete literature review is provided in the specific literature review sections in Chapters 4-6.

2.1 Rational and transrational decision making

2.1.1 Economics perspective: rational choice theory and extensions

In normative decision theory, individuals are assumed to make the best decision under a perfect condition. In this sense, individuals make rational and logical decisions to maximize their *expected utility* (e.g., total benefit). Rational choice theory is characterized by four well-known axioms (also known as the von Neumann–Morgenstern axioms) (Neumann & Morgenstern, 2007):

- *Completeness*: one alternative is well preferred to the other or $A \leq B$. For example, a person consistently prefers bicycling to driving.
- *Transitivity*: agent makes consistent choices: if $A \leq B$ and $B \leq C$ then $A \leq C$. For example, a person prefers walking to bicycling, bicycling to riding transit, then this [rational] person would prefer walking to riding transit.
- C*ontinuity*: if $A \leq B \leq C$, then there exists a probability $p \in [0, 1]$ such that B is equally good as $pA + (1-p)\ C$. This means if anything close to B must be preferred to A; and anything close to C must be preferred to B. This axiom

ensures that the agent is able to rank the alternatives from the most desirable to the least desirable.

- *Independence:* characterized by well-defined preference: adding an independent alternative C will not change the preference order, or if $A \leq B$ then $pA + (1\text{-}p)\ C \leq\ pB + (1\text{-}p)\ C$, with probability $p \in [0, 1]$. For example, if a person prefers walking to driving, then when presenting an independent alternative such as bicycling, she still prefers walking to driving.

Ben-Akiva and Lerman (1985) provide an overview of common decision rules based on normative decision theory in transportation. Among those, random utility maximization (Manski, 1977; Manski & McFadden, 1981) is the dominant rule thanks to its strong theoretical ground. This is also the basis of discrete choice modeling that is used in this dissertation.

Many studies in experimental economics have shown that individuals do not act rationally most of the time, for example, violating one or more of these four axioms. This fits another paradigm called descriptive decision theory that describes how actual irrational agents make decisions. An extension to the descriptive decision theory is bounded rationality (Simon, 1955), where individuals make decisions under limited conditions, such as the unavailability of time and information or cognitive limitations. This theory has been applied in transportation, such as route choice modeling (Ben-Elia & Avineri, 2015; S. Gao, Frejinger, & Ben-Akiva, 2011; Rasouli & Timmermans, 2015). Chorus and colleagues provide another framework to model route choice using an alternative framework, namely regret minimization, which assumes that individuals seek to minimize negative emotions aroused from the negative consequences of their expected outcomes (Chorus, Arentze, & Timmermans, 2008).

2.1.2 Behavioral economics perspective

Behavioral economists characterized human decision making as heuristics, such as using mental shortcuts or following routine thinking to make a decision (Kahneman, 2011). They also formulated decision making to complement the rational choice theory by extending the concept of utility and incorporate that into the utility maximization framework (Kahneman & Thaler, 2006; Kahneman, Wakker, & Sarin, 1997).

From the behavioral economics standpoints, Kahneman and Krueger (2006) explain how people make choice as follows:

> "[P]eople often make choices that bear a mixed relationship to their own happiness. A large literature from behavioral economics and psychology finds that people often make inconsistent choices, fail to learn from experience, exhibit reluctance to trade, base their own satisfaction on how their situation compares with the satisfaction of others and depart from the standard model of the rational economic agent in other ways." (Kahneman & Krueger, 2006, p. 3)

They also differentiate various types of utility, such as momentary utility (happiness at a cross section of time), experienced utility (the way people feel/experience in real time), and remembered utility (what people feel after the activity is over). In behavioral economics, remembered utility does not equal the sum (or temporal integral) of momentary utility. Instead, remembered utility is a weighted sum of all momentary utilities with greater weights placed at the end and peak of the experience. Remembered utility is duration-neglect, which means that it does not depend heavily on the activity duration (Kahneman & Krueger, 2006) (Kahneman, 2013). As evidenced in Kahneman & Krueger (2006), it is not the experienced utility, but the remembered utility that affects an individual's decision. Therefore, in mode

choice modeling, measuring remembered utility is necessary, as people tend to choose (or not choose) a mode based on their remembered experiences.

At the same time, as an individual chooses a mode based on their anticipated experience (expected/decision utility), Abou-Zeid & Ben-Akiva (2014) suggest a method to connect after-travel satisfaction (equivalent to remembered utility) to expected (decision) utility by asking respondents how their experience of the trip differs from what they expected. When these two types of utility align, satisfaction can be used to model mode choice.

2.1.3 Psychology perspective

Psychologists also proposed several frameworks for decision making. Some of these have been widely used in the transportation literature, such as the theory of planned behavior (Ajzen, 1991; Coogan, Karash, Adler, & Sallis, 2007; Dill, Mohr, & Ma, 2014; Spears, Houston, & Boarnet, 2013), motivation theory (Maslow, 1943a; Ryan & Deci, 2000), and habitual behavior (Aarts, Verplanken, & van Knippenberg, 1997; Verplanken & Orbell, 2003).

The theory of planned behavior was proposed by Ajzen (1991) as an expanded version of the theory of reasoned action (Fishbein & Ajzen, 1972) (Fishbein, 1975; Ajzen, 1980). This theory postulates that an individual's behaviors are shaped by one's attitude toward the behavior, subjective norms, and perceived behavioral control. Attitude toward the behavior is one's belief about the consequences of the behavior and the judgments about the ability to perform the behaviors. Subjective norms refer to one's perception of social pressures, or from significant others (e.g. parents, spouse, friends) to perform or not perform the behavior. Perceived behavioral control refers to one's perception of ease or difficulty of performing a behavior and the perceived factors that may facilitate or impede the performance of the behavior (Ajzen, 1991).

Various travel behavior studies grounded on the theory of planned behavior have long been tested in Europe and more recently have been emerging in North America (Coogan et al., 2007; Dill et al., 2014; Spears et al., 2013). Attitudes and perceptions about different aspects in transportation have been tested, including car availability or vehicle ownership (Choo & Mokhtarian, 2004), transit use (Spears et al., 2013), and bicycling and walking (Dill et al., 2014). Some significant effects of either attitude, norms, or perceived behavioral controls were detected. Attitude is usually found to have a significant effect on travel (Bamberg, Rölle, & Weber, 2003; Bohte, Maat, & van Wee, 2007; Coogan et al., 2007; Dill et al., 2014; Spears et al., 2013; Van Acker, 2015). Norms are found to be significant in fewer studies (Bamberg & Rees, 2017; Bamberg et al., 2003; Van Acker, 2015; Van Acker, Van Wee, & Witlox, 2010).

Several theories in psychology identify habit as a factor in decision making. The theory of repeated behavior states that initial behavior is driven by attitudes and beliefs. When an individual repeats the behavior, it becomes a habit. This habit is embedded in the decision making process and undermines the role of attitude and other factors (Ronis et al, 1989; Garling et al., 1998). As such, the activators of behavior are (1) unreasoned influences, (2) resources or enabling variables, and (3) reasoned influences (Van Acker et al., 2010). Interpersonal theory (Triandis, 1977) shares the same perspective with the theory of repeated behavior in the sense that it accounts for habit as a determinant of behavior. Many past studies also confirm the increase in the models' explanatory power when habit was added. Habit has been incorporated in a number of studies on mode choice and mode use. It was found to be a significant predictor of transit and car use (Bamberg et al., 2007; Gärling, 2003; Verplanken et

al., 2008). Fewer studies have accounted for habit in bicycling and walking choice. In a way, habitual decision making can be a special case of heuristics in behavioral economics.

Motivation is another theoretical basis from psychology that has been applied in a few transportation studies. Maslow (1943a, 1943b) proposed the pyramid-model of hierarchy of needs, which reflects human motivations from physiological needs (e.g., food, water; lowest level) to self-actualization (i.e., self-fulfillment; highest level). In transportation sense, this highest level of needs could range from connecting people to educational or employment opportunities, or a manifestation of one's core values, such as environmental concerns (e.g., when driving electric cars or using active travel modes) or social status (e.g., driving luxury cars) (Singleton, 2013). Alternatively, motivation can be viewed from intrinsic/extrinsic perspectives (Ryan & Deci, 2000). Extrinsic motivations are driven by an external goal; that is, travel enables people to participate in activities at destinations, thus travel can be seen as a means to an end. Intrinsic motivations, on the other hand, are the end goal itself. In transportation, travel could be intrinsic if travel is the main goal of the trips (e.g., to be outside and enjoy the landscape). Mokhtarian and colleagues (2005; 2015) and Singleton (2013) discussed motivations and its applications in transportation in detail.

Subjective well-being is a well-studied subject in positive psychology and recently has been applied in transportation. Diener (1984) posited that subjective well-being consists of three components, which are positive affect, negative affect (both are short-term), and cognitive evaluation (i.e., long term satisfaction). To date, one or all components of subjective well-being have been investigated in transportation contexts (Abou-Zeid & Ben-Akiva, 2012; De Vos & Witlox, 2017; Friman, Fujii, Ettema, Gärling, & Olsson, 2013; Singleton, 2017; Smith, 2017). However, most of these studies focused on the link from travel to well-being, not the

other way around. Mokhtarian (2018a) and De Vos and colleagues (2019; 2013) provided comprehensive reviews and general frameworks to fit well-being into other psychological components of travel behavior.

The effects of emotions and satisfaction in the decision making process are understudied and less strong in their theoretical ground, but more eminent in lab experiments in marketing research and neuroscience (Damasio & Carvalho, 2013; Reibstein & Lovelock, 1980). Damasio (Damasio, 2005) showed that patients who suffered injuries in part of the brain that regulates emotions have difficulty making decisions. Consumer behavior literature also documents numerous studies showing that satisfaction with products leads to the intention of repurchasing or actual repurchasing behavior (Oliver, 2014). An experiment showed that car users who used public transit during the study period and felt satisfied with transit were more likely to switch to transit after the experiment (Abou-Zeid & Ben-Akiva, 2012). A longitudinal, non-experimental study showed that transit riders who were less satisfied with transit service were more likely to switch to other modes a year later (Le et al., 2019).

A list of theories in travel behavior research is shown in Table 2. For a comprehensive review of behavioral theories, see Singleton (2013).

Table 2. Major behavioral theories and frameworks that have been applied in transportation

Theory	**Field of origin**	**Main concept**	**Transportation applications**
Utility maximization, random utility	Economics	Utility, expected utility	Plenty, core theory for choice modeling.

Theory	Field of origin	Main concept	Transportation applications
Bounded rationality	Economics	Bounded rationality	Few, mostly for route choice modeling.
Various theories in bias, memory distortion, and irrationality	Behavioral economics	Decision utility, momentary utility, remembered utility, peak-end rule, duration neglect, hedonic treadmill	Few, some in behavioral research on satisfaction and activity.
Theory of reasoned action and theory of planned behavior	Psychology	Attitude, norm, perceived behavioral control	Plenty in travel behavior.
Theory of repeated behavior, interpersonal theory	Psychology	Habit	Few, mostly in mode choice.
Motivation	Psychology		
Subjective well-being, satisfaction and affect	Psychology, neuroscience	Affect (mood and emotion), hedonia, eudaimonia, satisfaction, overall well-being	Small but growing.

2.2 Utility of travel

Travel has been considered a disutility (i.e., negative utility); the value of travel time has always been assumed to be positive. However, increasing empirical evidence has shown that travel may also have a positive utility in many cases. This section explores the debates on the utility of travel time, measurement of the positive utility of travel, and empirical evidence for its existence.

2.2.1 Overview

Rooted in time geography, activity and travel are closely related concepts, where travel is assumed to be a means to an end that allows people to reach destinations and perform activities. This later became the premise of the activity-based travel demand models, a marriage between time geography and transportation, where travel is assumed to only relate to activity demand. In this sense, activities are the primary purpose and carry a positive utility that agents tend to maximize (according to the utility maximization framework). On the other hand, travel is secondary, time-consuming, and is hence a disutility to minimize.

However, Hagerstrand noted that travel is a special case of activity (Ellegård, 2018). He did not go further into conceptualizing the benefit of travel. Small and Song (1992) used the term "excess commute" to indicate the longer commute than the optimal amount based on aggregate data. Mokhtarian and colleagues later coined the term "positive utility of travel" to refer to travel as a positive value (Mokhtarian & Salomon, 2001; Mokhtarian et al., 2001). A series of papers based on a paper-based survey in the San Francisco Bay Area explored this concept and provided empirical evidence for the positive utility of travel (Choo, Collantes, & Mokhtarian, 2005; Choo & Mokhtarian, 2004; Ory & Mokhtarian, 2009; Redmond & Mokhtarian, 2001). This concept was tested in a few other studies (Diana, 2008; Malokin, Circella, & Mokhtarian, 2019; Páez & Whalen, 2010; Singleton, 2017) and more fully conceptualized by Singleton (2017).

It was postulated that the positive utility of travel comes from three sources: activities at destinations, activities during travel, and travel itself as an activity (Mokhtarian, 2018a; Mokhtarian et al., 2001; Vos et al., 2013). As Choo et al. (2005) put it, the question is not whether the positive utility of travel exists, but how large it is. It is difficult to disentangle

travel satisfaction with activity satisfaction (at destinations). One can do so by measuring travel satisfaction and activity satisfaction separately. This has not been done in previous studies.

Singleton (2017) and Mokhtarian (2018a) tied together the concepts of travel's positive utility, motivation, and well-being. He categorized the measurement of the positive utility of travel into three main groups (Table 3). However, some of the measurement are special cases of others. For example, telecommuting is a special case of information and communication technology (ICT) usage (use the internet to work from home); non-shortest path route choice could be a special case of excess commuting (Choo et al., 2005). This categorization does not provide a clear distinction between excess commuting and excess travel indicators. Moreover, the teleportation test (i.e., asking respondents if they were willing to teleport to the destination if it were possible) and desired travel amount (Table 3) are quite specific if asked in a certain context (e.g., asked before trips of different purposes). Likewise, the value of travel time savings[1] is closely related to the desired travel amount. Table 3 shows a list of measurement by category.

[1] Daly and Hess (2019) argue that it should be label "value of travel time" instead of "value of travel time savings". Here I use the latter term as it is used most commonly while acknowledging the possibility that former is a more accurate term.

Table 3. Measuring the positive utility of travel (PUT)

Measurement[1]	Description	Convincingness of the measure[2]	Study[3]
General PUT			
Value of travel time savings	Negative or small positive value, indicating that people are willing spend time traveling.	Medium	Hess et al. (2005)
Travel time budgets	Travelers budget their daily time for travel, about 60-85 minutes per day. A person who telecommutes may generate more non-work trips to spend all budgeted time.	Low	Mokhtarian & Chen (2004)
Telecommuting	Commuters may enjoy their commute and thus are unwilling to forgo this trip. (Related: ICTs, excess commuting, travel time budget).	Low	Lachapelle et al. (2018), Mokhtarian (2003), Zhu (2012)
ICTs	Technologies such as online shopping, telecommuting, video-conferencing, socializing on through Skype, Messenger, and social media may not be able to replace real travel because people may not be willing to reduce their travel or already budget time for the trips. (Related: telecommuting, travel time budget).	Low	Lee et al. (2017), Suel & Polak (2017)

Measurement[1]	Description	Convincingness of the measure[2]	Study[3]
Teleportation test	Travelers may not choose to "teleport" because they enjoy the trip and wish to retain it. (Related: telecommuting, ICTs)	High	Mokhtarian & Salomon, (2001), Russell & Mokhtarian (2014)
Desired travel amounts	Travelers may choose non-zero travel time, or desire a longer time than the actual travel time.	High	Páez & Whalen (2010)
Excess commuting	Inefficient commute (longer than the optimal amount), mostly due to job-housing imbalance. Sometimes it also indicates that commuters are not willing to relocate in order to reduce commute time.	Very low	Mokhtarian & Salomon (2001)
Excess travel	People may make unnecessary trips, travel to farther destinations, or travel to unplanned destinations.	High	Cao et al. (2009), Handy et al. (2005)
Non-instrumental reasons for travel	People may travel for its own sake.	Very high	Handy et al. (2005), Jain & Lyons (2008), Mann & Abraham (2006), Steg (2005), Watts & Urry (2008)
Non-shortest path route choice	Travelers may incline to choose longer routes (i.e., due to variety seeking, enjoying the weather or scenery, or enjoy the process of travel).	Medium	Handy et al. (2005)

Measurement[1]	Description	Convincingness of the measure[2]	Study[3]
Coping with congesting	People might be less sensitive to congestion relief strategies and be willing to spend extra travel time.	Low	Cao & Mokhtarian (2005b, 2005a), Choo & Mokhtarian (2008)
Travel-based multitask-ing			
Activity conducted during trips	Travelers may conduct various activities during trips. Such activities may relieve the burden of travel and even increase utility for the trips. (Related: travel usefulness).	Very high	Berliner et al. (2015); Malokin et al. (2019); Guo et al. (2015); Jain & Lyons (2008); Kenyon & Lyons (2007); Keseru & Macharis (2017); Lyons et al. (2007); Lyons et al. (2013); Lyons & Urry (2005); Mokhtarian et al. (2014a)
Travel usefulness	Travelers may find their travel time useful, treating this time as an opportunity to refresh their mind, to	High	Frei et al. (2015); Singleton (2018b); Susilo et al. (2012)

Measurement[1]	Description	Convincingness of the measure[2]	Study[3]
	plan for the tasks to be performed at destinations, to exercise, to work, or to entertain. Therefore they're less likely to reduce their travel. (Related: activity conducted during trips).		
Travel experiences			
Satisfaction with travel	People may be satisfied with their trips. (Related: subjective well-being)	High	Abou-Zeid & Ben-Akiva (2012); Archer et al. (2013), St-Louis et al. (2014), Susilo et al. (2017), Ye & Titheridge (2016)
Affective response to travel	Travelers may experience negative affect (emotions or mood) during travel.	Very high	Ettema et al. (2017), Friman et al. (2017), Glasgow et al. (2018), Raveau et al. (2016)
Travel liking	People may express their fondness for travel.	High	Mokhtarian et al., 2014a; Mokhtarian & Salomon, 2001; Ory & Mokhtarian, 2005; Ory et al., 2004

Measurement[1]	Description	Convincingness of the measure[2]	Study[3]
,Subjective well-being (travel)	People may be satisfied and have positive affect during travel. (Related: satisfaction with travel).	Very high	Friman et al., 2013; Singleton, 2017; Smith, 2017; Vos et al., 2015

[1] *Based on Mokhtarian & Salomon (2001) and Singleton (2017).*

[2] *Convincingness (i.e., strength) of the measures was based on the classification in Singleton (2017).*

[3] *List of study is not exhaustive.*

On the other hand, travel-based multitasking (i.e., activities during travel), as later found in Singleton (2017, 2018b) and other studies (Kenyon & Lyons, 2007; Lyons et al., 2007, 2013), is often used as a way to deal with boredom and does not make travel time more productive, hence it may not be the most convincing measure of the positive utility of travel. It could also raise the concern of endogeneity, that is, people who tend to multitask also choose a travel mode that allows them to do so. In this sense, travel usefulness might be a better measure as compared to travel-based multitasking itself.

In the following section, I will discuss the details of each measurement category in studies focusing on the positive utility of travel.

2.2.2 Travel affinity

Travel affinity refers to the fondness of travel for its own sake, such as traveling excessively, taking longer routes, refusing to "teleport" (i.e., skipping trips), or being willing to spend more time on traveling. Singleton (2017) referred to these measurements as "general [measures of] PUT" and distinguished travel liking as travel experience. Depending on how it is measured, travel liking can be part of the travel experience (if measured after each trip) or part of the general travel affinity (if measured in the general term). It is important to separate activity experience from travel experience in survey questions. A list of measurements of travel affinity is provided in Table 3. In the following section, I only discuss measurements that are directly related to this dissertation.

Travel affinity and its measurements have been explored in multiple studies. Mokhtarian and colleagues (Mokhtarian, 2005; Mokhtarian & Salomon, 2001; Mokhtarian et al., 2001) measured it with the "teleportation test" by asking respondents if they were willing to teleport to the destination if it were possible. Using the teleportation test could be challenging

as the responses can be affected by the impossibility of teleportation or the excitement of trying a sci-fi technology (Mokhtarian et al., 2001; Russell & Mokhtarian, 2014). A few studies empirically tested this construct using descriptive statistics; no generalizability and inference can be made (O'Fallon & Wallis, 2012; Russell, 2012). The results of these studies are discussed in detail in Chapter 4.

Handy at al. (2005) investigated excess driving and explored multiple aspects of this travel affinity manifestation, such as making unnecessary trips to destinations, having unplanned destinations, choosing farther destinations, traveling more by car, and taking longer routes. Cao et al. (2009) explored one of these aspects (i.e., no intended destinations) in detail in a study of the San Francisco Bay Area residents who traveled without a destination in mind. Handy et al. (2005) also explored the concept of teleportation by asking respondents if they traveled "more than [they] need[ed]" and "more than [they] want[ed]."

Another way to measure travel affinity is by asking respondents about their acceptable travel time (Milakis, Cervero, van Wee, & Maat, 2015; O'Fallon & Wallis, 2012) and ideal travel time (Mokhtarian et al., 2001) for certain trips. The concepts were applied in several studies in the US, Canada, the Netherlands, and New Zealand, which showed that people were willing to spend some time commuting and were unwilling to forgo their commute completely (Milakis & van Wee, 2017; O'Fallon & Wallis, 2012; Páez & Whalen, 2010; Redmond & Mokhtarian, 2001). To the best of my knowledge, only Redmond and Mokhtarian (2001) and Páez and Whalen (2010) modeled the ideal travel time using econometric models. The details of these studies are discussed in Chapter 5.

2.2.3 Travel-based multitasking (activities during travel)

According to Kenyon (2010), multitasking is "*simultaneous activities, overlapping activities, concurrent activities, parallel activities, secondary activities and polychronic time use.*" Travel-based multitasking refers to activities conducted during transport trips, including but not limited to using a laptop/tablet/phone, listening to music or radio, working, reading, talking, and looking at the landscape. These activities are usually neglected in time-use surveys (the American Time Use Surveys), which focus on primary activities (e.g., driving, waiting at bus stops or train stations). However, a growing body of literature in time use, sociology, transportation, and time geography has shown the potential influence of multitasking and ICT in shifting travel demand and activity space (Ben-Elia, Alexander, Hubers, & Ettema, 2014; Ellegård, 2018).

Studies on travel-based multitasking have been growing since the 2000s with a series of studies from Glenn Lyons and colleagues (Kenyon & Lyons, 2007; Lyons et al., 2007, 2013; Lyons & Urry, 2005). Most studies on this topic focus on public transit users (especially train users) outside of the US (Keseru & Macharis, 2017). US-based studies are still rare, partly because of the low public transit ridership and the absence of a rail service in most metropolitan areas. Multitasking on various transport modes was the focus of a few studies in the Pacific West of the US (Malokin et al., 2019; Singleton, 2018b). An overview of travel-based research and relevant studies are provided in Keseru and Macharis (2017).

Travel-based multitasking studies have applied different methods to measure activities during travel, such as the duration of activities (Guo et al., 2015; Keseru & Macharis, 2017; Timmermans & Van der Waerden, 2008), the most frequent activity for each trip (Kenyon,

2010), and the types of activities conducted during each trip (Singleton, 2018b). Such measurements can be derived through observation of public transit users or self-report surveys completed by travelers.

Travel-based multitasking has been found to influence the way travel time is perceived. Specifically, it affects the perception of the usefulness of travel time, which also contributes to the positive utility of travel (Keseru & Macharis, 2017; Lyons & Chatterjee, 2008; Singleton, 2017). As Watts and Urry (2008) put it, *"saving travel time is then no longer what is at stake, since passenger travel time is not uniform clock time, but may be stretched and compressed in practices on-the-move."* Admittedly, these studies also found that many activities conducted during trips were aimed to avoid boredom, not to increase the usefulness of travel time, such as listening to music or window watching (Kenyon & Lyons, 2007; Lyons et al., 2007; Singleton, 2017).

Nonetheless, certain activities during trips may increase the utility of travel and thus increase the amount of travel as well. At the very least, even if these activities do not increase utility, they may still reduce the value of travel time savings and do not alleviate unnecessary travel demand (Choo et al., 2005; Singleton, 2017).

2.2.4 Travel experience: satisfaction and well-being

Subjective well-being is a person's cognitive and affective assessment of their experience (Diener, 1984). The transportation literature usually assesses subjective well-being with regard to one of its two components, affect and cognition, or both. Affect refers to how people feel, either in the form of mood or emotions (Jhangiani & Tarry, 2014). Cognition refers to how people think and evaluate an experience (Jhangiani & Tarry, 2014; Oliver, 2014).

Nordbakke and Schwanen (2014) summarized three dimensions of well-being: (1) subjective/objective, (2) hedonic/eudaimonic, and (3) universalist/contextualist. For the first dimension, subjective well-being refers to individual perceptions and experiences, while objective well-being refers to the normative criteria to assess the overall quality of a subject matter. These criteria are often predetermined by experts. An example of an objective well-being measure is the UN Human Development Index (HDI). The second dimension differentiates the stances held by Jeremy Bentham's utilitarianism (hedonic) and Aristotle's philosophical notion of happiness (eudaimonic) (Nordbakke & Schwanen, 2014). Hedonic well-being refers to the experience of pleasure/happiness and the absence of pain, and individuals calculate and maximize utility and minimize pain, which aligns perfectly with the utility maximization approach in economics. The transportation literature heavily relies on economic theories and models and therefore adopts this hedonic approach. Eudaimonic well-being, on the other hand, emphasizes meaning, potential, and purpose in performing activities for an individual's life.

With regards to the third dimension, according to Nordbakke & Schwanen (2014), well-being can be separated into two world views. A universalist view considers well-being singular and stable, and that it is temporally and spatially independent from situations and from the researcher (essentialist view). A contextualist view regards well-being as unstable, varying over a life-course. In this sense, well-being is temporally dependent, however, it is still independent of the researcher.

Based on these categorizations, [classical] economics – the ground for most travel behavior research – strongly emphasizes a subjective, hedonic, and universalist view of well-being (Mokhtarian, 2018a; Nordbakke & Schwanen, 2014). As mentioned above, travel could

be classified as eudaimonic if it enables another activity that creates achievement and meaning in life, or gives the traveler a sense of autonomy, personal growth, and self-fulfillment (Singleton, 2017). It can also be hedonic if the act of traveling itself or activities performed during travel generate satisfaction. The current transport literature focuses on this hedonic view, so does this dissertation. However, incorporating the eudaimonic approach is necessary for studies on the relationship between travel and life satisfaction/subjective well-being from an equity perspective (e.g., the well-being of older adults, low income and socially excluded population).

Eudaimonia has rarely been considered in transportation, except for a few studies that use a few items that are related to the eudaimonic aspect, such as “in control”, “adventurous”, “freedom” (Carrel, Sengupta, & Walker, 2016; Handy et al., 2005; Russell, 2012). Measuring eudaimonia in the transportation context is difficult, given that it can confound with attitude toward environment or health, personality, or can be intertwined with the travel mode than with traveling itself.

A growing body of literature has been exploring the influence of travel on subjective well-being (Morris & Guerra, 2014; Smith, 2017; Vos et al., 2013; Ye & Titheridge, 2016; J. Zhu & Fan, 2018a). However, little has been done to explore how subjective well-being affects travel patterns (Abou-Zeid & Ben-Akiva, 2012; De Vos, 2019; Singleton, 2017). The link between travel and well-being could be bidirectional. To the best of my knowledge, no studies have looked at this possible endogeneity effect between the two. A detailed review of literature in travel well-being is provided in Chapter 6.

2.3 Data collection using mobile technologies

Recently, more data collection methods that employ mobile technology have emerged, such as Bluetooth, GPS device, cell phone, Wi-Fi, smartphone application (app; with smartphone GPS). GPS tracking provides data with the highest spatio-temporal resolution. It is also a convenient way to collect data given that smartphones have become more popular. Smartphone apps can be a substitution for both paper-based (or web-based) surveys and GPS devices. This section focuses on studies that employed smartphone apps for travel survey purposes. Readers are referred to Shaheen et al. (2017, pp. 149–164) for an overview of mobility apps and Sullivan et al. (2016) for a review of health- and environment-related apps.

Transportation studies using smartphone apps have been increasing since 2005. Various studies have employed smartphone apps as a regular trip diary or activity diary (Ettema et al., 2017; Fan, Chen, Liao, & Douma, 2012; Raveau et al., 2016) or simply GPS tracking (Carrel et al., 2016; Montini, Prost, Schrammel, Rieser-Schüssler, & Axhausen, 2015). Some of these studies also provide interventions, such as giving feedback in order to change respondents' travel behavior (Calastri, Sourd, & Hess, 2018; Jariyasunant et al., 2015). A list of studies using smartphone apps can be found in Table 4. This list is not an exhaustive examination of all smartphone app studies; rather, it provides an overview of current practice in applying smartphone apps in travel research. The table is limited to (1) one study per research team and (2) smartphone studies for transportation purpose.

Overall, most app studies have smaller sample sizes as compared to similar studies on other survey modes (e.g., mail-out, web-based surveys, CATI). Tracking periods varied by study, ranging from a few days to a few months (Table 4). Several apps rely on a web-interface

for the survey components, while other apps include in-app surveys, which has become a common practice (Calastri et al., 2018; Carrel et al., 2016; Fan et al., 2012).

Table 4. Summary of recent smartphone app travel surveys

Author	Study / app	Year	Location	Sample size	Transport mode	Tracking period	App survey	Web interface	Intervention	Main purpose
Berger & Platzer (2015)	SmartMo	N/A	Graz, Austria	97 people	All modes	N/A	Yes	Yes	No	Route tracking
Bopp et al. (2016)	Active Lion	2015	University Park, PA	999 faculty, staff, and students	Active transport (main), all modes	N/A		Yes		
Calastri et al. (2018)	rMove, DECISIONS project	2017	Leeds, UK	452 people completed	All modes	2 weeks	Yes	Yes	Yes	Social network, behavioral change
Carrel et al. (2016)	San Francisco Travel Qualify Study	2013	San Francisco, CA	838 people	Transit (main), all modes	6 weeks	Yes	No	No	Satisfaction with transit service
Raveau et al. (2016)	Future Mobility Survey (FMS)	2013	Singapore	N/A	All modes	2 weeks	Yes	Yes	No	Happiness
Fan et al. (2012)	SmartTrAC (previously UbiActive, now Daynamica)	2011	Minneapolis, MN	23 faculty, staff, and students	All modes	3 weeks	Yes	No	Yes	Health and physical activity

Author	Study / app	Year	Location	Sample size	Transport mode	Tracking period	App survey	Web interface	Intervention	Main purpose
Jariyasunant et al. (2015)	The Quantified Traveler	2012	San Francisco, CA	135 people	All modes	3 weeks	No	Yes	Yes	Behavioral change
Montini et al. (2015)	PEACOX	2014	Vienna and Dublin	33 people	All modes	8 weeks	Yes	N/A	Yes	Behavioral change, decrease CO2
Susilo et al. (2017)	SbNavi & Game apps, METPEX FP7 study		8 European cities	231 & 414 responses in SbNavi and Game apps, respectively	Transit (main)		Yes			
Vich et al. (2017)	Campus Mobility app	N/A	Barcelona, Spain	233 faculty, students and staff		1-66 days	No	Yes	No	
Vij & Shankari (2015)	E-Mission	2014	San Francisco	45 students	All modes	N/A	Yes		No	Testing mode inference
Vlassenroot et al. (2015)	MOVE/Connect, Electric Vehicles in Action	2013	Ghent, Belgium	23 people	All modes	N/A	Yes	No	Yes	Opinion about electric vehicle

Compared to traditional paper-based or web-based surveys, smartphone-based surveys with GPS tracking have several advantages:

- Passively track travel patterns and reduce response burden significantly for long tracking period. Many smartphone apps apply machine learning algorithms to learn from past inputs from users.
- Provide high-resolution data on time, location, speed, and other data that are suitable for activity-travel research.
- Combine active and passive data collection (i.e., tracking and probe-person surveys at the same time).
- Support experience sampling method (i.e., prompting respondents at random moments), which is ideal for time-sensitive measurement and reduce recall bias. For example, smartphone apps prompt travelers as they are traveling and allow them to instantaneously report mood, satisfaction, and other psychological factors.

Compared to surveys using GPS devices, smartphone surveys overcome several challenges:

- Reduce data loss due to forgetting to carry and recharge GPS devices.
- Gyros, accelerometer, pedometer, magnetometer, and compass sensors in smartphones can provide additional information that facilitate mode detection.
- When collecting location data, many apps use the fused location provider in Android phones that combines signals from GPS, Wi-Fi, and cell networks, as well as built-in sensors (e.g., accelerometer, gyroscope, magnetometer) to provide location information. As such, smartphone apps offer higher accuracy

than GPS devices that only rely upon GPS signals for deriving location information.

- Modes and activities (i.e., trip purposes) can also be reported using app surveys. This is impossible for GPS devices, which relies solely on mode and activity imputation. Such imputation, if not done well, could have a negative impact on the overall quality of data and forecasting (Vij & Shankari, 2015).
- Smartphone surveys have no limits on the number of devices available to provide respondents as in surveys using GPS devices.

On the other hand, smartphone surveys have inherent shortcomings from GPS tracking in general, as well as several other unique disadvantages:

- Cold start: the beginning of trips may fail to register as the GPS takes time to start up. Battery drain can cause the phones to turn off, causing failure to record trips.
- High battery consumption when more location data are recording.
- Loss of GPS signals due to covered areas (underground), on high-speed vehicles (train), and inside urban canyons.
- Heterogeneous quality of data, depending on receptors, weather, and environments.
- Tend to get more biased samples: smartphone surveys are skewed toward younger, tech-savvy people.
- Need to provide more technical support: past studies have shown that smartphone studies need significant technical support (Carrel et al., 2016).

- High processing cost and effort: GPS data require significant effort to clean and process. Passive data collection also requires algorithms to detect trips, transportation modes, and travel purposes. Some smartphone apps are better at predicting such information.
- Privacy issue and breach of data: Privacy issue is a serious concern, as location and schedule data are too sensitive.
- Difficult to recruit study participants: Because of the technical difficulties and privacy concerns, smartphone surveys are not as appealing to participants as other types of surveys. On top of that, battery consumption is a hassle for respondents when phone life becomes shorter in new phone models.

As mentioned above, several difficulties persist in smartphone app studies. As Harding et al. (2017) pointed out, there are five notable problems with current smartphone app survey practices: (1) there are no universal metrics to measure app performance; (2) most apps were only applied to studies in a specific geographical area; (3) there are no cross-reference or cross-assessment of apps (i.e., the team who designed the app also assessed the app); (4) most apps did not collect, or collected few ground truth data; and (5) high battery consumption. This dissertation study seeks to address several challenges above (e.g., #2, 3, 4), leaving challenges #1 and #5 for future research.

3 Research design and data collection

3.1 Research design

This dissertation utilized a cross-sectional, repeated-measure survey with a non-probability sample of transport users in the Washington, DC, Blacksburg – Roanoke, VA, and Minneapolis, MN metropolitan areas. The study consists of an entry survey and a trip survey that record travelers' characteristics, travel patterns, attitude, perceptions, habit, satisfaction, activities, trips, and other characteristics. This section describes the design of the surveys and the data collection process and results.

3.1.1 Study areas

This study was conducted in the Washington, DC area[2], Blacksburg and Roanoke, VA area (main study), and Minneapolis, MN area (pilot study). With a small target sample size (300-500 participants), it is helpful to concentrate the effort on a few cities instead of multiple cities to minimize the heterogeneity among participants due to residing locations. Additionally, the built environment, infrastructure data, walk/bike scores, and other data are available in these three areas, which allows me to build comprehensive models of choice. All three areas have a high level of walking, bicycling, and riding public transit. Furthermore, the population of these cities are diverse in terms of culture, race, and ethnicity.

The Washington, DC metropolitan area, including Northern Virginia and Maryland, is an urban agglomeration of 6.1 million inhabitants (American Community Survey 2013-2017).

[2] The boundary of the study area is determined based on the US Census Bureau's boundary. This includes Washington–Arlington–Alexandria, DC–VA–MD–WV, and Silver Spring–Frederick–Rockville, MD.

This area is served by a developed multimodal network of automobile, bicycle and pedestrian facilities, and bus, heavy rail, and commuter rail systems.

The Blacksburg - Roanoke area is located in Southwest Virginia and is home to the main Virginia Tech campus. The population is 159.6 thousand people in the Blacksburg metropolitan area and 312.3 thousand people in the Roanoke metropolitan area (American Community Survey 2013-2017). This area consists of a mixture of urban, suburban, exurban, and rural areas. Transportation modes include car, bus, bicycle, and walking.

Minneapolis, MN is a major metropolitan area in the Upper Midwest with a population of 3.6 million people. The city is served by automobile, bus, light rail, commuter rail, bicycle, and pedestrian networks.

All in all, these three areas consist of diverse groups of population, built and natural environments, and represent different types of human settlements (e.g., very large, medium large, and small metropolitan areas) and different level of transport accessibility. They serve as suitable locations for this study.

3.1.2 Survey design

I used a two-part survey embedded in a mobile app to collect personal and trip data for this study. The first part is an entry questionnaire that records respondents' primary travel patterns, habits, attitudes and perceptions, as well as socio-demographic information. Each respondent answers to this part once. The second part is a smartphone-based trip diary (with GPS tracking) where respondents list their daily trips and relevant information about the trips (e.g., trip purpose, mode, moods, and satisfaction). Respondents will update this diary for multiple trips within seven days.

The survey questions are included in the Appendix. Overall, the survey presents the following measures:

- *Traveler characteristics* (part 1 – entry survey): mode availability, travel patterns, and socio-demographics were measured using standardized questions available in the National Household Travel Survey and American Community Survey.
- *Attitude, norms, and perceived behavioral control*[3] (part 1 – entry survey) were measured with a set of 7-point Likert-scale questions. These questions were initially developed by Ajzen (1991), and modified by Coogan et al. (2007) and Spears et al. (2013) and many other authors for transportation studies. The scale was reported as valid and reliable (Cronbach's $\alpha \geq 0.7$).
- *Habit* (part 1 – entry survey) was measured using the SRHI/SRBAI scale developed by Verplanken & Orbell (2003) and modified by Gardner et al. (2009). The scale was tested in other transportation studies (Bamberg et al., 2003). I also included questions about recent interrupted events and frequency of mode use in the past week to strengthen the measurement of habit.
- *Travel-related mood* (part 2 – trip survey) was measured using the Travel Mood Scale (Glasgow et al., 2018), which was validated in a pilot study at Virginia Tech.
- *Satisfaction with trip and satisfaction with activity* (part 2 – trip survey) each was measured using a single-item scale. The purpose was to separate these two concepts since they were likely to be confounded.

[3] Due to the small sample size, norms and perceived behavioral control variables were excluded in the third analysis (i.e., mode choice) in this dissertation.

- *Travel affinity* (part 2 – trip survey) was measured in two ways: (1) by asking for the ideal travel time for each trip, and (2) by asking for the willingness to make a trip. Both were proposed by Mokhtarian and colleagues and were applied with modification. I modified the teleportation test (Mokhtarian & Salomon, 2001) by asking whether or not travelers were willing to forgo a trip if it were possible for them to perform the activity without traveling. This reduced the possible probing of the high (but impossible) technology such as teleportation, which could produce bias (e.g., some people might select it because they like the technology, some people might not select it because they are in doubt of its feasibility).
- *Activities during travel (i.e., travel-based multitasking;* part 2 – trip survey): Respondents reported the tasks that they performed during trips.
- *Trip characteristics* (part 2 – trip survey): A GPS-based trip diary recorded daily trips during a week of study. Each trip is associated with a short trip survey to record trip purpose and travel mode.
- *Other variables* were derived from part 2 – trip survey, including home and work locations, actual accessibility to transit and non-motorized facilities, distance, travel time, cost, time of day, weather, travel route, and built environments around origins and destinations. GPS data are considered reliable for spatial traffic tracking (Nie, Li, Ghamami, & Ma, 2013).

3.1.3 Smartphone application

Data in this study were collected using Daynamica, an Android mobile app specialized for travel survey and activity research (Fan et al., 2015). The app is capable of tracking movements, detecting routes and modes used for each trip, as well as allowing users to report and

correct travel modes in the trip diary. This passive data collection method reduces the burden for participants and allows more reliable information compared to self-report, paper-based travel diaries. Importantly, the app enables instant, real-time entry of mood and satisfaction via a trip survey associated with each trip. This minimizes the unreliability of memory retrieval commonly seen in web- and paper-based surveys.

Figure 1 shows Daynamica's "calendar view", displaying the sequence of trips and activities inferred by the application. Modes of transport may be revised by users if needed. In this view, Daynamica provides information that can be obtained by traditional diary methods: start/end time, location, and travel mode. Daynamica's "map view" that is capable of displaying locational information associated with each activity and trip. The app user's interface is easy to navigate. A user's guide was available on the study website and within the app.

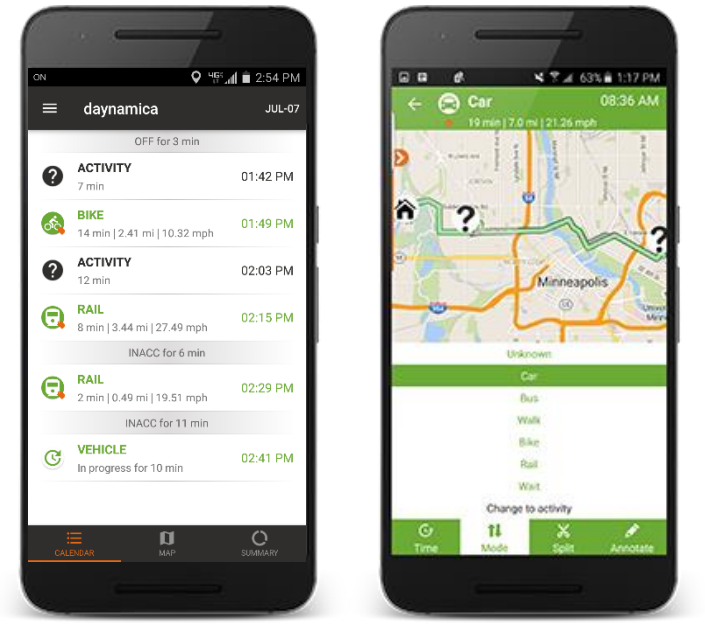


Figure 1 Calendar view (left) and map view (right) from the Daynamica app showing daily trips.

3.1.4 Pilot study and instrument validation

Glasgow et al. (2018) validated the Travel Mood Scale (and other items in the app-based trip survey) through a web survey of 780 Virginia Tech undergraduate students from February 2017 to May 2017. Administered along with the Satisfaction with Travel Scale (Ettema et al., 2011), the survey asked for respondents' experience with their most recent trips. The results showed that the scale is valid and reliable (Glasgow et al., 2018).

Another test for the above survey instruments was conducted via a pilot study during Fall 2016 and Spring 2017. The study attracted about 70 users for the entrance survey and 35 users for the trip surveys for the Fall 2016 study in Blacksburg, VA, and Washington, DC metropolitan areas. Based on feedback and results from this pilot study, I decided to retain most of the survey instruments for use in the main study. I combined the pilot study sample with the main study due to the latter's small sample size. This choice enables me to increase the statistical powers of the analyses.

3.2 Data collection

3.2.1 Procedure

The study was approved by the Virginia Tech IRB in August 2016 (IRB-16-268). The entire survey took one week to complete but respondents had the option to continue for another week. Participation in this study was on a voluntary basis. First, participants provided consent and took the entry survey either on the web (Qualtrics website) or phone (mobile Qualtrics embedded in the Daynamica app). The process lasted about 15 minutes. After that, they used the app to track their movement. The app detected travel routes and trips, and it prompted a trip survey after each trip. Every day at 7 PM, the app reminded respondents to complete the trip surveys if they had not done so and uploaded the data to the server. Every

week, I sent out an email reminder to notify participants who had completed their full week. I also checked in with other participants who had partially completed the study for further support. I regularly provided technical support through the study website, email, phone, and if applicable, in person.

In order to receive full compensation, respondents were required to answer the entry survey, complete at least 5 trip surveys, and track their travel for 7 days. I tested two compensation models in the pilot study. First, all participants were entered into a raffle from which I drew 10 participants to receive Amazon gift cards worth $50 each. However, this method was ineffective in attracting participants. Second, I compensated each respondent with a $10 Amazon gift card for their full participation. For the main survey, I decided to increase the amount of compensation in hopes that participation would also increase. In the first round of the main study, each participant received a $15 Amazon gift card for their full participation. Due to the small enrollment in the first round, I offered the second round of participants a $25 Amazon gift card. This compensation model was effective as most study participants enrolled during the second round. A description of the sample is provided in Section 3.3.

3.2.2 Participants and recruitment methods

The study was open to anyone who was at least 18 years old, possessed an Android smartphone, and lived in the study areas. The surveys were self-administered. All respondents were asked to complete the entry survey and at least 5 trip surveys over 7 days. The data were collected in Fall 2016 through Spring 2018, mostly concentrated from September through November and March through April. The study was inactive during holidays (e.g., Thanksgiving, Christmas) and inclement weather (e.g., windy weather, snow storms, sleet) to avoid abnormal travel patterns.

A significant amount of time for field work was dedicated to recruiting and retaining participants, app troubleshooting, following up with app users (to avoid attrition), and responding to inquiries about the study procedure. I recruited participants using multiple channels to obtain a diverse sample (i.e., people outside of the universities). I oversampled public transit and active transport users to balance the sample with multiple modes in order to understand the mechanism behind sustainable travel choice. However, due to the study requirement (e.g., possessing an Android smartphone), the participants were skewed toward the younger population and people who have more experience with smartphone applications (usually highly educated). A description of the survey results is presented in Section 3.3.

First, I partnered with a marketing firm to recruit participants from a pool of Android users in the Washington, DC area. Second, I contacted about 260 neighborhood/civic associations to reach a demographically and culturally diverse group of people in the Washington, DC area. Third, I sent invitations to members of bicycle and pedestrian advocacy groups, transportation and planning professional groups. I also contacted universities in the three study areas (i.e., Blacksburg, VA; Washington, DC; Minneapolis, MN) and used a sample of student, faculty, and staff at the University of Minnesota and at Virginia Tech's Northern Virginia and Blacksburg/Roanoke campuses. This is intended to reach a diverse group of transport users who bicycle, walk, or ride transit.

The study was also available on Amazon Mechanical Turk, an online service run by Amazon Inc. to hire workers for small tasks, including surveys. Studies have shown that the demographic attributes of Amazon Mechanical Turk users are not substantially different from the general population (Difallah, Filatova, & Ipeirotis, 2018). Additionally, I advertised

through Twitter, Facebook, Craigslist (in Blacksburg, Roanoke, Washington, DC, and Minneapolis/St. Paul), online forums, recruiting booths at public locations, and informal channels. A summary of recruitment channels and their sample characteristics is shown in Table 5 .

3.2.3 Response rates

In total, 469 participants started the study and only 247 participants completed the entire study. The response rates cannot be definitively calculated from this sample; however, some channels were more effective than others. For example, the commercial panel in Washington, DC and Virginia Tech listservs attracted most respondents. Overall, I estimate that the response rate from all channels was below 1% (Table 5). This is a common issue with smartphone data collection and GPS tracking where sample sizes are very low (see Section 2.3).

Other channels did not attract as many participants as the commercial panel and Virginia Tech listservs. For example, many emails to the neighborhood and civic associations were not delivered due to full inboxes or outdated email addresses. It is also unknown how many association chairs who received the email actually forwarded it to their listservs, as well as how many people viewed the online forum posts and social media posts.

The common reasons for attrition, according to email correspondence with the respondents who withdrew from the surveys, were technical difficulties with the app, such as minor app errors, battery drain, and the hassles of completing trip surveys. Respondents who completed the study (n = 41 people) reported similar issues, commonly citing battery drain and tedious trip surveys.

Table 5. Sample characteristics and response rates by recruitment channel

Recruitment channel	Population characteristics	Invitations	Participants started the survey	Response rate[1]
Virginia Tech listservs	Young, highly educated	About 6,000 people	100-120 people	Low (<2%)
Commercial panel (Washington, DC are only)	Diverse	>1,000 people	109 people	Medium (<10%)
Neighborhood associations	Diverse	>10,000 people	<10	Very low
Alternative transportation advocacy groups	Active bicyclists and transit users	1,000-2,000 people	<10	Very low
Amazon Mechanical Turk	Diverse	Unknown	107 people	N/A
Recruitment booth at public locations	Very diverse	>1,000 people	Unknown	Low to very low
Word of mouth	Unknown	Unknown	<10	N/A
Other channels (e.g., Craigslist, online advertisements, and other)	Diverse	>1,000 people	<10	Very low

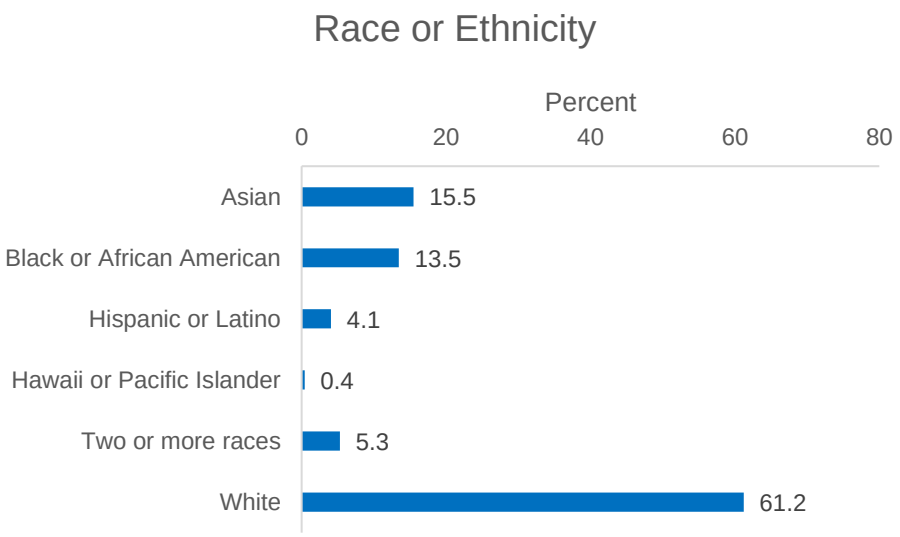
[1] *The response rate was estimated based on the number of invitations sent out and the approximated number of participants in each channel. Other than participants from Amazon Mechanical Turk and*

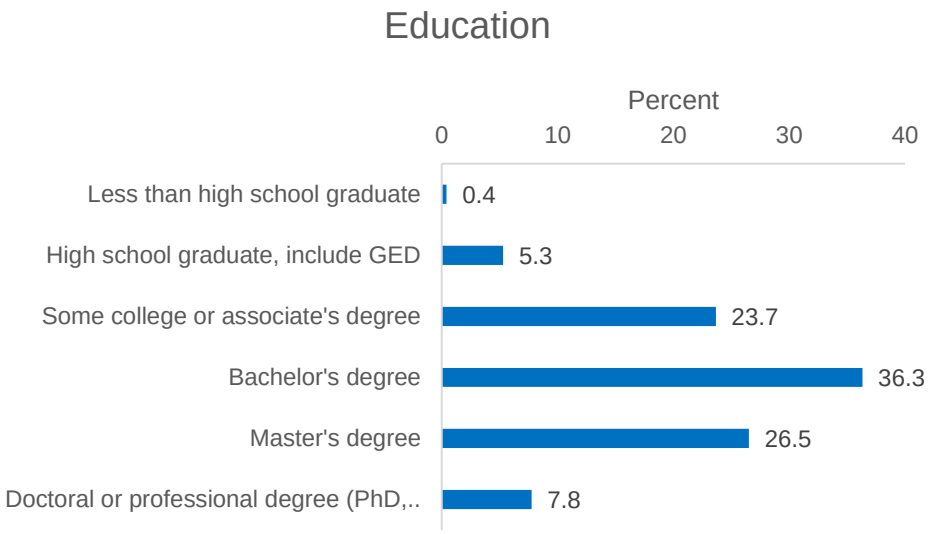
the commercial panel, most participants did not report how they learned about this study; this information was inferred based on location, email address (i.e., institution email) and the recruitment strategy employed at the time the participant started the survey.

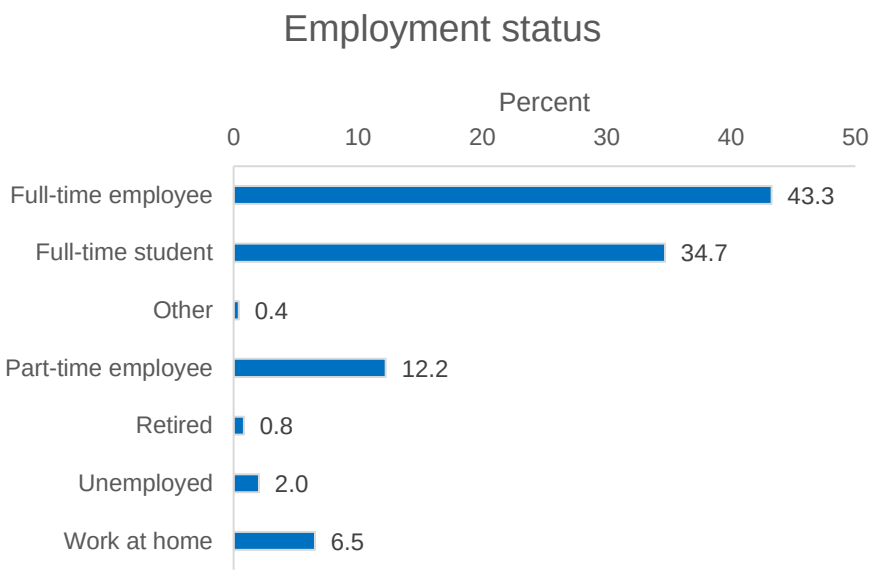
3.3 Overview of survey results

Of the 247 participants who completed the entire study, only 245 were retained for analyses. The mean age was 32 (SD = 11, median = 30). The sample consists of 57% female respondents. With regard to racial distribution, 60% identified as White, 14% Black or African American, 16% Asian, 4% Hispanic, and 6% other races. In terms of location, 37% of respondents lived in the Blacksburg – Roanoke area, 50% lived in the Washington, DC area, and 13% lived in the Minneapolis area. The demographic distributions of the sample are summarized in Figure 2.

The majority of the sample were highly educated with 36.3% had a Bachelor's degree and 34.3% had a Master's, PhD, or professional degree (Figure 2). About 43.3% of the respondents worked full-time and 34.7% studied full-time. With regard to household income, 14.5% of the sample earned less than $10,000 (i.e., college students), 12% earned more than $120,000 per year.


Race or Ethnicity
Percent
0
20
40
60
80
Asian
15.5
Black or African American
13.5
Hispanic or Latino
4.1
Hawaii or Pacific Islander
0.4
Two or more races
5.3
White
61.2


Education
Percent
0
10
20
30
40
Less than high school graduate
0.4
High school graduate, include GED
5.3
Some college or associate's degree
23.7
Bachelor's degree
36.3
Master's degree
26.5
Doctoral or professional degree (PhD,..
7.8



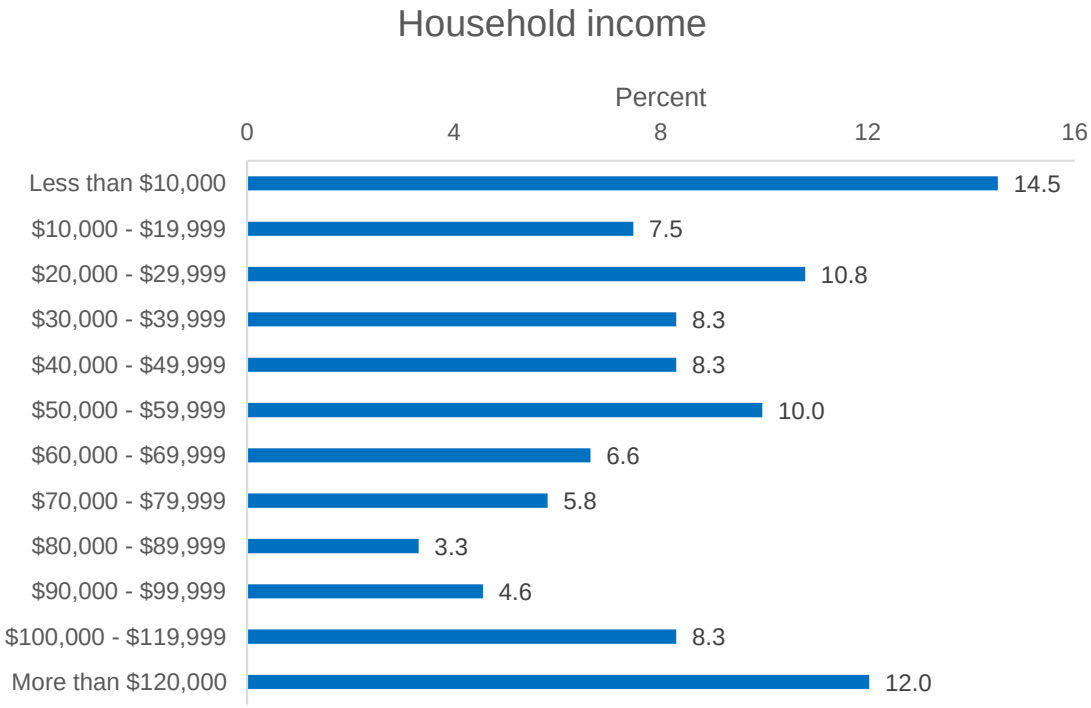


Figure 2. Demographics based on the study sample. The label shows the column percentage.

Table 6. Comparison of sample demographics with population of each study area and the nation

	Blacksburg/Roanoke area[1]		**Washington, DC area**		**Minneapolis area**		**Total**	
	This study	**ACS**[2]	**This study**	**ACS**	**This study**	**ACS**	**This study (3 metro areas)**	**ACS (national)**
Age (median) [4]	25	25-34	34	25-34	32	35-44	30	35-44
Gender (female)	45.6%	50.6%	64.2%	52.6%	40.6%	50.4%	56.7%	50.8%
Median household income[5]	Below $20,000	$51,509	$70-80,000	$77,649	$40-50,000	$72,274	$50-60,000	$57,652
Employment status (16y or older) [3]								
- *Employed*	28.9%	56.3%	86.2%	63.4%	62.5%	68.8%	62.0%	58.9%
- *Unemployed*	2.2%	3.2%	1.63%	5.5%	3.1%	3.1%	2%	4.1%
- *Not in labor force*	67.8%	40.4%	12.2%	30.5%	34.4%	28.0%	35.5%	36.6%
Education attainment (25y or older)								
- *Less than High School*	0%	11.3%	0.8%	9.7%	0%	6.8%	0.4%	12.7%
- *High School Graduate (Includes Equivalency)*	4.4%	29.2%	6.5%	17.6%	3.1%	22.5%	5.3%	27.3%
- *Some College*	26.7%	29.5%	22.8%	16.1%	18.8%	31.3%	23.7%	29.1%
- *Bachelor's Degree*	34.4%	17.3%	35.0%	23.8%	46.9%	25.8%	36.3%	19.1%
- *Master's Degree*	30.0%	8.2%	25.2%	20.2%	21.9%	9.6%	26.5%	8.4%
- *Professional School Degree or Doctorate Degree*	4.4%	4.6%	9.8%	12.6%	9.4%	4.0%	7.8%	3.4%

	Blacksburg/Roanoke area[1]		Washington, DC area		Minneapolis area		Total	
	This study	**ACS[2]**	**This study**	**ACS**	**This study**	**ACS**	**This study (3 metro areas)**	**ACS (national)**
Race								
- *White Alone*	54.4%	85.2%	62.6%	40.7%	75.0%	80.1%	61.2%	73.0%
- *Black or African American Alone*	3.3%	8.9%	23.6%	47.8%	3.1%	7.9%	13.5%	12.7%
- *Asian Alone*	28.9%	3.0%	5.7%	3.8%	15.6%	6.1%	15.5%	5.4%
- *Native Indian, Alaska, Hawaiian and Other Pacific Islander Alone*	0%	0.5%	0.8%	0.3%	0%	0.6%	0.4%	1%
- *Some Other Race Alone*	6.7%	0.8%	3.3%	4.6%	0%	2.1%	4.1%	4.9%
- *Two or More Races*	6.7%	2.0%	4.1%	2.9%	6.3%	3.2%	5.3%	3.1%
N	90		123		32		245	

[1] *Because Blacksburg and Roanoke areas are two separate metropolitan statistical areas, I combined the two and took the average of each measure based on the ACS data.*

[2] *American Community Surveys 2013-2017 (5-year estimates).*

[3] *This study only surveyed people who are 18 years or older.*

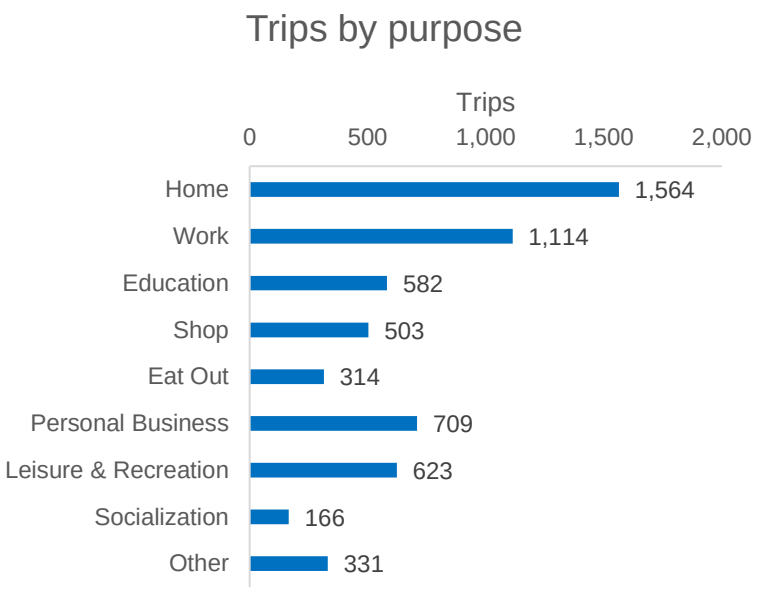
[4] *Age was measured continuously in this study and measured in interval in ACS.*

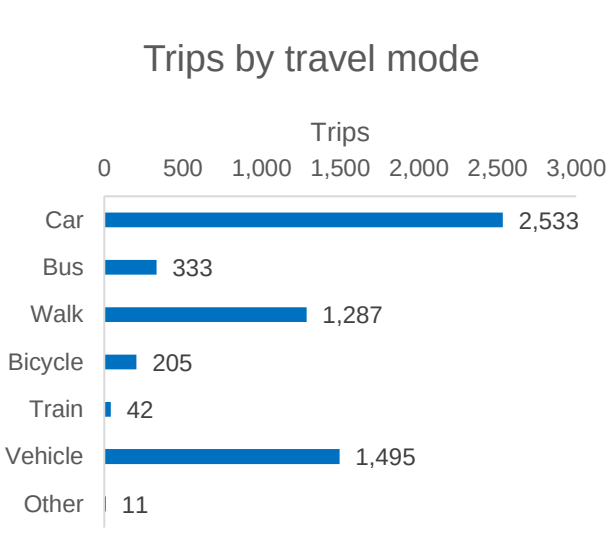
[5] *Income was measured in interval in study and was aggregated in a numeric form in ACS.*

A comparison of the sample and population characteristics are presented in Table 6. In general, this sample is younger than the national average. The Washington, DC sample is older, more likely to be employed, and more diverse than the Blacksburg and Minneapolis samples.

With regard to transportation access, 90% of respondents had a driver's license, 84% had access to a car, 55% had a monthly transit pass, 46% had access to a bicycle in working condition, and 47% had a parking permit at work. The mean one-way commute time was 27 minutes.

Figure 3 shows the distribution of trips by purpose, mode, and location. Commuting trips (i.e., to home, work, and school) account for the majority of the sample, followed by errand and leisure/ recreation trips. Car trips and vehicle trips (i.e., could be car or bus, undetected by the app and unreported by respondents) account for a large portion of the sample. The share of walking trips is much higher than the national share (McGuckin & Fucci, 2018). Washington, DC respondents made half of the trips in this sample (3,113 trips); Blacksburg – Roanoke participants made 2,102 trips. A map of trips in the Washington, DC and Blacksburg-Roanoke areas (the two major study areas) is shown in Figure 4.





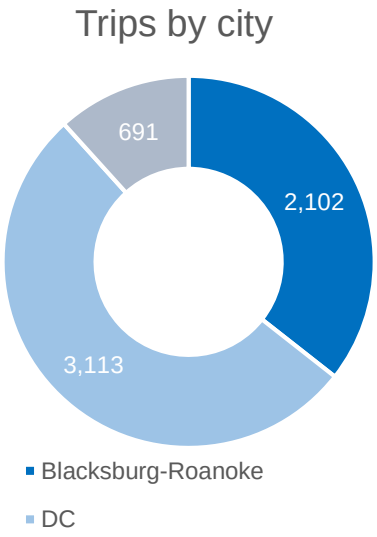


Figure 3. Trips by purpose, mode, and city. Numbers of trips are labeled in the charts.

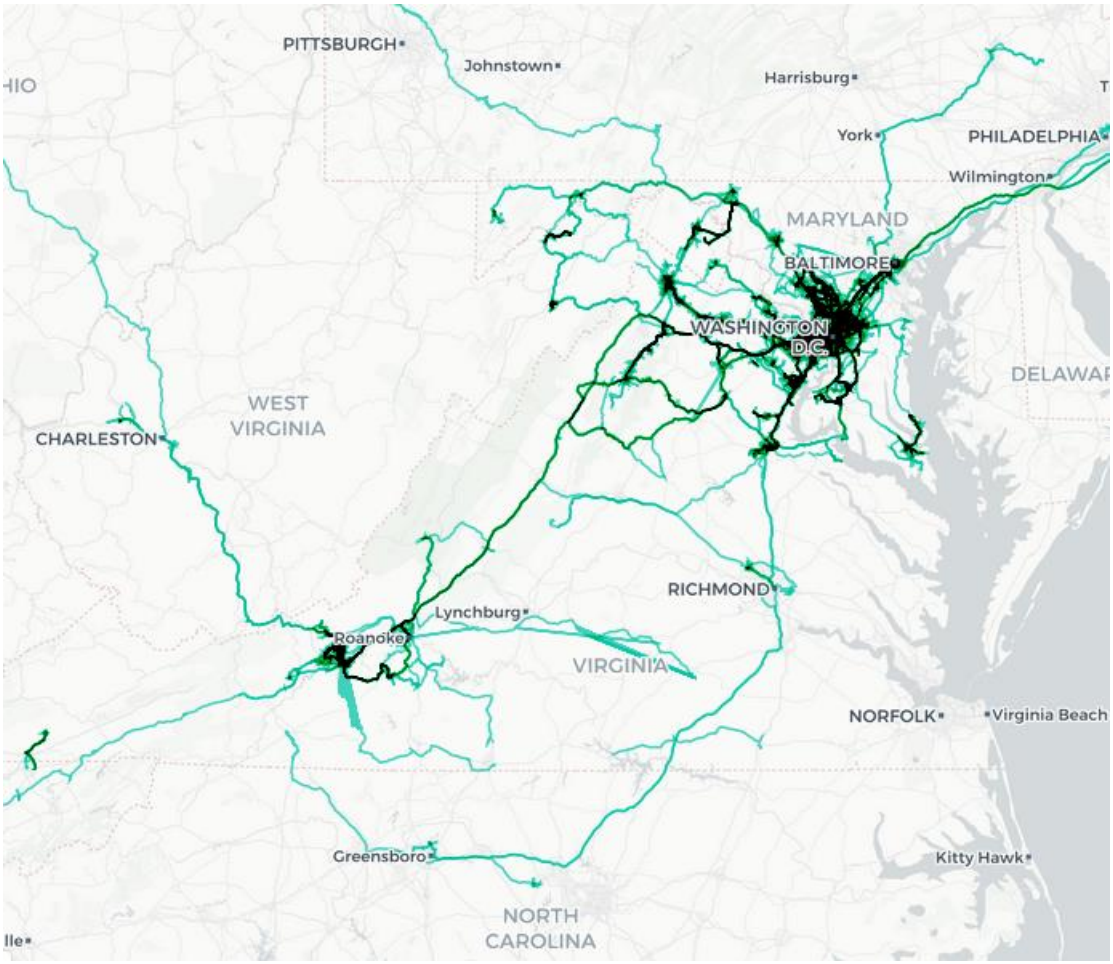


Figure 4. Map of trips in Washington, DC and Blacksburg, VA areas

3.4 Summary

In summary, I collected data from 247 participants in the Blacksburg – Roanoke, Washington, DC, and Minneapolis metropolitan areas across 1-2 weeks from Fall 2016 to Spring 2018. This chapter provides an overview of the study design and data collection effort. It describes the sample characteristics in comparison with the population demographics at the metropolitan and national levels. Detailed analyses using this sample will be described in Chapters 4 – 6.

4 Travel affinity: Desirability of trip making

4.1 Introduction

Managing travel demand is the goal of transportation agencies at all levels of government. The 4Ts – tolling, transit, technology, and telecommuting – are used (FHWA, 2009), but the effectiveness of such strategies still needs further exploration.

One of the premises of travel demand modeling and management is that (1) people make trips as a means to participate in activities and (2) travel has a negative utility (Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004; Legrain, Eluru, & El-Geneidy, 2015; Morris & Guerra, 2015). Therefore it is assumed that travelers aim to minimize their travel. A few more recent studies have shown that the act of travel itself may have a positive utility (Mokhtarian & Salomon, 2001; Mokhtarian et al., 2001). For example, travelers have been found to enjoy their trips and are unwilling to forgo the trips if it were possible.

Most studies on travel affinity, one of the subcategories of the positive utility of travel, often had a narrow focus on school- and/or work-related commuting trips. They also often used a retrospective approach through web-based or paper-based surveys to record past trip characteristics and satisfaction levels. However, this approach often results in recall bias in which participants may be unable to accurately remember their emotional experience because of memory distortion. It is also difficult for survey participants to recollect specific trip details such as trip routes and trip distance. These studies relied on participants' experience of a single trip to generalize all of their trips (Mokhtarian & Salomon, 2001; Mokhtarian et al., 2001; Ory & Mokhtarian, 2009; Páez & Whalen, 2010; Redmond & Mokhtarian, 2001).

One of the most common measures of travel affinity is the "teleportation test" (Mokhtarian & Salomon, 2001; Mokhtarian et al., 2001), which was found to be a strong and effective measure (O'Fallon & Wallis, 2012; Russell & Mokhtarian, 2014; Singleton, 2017). Moreover, travel affinity was either used as an explanatory variable or summarized for descriptive statistics to illustrate the positive utility of travel (Ibid). Little research has treated travel affinity as an outcome variable and used in an econometric model to identify its determinants (O'Fallon & Wallis, 2012). Few studies tested the validity of this measurement and compare it against other measures of the positive utility of travel.

Furthermore, it is reasonable to believe that travel affinity varies when a person is exposed to different travel environments. It also varies between individuals due to their personal characteristics. Therefore, in addition to analyzing between-individual variations, it is also necessary to holistically examine within-individual variations at multiple time points and multiple trip purposes.

To overcome these limitations, this study incorporated a multi-day smartphone survey that allows GPS tracking and instantaneous recording of travelers' experience over the course of a week. I measured travel affinity differently from the measurements used by Mokhtarian et al. (2001). Specifically, my main models focused on the desirability of trip making, which was measured after each trip with a question: *"If it were possible, would you like to arrive at the destination immediately without making the trip?"* The goals of this study were to (1) develop a modified version of the "teleportation test" and test its validity by comparing it with other measurements of the positive utility of travel; and (2) develop an econometric model to comprehensively assess how travel affinity relates to various trip- and personal-factors.

This study contributes to the small but growing literature on the positive utility of travel. Findings from this study will inform policy makers about the limitations of travel demand management strategies (e.g., telecommuting, online shopping, video conferencing, and other forms of ICT, reducing unnecessary travel). It will also help to identify the types of trips and population groups that are associated with lower travel affinity.

4.2 Literature review

A general discussion on the positive utility of travel and its measurement is provided in Chapter 2 of this dissertation. Here I will focus on the two major measures, namely activities during travel (travel-based multitasking) and travel affinity (trip-making desirability).

4.2.1 Activities during travel

Activities during travel (travel-based multitasking) were found to increase the positive utility of travel (Mokhtarian, 2005, 2018a; Mokhtarian & Salomon, 2001) by enhancing the "joy" of traveling or increasing the usefulness of travel time (Jain & Lyons, 2008). This is one of the fastest growing bodies of literature related to the positive utility of travel starting from the mid-2000s.

Most studies on this topic were first conducted outside of the US (e.g., the UK, Canada, the Netherlands, and Japan) and were based on riders of public transit, a mode that allows the largest number of activities during travel. Various methods have been used to study travel-based multitasking, such as ethnography (e.g., observation) (Guo et al., 2015; Russell et al., 2011), interviews (Jain & Lyons, 2008), and surveys (Guo et al., 2015; Lyons et al., 2007, 2013; Susilo et al., 2012). In one of the earliest studies in this research area, Lyons and Urry (2005) explored how British commuters spent their travel time, which they called a "gift," as

travel time acted as a buffer or time out between the activities at origins and destinations (Jain & Lyons, 2008).

Studies in other developed countries found a similar pattern of travel time use. Through field observation and a self-reported survey of 1,937 transit users in Vancouver, Canada, Guo et al. (2015) found that most observed activities were associated with ICT for entertaining or working during transit trips. Russell et al. (2011) observed 812 bus and train passengers in Wellington, New Zealand, and found that 65% of passengers were looking out of the windows during the trips. This pattern was more common on buses than trains. About 20% read, which was more common on trains than buses. Travelers also conducted other activities during trips, such as talking, texting, listening to mobile devices, or sleeping.

In the US, travel time use studies are still limited and applied mostly for multiple travel modes, as transit mode share is small. An exception is Timmermans and Van der Waerden (2008) who observed 161 BART passengers in the San Francisco Bay Area and found that travel duration and time of day are significant in activity participation models. Berlin et al. (2015) and Malokin et al. (2019) studied commuters in the San Francisco Bay Area and found that multitasking varies by mode of transport. Malokin et al. (2019) also showed that the ability to multitask during travel was significant in mode choice models, indicating a potential application of this measurement in modeling choice for non-active, non-driving modes, such as public transit, ride hailing, and autonomous vehicles. Singleton (2018b) studied 650 commuters in Portland, OR, and found that a majority of tasks performed during travel were conducted out of boredom. Nonetheless, 90% of this sample found their travel time useful, although the magnitude of usefulness varied by factors such as mode, activity, and number of commute days. A list of studies on this topic is presented in Table 7.

Kenyon and Lyons (2007) reviewed earlier studies of multitasking and its effect on travel and activities. Keseru & Macharis (2017) provided a comprehensive review of travel time use studies, as well as 75 variables to test for the impact on travel-based multitasking. These variables fall in 7 categories: socio-demographics (e.g., age, gender, access to car), trip characteristics (e.g., trip duration, distance, mode), attitude (e.g., expectation of travelers' and other people toward them), comfort level (e.g., quality of service, infrastructure, environment/weather), equipment for the trip (e.g., smartphone, laptop, book), spatial attribute, and time-use-related attribute (e.g., type of activity). They also found that within 58 studies in the developed world, only a few factors had sufficient evidence for the effect on travel time use, such as age, gender, trip duration, mode, trip purpose, time of day/week, and companionship.

A notable theme from past studies is that work-related tasks were rarely conducted during travel. Most travel-based multitasking involved activities for leisure, entertaining, or "killing time" rather than for productivity. Nonetheless, these non-work-related activities may still enhance the perception of travel time usefulness, reducing the value of travel time savings.

Table 7. List of studies focusing on activities during travel (travel-based multitasking)

Study [1]	Location	Data source	Measurement	Analytic method	Main finding
Frei et al. (2015)	Chicago, IL	Survey and observation of transit riders, n = 336, year 2010	Service value rating, activity type, demographics, transportation access, reasons to ride transit	Ordered logit models, logit models	Younger, employed people were more likely to listen to audio; older (above 30y) tended to read. People who used travel time for active leisure activities considered travel time more useful. The opposite was true for people who used their time for passive leisure activities (which were used to mask the boredom).
Guo et al. (2015)	Vancouver, Canada	Observation and survey, n= 1,937 bus passengers on buses, year 2012	Type of activities engaged, demographics, time of day/week, duration, weather, onboard environment	Multinomial logit models	Frequent riders are more likely to engage in smart device usage during trips. Longer trips tend to induce more smart-device usage. The most common activities onboard were listening, reading/writing, eating/drinking, talking on the phone or face-to-face.
Jain & Lyons (2008)	Great Britain	Focus group	N/A	Content analysis	Travel time can be viewed as transition time or time out (escaping from the obligations), enabled by the ability to make travel

Study [1]	Location	Data source	Measurement	Analytic method	Main finding
					time equipped time by bringing devices or books for the trips.
Lyons et al. (2007)	Great Britain	National mail-back survey, n = 26,221 rail passengers, year 2004	Time use, number of activities, duration of activities, percent of people conducting activities during travel	Descriptive statistics	The positive utility of travel exists. 40% of the time, travel-based multitasking is worthwhile. 13% worked or studied most of the time during their commutes and 30% did so for some of the time. The value of travel time might be different given the presence of travel-based multitasking.
Lyons et al. (2013)	Great Britain	National mail-back survey, n_1 = 22,866 rail passengers (2004) and n_2 = 19,715 rail passengers (2010)	Time use, number of activities, duration of activities, percent of people conducting activities during travel	Descriptive statistics	More ICT usage in 2010. More people found their travel time use was worthwhile, regardless of trip purposes. Conversely, fewer people reported that their travel time was wasted.
Malokin et al. (2019) [2]	Northern California	Survey, n = 2,229 commuters, year 2012	Activity type, attitude toward multitasking and travel, demographics	Binary and multinomial logit models	Activities during trips were significant in mode choice models. Ability to multitask

Study [1]	Location	Data source	Measurement	Analytic method	Main finding
					would boost the likelihood to choose transit or carpool
O'Fallon & Wallis (2012)	Auckland and Wellington, New Zealand	Online survey, n= 512 commuters, year 2011	Ideal commute time, travel time enjoyment, activities during travel.	Descriptive statistics	- Median ideal commute time was 10 minutes (all modes), or <20 minutes for >75% of drivers and pedestrians. Only 3% wanted zero commute time. - 40% enjoyed time spent commuting. Active travelers were more likely to enjoy their commutes. Reasons: transition time, think/relax, listening to music/radio, being out, and exercise. - 12% wanted to maintain the current amount of travel time. - 93% multitasked during travel. 20% worked or studied while commuting.
Russell et al. (2011)	Wellington, New Zealand	Observation, 812 bus and train riders			65% of passengers were looking at the windows during the trips (common on buses than trains), 20% read (more common on trains than buses). They also conducted

Study [1]	Location	Data source	Measurement	Analytic method	Main finding
					other activities such as talking, texting, listening, or sleeping.
Singleton (2018) [2]	Portland, OR	Self-report online survey, n = 650 commuters, year 2016	Travel time usefulness, activities during travel: type, duration	Ordered logit model	90% of active travelers found their commute time useful. Doing nothing or performed passive activities were negatively associated with travel-time usefulness. Walking and bicycling were associated with higher travel time usefulness due to their exercise benefits.
Susilo et al. (2012)	Great Britain	National Passenger Survey biannual survey of rail passengers, n = 19,715 passengers (2010)	Travel usefulness, satisfaction with train reliability, activity type, items carried onboard (i.e., equipment), demographics, trip purpose	Multinomial logit (satisfaction with travel)	The majority of passengers (87%) did not consider their travel time wasted. Most commons activities that affect appreciation of time use were reading, window gazing, texting, working, and listening.
Tang et al. (2017)	Shanghai–Nanjing corridor, China	High-speed rail passenger survey, n = 901, year 2016	Plan for travel time use, device equipped, demographics, internet usage	Multinomial probit models	Most passengers used ICT and conducted work-related activities during travel.

Study [1]	Location	Data source	Measurement	Analytic method	Main finding
Timmermans & Van der Waerden (2008)	San Francisco, CA	Observation on BART trains, n=161 passengers, year 2007	Activity types and duration, trip duration, travel companion, time of day, demographics	Canonical discriminant analysis, multinomial logit models, cluster analysis	Travel duration and time of day are the most important variables to predict onboard activity participation. Most passengers did nothing or talked socially for sometime during the trip.

[1] *All studies are cross-sectional and non-repeated measures. This is not an exhaustive list of studies on this topic.*

[2] *Studies with multiple modes of travel.*

4.2.2 Travel affinity measures and the teleportation test

As one of the measures of travel affinity, the teleportation test is a stated choice experiment, originally measured as follows: "*If you could snap your fingers or blink your eyes and instantaneously teleport yourself to the desired destination, would you do so?*" (Mokhtarian and Salomon, 2001, p. 711). The answer options could be yes/no or yes/maybe/no. If the utility of trips comes solely from the destination activities, the travelers may want to teleport (i.e., skip the trip). Conversely, if the utility comes, even partly, from the travel or activities onboard, then the travelers may not want to teleport. Of course, there might be an ambivelent preference where people are neutral (i.e., want to teleport and not teleport to some extent) (Mokhtarian and Salomon, 2001).

Only a few studies have applied this test on their samples. Some of them were qualitative (Handy et al., 2005; Russell & Mokhtarian, 2014); some are quantitative but only descriptive (O'Fallon & Wallis, 2012; Russell, 2012). A summary of the studies on this topic is presented in Table 8. Generally, previous studies found that about 75% of respondents wanted to teleport. In a focus group study in Austin, TX, Handy et al. (2005) found that travelers indicated fondness for travel and may travel more because they enjoyed driving or enjoyed the activities conducted during travel (e.g., listening to an audio book).

Russell and Mokhtarian (2012) conducted an in-depth interview with 48 bus and train passengers in Wellington, New Zealand and found a small difference compared to the findings from quantitative studies. They noted that choosing teleportation does not mean wanting zero travel time or considering travel time as wasted (Russell and Mokhtarian, 2014). The responses and validity of the test are also affected by the questions' order. That is, respondents need to consider other factors (e.g., activities during travel, the usefulness of travel, attitude

toward travel and time use) before answering this teleportation question in order to make the test valid. It could be that respondents were keen about trying a new technology. However, no effort has been made to date to adapt this teleportation question in a way that respondents choose it because of the new technology instead of being driven by travel affinity.

It is noteworthy that no studies have measured travel affinity for multiple trips made by the same individual. This is important because not all trips for the same purpose are experienced as onerous for the same person; some trips can be more onerous than others. Travel affinity is context-sensitive by nature; various factors (e.g., congestion, unexpected incidents, inclement weather, and time pressure) may make some trips less desirable than others. Additionally, evidence from North America is sparse. This study investigates the within- and between-person variations in travel affinity using a smartphone app to collect repeated-measure data within a week.

Table 8. Studies focused on the positive utility of travel with the teleportation question.

Study	Location	Data source	Measurement	Analytic method	Main finding
Mokhtarian & Salomon (2001)	San Francisco Bay Area, CA	Mail survey, n = 1,900	Standard teleportation test and many other measurements	Descriptive statistics	Positive utility of travel exists, teleport test could be an alternative to measure the willingness to travel.
Diana (2008)	France	Web survey for staff at the French National Institute for Transport and Safety Research n = 164, year 2004	Importance of activities during trips, travel motivations, trip-related feelings, desired trip length and teleport, mode performance, importance of activities performed at destinations	Factor analysis	Primary utility existed for users of all modes. Non-work trips had higher scores (utility) than work trips.
Handy et al. (2005) [1]	Austin, TX	3 focus groups at the University of Texas at Austin, year 2002	Reasons for excess travel: value of driving itself, value of activities while driving, variety seeking, habit, poor planning, misconception or lack of information	Content analysis	Travelers drove by choice rather than necessity. 27 out of 43 people reported that they had some excess driving, that they could have skipped the trips, used shorter routes, chose closer destinations, or used an alternative mode.

Study	Location	Data source	Measurement	Analytic method	Main finding
Jain & Lyons (2008)	Great Britain	Focus group	Standard teleportation test (i.e., ask for the teleport preference directly)	Content analysis	Teleportation means zero travel time, an option that very few people chose.
O'Fallon & Wallis (2012)	Wellington, New Zealand	Survey, n = 679	Standard teleportation test (i.e., ask for the teleport preference directly)	Descriptive statistics	79% wanted to teleport, 19% viewed that travel time is wasted. 21% reported that they wanted some travel time between home and work. Pedestrians were less likely to choose to teleport. Teleporters had longer median commute time than non-teleporter.
Russell & Mokhtarian (2014)	Wellington, New Zealand	Phone interview, n = 48 bus and train riders, year 2009-2010	Standard teleportation test (i.e., ask for the teleport preference directly)	Content analysis	66% wanted to teleport, 18% thought travel time was wasted. Teleport responses from this study softened the views in quantitative survey results. Accepting teleportation is not the same as wanting zero travel time. Teleportation decision may be inconsistent with

Study	Location	Data source	Measurement	Analytic method	Main finding
					other measures, such as usefulness of travel time and ideal travel time.

[1] *This study does not explicitly use the term "teleport".*

4.3 Methods

4.3.1 Data collection and processing

The data for this study were collected as part of the Mood State in Transport Environments study. The data collection effort was described in detail in Chapter 3. For the current research question, I used a dataset of 243 individuals and 5,854 trips in all cities. I excluded respondents who did not (a) submit trip data and (b) complete the entry survey. Further, due to inaccuracy in GPS tracking, I removed trips that were shorter than 5 minutes and those without a completed trip survey, as well as walking trips longer than 450 minutes.

The variable of interest is travel affinity, measured using a modified version of the "teleportation test" (Mokhtarian et al., 2001). In the trip survey after each trip, I asked: *"If it were possible, would you like to arrive at the destination immediately without making the trip?"* Rewording the question from the Mokhtarian et al. (2001) study was intended to remove the bias caused by the enthusiasm of trying a new technology (i.e., teleportation) or the hesitance to use an unfeasible travel option. Respondents had the option to choose yes (i.e., willing to forgo the trip), neutral (i.e., no strong feeling either way), or no (i.e., unwilling to forgo the trip). The variable was then coded as 0 if yes, 1 if neutral, and 2 as no. Also, this question was asked after each trip, after respondents had filled in the entry survey with multiple questions related to travel attitude and the usefulness of travel time; that is, they had considered other aspects of travel time use.

I also collected secondary data to control for environment variations, such as weather (e.g., rainfall and temperatures acquired from the National Oceanic and Atmospheric Administration). Some other data were derived from the GPS tracking, such as time of day (e.g., morning and afternoon rush hours, late night), and time of week (i.e., weekend).

4.3.2 Analysis

In order to better understand different measurements of the positive utility of travel, I compared several measures: (1) travel attitude and perception of travel usefulness (from the person sample), (2) activities during travel (from the trip sample), (3) desirability of trip making (from the trip sample), and (4) satisfaction with trips (from trip sample). Descriptions of these measurements were discussed in Section 2.2 of this dissertation.

I modeled the desire to travel using multilevel ordered logit models for the whole sample as well as for each major city in my sample. For a series of 5,748 trips clustered in 243 people, and conditional on a set of exploratory variables $\mathbf{X}_{ij}$ (e.g., trip purpose, mode, duration, activity during trips, time of day, weather, socio-economics), cutpoints κ, and random effects $\mathbf{u}_j$, where i = 1, …, 5748 is the number of trips, j = 1, …, 243 is the number of clusters (i.e., people).

The probability of observing outcome n for response $\boldsymbol{y_{ij}}$ is:

$$\begin{aligned}\Pr(y_{ij} = n|\boldsymbol{\kappa}, \mathbf{u_j}) &= \mathbf{Pr}(\kappa_{n-1} < \mathbf{X_{ij}\beta} + \mathbf{z_{ij}u_j} + \boldsymbol{\epsilon_{ij}} < \kappa_n) \\ &= \boldsymbol{\Lambda}(\kappa_n - \mathbf{X_{ij}\beta} - \mathbf{z_{ij}u_j}) - \boldsymbol{\Lambda}(\kappa_{n-1} - \mathbf{X_{ij}\beta} - \mathbf{z_{ij}u_j}) \\ &= \frac{1}{1+\exp(\mathbf{X_{ij}\beta} + \mathbf{z_{ij}u_j} - \boldsymbol{\kappa_n})} - \frac{1}{1+\exp(\mathbf{X_{ij}\beta} + \mathbf{z_{ij}u_j} - \boldsymbol{\kappa_{n-1}})}\end{aligned}$$

where $\boldsymbol{\Lambda}(.)$ is the logistic cumulative distribution function (CDF).

The model is expressed as follows:

$$\boldsymbol{y_{ij}^*} = \mathbf{X_{ij}\beta} + \mathbf{z_{ij}u_j} + \boldsymbol{\epsilon_{ij}} \quad (1)$$

$$\text{and } y_{ij} = \begin{cases} 0 \text{ (skipping trips) if } y_{ij}^* \leq \kappa_1 \\ 1 \text{ (neutral) if } \kappa_1 \leq y_{ij}^* \leq \kappa_2 \\ 2 \text{ (keeping trips) if } \kappa_2 \leq y_{ij}^* \end{cases}$$

where y_{ij} is the observed ordinal responses that are generated from the latent continuous responses y_{ij}^* and the error term $\boldsymbol{\epsilon_{ij}}$ follows a logistic distribution with mean 0 and variance $\pi^2/3$. ϵ_{ij} and u_j are independent.

Next, I performed several sensitivity analyses as follows: (1) multilevel ordered logit model for only walking, car, bus, and bicycle trips; and (2) random-effects ordered probit models for the full sample. The goal was to check the robustness of the main results.

For the random-effects ordered probit model, the probability of observing outcome n for response $\boldsymbol{y_{it}}$ is:

$$\begin{aligned}\Pr(y_{it} = n|\boldsymbol{\kappa}, \boldsymbol{\nu_t}) &= \mathbf{Pr}(\kappa_{n-1} < \mathbf{X_{it}\beta} + \boldsymbol{\nu_i} + \boldsymbol{\epsilon_{it}} < \kappa_n) \\ &= \Phi(\kappa_n - \mathbf{X_{it}\beta} - \boldsymbol{\nu_i}) - \Phi(\kappa_{n-1} - \mathbf{X_{it}\beta} - \boldsymbol{\nu_i}) \\ &= \frac{1}{1+\exp(\mathbf{X_{it}\beta} + \boldsymbol{\nu_i} - \kappa_n)} - \frac{1}{1+\exp(\mathbf{X_{it}\beta} + \boldsymbol{\nu_i} - \kappa_{n-1})}\end{aligned}$$

where $i = 1,\ldots, I$ people, $t = 1,\ldots, T$ trips, random effects $v_i \sim i.i.d.\ N(0, \sigma_v^2)$, and $\kappa = \kappa_{1,\ldots,} \kappa_n$ is a set of cutpoints (n=3 outcomes). $\Phi(.)$ is the standard normal CDF.

The model is expressed in the linear form as follows:

$$\mathbf{y_{it}^*} = \mathbf{X_{it}\beta} + \boldsymbol{\nu_i} + \boldsymbol{\epsilon_{it}} \quad (1)$$

$$\text{and } y_{it} = \begin{cases} 0 \text{ (skipping trips) if } y_{it}^* \leq \kappa_1 \\ 1 \text{ (neutral) if } \kappa_1 \leq y_{it}^* \leq \kappa_2 \\ 2 \text{ (keeping trips) if } \kappa_2 \leq y_{it}^* \end{cases}$$

where the error term ϵ_{it} ~N(0,1) and is independent of $v_{i.}$

Since the order assumption (i.e., proportional odds) might not hold, I also tested the results based on the logit model. I ran two multilevel binary logit models with two dependent

variables: skipping trip/other, and keeping trip/other. These models, however, did not allow simultaneous comparison of all three outcomes (skipping trip, neutral, keeping trip).

4.4 Results

4.4.1 Descriptive statistics

The demographics and trip characteristics of this dataset were described in Section 3.3 of this dissertation. With regard to trips, among the 5,864 trips retained after data cleaning, 2,101 trips (36%) were made by Blacksburg participants, 3,082 trips (53%) by Washington, DC participants, and 681 trips (12%) Minneapolis participants. All participants were multi-modal (i.e., used two or more modes of travel within 1-2 weeks). The dataset consists of 2,533 car trips (43%), 333 bus trips (6%), 1,287 walking trips (22%) (including walking to transit), 205 bicycle trips (4%), 1,495 vehicle trips (25%) (either car or bus, unreported by users), and 11 trips by other modes (0.19%). Work and school trips accounted for 19% and 10%, respectively.

Table 9 shows the share of activities during travel by mode of transport. Car and bus users tended to listen to music or radio more often. Talking was least likely and reading was most likely to be performed by bus riders, partly because of the privacy concerns and conventions of politeness in public. Using the phone and working were not prevalent in any mode of transport. Pedestrians and cyclists tended to enjoy the landscape more than other users.

Not all trip purposes had the same pattern of travel-time use (Table 10). While listening to music/radio is quite universal for all trips, it is more common in commute-related trips (e.g., going home, going to work or school) and for utilitarian purposes (e.g., shopping, personal business). Talking was more common for socializing trips, eating out, shopping, or go-

ing home. Using the phone, working, and looking at the landscape remained low in this sample. The few work-related activities were associated with commuting trips, indicating some intention to use commute travel time productively.

Table 9. Description of activities during travel by travel mode.

Activity	**Car**	**Bus**	**Walk**	**Bicycle**	**Vehicle**	**Other**	**Total**
Listening to music or	734	45	113	16	556	2	1,466
radio	*29%*	*14%*	*9%*	*8%*	*37%*	*18%*	*25%*
Talking	948	37	374	23	536	4	1,927
	37%	*11%*	*29%*	*11%*	*36%*	*36%*	*33%*
Using the phone	155	25	85	1	54	1	321
	6%	*8%*	*7%*	*0%*	*4%*	*9%*	*5%*
Working	37	4	16	3	7	0	68
	1%	*1%*	*1%*	*1%*	*0%*	*0%*	*1%*
Reading (including au-	5	58	56	3	22	0	170
dio book)	*0%*	*17%*	*4%*	*1%*	*1%*	*0%*	*3%*
Looking at landscape	90	22	103	20	60	1	296
	4%	*7%*	*8%*	*10%*	*4%*	*9%*	*5%*
No activity	155	36	255	66	160	1	673
	6%	*11%*	*20%*	*32%*	*11%*	*9%*	*11%*
Other activity	89	12	65	2	26	0	196
	4%	*4%*	*5%*	*1%*	*2%*	*0%*	*3%*
Total	2,533	333	1,287	205	1,495	11	5,864

Note: Row percentage is shown in italic text.

Table 10. Description of activities during travel by trip purpose.

Activity	Home	Work	Education	Shop	Eat Out	Personal Business	Leisure & Recreation	Socialization	Other	Total
Listening to music or radio	425	366	117	137	52	182	77	30	80	1,466
	27%	*33%*	*20%*	*27%*	*17%*	*26%*	*13%*	*18%*	*24%*	*25%*
Talking	497	131	121	205	167	241	342	111	107	1,922
	32%	*12%*	*21%*	*41%*	*54%*	*34%*	*56%*	*67%*	*33%*	*33%*
Using the phone	96	79	35	23	16	37	13	3	19	321
	6%	*7%*	*6%*	*5%*	*5%*	*5%*	*2%*	*2%*	*6%*	*5%*
Working	0	58	5	0	0	2	1	0	1	67
	0%	*5%*	*1%*	*0%*	*0%*	*0%*	*0%*	*0%*	*0%*	*1%*
Reading (including audio book)	41	57	17	2	2	4	18	0	3	144
	3%	*5%*	*3%*	*0%*	*1%*	*1%*	*3%*	*0%*	*1%*	*2%*
Looking at land-scape	69	59	36	31	10	39	34	4	14	296
	4%	*5%*	*6%*	*6%*	*3%*	*6%*	*6%*	*2%*	*4%*	*5%*
No activity	170	189	78	52	29	73	31	14	37	673
	11%	*17%*	*13%*	*10%*	*9%*	*10%*	*5%*	*8%*	*11%*	*11%*
Other activity	37	27	10	14	9	34	22	3	38	194
	2%	*2%*	*2%*	*3%*	*3%*	*5%*	*4%*	*2%*	*12%*	*3%*
Total	1,559	1,099	578	501	312	707	615	166	327	5,864

Note: Row percentage is shown in italic text.

4.4.2 Comparisons of the positive utility of travel measurements

a. Desirability of trip making

Desirability of trip making is the main variable of interest in my study and is one of the strongest measures of travel affinity. Within my sample, respondents indicated that they were willing to forgo 56% of the total trips and keep 22% of them even if they had a chance to skip the trips. Table 11 breaks down the desire for taking trips by mode, trip purpose, and city.

Table 11. Desire for taking trips by mode, trip purpose, and city.

	Forgo trip	**Neutral**	**Keep trip**	**Total**
Travel mode				
Car	1,468 (59%)	573 (23%)	453 (18%)	2,494
Bus	228 (70%)	59 (18%)	41 (13%)	328
Walk	568 (45%)	254 (20%)	440 (35%)	1,262
Bicycle	60 (30%)	34 (17%)	106 (53%)	200
Vehicle	888 (61%)	353 (24%)	220 (15%)	1,461
Other	2 (22%)	2 (22%)	5 (56%)	9
City				
Blacksburg	1,067 (52%)	468 (23%)	520 (25%)	2,055
DC	1,729 (57%)	668 (22%)	624 (21%)	3,021
Minneapolis	418 (62%)	139 (21%)	121 (18%)	678
Trip purpose				
Home	951 (62%)	328 (21%)	262 (17%)	1,541
Work	649 (61%)	231 (22%)	188 (18%)	1,068
Education	326 (57%)	126 (22%)	119 (21%)	571
Shop	258 (53%)	117 (24%)	114 (23%)	489
Eat Out	152 (49%)	69 (22%)	89 (29%)	310
Personal Business	393 (57%)	147 (21%)	152 (22%)	692
Leisure & Recreation	218 (37%)	124 (21%)	252 (42%)	594

	Forgo trip	Neutral	Keep trip	Total
Socialization	83 (50%)	41 (25%)	41 (25%)	165
Other	184 (57%)	92 (28%)	48 (15%)	324
Total	3,214 (56%)	1,275 (22%)	1,265 (22%)	5,754

Note: Row percentage is shown in parentheses.

According to Table 11, trips by bicycle and "Other" modes (e.g., taxicab, ride hailing, scooter, and skateboard) were most desired at 53% and 56%, respectively. Blacksburg participants enjoyed their trips more often, at 25% compared to 21% in Washington, DC and 18% in Minneapolis. Leisure /recreation, and eating out were the most enjoyed trips, at 42% and 29%, respectively.

b. Travel attitude:

The affinity for travel was expressed in the responses for a set of questions on travel attitude adapted from Mokhtarian et al. (2001). Only 21% of the respondents disagreed with the statement "*I enjoy the process of traveling*," 29% agreed with the statement *"The only good thing about traveling is arriving at your destination,"* and 21% disagreed with the statement *"My commute trip is a useful transition between home and work."* About 40% agreed with the statement *"My travel time is wasted time."* This suggests that a considerable number of people expressed a travel liking tendency (i.e., they enjoyed traveling and viewed their commute as useful) and a potential unwillingness to forgo travel.

c. Satisfaction with trips

In this dissertation project, I measured travel-related satisfaction with the Travel Mood Scale (Glasgow et al., 2018), which covered the affective dimension, and a single-item measure of satisfaction (*"Overall, were you satisfied with the trip itself?"*), which covered the cognitive dimension. Answers ranged from 1 to 11, with 11 being the highest satisfaction

level. Findings based on the affective dimension and based on trip characteristics are presented in Glasgow et al. (under review). In this chapter, I only focused on the single-item measure of satisfaction. Overall, I found that satisfaction was weakly associated with travel affinity, measured by the desire to travel. Table 12 shows that, in general, people wanted to keep trips that were satisfactory, but there were cases in which they wanted to forgo satisfactory trips.

Table 12. Satisfaction with trips and desire to take trips.

Satisfaction	Forgo trip	Neutral	Keep trip	Total
1	4	0	1	5
	80%	*0%*	*20%*	
2	44	6	8	58
	76%	*10%*	*14%*	
3	117	14	21	152
	77%	*9%*	*14%*	
4	258	55	43	356
	72%	*15%*	*12%*	
5	373	104	70	547
	68%	*19%*	*13%*	
6	417	276	136	829
	50%	*33%*	*16%*	
7	456	293	188	937
	49%	*31%*	*20%*	
8	585	251	271	1,107
	53%	*23%*	*24%*	
9	432	143	306	881
	49%	*16%*	*35%*	
10	297	57	181	535
	56%	*11%*	*34%*	
Total trips	2,983	1,199	1,225	5,407

Note: Row percentage is shown in italic text.

4.4.3 Desire for travel: Model results

The results of the multilevel ordered logit model of travel affinity are shown in Table 13. The cut-off significance level was $p<0.05$, although coefficients that were significant at the $p<0.10$ level were still reported as they indicated a further need for investigation in a different context.

a. Core model of all cities (M1)

Relative to trips taken in Blacksburg, trips in Minneapolis were less likely to be desired. Car trips and bus trips (and trips in vehicles in general) were less desired than walking trips, which in turn were less desired than bicycle trips. Trip duration was positively associated with a trip's desirability: the longer the travel time, the more likely the traveler found the trip neutral or desirable. Compared to socializing trips, commute, homebound, errand (including shopping), and other trips were less likely to be desired. Leisure/recreation trips were the most likely to be desirable trips.

With regards to activities during trips, talking was more likely to boost the positive utility of travel, while using the phone or doing nothing were less likely to have such an effect. I did not find that other activities during travel, the weather (e.g., rain, temperature), and time scheduling variables (e.g., morning and afternoon rush hours, late night, and weekend) had a significant effect on travel affinity. Most demographic variables (e.g., income, age, race, education) were not significant. I also tested other variables such as health status and mobile disability; however, they were not significant and thus were removed from the final models.

Table 13. Multilevel ordered logit models of travel affinity (desirability of trip making)

	M1: All cities		M2: Blacksburg		M3: Washington, DC		M4: Minneapolis	
	Coef.	**p>z**	**Coef.**	**p>z**	**Coef.**	**p>z**	**Coef.**	**p>z**
Residency (ref: living in Blacksburg)			–		–		–	
Living in Washington, DC	0.02	0.908	–		–		–	
Living in Minneapolis/other city	-0.36 *	0.07	–		–		–	
Travel mode (ref: walk)								
Bus	-0.92 *	0	-0.94 *	0	-0.59 *	0.039	-1.33 *	0.014
Car	-1.07 *	0	-0.82 *	0	-1.38 *	0	-1.29 *	0
Bicycle	0.61 *	0.004	0.42	0.197	-0.10	0.788	2.28 *	0
Vehicle	-0.81 *	0	-0.80 *	0	-1.09 *	0	-0.88 ◦	0.061
Trip duration	-0.01 *	0.034	-0.01	0.293	-0.01	0.131	-0.02	0.187
Trip duration, squared	0.00	0.872	0.00	0.351	0.00	0.661	0.00	0.577
Trip purpose (ref: socializing trips)								
Commute trip	-0.63 *	0.002	-0.86 *	0.013	-0.42	0.119	-0.68	0.35
Homebound trip	-0.74 *	0	-1.06 *	0.002	-0.51 ◦	0.051	-0.72	0.303
Leisure trip	0.41 *	0.045	0.04	0.913	0.57 *	0.04	0.72	0.301
Errand trip	-0.41 *	0.031	-0.60 ◦	0.08	-0.20	0.442	-0.59	0.38
Other trip purpose	-0.52 *	0.025	-1.22 *	0.005	-0.23	0.45	0.17	0.844
Activity during travel								
Talking	0.39 *	0.004	0.31	0.131	0.81 *	0.01	0.48 ◦	0.084

	M1: All cities		M2: Blacksburg		M3: Washington, DC		M4: Minneapolis	
	Coef.	**p>z**	**Coef.**	**p>z**	**Coef.**	**p>z**	**Coef.**	**p>z**
Using the phone	-0.40 *	0.048	-0.40	0.228	-0.03	0.944	-0.59	0.606
Working	0.36	0.325	0.86	0.297	0.60	0.24	-0.82	0.634
Reading	-0.30	0.276	-0.57	0.293	0.15	0.706	-1.74	0.161
Looking at the landscape	0.24	0.22	0.42	0.183	0.57	0.115	-0.74	0.357
Listening to music/radio	-0.12	0.467	-0.42 °	0.094	0.43	0.187	-0.71	0.324
No activities	-0.49 *	0.003	-0.71 *	0.004	0.15	0.668	-0.81 °	0.073
Other activities	0.16	0.492	0.60	0.138	0.22	0.589	2.09 *	0.022
Time of day/week								
Morning rush hour	-0.31	0.102	-0.22	0.38	-1.35 *	0.004	0.22	0.597
Afternoon rush hour	0.06	0.528	-0.03	0.826	0.10	0.427	-0.02	0.964
Late night	-0.07	0.458	-0.16	0.337	-0.07	0.576	0.41	0.28
Week end	0.03	0.706	0.24	0.12	0.04	0.741	-0.49 °	0.057
Rain	-0.01	0.908	-0.17	0.289	0.02	0.866	-0.17	0.465
Average daily temperature	0.00	0.361	0.01	0.184	-0.01	0.347	-0.02 °	0.078
Age	0.01	0.624	-0.05	0.119	0.01	0.741	-0.03	0.39
Female	0.14	0.599	0.04	0.923	-0.08	0.83	0.41	0.487
Non-White	-0.37	0.18	-0.41	0.336	-0.58	0.13	0.48	0.5
Annual household income (ref: <$30,000)								

	M1: All cities		M2: Blacksburg		M3: Washington, DC		M4: Minneapolis	
	Coef.	**p>z**	**Coef.**	**p>z**	**Coef.**	**p>z**	**Coef.**	**p>z**
Income $30,000 - 59,999	-0.47	0.209	0.05	0.923	-1.41 *	0.02	0.48	0.557
Income $60,000 - 89,999	-0.47	0.302	-0.70	0.357	-0.96	0.128	-0.16	0.889
Income $90,000 - 119,999	-0.78	0.132	0.11	0.894	-1.35 °	0.057	0.16	0.906
Income $120,000 or more	-0.67	0.227	-21.81	0.997	-0.69	0.33	-0.76	0.528
Education (ref: doctoral/professional degree)								
Less than high school graduate	0.45	0.2	0.66	0.217	0.30	0.531	0.07	0.927
High school graduate, include GED	0.48	0.415	1.49	0.125	-1.14	0.137	3.13 *	0.005
Some college or associate's degree	-0.38	0.527	-0.26	0.778	-0.89	0.236	0.89	0.624
Bachelor's degree	0.83	0.667	Omitted		0.70	0.717	Omitted	
Master's degree	0.69 °	0.082	1.65 *	0.006	0.11	0.839	1.12	0.271
Employment (ref: full-time student)								
Part-time employee	-0.03	0.945	0.58	0.446	-0.02	0.973	1.04	0.346
Retired	0.73	0.614	Omitted		1.01	0.514	Omitted	
Unemployed	-1.45	0.114	-2.75	0.044 *	-0.67	0.679	-0.32	0.831
Work at home	-0.28	0.654	-0.01	0.997	-0.09	0.911	-3.28	0.101
Full-time employee	-0.28	0.472	0.11	0.863	-0.09	0.885	-0.92	0.332
Other	1.79	0.349	0.57	0.753	Omitted		18.93	0.995
First cut	-1.04	0.095	-1.75	0.1	-1.82	0.065	-1.69	0.269

	M1: All cities		M2: Blacksburg		M3: Washington, DC		M4: Minneapolis	
	Coef.	**p>z**	**Coef.**	**p>z**	**Coef.**	**p>z**	**Coef.**	**p>z**
Second cut	0.59	0.347	-0.17	0.873	-0.09	0.93	0.00	1
Number of trips	5,748		2,055		3,018	675		
Number of people	243		99		134	60		

Dependent variable: Desirability of trip making (outcomes: skipping trip, neutral, and keeping trip).

Significant codes: (^{o}): 0.05 ≤ p <0.1, (*): p < 0.05. Some variables were omitted because of multicollinearity.

b. City-specific models

Results for the city-specific models are shown in Table 13 (M2-M4). In general, the results are consistent with those from the core model of all cities. A few exceptions are the significant effects of income in Washington, DC. The sign of the coefficients are intuitive. In Blacksburg, most trips (e.g., commute, homebound, errand, other purposes) were less desirable than socializing trips. In Washington, DC, only homebound trips were less likely to be viewed positively ($p < 0.1$), while leisure trips were more likely to be perceived as desirable. I found no significant effect of trip purpose on the utility of travel in Minneapolis.

In all cities, bus and car trips were significantly less likely to be desired compared to walking trips. Trips that involved talking (in all 3 city-models) and "Other" activities (in the Minneapolis model) were more likely to be desired. Conversely, doing nothing (in all 3 city-models) and listening to music (in the Blacksburg model) were associated with a lower desirability for trips. Several time schedule variables were significant in the models (e.g., morning rush hour in the Washington, DC model, and weekend in the Minneapolis model).

4.4.4 Sensitivity analyses

The models for utilitarian and non-utilitarian trip purposes are shown in Table 14. Not all demographic variables were significant. For utilitarian trips, bus trips were not significantly different from walking trips when it came to the affinity for travel, while bicycle trips were more likely to be desired than both walking and bus trips. However, for non-utilitarian trips, bus trips were less desirable and bicycle trips were not significantly different from walking trips.

Longer utilitarian trips were less likely to have high affinity, but this was not the case for non-utilitarian trips. Talking had a positive effect for utilitarian trips but not non-utilitarian

trips; conducting no activities are negative in both cases. Finally, morning rush hours had a negative effect on non-utilitarian trips but not for utilitarian trips.

Table 14. Multilevel ordered logit models of travel affinity by trip purpose

	Utilitarian travel			**Recreation, social, and other travel**		
	Coef.	**SE**	**p > z**	**Coef.**	**SE**	**p > z**
Residency						
Living in Washington, DC	0.42	0.24	0.079	-0.29	0.45	0.519
Living in Minneapolis/other city	-0.34	0.22	0.127	-0.45	0.46	0.336
Travel mode (ref: walk)						
Bus trip	-0.80	0.19	0	-1.25 *	0.62	0.042
Car trip	-0.92 *	0.13	0	-1.77 *	0.24	0
Bicycle trip	1.02 *	0.24	0	-0.85	0.55	0.126
Vehicle trip	-0.67 *	0.14	0	-1.74 *	0.28	0
Trip duration	-0.02 *	0.01	0.005	0.00	0.01	0.848
Trip duration, squared	0.00	0.00	0.58	0.00	0.00	0.5
Activity during trips						
Talking	0.59 *	0.16	0	-0.17	0.36	0.628
Using the phone	-0.32	0.22	0.159	-0.44	0.58	0.455
Working	0.45	0.38	0.238	3.32	1.88 °	0.078
Reading	-0.42	0.31	0.176	-0.46	0.73	0.529
Looking at the landscape	0.30	0.22	0.18	-0.05	0.52	0.921
Listening to music/radio	-0.06	0.18	0.751	-0.17	0.42	0.68
No activities	-0.42 *	0.18	0.022	-0.93 *	0.46	0.044
Other activities	0.14	0.28	0.624	-0.16	0.50	0.749
Time of day/week						
Morning rush hour	-0.15	0.20	0.439	-2.38 *	0.75	0.002
Afternoon rush hour	0.09	0.10	0.372	-0.24	0.24	0.319
Late night	-0.07	0.11	0.528	-0.32	0.22	0.136
Week end	0.08	0.10	0.436	0.00	0.19	0.981
Rain	-0.04	0.09	0.635	0.21	0.19	0.267

	Utilitarian travel			Recreation, social, and other travel		
	Coef.	**SE**	**p > z**	**Coef.**	**SE**	**p > z**
Average daily temperature	0.00	0.00	0.849	-0.01	0.01	0.403
Age	0.01	0.02	0.682	0.01	0.02	0.562
Female	0.16	0.27	0.548	-0.29	0.40	0.47
Non-White	-0.35	0.28	0.225	-0.61	0.40	0.124
Annual household income (ref: <$30,000)						
Income $30,000 - 59,999	-0.49	0.38	0.201	-0.60	0.58	0.296
Income $60,000 - 89,999	-0.44	0.47	0.349	-0.62	0.69	0.37
Income $90,000 - 119,999	-0.77	0.53	0.142	-0.34	0.75	0.645
Income $120,000 or more	-0.87	0.57	0.131	-0.03	0.81	0.974
Education (ref: doctoral/professional degree)						
Less than high school graduate	0.41	0.36	0.256	0.41	0.51	0.426
High school graduate, include GED	0.46	0.60	0.444	0.55	0.84	0.511
Some college or associate's degree	-0.46	0.61	0.449	-1.31	0.97	0.179
Bachelor's degree	0.86	1.94	0.659	-20.27	8689.75	0.998
Master's degree	0.56	0.40	0.168	0.89	0.58	0.125
Employment (ref: full-time student)						
Part-time employee	-0.16	0.47	0.732	-0.57	0.74	0.44
Retired	0.53	1.46	0.717	-0.10	1.77	0.955
Unemployed	-1.57	0.93	0.091	-2.06	1.40	0.142
Work at home	-0.70	0.65	0.28	-0.25	0.87	0.772
Full-time employee	-0.49	0.40	0.226	-0.71	0.57	0.213
Other employment	2.04	1.92	0.289	0.16	2.60	0.951
First cut	-0.21	0.62	0.734	-2.67	1.01	0.009
Second cut	1.44	0.62	0.021	-0.88	1.01	0.383

	Utilitarian travel			Recreation, social, and other travel		
	Coef.	**SE**	**p > z**	**Coef.**	**SE**	**p > z**
Number of trips	4,667			1,081		
Number of people	242			188		

Dependent variable: Desirability of trip making (outcomes: skipping trip, neutral, and keeping trip). Significant codes: (°): 0.05 ≤ p <0.1, (*): p < 0.05.

I also ran a random-effects probit model to test the robustness of the core models (Table 15). The results are consistent with findings from other models in this section.

Table 15. Random-effects probit model of desire to take trips in three cities

	Coef.	**SE**	**p>z**
Residency (ref: Blacksburg)			
Living in Washington, DC	0.04	0.12	0.728
Living in Minneapolis/other city	-0.22 °	0.12	0.058
Travel mode (ref: walk)			
Bus trip	-0.52 *	0.10	0
Car trip	-0.63 *	0.06	0
Bicycle trip	0.34 *	0.12	0.006
Vehicle trip	-0.47 *	0.07	0
Trip duration	-0.01 °	0.00	0.066
Trip duration, squared	0.00	0.00	0.943
Trip purpose (ref: socializing trips)			
Commute trip	-0.37 *	0.12	0.002
Homebound trip	-0.45 *	0.11	0
Leisure trip	0.22 °	0.12	0.07
Errand trip	-0.25 *	0.11	0.028
Other trip purpose	-0.33 *	0.14	0.016
Activity during travel			
Talking	0.23 *	0.08	0.004
Using the phone	-0.23 °	0.12	0.05

	Coef.	SE	p>z
Working	0.22	0.21	0.295
Reading	-0.21	0.16	0.182
Looking at the landscape	0.13	0.12	0.244
Listening to music/radio	-0.07	0.09	0.481
No activities	-0.28 *	0.10	0.003
Other activities	0.11	0.13	0.414
Time of day/week			
Morning rush hour	-0.18	0.11	0.1
Afternoon rush hour	0.03	0.05	0.531
Late night	-0.03	0.06	0.655
Week end	0.03	0.05	0.553
Rain	-0.01	0.05	0.839
Average daily temperature	0.00	0.00	0.434
Age	0.00	0.01	0.673
Female	0.09	0.15	0.565
Non-White	-0.23	0.16	0.151
Annual household income (ref: <$30,000)			
Income $30,000 - 59,999	-0.29	0.21	0.182
Income $60,000 - 89,999	-0.27	0.26	0.298
Income $90,000 - 119,999	-0.45	0.29	0.124
Income $120,000 or more	-0.39	0.31	0.209
Education (ref: doctoral/professional degree)			
Less than high school graduate	0.25	0.20	0.204
High school graduate, include GED	0.29	0.33	0.386
Some college or associate's degree	-0.21	0.34	0.536
Bachelor's degree	0.47	1.09	0.67
Master's degree	0.39 °	0.22	0.08
Employment (ref: full-time student)			
Part-time employee	-0.02	0.26	0.925
Retired	0.41	0.82	0.616

	Coef.	SE	p>z
Unemployed	-0.81	0.52	0.12
Work at home	-0.17	0.35	0.634
Full-time employee	-0.18	0.22	0.428
Other	0.95	1.08	0.377
/cut1	-0.62 °	0.36	0.082
/cut2	0.32	0.36	0.367
/sigma2_u	1.03	0.12	

Dependent variable: Desirability of trip making (outcomes: skipping trip, neutral, and keeping trip). Significant codes: (°): 0.05 ≤ p <0.1, (*): p < 0.05.

Two binary logit models with *skipping trip* and *keeping trip* as outcome variables showed similar results in terms of coefficient signs and significance levels (Table 16). The core models (Table 13) were therefore robust and insensitive to changes of outcome specifications.

Table 16. Multilevel binary logit models of the desirability of trip making

	Skipping trips		Keeping trips	
	Coef.	SE	Coef.	SE
Residency				
Living in Washington, DC	-0.07	0.24	0.29	0.28
Living in Minneapolis	0.51	0.23	-0.23	0.28
Travel mode (ref: walk)				
Bus trip	0.88*	0.20	-1.07*	0.25
Car trip	0.89*	0.13	-1.43*	0.14
Bicycle trip	-0.41	0.25	0.66*	0.24
Vehicle trip	0.65*	0.14	-1.11*	0.16
Trip duration	0.02*	0.01	0.00	0.01
Trip duration, squared	0.00	0.00	0.00	0.00
Trip purpose (ref: socializing trips)				

	Skipping trips		Keeping trips	
	Coef.	**SE**	**Coef.**	**SE**
Commute trip	0.54*	0.23	-0.79*	0.27
Homebound trip	0.76*	0.22	-0.89*	0.26
Leisure trip	-0.41**o**	0.24	0.36	0.27
Errand trip	0.43**o**	0.22	-0.46**o**	0.26
Other trip purpose	0.52**o**	0.27	-0.74*	0.34
Activity during trips				
Talking	-0.25	0.15	0.55*	0.18
Using the phone	0.41**o**	0.23	-0.51**o**	0.28
Working	-0.57	0.43	0.30	0.43
Reading	0.20	0.31	-0.78*	0.37
Looking at the landscape	-0.12	0.22	0.24	0.26
Listening to music/radio	0.17	0.18	-0.19	0.22
No activities	0.53*	0.18	-0.59*	0.22
Other activities	-0.17	0.27	0.27	0.29
Time of day/week				
Morning rush hour	0.39**o**	0.21	-0.39	0.27
Afternoon rush hour	-0.02	0.10	0.14	0.12
Late night	0.07	0.11	-0.02	0.13
Week end	-0.12	0.10	0.07	0.12
Rain	0.03	0.09	0.02	0.11
Average daily temperature	0.00	0.00	0.00	0.01
Age	-0.02	0.02	-0.01	0.02
Female	0.01	0.29	0.16	0.31
Non-White	0.24	0.30	-0.70*	0.33
Annual household income (ref: <$30,000)				
Income $30,000 - 59,999	0.40	0.41	-0.61	0.45
Income $60,000 - 89,999	0.59	0.49	-0.29	0.54
Income $90,000 - 119,999	0.66	0.56	-0.65	0.61
Income $120,000 or more	0.71	0.60	-0.57	0.66

	Skipping trips		Keeping trips	
	Coef.	**SE**	**Coef.**	**SE**
Education (ref: doctoral/professional degree)				
Less than high school graduate	-0.34	0.38	0.45	0.42
High school graduate, include GED	-0.24	0.63	0.75	0.69
Some college or associate's degree	0.50	0.64	-0.37	0.70
Bachelor's degree	-0.22	2.06	1.65	2.21
Master's degree	-0.49	0.43	0.83 **o**	0.46
Employment (ref: full-time student)				
Part-time employee	0.14	0.50	-0.37	0.55
Retired	-0.46	1.55	0.79	1.59
Unemployed	1.59	0.99	-1.18	1.09
Work at home	0.46	0.66	-0.27	0.71
Full-time employee	0.32	0.43	-0.64	0.46
Other employment	-1.19	2.07	1.88	2.09
Constant	-1.12**o**	0.68	-0.26	0.75
Random-effects	1.93	0.12	1.96	0.14
Number of trips	5,858		5,858	
Number of people	244		244	

Dependent variable: Desirability of trip making [outcomes: skipping trip vs. otherwise (model 1) and keeping trips vs. otherwise (model 2)]. Significant codes: (°): 0.05 ≤ p <0.1, (*): p < 0.05.

4.5 Discussion

4.5.1 Discussion of results

This study addresses several shortcomings from previous studies by measuring trip characteristics objectively (i.e., GPS tracking) instead of using self-report surveys, measuring

multiple trips during a week, and measuring travel affinity instantaneously after each trip. This results in lower recall bias and increased accuracy of trip details. The repeated measure allows for assessment of within- and between-individual changes of travel affinity as well. Further, this is the only study to date that modeled the positive utility of travel using the modified version of the teleportation test and testing on a large sample of trips with different purposes.

This study provides further evidence of the positive utility of travel using various measures suggested by Mokhtarian & Salomon (2001), Russell and Mokhtarian (2012), and Singleton (2017), such as travel liking attitude, travel-based multitasking (i.e., activities during trips), satisfaction with travel, and desire to travel. I found that the positive utility of travel was exhibited through the travel liking attitude and desirability of trip making. Satisfaction with travel seems to relate to the desire to travel. That is, travelers wanted to keep satisfactory trips; however, this was not always the case.

The models of the desirability of trip making suggest that travel affinity varied across modes. Bicycle trips (and sometimes walking trips—in the case of leisure and recreation) were more desirable than trips using other modes. This strengthens previous findings that bicycle trips are more enjoyable and satisfactory compared to trips by other modes (Morris & Guerra, 2014; Páez & Whalen, 2010; Smith, 2017). In my exploratory analysis, I found that while the possibility of multitasking is lower, bicyclists and pedestrians enjoyed looking at the landscape more than other mode users. This may indicate the benefit of mindfulness or being "present" and focusing on one activity at a time, versus conducting multiple tasks out of boredom. In addition, the differences in desirability could be attributed to the physical and mental health benefits gained from exercising while bicycling and walking. At the same time, although the two concepts (i.e., desire to travel vs. satisfaction/enjoyment) do not completely

overlap, they are both manifestations of the positive utility of travel. Therefore, understanding these two concepts as highly related lends support to the finding that bicycle trips tend to have higher utility and validates the modified teleportation test as a measure of utility.

I also found that the affinity for travel in utilitarian trips does not differ between bus trips and walking trips. This might not seem intuitive at first; however, this is consistent with findings by Zhu and Fan (2018b), which found that utilitarian walking trips are associated with negative emotions. It could be possible that such trips involve time pressure or carrying heavy personal items – an aspect that my models did not control for.

My results show that commute trips were less desirable as compared to other trip purposes, possibly owing to the fact that commute trips are generally more onerous due to their boredom and association with higher traffic volume. Kahneman et al. (2004) found that commuting is among the lowest rated daily activities. However, descriptive statistics from the person sample show that many travelers perceived commute time as useful, or at least, not wasted. It is possible that the willingness to take trips of the same type (i.e., commute trips or errand trips) varies even within individuals; for example, commute trips can be generally acceptable for a person, but some days s/he may find commuting more burdensome, depending on many trip characteristics (e.g. congestion, weather, incidents happened during the trip).

Some activities performed during a trip were associated with a higher or lower likelihood of enjoying the trip. Talking with people may boost travel satisfaction, as found in Ettema et al. (2012) and Goulias et al. (2013), indicating a convergence validity of trip desirability and satisfaction measurement. Some activities, such as using the phone, reading, or doing nothing, were negatively associated with trip desirability. Mokhtarian et al. (2014b) suggested that this might be a reversed causality, in that during a boring trip, travelers attempt

to entertain themselves with these activities; these activities do not inherently bring boredom to the trip. In my study, I did not find that many activities significantly affected the desirability of the trips; these non-work activities may have been used to cope with boredom. In other words, travelers may have enjoyed these activities to some extent but the utility from these activities failed to compensate the disutility of the trips.

Trip duration is negatively associated with trip desirability in this study. On the other hand, past studies found a negative significant effect of duration on travel satisfaction (Friman et al., 2017; Mokhtarian et al., 2014b; Morris & Guerra, 2015), showing some consistency between these two measurements. I tested a non-linear specification of travel time but did not find any significant effect of the squared term of duration. This should be continually tested in future studies.

4.5.2 Implications

This study has several implications for research and practice. First, it provides a validation of the modified teleportation test (i.e., to reduce the bias caused by the question wording). My initial results showed some convergence validity of this measurement compared to other measures, such as satisfaction or happiness from other studies; however, these measurements do not overlap, as shown in the descriptive statistics.

The study also provides further evidence for the positive utility of travel and the desire to travel for its own sake. This means trip reduction, telecommuting, and other travel demand management strategies may not be effective. However, in many circumstances, travelers may want to keep some trips while forgoing others. Thus, there is potential to replace such trips and activities with home-based ICT (e.g., online shopping, video conferencing, and telecommuting). For example, employees might not want to telecommute for the entire week, but

telecommuting may be more appealing if they are given the option to work at home several days per week or per month. Even if online shopping does not completely replace all shopping trips, less enjoyable shopping trips may be replaced with home delivery. Other alternatives to avoid generating a new trip that do not involve technologies are combining or chaining multiple trip purposes and carpooling. Replacing trips with the above alternatives would be beneficial to decrease congestion, reduce pollution, and save energy.

Given that some activities during travel were linked to higher desirability of trips, it could be the case that travel modes with a higher possibility to multitask would be more appealing, such as ride hailing, autonomous vehicles, or public transit. These results need to be tested in future studies. Nonetheless, my research suggests that travelers would benefit from transport environments that are conducive to multitasking, safe for active travel, and aesthetically pleasing. For example, transit agencies may improve onboard amenities (e.g., Wi-Fi connection), comfort (e.g., increase seating and fleet size), and spatial coverage, as well as provide reliable and frequent transit service. For non-motorized transportation, practitioners may invest in bicycle and pedestrian facilities and route trails around pleasant landscapes.

4.5.3 Limitations and future directions

This study suffers from a few limitations that can be addressed in future studies. The sample is small, unbalanced, and unrepresentative of the total population. The models did not include variables such as personality and travel environments (e.g., types of infrastructure for active travelers, critical incidents, transit service quality, and parking conditions). Although personality is not modifiable, it may affect the relationship between travel affinity and other modifiable variables. Knowing this relationship is important for making policies sensitive to

different population segments. Travel environment variables have not been tested in past studies and deserve future attention.

Additionally, future studies can also replicate the results in different contexts and with a more representative sample in multiple jurisdictions. Panel data would be helpful in addressing causal inference. Smartphone apps with gamification or other intervention functions may be used for behavioral change (i.e., nudging travelers toward more sustainable behaviors). For example, the app may provide feedback on energy consumption and emissions. This feedback allows for performance comparison among users, which could prompt them to adjust their amount of travel and energy usage.

In this survey, I did not explicitly ask participants their willingness to conduct activities remotely but instead asked their willingness to forgo trips and still be able to conduct destination activities. Future studies may want to explore the possibility of replacing ICTs (e.g., telecommuting, socializing through social media, online shopping) for travel and the willingness to chain trips or bulk shop using stated-preference surveys. Finally, I did not measure travel usefulness for each trip, but instead measured travel wastefulness for each person in the entry survey. Future studies should employ both ways of measuring usefulness in trip and person surveys and compare this measurement with the teleportation test results.

Another limitation is the appropriateness of the ordered logit model. The responses did not strictly follow an order and thus the proportional odds assumption might be violated. However, other tested non-ordered models showed similar significant results and directions of effects, suggesting that the ordered logit models also yielded appropriate results. Other modeling techniques could replace the ordered logit model (with panel data), such as the mixed logit model.

4.6 Chapter conclusions

This study examines the patterns of travel affinity with various travel modes, trip purposes, and activities during trips. Travel affinity was measured by asking participants their willingness to forgo a trip when there was an opportunity to do so; thus, it is a proxy for the desire to travel. I found that travelers were more willing to make trips when they traveled on foot or bicycle, talked with someone during trips, and took shorter trips. Additionally, commute trips were less likely to be enjoyed, as are "Other" trips.

The results offer some implications for research and practice. First, the modified teleportation test is a reliable and valid measure of the positive utility of travel. Second, this study suggests that using ICTs for travel demand management is potentially ineffective. Third, since active travel was found to be enjoyable, practitioners could devise strategies to encourage active travel and physical activity. Fourth, transit agencies may create sustainable travel options that are conducive to multitasking to make transit trips more productive and desirable.

5 Travel affinity: Desired travel time

5.1 Introduction

The value of travel time savings has often been used for benefit-cost analysis and assessing the return on investment (ROI) of infrastructure. This value is based on the notion that people are always willing to reduce or completely eliminate their travel time – an assumption that has been rejected in several studies (O'Fallon & Wallis, 2012; Redmond & Mokhtarian, 2001; Russell & Mokhtarian, 2014).

Past research found that travel has a positive utility; in this particular case, travelers may not want zero travel time, as travel time serves many desirable purposes, such as a transition between two locations, a personal time to be on one's own, and an opportunity to be outside (Handy et al., 2005; Jain & Lyons, 2008; Lyons & Urry, 2005). On the other hand, desired travel time varies across trip purpose, mode, time of day, and by level of traffic congestion. However, empirical evidence for the desired travel time is very limited and has only been tested quantitatively in the San Francisco Bay Area (Redmond & Mokhtarian, 2001), Hamilton, Canada (Paéz & Whalen, 2010), and Wellington, New Zealand (O'Fallon & Wallis, 2012). All studies on desired travel time have focused on a single trip purpose (e.g., commute) or single time point and could not accurately capture variation within individuals and across multiple travel environments.

This study aims to address these limitations by repeated measurement of desired travel time for each trip that survey participants made. I employed a smartphone-based survey to track travel patterns of 185 users making 4,397 trips in the Washington, DC and Blacksburg, VA metropolitan areas. Desired and actual travel times were compared and modeled to determine the factors associated with higher desired travel time as compared to actual travel time.

This study adds additional evidence for the existence of the positive utility of travel, in which desired travel time is one of the strongest measures of the willingness to travel (Singleton, 2017). This would may inform transportation strategies and policies, such as evaluating the value of travel time saving, managing travel demand, and shifting travel to more sustainable options.

5.2 Literature review

5.2.1 Actual, acceptable, and ideal travel time

The positive utility of travel, a concept proposed by Mokhtarian and Salomon (2001), refers to the benefit of travel, usually generated from the activities during travel or by the act of traveling itself. As part of the positive utility of travel, travel affinity refers to the fondness of travel, manifested through the travel liking attitude, refusing to "teleport", and the choice of longer routes or longer travel time, among others. Chapter 2 of this dissertation provides an overview of travel affinity and measurements of the positive utility of travel.

Travel affinity can be exhibited through non-zero desired (ideal) travel time or acceptable time (Milakis et al., 2015; Mokhtarian & Salomon, 2001). Ideal travel time is usually measured as follows: *"Some people may value their commute time as a transition between work and home, while others may feel it is stressful or a waste of time. For you, what would be the ideal one-way commute time"* (Redmond & Mokhtarian, 2001). This construct can also be measured in terms of relative desired travel amount, such as asking respondents to indicate whether or not they like to travel more than their current travel amount (e.g., time or distance) using a Likert scale. An alternative way to calculate the gap between ideal and actual travel times (e.g., deriving the ratio or difference between the two amounts). Redmond and Mokh-

tarian (2001) subtracting ideal from actual travel time, then assigning intervals from this difference. Paéz and Whalen (2010) took the ratio between ideal travel time and actual travel time, then subtracting one. Milakis et al. (2015) proposed another way to measure these two concepts by asking *"Is there a commute time that you would consider as closer to your sense of ideal/acceptable?"* Acceptable travel time follows the satisficing rule in decision theory, where if the goodness of an attribute exceeds a threshold, an improvement of that attribute no longer makes the alternative more attractive (Milakis et al., 2015).

Only a handful of studies have focused on ideal travel time (O'Fallon & Wallis, 2012; Páez & Whalen, 2010; Redmond & Mokhtarian, 2001; Russell & Mokhtarian, 2014) and only three studies have focused on the acceptable travel time (He, Zhao, & He, 2016; Milakis et al., 2015; Milakis & van Wee, 2017). Notably, in a series of papers published from a study in the San Francisco Bay Area, Mokhtarian and colleagues (Mokhtarian & Salomon, 2001; Redmond & Mokhtarian, 2001) found that most people did not want zero travel time. This result is consistent with findings from many later studies in Austin, TX (Handy et al, 2005), Berkeley, CA (Milakis et al., 2015), Delft, the Netherlands (Milakis & van Wee, 2017), Wellington, New Zealand (O'Fallon & Wallis, 2012; Russell & Mokhtarian, 2014), and Hamilton, Canada (Paéz & Whalen, 2010). The actual and ideal travel times varied in these studies, so did the thresholds that they can tolerate for their travel (i.e., acceptable commute time).

A list of studies focusing on ideal and acceptable travel time is listed in Table 17. In general, average actual travel time ranged between 20-35 minutes, while ideal travel time ranged between 15-20 minutes and acceptable time ranged between 30-40 minutes. Travel liking and actual travel amount were found to greatly influence the desired travel amount (Páez & Whalen, 2010; Redmond & Mokhtarian, 2001), perhaps due to the anchor point effect

(i.e., people choose a number based on a similar number that they have, in this case, the actual travel time) (Kahneman, 2011). In their study in Hamilton, Canada, Paéz & Whalen (2010) found that active travelers (e.g., bicyclists and pedestrians) are less dissatisfied with their travel time than other mode users.

Qualitative studies by Handy et al. (2005) in Austin, TX and Russell and Mokhtarian (2015) in Wellington, New Zealand found the narrative underlying the travel affinity and how it manifests in actual behavior. For example, the Austin study found many reasons behind not wanting to reduce travel time, such as enjoying driving or enjoying activities conducted during trips (e.g., spending time with family members, listening to audiobooks or podcasts) (Handy et al., 2005). The Wellington study (Russell & Mokhtarian, 2014) noted several issues with measurement of travel time: respondents tend to confuse (1) the amount of travel and duration of activities at destinations, and (2) the desirable amount of travel with a realistic or acceptable amount of travel. They encouraged researchers to compare several measurements and continually test their validity. Nonetheless, Singleton (2017) considered the desired travel amount a convincing measurement of the positive utility of travel if it was measured appropriately.

Two other qualitative studies compared ideal travel time and/or acceptable commute time among groups in Berkeley, CA (Milakis et al., 2015) and Delft, the Netherlands (Milakis & van Wee, 2017). They found a difference between travelers in these two cities, which may be attributable to traffic congestion, spatial structures, and accessibility. However, it is consistent that the desire and acceptance of non-zero travel time may be universal (He et al., 2016; Milakis et al., 2015). Both types of travel time are influenced by the perception of being productive, the current amount of travel, life stage, income, and companionship, among others factors.

All of the studies on ideal-actual travel time were cross-sectional with a single time point applied for typical commute trips (except for Choo et al. (2004) where the measures were applied to all trip purposes). Commute trips may be stable, whereas travel time for other trip purposes may be more unstable. Thus, it is necessary to investigate the desired travel amount for both commute and non-commute trips, especially when it may be influenced by changes in the surrounding environment (e.g., congestion, time of day or week, weather, companionship, mental status). Such investigation also contributes to our knowledge about commuting behavior, such as the responses to telecommute, flexible work hour policy, or short-term decisions related to commuting.

5.2.2 Other factors associated with travel experience

Travel companionship has been shown to influence travel experience and perception of travel time. Zhu and Fan (2018b) found that traveling with friends or family members was associated with more positive emotions during travel. Milakis et al. (2015) found that companionship influenced the desired travel time while Timmermans and Van der Waerden (2008) found that companionship was associated with the perception of travel time usefulness. These have been among the few studies on companionship and travel affinity.

Travel-based multitasking (i.e., activities during travel) has been found to be associated with more positive travel experience, such as positive mood (Glasgow et al., 2019, Fan et al., 2019) and overall well-being (Singleton, 2017). A list of studies on multitasking and related measures can be found in Chapter 3 and Chapter 4 of this dissertation.

Table 17. Summary of studies on desired travel time.

Study	Location	Data Source	Measurement	Trip purpose	Analytic method	Finding
Choo, Collantes, & Mokhtarian (2004)	San Francisco Bay Area, CA	Mail survey, n = 1,357, year 1999	Relative desired mobility (travel less/much less, the same, or more/much more than the current amount)	All purposes	Censored ordered probit	Travel liking attitude dictates the desired amount of travel. Subjective mobility was negatively associated with relative desired mobility.
Handy et al. (2005)	Austin, TX	3 focus groups at the University of Texas at Austin, year 2002	Reasons for excess travel: value of driving itself, value of activities while driving, variety seeking, habit, poor planning, misconception or lack of information	All purposes	Content analysis	People may intentionally choose not to minimize their travel time, which results in excess driving.
He, Zhao, & He (2016)	Kunming, China	Survey, n = 753, year 2014	Interval of tolerance commute threshold, demographics	Commute	Ordered logit models	Threshold peaked at 30-40 minutes and 81% of commuters had a threshold of 50 minutes or more. Age, gender, education, income,

Study	Location	Data Source	Measurement	Trip purpose	Analytic method	Finding
						presence of children, mode, and home location were significant.
Milakis et al. (2015)	Berkeley, CA	Semi-structured interviews, n = 20 people in Berkeley, year 2013	Actual travel time, ideal travel time, acceptable travel time, demographics, perceptions, feelings, attitudes and life experiences.	Commute	Content analysis	Actual, ideal and acceptable travel times are 33.6, 18.4 and 42.8 minutes on average. Ideal time by mode: bicycling 26.9, walking 12.5, public transport 23.8, car 16.9, carpool 12 minutes. 30% described at least one factor that affects their acceptable commute time, such as being productive, commute frequency, driving or being passengers, life stage, income, and travel companions.
Milakis & van Wee (2017)	Berkeley, CA and Delft, the Netherlands	Mixed method, semi-structured interview with both close- and open-	Actual travel time, ideal travel time, acceptable travel time, demographics, perceptions, feelings, attitudes and life experiences.	Commute	Concurrent triangulation, content analysis, descriptive statistics,	Actual, ideal and acceptable travel times: Berkeley 30.9, 20 and 42.5 minutes, Delft 27.6, 14.7 and 36.4 minutes. Bicycling had the greatest ideal travel time in Berkeley; walking and public transport had the greatest travel time in Delft.

Study	Location	Data Source	Measurement	Trip purpose	Analytic method	Finding
		ended questions. n = 32 (16 people in each city), years 2013-2014			Mann-Whitney U test	Results support the relationship between intrinsic utility and travel time. Intrinsic utility peaked at the ideal travel time. The difference in acceptable time between Delft and Berkeley travelers may be due to differences in congestion, the city structure, and accessibility.
O'Fallon & Wallis (2012)	Wellington, New Zealand	Survey, n = 679	Ideal travel time, demographics	Commute	Descriptive statistics	Median actual commute time is 20 minutes, 75% had an ideal commute time of ≤ 20 minutes, 3% chose zero commute time.
Ory et al. (2004)	San Francisco Bay Area, CA	Mail survey, n = 1,358, year 1999	Objective and subjective mobility, desired mobility, attitudes, personality, lifestyle, excess travel, mobility constraints, sociodemographics	Commute	OLS, censored ordered probit	Desired mobility was influenced by the current amount of travel and travel liking attitude.

Study	Location	Data Source	Measurement	Trip purpose	Analytic method	Finding
Paéz & Whalen (2010)	McMaster University campus, Hamilton, Canada	Campus survey, cross-sectional, N = 1251, year 2008	Ideal travel time, relative desired commute time, attitude toward traveling and time use, perceptions, demographics	Commute	Linear regression with spatial filter	Mean actual and ideal travel times were 23.91 and 13.50 minutes Active travelers were less dissatisfied with their commute time than car and transit users. Some cyclists and pedestrians were willing to spend more time on commuting. Most travel attitudes were significantly associated with relative desired commute time.
Redmond & Mokhtarian (2001)	San Francisco Bay Area, CA	Mail survey, n = 1,300, year 1999	Ideal commute time, relative desired commute time, attitude, demographics	Commute	Tobit, ordered probit	Ideal commute time mostly ranged from 15-19 minutes, average 16 minutes. 32% reported ideal times of 20 minutes or more. 42% had ideal commute times fell within 5 minutes of their actual commute time. 7% had their ideal commute times exceed the actual commute time by 5 minutes or more (i.e., want to commute more). Ideal commute time was associated with the current travel amount, travel liking, attitudes, lifestyle/personality, and demographics.

Study	Location	Data Source	Measurement	Trip purpose	Analytic method	Finding
Russel (2012), Russell & Mokhtarian (2014)	Wellington, New Zealand	Phone interview, n = 48 bus and train riders, year 2009-2010	Ideal travel time, teleportation, demographics	Commute	Content analysis	Ideal travel time ranged from 5-10 minutes to their current commutes. A third of participants wanted ≤ 20 minutes each way for ideal travel time. A quarter gave an ideal length of 30 minutes. 4 people wanted zero travel time. 18% viewed their travel time as too long, 81% viewed their travel time as "about right".

5.3 Methods

5.3.1 Data collection and processing

This study is based on data from the Mood State in Transport Environments study during Fall 2016 to Spring 2018. The study was open to anyone who was 18 years or older, lived in one of the three study areas (Blacksburg – Roanoke, VA; Washington, DC; and Minneapolis, MN metropolitan areas), and possessed an Android phone. Respondents installed a smartphone app named Daynamica (Fan et al., 2012) and tracked their travel for 7-14 consecutive days. They answered an entry survey, which includes information about their sociodemographic background, travel patterns, and attitudes. They also reported their trip characteristics in a trip survey associated with each trip tracked by the app. Details about this study, including recruitment method, are provided in Chapter 3.

I measured the positive utility of travel in multiple ways. In the entry survey, I asked respondents about their attitudes toward travel and activity demand in a series of statement with Likert-scale responses from 1 (strongly disagree) to 7 (strongly agree) as follows: *"I enjoyed the process of traveling"*, *"My commute trip is a useful transition between home and work"* [based on the original questions proposed by Mokhtarian and Salomon (2001)], *"My travel time is wasted time"*, and *"I want to participate more in out-of-home activities."* Given that travel demand and activity demand usually tie together, measuring both and controlling for activity demand in the model would potentially separate the intrinsic demand for travel, which is the construct of interest in this study. Respondents also provided their average actual one-way commute time and their ideal commute time in the entry survey.

Other measures of the positive utility of travel were included in the trip survey. After each trip, I asked the respondent their ideal travel time for that trip then contrasted this with

the actual travel time obtained from the GPS tracking. I derived the desired travel time savings (DTTS) by taking the difference between actual and ideal travel time, then divided them into 5 intervals (1 if equal or below 0 minute; 2 if between 0 and 5 minutes; 3 if between 5 and 10 minutes; 4 if between 10 and 20 minutes; 5 if above 20 minutes). The goal was to test the non-linearity of this variable and the sensitivity of the ideal travel time measurement.

I measured satisfaction with travel with a single item in a Likert scale ranging from 1 (very dissatisfied) to 11 (very satisfied). After each trip, I asked if respondents wanted to forgo that trip if they had the opportunity to arrive at the destination immediately (i.e., a modified version of the teleportation test). These measurements were then compared with the ideal travel time to test the validity of this measurement.

I performed several basic data cleaning tasks for this study. I excluded train trips that were broken due to the lack of GPS signal underground and all trips that lasted shorter than 5 minutes. Because of missing variables, I only used data collected from Fall 2017 to Spring 2018 in the Blacksburg – Roanoke, VA or Washington, DC metropolitan areas (no data from Minneapolis were collected during this period). The final dataset consisted of 4,379 trips made by 186 participants.

5.3.2 Analysis

This study consists of a two-part analysis. First, I descriptively compared various measures of the positive utility of travel, such as ideal travel time, teleportation test, and satisfaction with travel. Next, I modeled the ideal travel time based on a set of variables from the person and trip levels. The dependent variable (ideal travel time) is bounded at 0 (i.e., no values are smaller than 0), which approximately follows a truncated normal distribution. Each

person made multiple trips during the study period, thus panel models are appropriate. Therefore, I estimated a set of random-effects Type I Tobit models with left censoring, focusing on the ideal travel time in both cities and individually for each city.

The Type I Tobit model is expressed as follows:

$$y_{it}^{*} = \boldsymbol{X}_{it}\boldsymbol{\beta} + \boldsymbol{\nu_i} + \boldsymbol{\epsilon_{it}}$$

And the indicator function as $I_{it} = \begin{cases} y_i^{*} \text{ if } y_{it}^{*} > 0 \\ 0 \text{ if } y_{it}^{*} \leq 0 \end{cases}$

Where 0 is the left censoring value (i.e., below which, *y* is no longer observable but *x* is). y_i is the observed value of a latent variable y_i^{*}. $i = 1,\ldots, I$ people, $t = 1,\ldots, T_i$ trips. Random effects ν_i ~N(0, σ_ν^2) and is independent of ϵ_{it} ~N(0, σ_ϵ^2)

The panel-level likelihood is:

$$L_i = \int_{-\infty}^{+\infty} \left\{ \prod_{t=1}^{T_i} \left[\Phi\left(\frac{-\boldsymbol{X}_{it} - \boldsymbol{\nu_i}}{\sigma_\epsilon} \right) \right]^{I_{it}} \left[\frac{1}{\sigma_\epsilon} \Phi\left(\frac{y_{it} - \boldsymbol{X}_{it} - \boldsymbol{\nu_i}}{\sigma_\epsilon} \right) \right]^{(1-I_{it})} \right\} \Phi\left(\frac{\boldsymbol{\nu_i}}{\sigma_\nu} \right) d\nu_i$$

The integral was approximated by the Gauss-Hermite quadrature in Stata IC 14. The log-likelihood is the sum of all the logs of panel-level likelihood L_i.

I also checked the sensitivity of the results in three ways. First, I estimated a random-effects Tobit model for only commute and homebound trips. Second, I tested the mode self-selection effect or mode consonance (i.e., traveling with one's preferred mode of transport) with only bus, car, bicycle, and walking trips. This model did not include unknown modes because they did not have mode self-selection information). Third, I estimated a set of random-effects ordered probit models with the DTTS (ordered outcome) as the dependent variables and compared the results with the core models. Redmond and Mokhtarian (2001) showed that DTTS was relatively close to the relative desired travel amount (i.e., measured in intervals

of *travel more*, *travel the same amount*, and *travel less than the current amount*). The method and formulas of the random-effects ordered probit models are shown in Section 4.3.2 of this dissertation.

All models include variables that were found important for the travel experience, such as travel modes, trip purposes, activities conducted during travel, travel companionship, actual travel time, satisfaction with travel, weather, time of day and week, travel attitude (e.g., travel liking, perception of travel usefulness). I included the "desire for out-of-home activities" variable to control for activity demand (which might be confounded with travel demand), as well as scheduling constraints (i.e., travelers may want to have extra time to complete more activities).

Sociodemographics were used as control variables. I controlled for family structure which acts as a proxy for scheduling constraints, such as dual-worker status or presence of young children (below 16 years old). The models also include variables that were found important in other studies, such as income, employment status (these two variables were proxies for the actual value of travel time savings), age, and location (i.e., metropolitan area), as well as basic demographic information (e.g., race, gender, and educational attainment).

5.4 Results

5.4.1 Travel time: Descriptive statistics

For the person sample (i.e., data from the entry survey), the mean commute time was 27.7 minutes (median 20 minutes) and the ideal commute time reported by respondents was 16.5 minutes (median 15 minutes). Only 6 respondents desired a zero commute time (3%). About 26% of the respondents stated that they wanted similarly long or longer commute time.

Accounting for multiple trips per person (i.e., multiple trip purposes), the mean and median actual travel times were 18.1 and 13 minutes, respectively. Respondents reported a mean and median ideal travel time of 11.2 and 8 minutes. It is notable that respondents wanted zero travel time for 16% of the trips in this sample.

A summary of travel times by mode is presented in Table 18. Figure 5 shows a histogram of the actual and ideal travel times of the overall sample. In general, bicycle and walking trips tended to be shorter (in time) than trips made by other modes. Likewise, the relative desired travel time savings were smaller for these two modes, suggesting the small discrepancy between the actual and ideal travel time in active travel trips. Trips made by cars and other modes (e.g., motorcycle, scooter, taxicab) tended to have higher DTTS.

Table 18 and Figure 6 summarize travel times by trip purpose. Mean actual travel times were relatively similar across all trip purposes (between 18-21 minutes), except for errand trips that lasted 15 minutes on average. Commute and homebound trips had the highest DTTS as compared to other trip purposes.

Table 18. Descriptive statistics of actual travel time, ideal travel time and DTTS by mode and trip purpose

	Variable (minutes)	Obs.	Mean	Median	SD	Min	Max
Travel mode							
Car	Actual time	1,987	20.92	14	18.64	5	148
	Ideal time	1,987	11.52	9	13.82	0	147
	DTTS	1,987	9.40	6	15.01	-89	142
Bus	Actual time	184	15.76	12	12.14	5	72
	Ideal time	184	9.07	5	11.38	0	60
	DTTS	184	6.70	6	9.09	-9	61
Walk	Actual time	831	11.54	9	7.91	5	70
	Ideal time	831	9.21	5	10.06	0	80

	Variable (minutes)	Obs.	Mean	Median	SD	Min	Max
	DTTS	831	2.33	2	8.18	-62	30
Bike	Actual time	78	14.40	13	10.06	5	66
	Ideal time	78	11.13	10	9.37	0	60
	DTTS	78	3.27	2	5.66	-10	26
Vehicle [1]	Actual time	1,310	18.65	13	17.02	5	149
	Ideal time	1,310	12.41	10	13.23	0	150
	DTTS	1,310	6.24	3	14.11	-44	124
Other mode	Actual time	7	25.29	25	17.09	5	48
	Ideal time	7	15.43	10	11.39	0	29
	DTTS	7	9.86	5	14.02	-1	38
Trip purpose							
Homebound	Actual time	1,144	18.92	13	16.63	5	129
	Ideal time	1,144	10.56	8	12.14	0	130
	DTTS	1,144	8.37	5	13.70	-42	124
Commute	Actual time	1,222	19.16	13	16.99	5	142
	Ideal time	1,222	12.10	10	12.23	0	120
	DTTS	1,222	7.06	4	14.78	-82	142
Leisure	Actual time	418	21.01	14	19.44	5	145
	Ideal time	418	15.03	10	15.32	0	120
	DTTS	418	5.98	3	16.36	-62	135
Errand	Actual time	1,181	15.35	11	13.89	5	149
	Ideal time	1,181	9.64	6	11.31	0	150
	DTTS	1,181	5.71	4	10.61	-34	121
Social	Actual time	165	18.82	13	19.02	6	148
	Ideal time	165	11.88	9	17.96	0	147
	DTTS	165	6.94	4	14.44	-89	62
Other pur-	Actual time	267	17.69	12	17.78	5	141
pose	Ideal time	267	11.11	5	15.79	0	150
	DTTS	267	6.58	3	13.58	-31	100

[1] *Vehicle is an unreported and undetected mode, which could either be bus or car.*

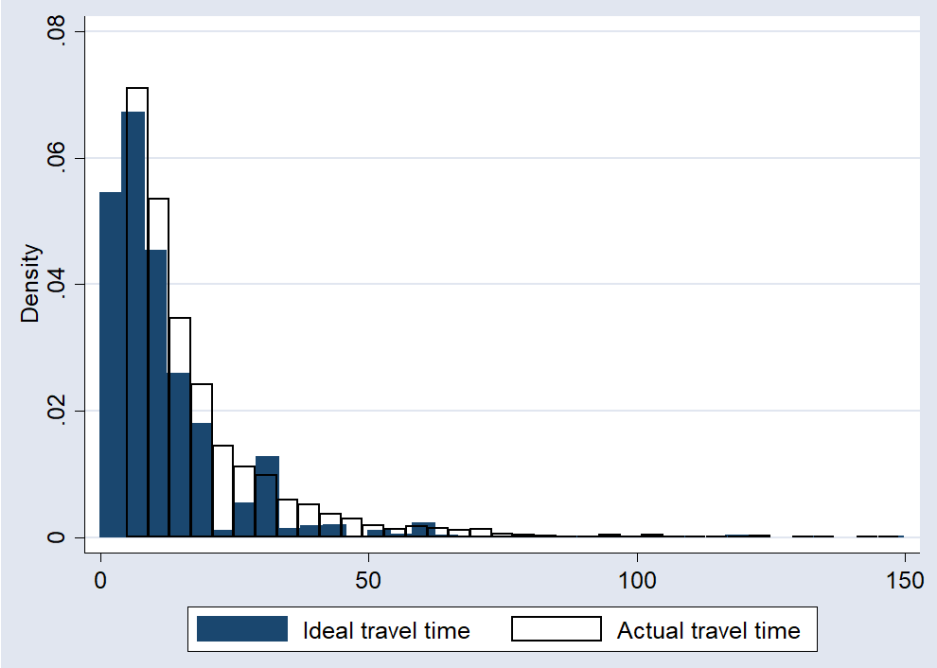
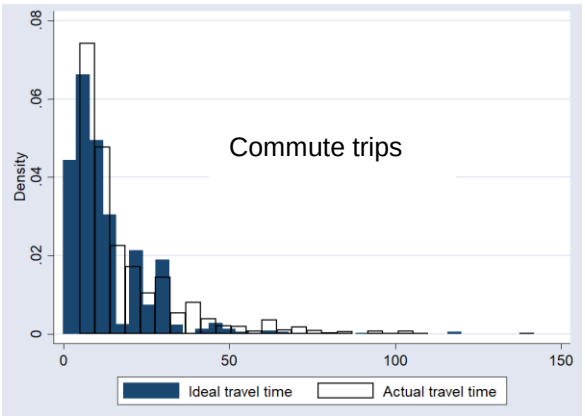
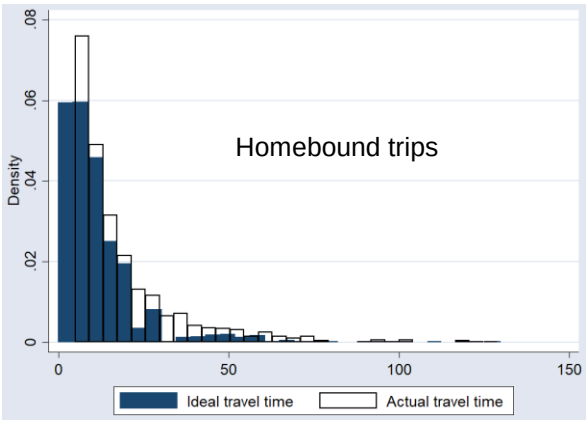
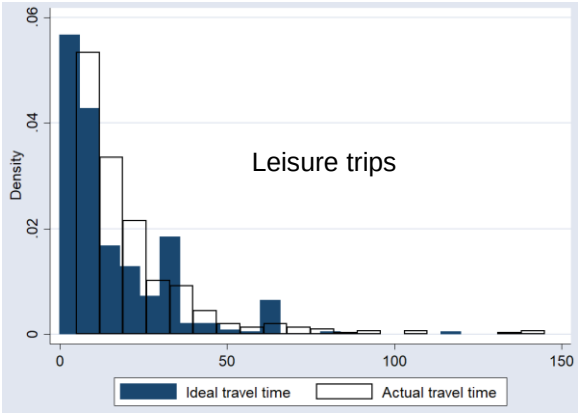
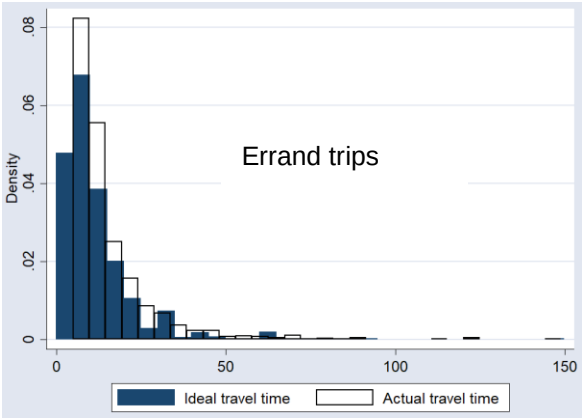


Figure 5. Histogram of actual and ideal travel times for all trips









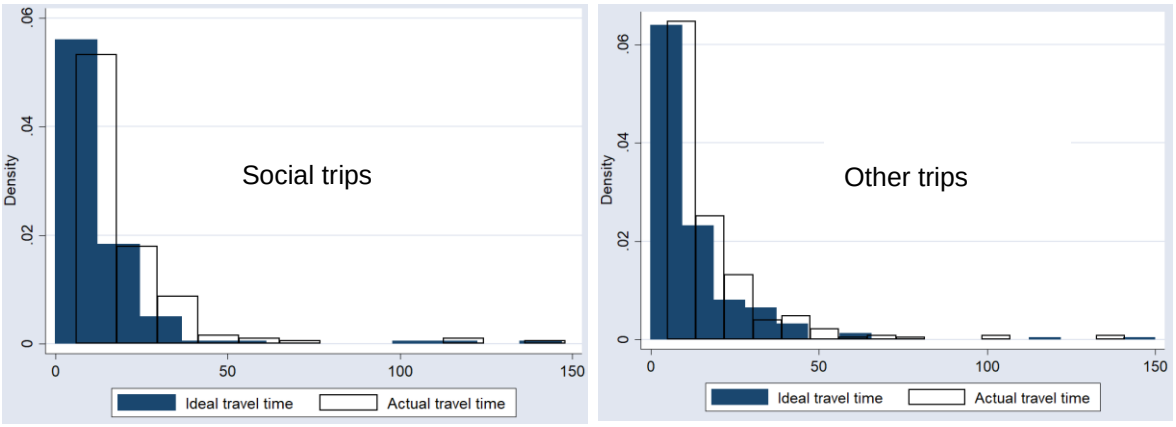


Figure 6. Histograms of ideal and actual travel time by trip purpose

Travelers engaged in one or more activities during most trips (Table 19). The most common types of activities were listening to music/radio and talking. Trips that involved some activities were more likely to have DTTS of 1-5 minutes.

Table 19. Activities conducted during travel and DTTS

	Less than or equal to 0 min.	**1-5 min.**	**5-10 min.**	**11-20 min.**	**Above 20 min.**	**Total**
Listening to music or radio	293	503	295	231	141	1,463
	20%	*34%*	*20%*	*16%*	*10%*	
Talking	416	456	254	207	120	1,453
	29%	*31%*	*17%*	*14%*	*8%*	
Using the phone	56	100	68	51	45	320
	18%	*31%*	*21%*	*16%*	*14%*	
Working	13	14	8	13	12	60
	22%	*23%*	*13%*	*22%*	*20%*	
Reading (including audio-books)	23	29	14	15	10	91
	25%	*32%*	*15%*	*16%*	*11%*	
Looking at landscape	75	102	61	35	22	295
	25%	*35%*	*21%*	*12%*	*7%*	

	Less than or equal to 0 min.	1-5 min.	5-10 min.	11-20 min.	Above 20 min.	Total
No activity	167	174	102	53	38	534
	31%	*33%*	*19%*	*10%*	*7%*	
Other activity	74	60	25	12	5	176
	42%	*34%*	*14%*	*7%*	*3%*	
Total	1,117	1,440	827	620	393	4,397
	25%	*33%*	*19%*	*14%*	*9%*	

Note: Row percentages are shown in italics. DTTS *is the difference between actual and ideal travel time (interval, ordered outcome).*

5.4.2 Ideal travel time, DTTS, and other positive utility of travel measurements

In this section, I compared descriptive results of travel time measurement and other positive utility of travel measures, such as desirability for trip making and satisfaction with trips. The desirability for trip making was described in Section 4.3 of this dissertation.

Figure 7 shows the comparison of the ideal travel time from 0 to 10 minutes and the desirability of making trips. Most people rounded their ideal travel time to 5, 10, 15, or 20 minutes. At a glance, most people wanted to forgo trips when the ideal time was shorter, suggesting some association between ideal travel time and desirability of the trip. Although the ideal travel time above 10 minutes was not included in this chart, the pattern was similar to this first 10 minutes.

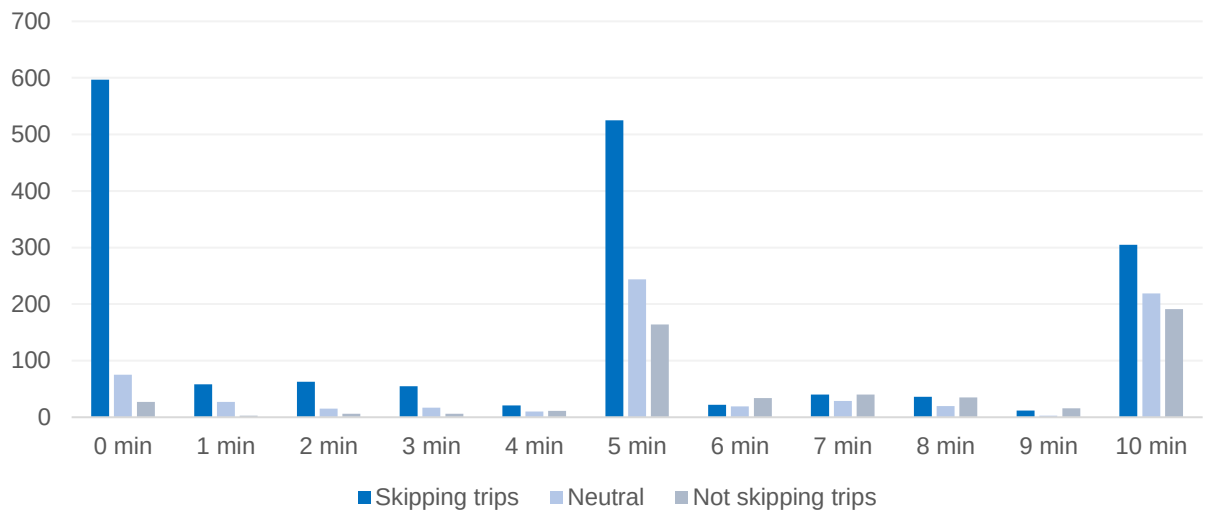


Figure 7. Distribution of ideal travel time (only showing from 0 to 10 minutes) and desire for trip making. Vertical axis shows the number of trips.

In terms of relative desired travel time, more trips were chosen to skip when the discrepancy between actual and travel time increases, and vice versa (

Table 20; Spearman's *rho* = -0.3, $p<0.05$).

Table 20. DTTS and desirability of trip making

	Less than or equal to 0 min.	1-5 min.	5-10 min.	11-20 min.	Above 20 min.	Total
Skipping trip	414	702	569	439	305	2429
	39%	*50%*	*69%*	*71%*	*78%*	*56%*
Neutral	279	390	147	114	56	986
	26%	*28%*	*18%*	*18%*	*14%*	*23%*
Not skipping trips	368	325	104	64	30	891
	35%	*23%*	*13%*	*10%*	*8%*	*21%*
Total	1061	1417	820	617	391	4306

Note: Spearman's rho = -0.3, p<0.05. Column percentages are shown in italic.

The association between DTTS and satisfaction with trips was less pronounced (Table 21), with Spearman's *rho* = -0.17 (p<0.05). It is intuitive that satisfactory trips tend to have smaller relative desired travel time.

Table 21. Satisfaction with trips and DTTS

Satisfaction	Less than or equal to 0 min.	1-5 min.	5-10 min.	11-20 min.	Above 20 min.	Total
1	2	2	5	5	12	26
	0%	*0%*	*0%*	*0%*	*1%*	*2%*
2	7	17	26	20	25	95
	1%	*2%*	*2%*	*2%*	*2%*	*9%*
3	23	19	45	29	18	134
	2%	*2%*	*4%*	*3%*	*2%*	*13%*
4	30	68	61	63	42	264
	3%	*6%*	*6%*	*6%*	*4%*	*25%*
5	4	9	4	6	4	27

Satisfaction	Less than or equal to 0 min.	1-5 min.	5-10 min.	11-20 min.	Above 20 min.	Total
	0%	*1%*	*0%*	*1%*	*0%*	*3%*
6	141	228	126	91	65	651
	13%	*21%*	*12%*	*8%*	*6%*	*61%*
7	203	255	131	102	59	750
	19%	*24%*	*12%*	*10%*	*6%*	*70%*
8	260	366	198	121	55	1000
	24%	*34%*	*18%*	*11%*	*5%*	*93%*
9	151	244	100	76	49	620
	14%	*23%*	*9%*	*7%*	*5%*	*58%*
10	250	213	117	92	50	722
	23%	*20%*	*11%*	*9%*	*5%*	*67%*
Total	1071	1421	813	605	379	4289

Note: Spearman's rho = -0.17, p<0.05. Column percentages are shown in italic.

5.4.3 Modeling desired travel time

I estimated a set of random-effects Tobit models for both cities and individually for each city (Table 22). The results are generally similar across these models in terms of significance and directions of effect. I also tested the models with the frequency of telework and household structure (e.g., dual-worker household status and having children below 16) and found insignificant results, thus these variables were not included in the final models.

In the main (two-city) model (M1, Table 22), I found that walking trips were more likely to be longer in ideal travel time than car trips. This pattern also applies to vehicle trips, which is a combination of car and bus trips that respondents did not report which mode they used. Ideal travel time also varied by trip purpose, controlling for other variables. Specifically, commute trips, homebound trips, errand trips, and other non-social trips tended to have a

greater ideal travel time as compared to leisure trips. Homebound trips and errand trips had the most negative coefficients, indicating that these trips were less desirable than other trips.

The M1 model also shows that some activities during trips were associated with longer ideal travel time. For example, talking or using the phone during trips, looking at the landscape, or conducting other activities have positive coefficients, meaning that they were viewed as positive to travel time use. Desired travel amount while traveling with family members or dogs was not statistically different from traveling with friends; however, traveling with acquaintances was associated with shorter ideal travel time, while traveling with strangers was associated with longer ideal travel time, holding other factors constant. The desired amount of travel is also highly and positively correlated with the actual travel time. Trips during weekends tended to have greater ideal travel time. When travelers were satisfied with their trips, they were more likely to desire a longer travel time of those trips. There was no significant difference in desired amount of travel in different times during weekdays.

At the personal level, travelers living in the Washington, DC region chose longer desired travel time. Most socioeconomic variables were not significant, except for income. Compared to people who earned less than $30,000 annually, people or households that earned between $30,000 to $59,999 desired less travel time. Several variables were included in the models, such as travel liking attitude, travel time use (e.g., viewing travel as wasted time), and desire for out-of-home activities. Only travel time use attitude was significant in the model, suggesting that people who did not view travel time as wasted time, also were more likely to have a longer ideal travel time.

Models M2 and M3 (Table 22) for Blacksburg and Washington, DC respectively, also suggest similar results. A few exceptions include longer ideal travel time from the white respondents in Blacksburg. The desire for more out-of-home activities was also significant in the Blacksburg model. However, none of the attitude variables or out-of-home activity demand were significant in the Washington model. Talking and using the phone did not have any significant effect on the ideal travel time. However, bicycle trips were positively associated with the ideal travel time.

Table 22. Random-effects Tobit model for the ideal travel time

	Both cities (M1)		**Blacksburg (M2)**		**Washington, DC (M3)**	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Travel mode (ref: car)						
Bus	-0.45	0.98	-0.99	1.32	1.78	1.36
Bicycle	1.59	1.35	1.16	1.48	6.49 *	2.40
Walking	2.23 *	0.54	2.53 *	0.72	3.22 *	0.77
Vehicle	1.10 *	0.49	1.67 *	0.74	0.88	0.64
Other mode	1.28	3.65	3.73	4.63	-1.45	5.15
Trip purpose (ref: leisure trips)						
Commute trip	-1.79 *	0.62	-1.05	0.88	-1.53 º	0.84
Homebound trip	-3.12 *	0.60	-2.06 *	0.87	-3.11 *	0.79
Errand trip	-2.42 *	0.60	-1.24	0.84	-2.84 *	0.79
Other trip	-2.27 *	0.87	-2.50 º	1.48	-2.05 º	1.08
Social trip	-1.14	0.93	0.42	1.28	-2.24 º	1.25
Activity during travel (ref: no activities)						
Talking	2.70 *	0.66	3.61 *	0.91	1.38	0.90
Using the phone	2.13 *	0.79	3.35 *	1.14	1.08	1.04
Working	1.96	1.71	1.99	4.20	1.59	1.95
Reading	1.53	1.24	1.58	1.92	0.57	1.58

	Both cities (M1)		Blacksburg (M2)		Washington, DC (M3)	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Looking at the landscape	3.19 *	0.80	3.94 *	1.08	1.94 º	1.10
Listening to music/radio	0.41	0.61	1.30	0.86	-0.58	0.83
Other activities	2.01 *	0.98	0.48	1.61	1.97	1.25
Actual travel time	0.52 *	0.01	0.61 *	0.02	0.47 *	0.01
Companionship (ref: friend)						
Family member	-0.18	0.50	-0.23	0.76	-0.20	0.65
Acquaintance	-6.82 *	2.40	-5.35	3.78	-7.33 *	3.04
Stranger	2.04 º	1.16	-0.67	1.58	5.11 *	1.61
Dog	0.37	1.68	0.02	3.30	-0.26	1.98
Satisfaction with trip	0.93 *	0.09	1.08 *	0.15	0.76 *	0.11
Weather and time						
Rain	0.02	0.37	0.63	0.70	-0.08	0.44
Temperature	-0.03	0.02	0.00	0.03	-0.01	0.03
Late night	-0.13	0.42	-0.74	0.57	0.50	0.57
Morning rush hour	1.55	2.11	6.36	7.93	1.38	2.28
Afternoon rush hour	0.49	0.44	0.00	0.63	0.83	0.57
Weekend	0.95 *	0.41	0.92	0.62	0.95 º	0.52
Like travel	0.10	0.30	0.03	0.41	0.07	0.40
Travel is wasted time	-0.63 *	0.28	-0.90 *	0.33	-0.29	0.41

	Both cities (M1)		Blacksburg (M2)		Washington, DC (M3)	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Desire for more out-of-home activities	0.06	0.38	0.47	0.47	0.04	0.56
Age	0.07	0.09	0.18	0.12	0.08	0.11
Female	1.23	1.36	0.76	1.62	1.40	1.98
Annual household income (ref: <$30,000)						
Income $30,000 - 59,999	-3.75 *	1.90	-2.46	2.17	-5.39 ⁰	3.11
Income $60,000 - 89,999	0.62	2.19	1.82	3.07	-0.70	3.21
Income $90,000 - 119,999	-0.93	2.42	0.07	3.02	-2.52	3.63
Income $120,000 or more	-1.02	2.69	-3.37	4.67	-2.30	3.62
Education (ref: bachelor's degree)						
Less than high school graduate	6.68	8.34	2.13	1.96	2.64	9.44
High school graduate, include GED	5.47	8.62	1.88	3.92	2.66	9.94
Some college or associate's degree	0.56	8.81	-1.78	4.36	-0.98	10.12
Master's degree	5.45	8.37	1.73	2.29	2.53	9.59
Doctoral or professional degree	4.79	8.43		(omitted)	2.87	9.61
Employment status (ref: working part-time)						
Full time employee	-1.52	2.09	-2.52	3.05	-1.56	2.64
Full time student	-1.69	2.18	-2.11	2.48	-0.25	3.53

	Both cities (M1)		Blacksburg (M2)		Washington, DC (M3)	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Retiree	-1.74	6.37		(omitted)	-3.08	7.39
Unemployed	-3.36	6.47		(omitted)	-2.01	7.36
Work at home	-4.22	2.88	-5.19	4.77	-3.43	3.72
Living in Washington, DC	2.27 *	0.89				
Non-white	2.03	1.34	2.85 °	1.66	1.26	1.93
Intercept	-11.80	10.12	-15.74 *	6.08	-4.83	12.92
sigma_u	7.75 *	0.49	5.72	0.61	8.69 *	0.67
sigma_e	8.99 *	0.11	7.62	0.16	9.36 *	0.14
Rho	0.43	0.03	0.36	0.05	0.46	0.04
Number of observations	4,250		1,494		2,756	
Number of people	183		81		119	

Dependent variable: Ideal travel time (in minute). Significant codes: (°): 0.05 ≤ p <0.1, (*): p < 0.05. Some variables were omitted due to multicollinearity or having too few observations.

5.4.4 Sensitivity analysis

The first sensitivity analysis with only commute and homebound trips (Table 23) shows that most variables have similar significance and directions of effect as compared to the core model of both cities (Table 22). However, many more activities became significant and positive, such as working and listening to music or radio.

Table 23. Sensitivity analysis: Ideal travel time for commute and homebound trips (whole sample).

	Coef.	**SE**	**P>z**
Travel mode (ref: car)			
Bus	-1.12	1.11	0.313
Bike	1.69	1.69	0.317
Walking	0.05	0.74	0.949
Vehicle	0.76	0.65	0.238
Other mode	-2.94	6.25	0.638
Activity during travel (ref: no activities)			
Talking	3.40*	0.87	0
Using the phone	3.65*	0.97	0
Working	3.34 **o**	1.81	0.065
Reading	0.81	1.44	0.574
Looking at the landscape	3.66*	1.02	0
Listening to music/radio	2.00*	0.77	0.01
Other activities	4.30*	1.49	0.004
Actual travel time	0.43*	0.01	0
Companionship (ref: friend)			
Family member	-0.19	0.74	0.801
Acquaintance	-9.76*	3.38	0.004
Stranger	3.24*	1.29	0.012
Dog	3.37	2.27	0.137
Satisfaction with trip	0.48*	0.12	0

	Coef.	SE	P>z
Weather and time			
Rain	-0.37	0.48	0.438
Temperature	-0.01	0.03	0.663
Late night	0.42	0.55	0.448
Morning rush hour	-1.07	2.45	0.661
Afternoon rush hour	0.99 **o**	0.58	0.088
Weekend	0.17	0.60	0.774
Like travel	0.14	0.33	0.674
Travel is wasted time	-0.76*	0.30	0.012
Desire more out-of-home activities	-0.31	0.41	0.453
Age	0.08	0.10	0.379
Female	0.55	1.46	0.704
Annual household income (ref: <$30,000)			
Income $30,000 - 59,999	-3.80 **o**	2.08	0.067
Income $60,000 - 89,999	-0.14	2.46	0.953
Income $90,000 - 119,999	-0.88	2.69	0.744
Income $120,000 or more	-1.50	2.93	0.61
Education (ref: bachelor's degree)			
Less than high school graduate	9.46	8.70	0.277
High school graduate, include GED	8.85	9.03	0.327
Some college or associate's degree	4.86	9.19	0.597
Master's degree	8.45	8.73	0.333
Doctoral or professional degree	8.64	8.81	0.327
Employment status			
Full time employee	-0.24	2.26	0.914
Full time student	-1.56	2.37	0.509
Retiree	-4.67	6.84	0.495
Unemployed	-5.60	7.03	0.426
Work at home	-3.98	3.65	0.277
Non- white	2.29	1.46	0.116

	Coef.	SE	P>z
Living in Washington, DC	2.92*	1.26	0.02
Having children	0.40	1.61	0.804
Telework at least one day per week	-0.84	1.78	0.636
Constant	-12.37	10.90	0.256
/sigma_u	7.89	0.54	0
/sigma_e	8.41	0.14	0
rho	0.47	0.04	
Number of trips	2,286		
Number of people	173		

Dependent variable: Ideal travel time (in minute). Significant codes: (°): 0.05 ≤ p <0.1, (*): p < 0.05.

In the second analysis, I estimated a Tobit model with mode self-selection effect (so called mode consonance) (Table 24). The overall results were similar to the core models. After controlling for the mode self-selection effect, walking and bicycle trips had a positive association with the ideal travel time, however, only walking trips were statistically significant (p<0.05). Mode self-selection was positively significant at the *p*<0.1 level, meaning that trips with preferred modes had longer ideal travel time.

Table 24. Random-effects Tobit model with mode consonance and household structure

	Coef.	SE	P>z
Travel mode (ref: car)			
Bus	-0.34	0.98	0.73
Bicycle	1.29	1.37	0.35
Walking	1.97*	0.56	0.00
Vehicle	1.89*	0.66	0.00
Other mode	2.28	3.68	0.54
Mode consonance	1.16 **o**	0.65	0.08

	Coef.	SE	P>z
Trip purpose (ref: leisure trips)			
Commute trip	-1.75*	0.62	0.01
Homebound trip	-3.07*	0.60	0.00
Errand trip	-2.39*	0.60	0.00
Other trip	-2.25*	0.87	0.01
Social trip	-1.06	0.93	0.26
Activity during travel (ref: no activities)			
Talking	2.67*	0.66	0.00
Using the phone	2.12*	0.79	0.01
Working	2.00	1.71	0.24
Reading	1.45	1.24	0.24
Looking at the landscape	3.17*	0.80	0.00
Listening to music/radio	0.37	0.61	0.54
Other activities	2.02*	0.98	0.04
Actual travel time	0.52*	0.01	0.00
Companionship (ref: friend)			
Family member	-0.21	0.50	0.67
Acquaintance	-6.67*	2.40	0.01
Stranger	2.06 **o**	1.16	0.08
Dog	0.13	1.68	0.94
Satisfaction with trip	0.92*	0.09	0.00
Weather and time			
Rain	0.01	0.37	0.97
Temperature	-0.03	0.02	0.10
Late night	-0.14	0.42	0.73
Morning rush hour	1.52	2.11	0.471
Afternoon rush hour	0.48	0.44	0.267
Weekend	0.95*	0.41	0.02
Like travel	1.15*	0.47	0.01
Travel is wasted time	-0.13	0.43	0.77

	Coef.	SE	P>z
Desire for more out-of-home activities	-0.48	0.51	0.35
Age	0.04	0.09	0.64
Female	1.14	1.37	0.40
Annual household income (ref: <$30,000)			
Income $30,000 - 59,999	-3.77 **o**	1.90	0.05
Income $60,000 - 89,999	1.47	2.24	0.51
Income $90,000 - 119,999	-0.99	2.50	0.69
Income $120,000 or more	-1.02	2.77	0.71
Education (ref: bachelor's degree)			
Less than high school graduate	8.86	8.34	0.29
High school graduate, include GED	8.70	8.66	0.32
Some college or associate's degree	2.43	8.74	0.78
Master's degree	8.14	8.39	0.33
Doctoral or professional degree	6.89	8.41	0.41
Employment status (ref: working part-time)			
Full time employee	-1.78	2.29	0.44
Full time student	-2.20	2.17	0.31
Retiree	0.00	6.41	1.00
Unemployed	-1.30	6.44	0.84
Work at home	-3.68	2.85	0.20
Living in the Washington, DC area	2.09*	0.90	0.02
Non-white	2.28 **o**	1.34	0.09
Dual-worker household	1.67	1.93	0.39
Having children under 16 years old	1.50	1.50	0.32
Constant	-19.34	10.24	0.06
sigma_u	7.70	0.49	0
sigma_e	8.99	0.11	0
Rho	0.42	0.03	
Number of trips	4,250		
Number of people	183		

Dependent variable: Ideal travel time (in minute). Significant codes: (°): 0.05 ≤ p <0.1, (*): p < 0.05.

The random-effects ordered probit models (Table 25; third sensitivity analysis) for DTTS provided similar results as compared to the core models. This suggests that the core models were robust.

Table 25. Sensitivity analysis: Random-effects ordered probit models of DTTS

	All cities		Blacksburg		Washington, DC	
	Coef	**SE**	**Coef**	**SE**	**Coef**	**SE**
Travel mode (ref: car)						
Bus	0.04	0.11	0.40 *	0.17	-0.40 *	0.16
Bicycle	-0.39 *	0.17	-0.15	0.21	-1.19 *	0.31
Walking	-0.41 *	0.07	-0.32 *	0.10	-0.59 *	0.10
Vehicle	-0.22 *	0.06	-0.27 *	0.10	-0.19 *	0.08
Other mode	-0.44	0.43	-0.98	0.71	0.08	0.58
Trip purpose (ref: leisure trips)						
Commute trip	0.17 *	0.08	-0.11	0.12	0.28 *	0.10
Homebound trip	0.37 *	0.07	0.07	0.12	0.48 *	0.09
Errand trip	0.23 *	0.07	0.06	0.12	0.34 *	0.09
Other trip	0.19 º	0.11	0.38 º	0.21	0.19	0.13
Social trip	0.15	0.11	-0.24	0.18	0.44 *	0.15
Activity during travel (ref: no activities)						
Talking	-0.31 *	0.08	-0.37 *	0.13	-0.19 º	0.11
Using the phone	-0.07	0.09	-0.29 º	0.16	0.12	0.12
Working	0.20	0.22	0.00	0.64	0.31	0.24
Reading	0.01	0.15	0.04	0.26	0.10	0.19
Looking at the landscape	-0.32 *	0.10	-0.35 *	0.15	-0.19	0.13

	All cities		Blacksburg		Washington, DC	
	Coef	**SE**	**Coef**	**SE**	**Coef**	**SE**
Listening to music/radio	-0.08	0.07	-0.10	0.12	0.00	0.10
Other activities	-0.16	0.12	-0.18	0.23	-0.08	0.15
Actual travel time	0.05 *	0.00	0.05	0.00	0.06 *	0.00
Companionship (ref: friend)						
Family member	-0.01	0.06	0.16	0.11	-0.04	0.08
Acquaintance	0.49 º	0.28	1.35 *	0.56	0.39	0.34
Stranger	-0.12	0.13	-0.14	0.21	-0.24	0.19
Dog	0.03	0.21	0.47	0.47	0.02	0.24
Satisfaction with trip	-0.13 *	0.01	-0.18 *	0.02	-0.10 *	0.01
Weather and time						
Rain	0.05	0.05	0.04	0.10	0.05	0.05
Temperature	0.01 *	0.00	0.00	0.00	0.00	0.00
Late night	-0.08	0.05	0.04	0.08	-0.16 *	0.07
Morning rush hour	0.09	0.25	-0.32	1.10	0.09	0.26
Afternoon rush hour	-0.15 *	0.05	-0.07	0.09	-0.22 *	0.07
Weekend	-0.16 *	0.05	-0.19 *	0.09	-0.14 *	0.06
Age	0.01	0.01	-0.03 º	0.02	0.01	0.01
Female	-0.12	0.16	-0.12	0.23	-0.16	0.23
Annual household income (ref: <$30,000)						

	All cities		Blacksburg		Washington, DC	
	Coef	**SE**	**Coef**	**SE**	**Coef**	**SE**
Income $30,000 - 59,999	0.38 º	0.23	0.35	0.31	0.61 º	0.36
Income $60,000 - 89,999	-0.04	0.26	-0.31	0.44	0.21	0.37
Income $90,000 - 119,999	0.16	0.29	0.65	0.43	0.21	0.42
Income $120,000 or more	0.15	0.33	0.39	0.67	0.20	0.43
Education (ref: bachelor's degree)						
Less than high school graduate	-0.99	1.00	-0.02	0.28	-0.38	1.09
High school graduate, include GED	-1.12	1.04	-0.58	0.58	-0.57	1.15
Some college or associate's degree	-0.42	1.06	0.30	0.61	-0.30	1.17
Master's degree	-0.88	1.01	0.26	0.33	-0.50	1.11
Doctoral or professional degree	-0.99	1.01	0.00	(omitted)	-0.59	1.11
Employment status (ref: working part-time)						
Full time employee	0.06	0.25	-0.30	0.44	0.21	0.31
Full time student	0.01	0.26	-0.11	0.35	-0.29	0.41
Retiree	-0.62	0.77	0.00	(omitted)	-0.32	0.86
Unemployed	0.51	0.78	0.00	(omitted)	0.36	0.85
Work at home	0.48	0.35	0.11	0.68	0.54	0.43
Being White	-0.20	0.16	-0.35	0.24	-0.14	0.22
Living in Washington, DC	-0.41 *	0.11				
Like travel	0.00	0.04	0.01	0.06	0.01	0.05

	All cities		Blacksburg		Washington, DC	
	Coef	**SE**	**Coef**	**SE**	**Coef**	**SE**
Travel is wasted time	0.07 *	0.03	0.11 *	0.05	0.05	0.05
Desire for more out-of-home activities	0.01	0.05	-0.07	0.07	0.01	0.07
First cutoff	-1.70	1.22	-2.92 *	0.86	-0.20	1.50
Second cutoff	-0.38	1.22	-1.53 ⁰	0.86	1.13	1.50
Third cutoff	0.56	1.22	-0.44	0.86	2.01	1.50
Fourth cutoff	1.75	1.22	0.84	0.86	3.22 *	1.50
Number of observations	4,250		1,494		2,756	
Number of people	183		81		119	

Dependent variable: DTTS *(ordered outcome). Significant codes: (⁰): 0.05 ≤ p <0.1, (*): p < 0.05. Some variables were omitted because of multicollinearity.*

5.5 Discussion

5.5.1 Discussion of results

This study explores and applies the concept of ideal travel time in the context of the positive utility of travel. It is among the few studies that looked at the positive utility of travel using ideal travel time as a measurement. Unlike previous studies that only focused on a typical commute trip (O'Fallon & Wallis, 2012; Páez & Whalen, 2010; Redmond & Mokhtarian, 2001) and measured more personal traits (Redmond & Mokhtarian, 2001), this study focuses on the trip level by exploring multiple trips made by the same individual during a long period (a week or more) and investigating all trip purposes.

Comparing different measures of travel time, I found that the ideal travel time was very weakly associated with the desirability of trip making and satisfaction with trips. Although few people wanted zero commute time (3%), the number of trips that had zero ideal travel time was much higher (16%), indicating that the desired travel amount may vary across different trip and environmental characteristics and purpose. While the finding of the ideal commute time corroborates results of previous studies (Páez & Whalen, 2010; Redmond & Mokhtarian, 2001), the variability in ideal travel time among trips is perhaps due to the diversity of trip characteristics in this sample. It is possible that travelers easily tolerate commute trips as commuting is a habit and is part of their daily travel time budgets, while other trips may occur without plan or time budget.

It is worth noting that a negative utility exists alongside the positive utility of travel as suggested by the descriptive results of this study. At the aggregate level, the mean actual commute time is greater than the mean ideal commute time (28 minutes versus 17 minutes), suggesting that in general, travelers wished to reduce their commute time but not completely. At

the individual level, the positive utility was expressed differently: some wished to retain the same amount of commute time, some wanted to forgo it completely, while the majority wanted to keep a small amount of time for commuting. Of course it could be the case that many people did not think that it would be possible to have zero travel time. However, to some extent, this suggests certain demand for traveling itself (not purely derived from activities at the destinations), although this amount of travel should not be too much.

I also found several factors that were positively associated with ideal travel time, such as mode (walking and sometimes bicycling), trip purpose (e.g., leisure trips), activities during trips (e.g., talking, using the phone, looking at the landscape), companionship, and time (e.g., weekend). These results corroborate findings in many other studies focused on travel emotions and well-being, which found that active travelers were more likely to experience happiness and satisfaction from travel (Morris & Guerra, 2014; Páez & Whalen, 2010; Smith, 2017). The insignificant coefficients for bicycle trips in some models may be attributable to the small number of cases reporting this mode. Similar to this study, many other studies also found the positive effect of activities during trips on travel usefulness.

The effect of trip purpose may be due to the fact that the joy or expectation for the activities conducted at destinations inflated the desired travel amount. It could also be the case that leisure trips are more relaxed in general, while utilitarian trips are more time-pressured and therefore people were less willing to spend time on the latter.

Some activities during a trip were not significant in my study, such as working or reading, which may be due to the small number of these activities in our sample. Such activities are likely to influence the perception of travel time usefulness and may increase the desired travel amount. One can also argue that travelers may choose to work during their trips

because they cherish time (i.e., have a higher value of travel time savings). This deserves more exploration in future studies.

Several attitudinal factors were included in the models, however, I did not find any significant effect of the travel liking attitude, even in the model for commute and homebound trips. Two previous studies found this variable significant (Páez & Whalen, 2010; Redmond & Mokhtarian, 2001). Also, Choo et al. (2005) noted that travelers may confuse the desire for travel and desire for activities at destinations. I controlled for this activity demand in the models but did not find any significant effect. However, attitude toward travel time use (e.g., viewing that travel time is wasted) was significant, suggesting that people who think of travel as not wasted time would be more likely to choose a longer ideal travel time.

The results on companionship are unexpected, as ideal travel time while traveling with family members or other companions were not statistically different from traveling with friends; however, traveling with acquaintances was negatively associated with the desired travel amount (both in absolute and relative terms). Conversely, traveling with strangers was positively associated with travel desirability. It could be the case that travelers enjoyed meaningful talks but did not want to be involved in small talks during trips, which happened more often with acquaintances. Furthermore, most sociodemographic variables were insignificant in the models. More research is needed to shed light on this issue.

5.5.2 Implications

This study has several implications for transportation planning practice. First, it challenges the common assumptions of travel demand management strategies, such as reducing travel time as a way to promote well-being and overestimating the value of travel time savings without accounting for the factors beyond travel time (and cost). This study found that people

were willing to spend time traveling to some extent, even with a longer amount of time than their current amount in some cases.

Second, conducting activities during travel (e.g., not only listening to music/radio but also working, reading, playing with the phone) were associated with longer desired travel time. This implies that travel modes such as public transit, ride hailing and shared autonomous vehicles (AV) might become more attractive as they free travelers from the driving task and let them focus on other work during travel (Malokin et al., 2019; Mokhtarian, 2018b; Singleton, 2018a). Practitioners should pay more attention to travel-based multitasking and incorporate them into travel demand models. The estimation of travel time savings should not be relied solely on traditional method, but instead accounting for the willingness to travel with different modes and purposes. Travel time should be estimated realistically with the emergence of new travel modes (e.g., ride hailing and AV).

Additionally, active travel has a positive association with ideal travel time, indicating that these modes may provide more short-term utility of travel in addition to long-term health benefits. These modes should be promoted by providing more satisfactory environment for their users, such as installing and improving facilities (e.g., sidewalk, benches, crosswalk), safety (e.g., yielding, signal prioritization), traffic law reinforcement, among other strategies.

5.5.3 Limitations and future directions

This study suffers from limitations related to sampling method, as pointed out in Section 4.5.2 of this dissertation. Additionally, the validity of the measurement needs further examination as some travelers may confuse the ideal travel time with their realistic option (i.e., incorporating their concerns and time constraints), hence they may be reluctant to choose zero travel time. Nonetheless, the results suggested little or no confusion between acceptable (or

realistic) travel time and ideal travel time given that scheduling constraint (of which the needs for more out-of-home activities, household structure, and employment status served as proxies) was statistically insignificant. Future research should continue to test the relationship between scheduling constraints (both in-home and out-of-home activities), acceptable travel time, and ideal travel time by using subjective and objective measures (e.g., spatial analysis of job-housing balance).

Furthermore, activity duration might be one factor that affects the amount of time that people are willing to spend on trips. Future studies may consider controlling for this variable to get a better model estimation and develop other measurements that could separate the effect of daily scheduling constraint and pure desire of traveling.

Several variables were not included in my study, such as built environment, neighborhood characteristics, and personality. It would be useful to see how these factors modify other trip-related variables in the models. Personality could partially account for the variation in ideal travel time and the relative desired travel amount. Future studies may include such variables to test both within- and between-individual variation of travel affinity.

5.6 Conclusions

This chapter investigates travel affinity through the lens of travel time. I measured the willingness to travel by asking respondents to report their ideal travel time. With a sample of 185 travelers and 4,397 trips, I found that 16% of the trips had a desired travel time of 0, while only 3% of people in my sample wanted zero commute time. Model results suggest that ideal travel time and DTTS varied by mode, purpose, and activities during trips. This study suggests the need for more realistic estimation of the value of travel time savings and quantifying the effect of multitasking during travel on the willingness to reduce travel time. Practitioners

should also consider providing better means for pedestrians and cyclists to fulfill their trips, as their ideal travel times closely matched the actual travel times.

6 Travel experience: Satisfaction, travel affinity, and mode choice

6.1 Introduction

Mode choice is an important component in travel demand models and the planning process. Mode choice has recently gained more attention as driving alone has become less dominant, and new theories and methods were created to build and estimate more sophisticated models. Traditionally, mode choice models are based on the rational choice approach and often comprise of time, cost, and demographic variables. However, various studies have shown the importance of psychological factors in decision making, such as attitude, habit, perceptions, norms, and recently, satisfaction (Abou-Zeid & Ben-Akiva, 2012, 2014; Ajzen, 1991; Axhausen & Gärling, 1992; Carrel & Walker, 2017; De Vos et al., 2016; Singleton, 2017). This necessitates an update of current choice models to approximate the actual human decision making process. Additionally, when including only travel time and cost in the choice process, modelers may overestimate the effects of these two factors, which lead to overestimating the effectiveness of policies related to regulating travel time and cost (e.g., congestion pricing).

Satisfaction with travel has been widely considered in the transportation literature (Morris & Guerra, 2014; Olsson, Gärling, Ettema, Friman, & Fujii, 2012; Vos et al., 2015). However, only a few studies modeled choice based on satisfaction (Abou-Zeid & Ben-Akiva, 2012; Singleton, 2017) or continual usage of a mode (De Vos et al., 2016; Le et al., 2019). The reason is, in part, because measuring satisfaction and trip characteristics across modes is

tedious. Additionally, satisfaction usually has been measured at a single time-point, which poses difficulty in generalizing to the whole medium- or long-term commute experience.

This study aims to address this gap by adding rare evidence for the role of satisfaction in multimodal mode choice for commute trips. I measured satisfaction with travel repeatedly over a week and aggregated this measurement to get the overall satisfaction with travel for choice models. A number of attitudinal variables were also included to quantify their effects on mode choice. The results from this study will help policy makers and practitioners create policies and planning practice that nudge people toward sustainable behavioral change. Results also challenge the assumption that travel cost and travel time are the drivers of mode choice decisions and suggests possible approaches to incorporate satisfaction and travel affinity in forecasting models for bicycling, walking, and public transit.

6.2 Literature review

6.2.1 Travel satisfaction

A small body of literature has explored how satisfaction is associated with mode use. Although early studies in the field focused on public transit riders, recent studies have focused more on transport users of different modes (Abou-Zeid & Ben-Akiva, 2012; Bergstad et al., 2011; Y. Gao, Rasouli, Timmermans, & Wang, 2017; Morris & Guerra, 2014; Olsson et al., 2012; Páez & Whalen, 2010; Smith, 2017; Vos et al., 2015). Using the American Time Use Survey (ATUS), Morris & Guerra (2015) found a very weak negative association between trip duration and mood, which is consistent with other empirical studies (Paige Willis et al., 2013; Smith, 2017; St-Louis et al., 2014). This relationship is only significant for drivers but not for passengers due to the increasing stress and fatigue. The relationship between travel time and mode are different across modes. Specifically, long bicycle trips are more physically

exhausting than shorter trips; long car and transit trips are associated with lower mood. In a related study, Morris & Guerra (2014) found that bicyclists have the most positive mood in general, followed by car drivers. Transit users are found to have the worst mood compared to other modes' users. However, the marginal effects and variance explained are very small, and the statistical significance of results could be attributed to the large sample size (about 36,000 observations or more in all models).

A study by Smith (2016) in Portland, OR, using an adjusted version of the Satisfaction with Travel Scale (STS) for commute trips, found that mode, travel time, and attitude are significant predictors of travel satisfaction, controlling for socio-demographics and the perceptions about their neighborhoods and job. Bicycling and walking have a positive effect on satisfaction, in line with results from other studies (Paige Willis et al., 2013; Abou-Zeid & Ben Akiva, 2012; Friman et al., 2013; Páez & Whalen, 2010). Similar results were also found in another study of commuters in Portland, OR by Singleton (Singleton, 2019), also using the adjusted STS.

Various measurement scales have been used in travel well-being research, from general-use multi-item scales such as PANAS (Watson et al., 1988), the scale of positive and negative experience (Diener et al., 2010), to the Swedish Core Affect scale (Västfjäll et al., 2002). The ATUS used an invalidated scale with five items. Two recently developed scales for transportation are the STS (Ettema et al., 2011) and TMS (Glasgow et al., 2018). Many studies also employed a single-item scale (Handy & Thigpen, 2018; Mao, Ettema, & Dijst, 2016; Waygood, Friman, Taniguchi, & Olsson, 2018; J. Zhu & Fan, 2018a). For comprehensive reviews on travel and well-being, including theories, operationalization (measurement),

and modeling methods, see De Vos et al. (2013), De Vos (2019), Nordbakke and Schwanen (2014), and Mokhtarian (2018a).

While a large number of studies focus on the link between mode use and satisfaction, only a few studies have focused on the opposite link from satisfaction to mode choice. De Vos (2019, p. 12) argued that "the effect of travel mode on travel satisfaction might be overestimated," and that one should look at the attitude toward modes in addition to satisfaction to fully understand travel behavior. Only one study considered both factors (i.e., satisfaction and attitude) at the same time in modeling choice. De Vos et al. (2015, 2016), in a study of leisure trips and travel satisfaction in Ghent, Belgium, found that active travel mode choice is affected by attitude, the built environment, and satisfaction with previous trips. This is also the only study to date that addresses the cyclical relationship between attitude and satisfaction, and thus identifies the need for non-recursive structural equation modeling (SEM) when modeling such bidirectional effects. Le et al. (2019) investigated the effect of transit satisfaction on the decision to use transit based on a 2-wave longitudinal study of transit rider in San Francisco, CA. They found that dissatisfaction with transit service was the major factor for travelers to stop or decrease their transit usage.

While the two studies above focused on one type of travel (i.e., active travel or transit), a few other studies focused on multiple travel modes. In an interview of 18 commuters in the UK, Mann and Abraham (2006) found that affect was relevant when a person chose a mode of commute. Having personal space was also important. Abou-Zeid et al. (2012) and Abou-Zeid & Ben-Akiva (2012, 2014) also incorporate satisfaction into mode choice models. The authors conducted two quasi-experiments in Geneva & Lausanne, Switzerland and on the Massachusetts Institute of Technology campus to see how satisfaction affects mode switching

from the car to public transit. When happiness (or satisfaction) was included, the coefficient estimates were consistent and even more efficient (Abou-Zeid, 2009). Singleton (2017) is perhaps the most complete study on satisfaction and mode choice using a sample of commuters in Portland, OR. The study found that satisfaction and travel-based activities while traveling with one mode was positively associated with a higher probability of choosing that mode. The inclusion of these two variables improved the overall model fit.

Decision and choice process involves different types of utility. Kahneman & Krueger (2006) differentiated various types of utility, such as momentary utility (happiness at a cross section of time), experienced utility (the way people feel/experience in real time), and remembered utility (what people feel after the activity is over). As evidenced in Kahneman & Thaler (2006), not the experienced utility, but instead the remembered utility affects an individual's decision. Therefore, in mode choice modeling, measuring remembered utility is necessary, as people tend to choose (or not choose) a mode based on their remembered experiences. At the same time, individuals choose a mode based on their anticipated experience (expected utility). Abou-Zeid & Ben-Akiva (2014) suggested a method to connect post-travel satisfaction (equivalent to remembered utility) to expected utility (or decision utility) by asking respondents how their experience of the trip was different from what they expected. When these two types of utility align, satisfaction is then used to model mode choice.

6.2.2 Travel attitude

Attitude toward a mode has been found to be associated with usage of that mode. For example, people who are in favor of transit tend to ride transit more often (De Vos, 2018; Spears et al., 2013). Satisfaction might also play a role in this relationship (De Vos, 2019).

That is, satisfaction may affect mode attitude and behavior at the same time; mode attitude and behavior may also influence each other (De Vos, 2019).

Travel attitude, such as travel liking or affinity is documented in other studies. In a focus group study, Handy et al. (2005) found that it may be relevant to mode choice (although mode choice was not the focus of the study). Singleton (2017), however, did not find travel liking to be significant in the choice model. Activity participation (i.e., travel-based multitasking) was found to be a significant driver of mode choice (Malokin et al., 2019; Singleton, 2017). Attitude toward travel time use (e.g., desire to use commute time for working or recreation/entertainment) was also found to be associated with mode choice (Malokin et al., 2019).

6.2.3 Cost

Travel cost reflects a time or monetary cost associated with travel, such as travel time, waiting and transferring time, fare, parking fees, toll, and fuel cost, among others. It could also be mental and physical efforts associated with traveling (e.g., hill or long distance for pedestrians and cyclists). In rational choice models, cost refers to disutility, a negative aspect of travel, and that trip makers tend to avoid or reduce it.

Past studies have found that increasing costs will decrease the use of the corresponding mode, such as transit (Bento et al., 2005) and car (Chatman, 2005; Levinson & Krizek, 2008). Higher slopes and steeper terrain decrease the likelihood of walking or bicycling (Cervero & Duncan, 2003; Rodríguez & Joo, 2005). The literature on the relationship between cost and bicycling or walking choice is still rare.

6.2.4 Socio-demographics

Various studies show how different segments of the population are associated with different travel patterns. Personal factors such as socioeconomic characteristics (e.g. income, household size, auto ownership) are shown to significantly affect transit patronage (Liu, 1993; Gomez-Ibanez, 1996; Taylor, 2003). In a study at the national scale, Bento et al. (2005) found that transit riders, especially bus riders, are more likely to be low income, lower educated, and more likely to be non-white. Low-income populations were also found to drive less. Cyclists are often male, young adults, and in a good health (Moudon et al., 2005).

Socioeconomic characteristics can also be seen as a proxy for lifestyle and activity scheduling, which is commonly used in activity-travel studies and background information for activity-based modeling (Kitamura, 2002; Waddell, 2001). American millennials were found to drive less, use multiple modes, acquire a driver's license and purchase a car later in their lives as compared to the previous generations (Blumenberg et al., 2012; Circella et al., 2017). They also tend to use information and communication technology (e.g., smartphones and social media) more often, which may result in different travel patterns compared to other socio-economic groups. Women, on the other hand, make more trips than men, but cover shorter trip distances and travel for shorter times (McGuckin & Nakamoto, 2004; Schneider & Holz-Rau, 2017). Women, and men to a lesser extent, with young children also tend to chain more non-work trips into their commutes (i.e., making multiple trips, usually for multiple purposes, in which one trip's destination becomes the origin of the other with a less-than-30-minute stop) as their activity schedule is complicated with the presence of children. Therefore, women with school-aged children are more likely to drive than take transit or bicycle.

6.3 Methods

In this study, a mobile app with GPS capability was employed to instantaneously measure respondents' mood and satisfaction after each completed trip. The study used a convenience sample consisting of mostly Virginia Tech and University of Minnesota faculty, staff, and students. The survey was also available to all residents of the Blacksburg – Roanoke, VA, Washington, DC areas (Virginia Tech campuses), and the Minneapolis metropolitan area (University of Minnesota campus). Details about the survey design and participant recruitment were provided in Chapter 3 of this dissertation.

6.3.1 Measurement and processing

For the purpose of modeling, I included various individual-specific variables (coefficients of these variables change across alternatives) and alternative-specific variables (whose coefficients are the same for all alternatives, also known as generic coefficients). The former type includes attitude and socio-demographic variables. The latter type includes travel time, cost, and satisfaction, which I measured (or imputed) for each alternative.

a. Individual-specific variables

Attitude was measured with a series of 7-point Likert scale statements (7 statements in total) ranging from 1 (strongly disagree) to 7 (strongly agree). For mode attitude, I asked respondents whether they agreed or disagreed with the statements: "I like driving", "I like walking", "I like bicycling", "I like riding transit". For travel attitude, I asked if respondents enjoy traveling and whether they found commuting useful, following (Mokhtarian, Salomon, & Redmond, 2001). These questions were included in the entry survey (answered once by each respondent).

Additionally, respondents reported their socio-demographic characteristics in the entry survey, such as age, gender, education, income, family composition, access to each mode of transport and parking.

b. Alternative-specific variables

Alternative-specific variables are variables that vary across alternatives. Their coefficients are the same in all alternatives. It is important to measure such variables in all alternatives in order to correctly specify the choice model.

I used a series of statements to measure satisfaction, mode attitude, and travel attitude. Satisfaction was measured by asking "How satisfied were you with the trip" on an 11-point Likert scale from 0 (very dissatisfied) to 10 (very satisfied). I also used an 8-item travel mood scale to measure the affective dimension of satisfaction (Glasgow et al., 2018); however, due to missing values, I opted to use the single-item satisfaction measure, which was highly correlated with the composite mood score from the mood scale ($r = 0.73$). These measurements were included in the trip survey and were measured directly after each trip. To be incorporated into the choice process, satisfaction has to be measured before the trip, however, this was impossible. Therefore I employed the method proposed by Abou-Zeid & Ben-Akiva (2014) to match remembered utility with expected utility by asking whether the trip experience was as expected; if yes, then satisfaction can be incorporated into the mode choice process.

Actual travel time and distance of each trip were obtained directly from the GPS traces. For unchosen travel alternatives, I queried travel time from the Google Maps API for each travel option (i.e., travel time by car, by bicycle, by walking, by train and/or bus based on the routes that had the shortest travel time). Travel cost was calculated based on (1) distance (for driving) or transit fare reported by the local transit agencies, (2) parking cost at the workplace

based on location, and (3) the cost that respondents provided. Bicycling and walking were assumed to have no monetary cost.

In this study, I only focused on commute trips and excluded all other trip purposes due to different mechanisms in the mode choice process (i.e., other factors may affect mode choice for commute trips but not for other trips, and vice versa). Due to the small number of observations, I grouped modes into three groups: (1) bicycling and walking, (2) driving alone and carpooling (namely car), (3) bus and metro (namely transit). This approach is reasonable given that satisfaction is quite similar between bicycling and walking, driving and carpooling, and public transit modes (although bus users were usually found to be less satisfied than train users) (Morris & Guerra, 2014; Páez & Whalen, 2010; Smith, 2017).

The dataset contains 247 respondents and approximately 9,000 trips. Excluded respondents are those who (a) did not submit trip data, and (b) did not complete the entry questionnaire. Further, due to inaccuracies in GPS recording, I removed trips that are shorter than 5 minutes and those without a completed trip survey, as well as walking trips longer than 450 minutes. This results in 5,906 trips completed by 217 respondents.

6.3.2 Imputation process

Satisfaction for actual trips was recorded in the survey. However, unchosen modes (i.e., hypothetical satisfaction level) were unavailable. Therefore, I imputed satisfaction of unchosen commute modes using satisfaction of similar trips made by other modes made by all users. I used the whole sample of 5,906 trips made by these 217 individuals to develop a random forest model for imputation. This model accounted for attitude toward modes and various trips and personal characteristics of the trip makers. I then predicted the satisfaction

level of each individual while traveling by each travel mode. Satisfaction was then entered in the choice models.

I used a random forest imputation procedure to produce satisfaction value of trips that do not have satisfaction reported. Random forest is a supervised machine learning algorithm that is based on decision tree models. The outcome variable is satisfaction. The input variables are sociodemographics, attitude toward travel modes, attitude toward travel time use, and trip characteristics (e.g., mode, purpose, activities during travel).

First, the training sample is repeatedly sampled to grow 5000 decision (regression) trees. In order to de-correlate trees and produce better results, only 15 variables out of 50 input variables were considered at each slip. The trees were then averaged to produce the final results. I also performed 10-fold cross-validation with 99 iterations to avoid overfitting. The prediction was moderate with an average mean squared error of 2.5. The model explained 40% of the variance in the sample. Modeling was performed in R (*randomForest* package).

The random forest model was applied to predict satisfaction level for trips made by hypothetical modes (e.g., if the chosen mode was car, the hypothetical modes were transit and active travel). Satisfaction was then averaged by each mode for all commute trips made by the same person (i.e., each person had 3 satisfaction levels for 3 modes, namely car, transit, and active travel). These averaged values were used for the final choice model.

6.3.3 Choice modeling

Choice models are the main analysis of this study. I developed 3 logit models for the mode choice decision using car as the base category. Model 1 does not include any psychological factors (e.g., satisfaction, attitude). Model 2 includes attitude but not satisfaction, as traditionally modeled in planning. Model 3 includes satisfaction and attitude variables. The

utility functions for car, public transit, and bike and walk are shown in equations 1-3, respectively.

$$U_{car} = V_{car} + \epsilon_{car} = \beta_t\, Time_{car} + \beta_c\, Cost_{car} + \beta_s\, Sat_{car} + \beta_x^{car}\, X \quad + \epsilon_{car} \text{ (1)}$$

$$U_{PT} = V_{PT} + \epsilon_{PT} = \beta_t\, Time_{PT} + \beta_c\, Cost_{PT} + \beta_s\, Sat_{PT} + \beta_x^{PT}\, X \quad + \epsilon_{PT} \text{ (2)}$$

$$U_{BW} = V_{BW} + \epsilon_{BW} = \beta_t\, Time_{BW} + \beta_c\, Cost_{BW} + \beta_s\, Sat_{BW} + \beta_x^{BW}\, X \quad + \epsilon_{BW} \text{ (3)}$$

In which $\epsilon_{car}, \epsilon_{PT}, \epsilon_{BW}$ are the error term that following i.i.d. Extreme Value type I. We have:

$$\Pr(Car|\epsilon \;) = \frac{\exp(V_{car})}{\exp(V_{car}) + \exp(V_{PT}) + \exp(V_{BW})}$$

All individual-specific variables (e.g., demographics, general attitude; denoted as **X** in the above equations) had a set of coefficients for each mode ($\beta_x^{car}, \beta_x^{PT}, \beta_x^{BW}$). Alternative-specific variables (e.g., time, cost, satisfaction) received general coefficients (each variable had one coefficient for all modes: $\beta_t, \beta_c, \beta_s$). The models were estimated using Python Biogeme (Bierlaire, 2003) version 2.6.

Initially, I summarized attitudes into latent variables (i.e., through a measurement model) and simultaneously estimated this model with the choice models using the integrated choice and latent variable modeling (hybrid choice) framework. However, such practice significantly increases the computational cost while reducing the statistical power (especially with a small dataset like this sample). Plus, the attitude variables were also not highly correlated to form a composite latent variable. The model was unable to converge or successfully estimated. Therefore I decided to enter the attitude variables directly into the models.

6.3.4 Scenario analysis

I performed a simulation analysis to test different scenarios in changing travel time and satisfaction of each travel mode. The scenarios include changes in travel time for car and transit by 25% each (e.g., by introducing road diet, reducing speed limits, adjusting signal timing to prioritize pedestrian crossing), and increase in the satisfaction levels of each mode by 2 points out of 11 points in total (e.g., by applying strategies to increase user satisfaction, such as more frequent and reliable transit service to boost transit satisfaction, or remove barriers to driving for car users, or adding facilities and safe crossing for active transportation users). The goal was to demonstrate how changes in travel conditions would affect the final mode share. I obtained the final mode shares for these scenarios and compared with the current share. The analysis was performed using Python Biogeme 2.6.

6.4 Results

6.4.1 Descriptive statistics

Descriptive statistics of the sample are described in Table 26. The total sample consists of 217 respondents with 44% living in the Washington, DC region. Female travelers account for 54% of the sample, while people of color account for 44%. The average age was 30 years old. Average travel times by car and transit were 15 and 39 minutes, respectively. For the equivalent travel distance, the average times if travelers in this sample walked or bicycled are 148 and 50 minutes, respectively. It is noted that most long-distance commutes were made by car or transit. For anyone whose commute distance was long enough (longer than 45 minutes bicycling or walking), bicycle and walk were excluded from their choice set.

Table 26. Descriptive statistics

Variable	Percent	Mean	SD	Min	Max
Age		30.34	9.61	18	65
Travel time by car (minutes)		15.29	13.73	0.73	86.50
Travel time by transit (minutes)		39.46	38.25	1.32	204.23
Travel time by walking (minutes)		148.05	211.53	1.32	1619.92
Travel time by bike (minutes)		50.21	71.77	0.85	553.22
Travel cost by car ($)		4.21	3.46	0.09	15.16
Travel cost by transit ($)		2.07	2.27	0 [a]	8
Satisfaction when traveling by car [b]		6.83	0.54	4.67	8.81
Satisfaction when traveling by walk or bike [b]		7.25	0.77	4.82	9.44
Satisfaction when traveling by transit [b]		7.11	0.78	4.11	9.80
Living in the DC region	43.78				
Income <$30,000	27.19				
Income $30,000 -60,000	22.12				
Income $60,000-90,000	14.75				
Income >$90,000	35.94				
Female	54.38				
Non White	44.7				

[a] *Virginia Tech students and faculty ride Blacksburg Transit for free.*

[b] *Satisfaction was averaged by person for all commute trips.*

6.4.2 Choice model results

Choice model results are shown in Table 27. Because of the small sample size, I chose $\alpha = 0.1$ for all significance tests, although coefficients that were significant at the $p<0.05$ level were also noted. ρ^2 increased as attitude and satisfaction variables were added into the models.

Model AIC decreased accordingly, indicating that added variables explain more variance. Car was used as the base category; the probabilities of choosing transit or bicycling and walking were interpreted relative to commuting by car. In all models, travel time (generic coefficients) was negative and significant, meaning that these elements reduced utility for the trip. The time coefficient became smaller (i.e., more negative) when attitude, travel affinity, and satisfaction were added into the model. However, cost was insignificant in the models. Having parking at the workplace was associated with a lower likelihood to walk, bike, or ride transit.

In Model 1 (without attitude and satisfaction), I found that all sociodemographic variables were insignificant. In Model 2, I entered seven attitudinal variables, including the desire to use travel time productively, environmental attitude, physical activity, and attitude toward each mode of transport. This model shows that older people were less likely to walk and bicycle for the commute. Compared to people with an annual income of less than $30,000, commuters with middle income ($60,000-90,000) were more likely to walk and bike. Female travelers were also more likely to use active transport.

Several attitudinal variables were significant in Model 2. Having more positive car attitude was linked to a lower probability of biking, walking, or riding transit. Positive attitude toward walking was associated with a lower probability to take transit, while positive attitude toward transit was associated with a higher probability to take transit. Commuters who desired more physical activity were more likely to ride transit, bicycle, or walk. Commuters who considered travel time as wasted time were less likely to use active transport for commuting. In other words, active travelers were less likely to view travel time as wasted. Those who viewed commute time as a useful transition between home and work were less likely to use transit.

Travel liking attitude (i.e., like the process of daily travel) and the desire to use travel time productively were not significant in this model.

When adding satisfaction into Model 3, I found that satisfaction was significant for mode choice. The positive coefficient implies that satisfaction increased the utility of the trip. Most variables show similar sign and significance level as in Model 2, except that the desire for physical activity was no longer significant for bicycling and walking. Travel liking became significant for transit.

A number of variables were insignificant in all models. Initially, I included other socio-demographic variables, such as employment/student status and race, but none of these was significant. Therefore, I removed these variables from the model to increase parsimony and power. I retained basic demographic variables in the model although they were insignificant (e.g., gender). Most people in my sample did not have small children, thus I removed this variable from the estimation as well.

Table 27. Logit models of mode choice

	Model 1				**Model 2**				**Model 3**			
	Coef.	**SE**	**Coef.**	**SE**	**Coef.**	**SE**	**Coef.**	**SE**	**Coef.**	**SE**	**Coef.**	**SE**
Cost	0.00	0.07			0.14	0.09			0.14	0.09		
Time	-0.04*	0.02			-0.05*	0.03			-0.05 **o**	0.03		
Satisfaction									1.28*	0.63		
	Public Transit		**Walk & Bike**		**Public Transit**		**Walk & Bike**		**Public Transit**		**Walk & Bike**	
Age	-0.01	0.03	-0.05	0.04	-0.05	0.03	-0.13*	0.05	-0.07 **o**	0.04	-0.16*	0.06
Income $30,000 - $60,000	0.05	0.63	0.08	0.60	-0.39	0.84	0.16	1.22	-0.78	0.89	-0.33	1.32
Income $60,000 - $90,000	0.17	1.00	0.87	0.91	1.60	1.81	2.88 **o**	1.71	2.27	2.11	3.53 **o**	2.02
Income $90,000 or more	-0.43	0.88	-0.75	1.15	-0.80	1.19	0.99	1.58	-1.11	1.08	0.39	1.55
Female	-0.12	0.50	-0.64	0.54	-0.36	0.56	-1.18*	0.62	-0.30	0.57	-1.26*	0.65
Non White	0.08	0.57	-0.30	0.54	0.46	0.66	0.74	0.69	0.28	0.66	0.58	0.63
Having parking at work	-2.57*	0.63	-2.37*	0.59	-3.65*	1.31	-2.82*	1.07	-3.46*	1.30	-2.87*	1.11
Living in the Washington, DC region	0.04	0.81	-1.28	0.83	1.43	0.99	-1.08	1.07	1.35	0.95	-0.84	1.08
Environmental attitude					-0.03	0.14	0.17	0.15	-0.08	0.17	0.16	0.16
Desire for physical activity					0.72*	0.31	0.67 **o**	0.38	0.62*	0.29	0.59	0.38
Travel liking					0.35	0.23	0.08	0.23	0.57*	0.26	0.26	0.26
Travel time is wasted time					-0.63	0.40	-0.75*	0.37	-0.52	0.36	-0.66 **o**	0.35
Commute as a useful transition					-0.69*	0.25	0.24	0.22	-0.73*	0.25	0.28	0.23

	Model 1		Model 2		Model 3							
	Coef.	**SE**	**Coef.**	**SE**	**Coef.**	**SE**	**Coef.**	**SE**	**Coef.**	**SE**	**Coef.**	**SE**
Attitude toward bicycling					-0.15	0.19	0.30	0.32	-0.10	0.20	0.30	0.34
Attitude toward driving					-0.88*	0.36	-0.85 *	0.36	-1.01*	0.42	-0.98*	0.44
Attitude toward transit					0.74*	0.28	0.03	0.22	0.78*	0.29	0.06	0.22
Attitude toward walking					-1.05*	0.40	-0.21	0.39	-0.88*	0.36	-0.10	0.36
Desire to use commute time productively					-0.23	0.22	-0.09	0.23	-0.28	0.22	-0.17	0.24
Constant	1.70	1.07	2.53*	1.17	10.30*	4.94	4.21	5.21	9.66 **o**	5.07	4.35	5.62
Sample size	217				217				217			
ρ^2	0.42				0.58				0.59			
ρ^2 bar	0.32				0.38				0.39			
AIC	279				253				250			
BIC	347				388				388			

*Note: Car was used as the base category. Significant code: **(o)**: 0.05≤p<0.1; (*) p <0.05. All standard errors are robust standard errors.*

6.4.3 Scenario analysis

I tested different scenarios of changes in travel time and satisfaction as shown in Table 28. The resulting mode shares are presented in Figure 8. At the current level, car mode share is 58%, which slightly reduces to 57% if travel time increases by 25% (Scenario S1). Similarly, transit mode share decreases from 33% at the base level to 30% when travel time increases by 25% (Scenario S2). This shows that travel time is not as a big concern for travelers when choosing a commute mode.

Table 28. Sensitivity analysis: scenarios development

Scenario	Description
S1	Car travel time increases by 25% of the current level.
S2	Transit travel time increases by 25% of the current level.
S3	Satisfaction level for car trips increases by 2 points.
S4	Satisfaction level of transit trips increases by 2 points.
S5	Satisfaction level of active travel increases by 2 points.
S6	Satisfaction level of transit and active travel increase by 1 point each.

Note: Satisfaction was measured in an 11-point scale from very dissatisfied (0) to very satisfied (11). All other factors in the models were held constant for each scenario.

I tested the sensitivity of satisfaction in mode choice by manipulating the satisfaction level of each travel mode (one by one; Figure 8). When satisfaction for car traveling increases 2 points in the original 11-point scale, the car mode share increases substantially from 58% to 72% at the cost of the transit share (from 33% to 22%) (Scenario S3). Conversely, when satisfaction for transit trips increases by the same amount, transit mode share increases from 33% to 52%, drawing users from both car and active travel (Scenario S4). In Scenario S5, when people are more satisfied with active travel, more transit riders switch to bicycling and walking than car users.

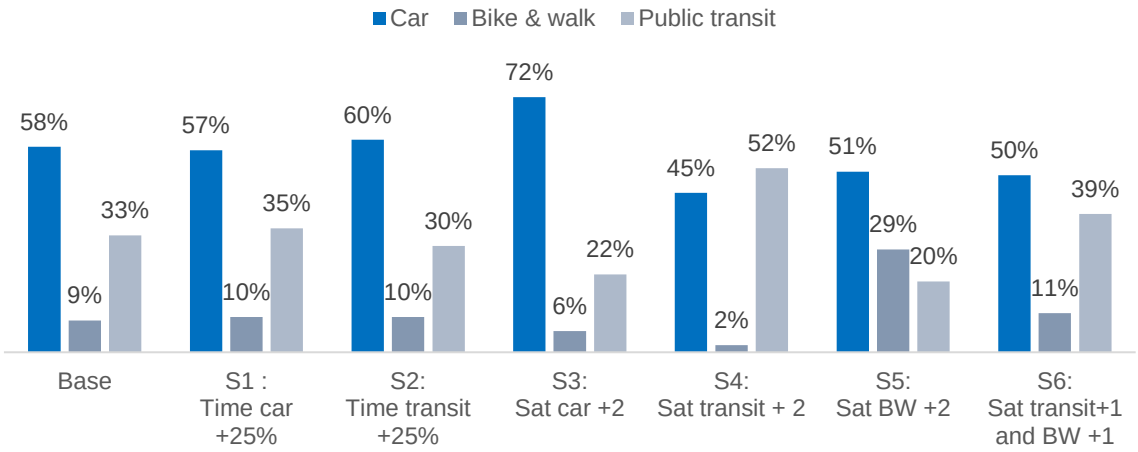


Figure 8. Effects of changes in travel time and satisfaction level on mode share

Another option is to increase the satisfaction level for transit riders and active travelers (Scenario S6; Figure 8). Transit mode share increases more than bicycle and walking shares, mostly drawing from car drivers. In all scenario, car drivers were less likely to switch mode among all commuters.

6.5 Discussion

6.5.1 Discussion of results

This study provides evidence for the association of satisfaction and mode choice. These results show that satisfaction and travel affinity were significantly associated with mode choice. I also controlled for mode and travel attitude to demonstrate how attitude and satisfaction improved the model fit.

The results are consistent with findings from previous studies of multimodal mode choice with regard to the role of satisfaction and travel affinity in choice behavior (Abou-Zeid & Ben-Akiva, 2014; Mann & Abraham, 2006; Singleton, 2017). Travelers who have higher satisfaction with travel of one mode would be more likely to choose that mode for their commute. Additionally, I found that transit commuters were less likely than car commuters to

consider commute time a useful transition between home and work, perhaps due to the fact that car drivers have full control over their surrounding environment (inside the vehicle); they are more likely to have "me time" to be quietly on their own and get ready for work. In contrast, transit riders usually have more stimuli in their surrounding environment (e.g., noise, smell, light), which makes travel time no longer rest time.

It was expected that travel time use (and ability to multitask during trips) would be an important factor in mode choice. However, travel usefulness was not significant in the models, although previous work has found that activities during trips increase travel utility (Malokin et al., 2019; Singleton, 2017). Besides using a different measurement, this study was also based on a small sample of commuters in Blacksburg, VA and Washington, DC who have short enough of a commute to skip working or use commute time productively during travel. In addition, many studies on public transit have found that people commonly engaged in non-work-related activities on the train or bus.

In general, other model results were consistent with previous studies. Having access to car parking at the workplace and having a positive attitude toward driving made people more likely to drive and less likely to use alternative modes. Younger people were more likely to walk and bike for commute.

I did not find any effect of cost and socio-demographic attributes on the mode choice decision. It is possible that my sample is too small and does not have enough variation to detect the effect. Additionally, it could be the case that transportation costs did not vary substantially across modes in each area. For example, driving in Blacksburg costs very little, and the transit fare is a sunk cost given that it is included in the student semester comprehensive fees. Likewise, in the DC area, although driving is much more expensive than in other areas,

riding transit is quite costly as well, while travel time by transit is greater than travel time by car.

6.5.2 Limitations and future directions

This study has several limitations pertaining to sampling and method. I have a small sample and low power to detect effects (with 41 parameters to estimate in Model 3). I collected data from a non-probability sample of Android users, which is subject to sampling bias. Further, I grouped 6 transportation options into 3 groups (i.e., driving along and carpool, bus and metro, bike and walking) to facilitate the estimation process. Despite the justification that I considered for this approach (see Section 6.3), it is ideal to separate into 5-6 modes due to the different nature of each mode.

Another limitation arises with the imputation of satisfaction for the unchosen modes, which may introduce errors and uncertainty into the mode choice model. Ideally, hypothetical satisfaction should be measured for unchosen modes, but this practice is not without difficulties. Singleton (2017) asked commuters how satisfied they would have been if they commuted by another mode rather than their chosen commute mode. This practice eliminates errors from imputation and eases the modeling process. However, this approach is cumbersome for respondents as they have to report this hypothetical satisfaction repeatedly for each trip. Additionally, measurement error may present as hypothetical satisfaction was measured after the fact (i.e., when the trip already happened), not before the person made the decision. Malokin et al. (2019) also employed an imputation approach for travel-based multitasking. Without hypothetical satisfaction, I believe using past satisfaction with certain modes for imputation is justifiable given that past satisfaction may reliably inform future choice.

Another limitation of this study is the potential endogeneity of satisfaction and mode choice, as noted in De Vos et al. (2013) and De Vos (2019). Future studies may consider modeling these bidirectional relationships with appropriate modeling methods [e.g., structural equation modeling (SEM) with two-stage least square (2SLS) estimation]. Additionally, other measurement methods may be appropriate, such as validated multi-item scales. In this study, I tested a single-item measurement of satisfaction and compared it with the TMS results to gain more confidence. Single items like this can be an advantage for imputation models, but at the same time, it cannot outperform a multi-item scale that have a holistic view of the affect and cognition aspects of travel.

Future research can build on this study to incorporate satisfaction into choice models. More studies are needed to consider the bidirectional flows between satisfaction and mode choice, which can be done using panel data or repeated measures. Researchers should also investigate the role of satisfaction in mode choice for non-work trips, such as recreation, socializing/visiting trips, or route choice and activity choice. Finally, I acknowledge that choice is habitual in nature; future research should look more closely at habit and its role on choice as well.

6.5.3 Contributions and implications

This study is unique in that I look at the role of satisfaction in the mode choice process using a revealed preference survey. Most previous studies on satisfaction only consider the association of mode use and satisfaction (i.e., how satisfaction differs among users of different modes) while only a few studies considered the opposite direction from satisfaction to mode choice. This is also one of the very rare studies that use trip-level satisfaction that varies across choice alternatives and the only one that measures satisfaction repeatedly over a week and

uses average satisfaction for modeling. Other mode choice studies do not go beyond treating psychological factors as individual-specific [except for a few studies, such as Singleton (2017)]. Such treatment implies that those factors have different effects across modes, and that policy makers need to target changes at the individual level. My approach of treating satisfaction as generic (same for all modes) implies that practitioners can target changes from external factors, such as the transportation systems and the built environment.

Additionally, this study proposes an approach for imputing satisfaction based on a machine learning algorithm applied to a large dataset of past satisfaction and travel patterns. If done well, this approach potentially replaces the method of asking respondents to report a hypothetical experience and reduce response burden. Nonetheless, in the future, these two methods should be employed and cross-validated.

This work has several implications for practice. I demonstrated how satisfaction can (and should) be incorporated into mode choice models. Not only was satisfaction significantly associated with mode choice, it also modified the time and cost coefficients (however, only the time variable was significant). This means that without including satisfaction and other psychological factors, the value of travel time saving, and potentially its cost, might be mis-estimated (the amount is yet unknown). Planners need to look beyond these two factors and incorporate satisfaction – and potentially well-being – into practice to induce behavioral change, especially in mode choice. This could be done by creating satisfactory environments for pedestrians and cyclists, such as more infrastructure for bicycle and walking, well-designed and safe intersections, better urban design, and denser urban areas, among other strategies.

Policies should target transit riders' satisfaction by providing reliable transit service, comfortable onboard experiences, and pleasant customer service. Some policies that are in favor of bicycling, walking, and transit may also affect car drivers (e.g., road diets to allow more room for bike and walking facilities and streetscapes, signal priority for transit vehicles at intersections, or dedicated transit lanes), however, nudging travelers toward sustainable transport is necessary to achieve sustainable goals (e.g., reduce emissions, improve equity and accessibility, improve health). Moreover, given that parking access at work increased one's likelihood to drive for commute, practitioners should also encourage employers to provide cash-out and incentivize non-auto commute, as well as managing parking price and access.

6.6 Chapter conclusions

This study focused on incorporating satisfaction and travel attitude into mode choice models. I found that satisfaction was positively associated with trip utility, and it modifies the role of travel time in the models. This is among very few studies that models mode choice through the use of satisfaction and travel attitude on revealed preference data.

This study contributes to the existing literature on travel satisfaction, travel liking attitude, and time use perception. Findings from this study add further evidence for the role of satisfaction on choosing sustainable modes of transport (e.g., walking, bicycling, and public transit); similarly, these findings may help develop strategies to increase satisfaction for sustainable modes, and in turn, promote more physical activity. The importance of satisfaction and attitude on mode choice also challenges the traditional roles of travel time (and potentially cost) in mode choice decisions.

7 Conclusions

7.1 Summary

This dissertation seeks to understand travel satisfaction, travel affinity, and other psychological factors in relation to travel demand, such as the desire for trip making, willingness to spend time traveling, and choice of travel mode. The study was based on the Mood State in Transport Environments survey of 247 Android users in the Blacksburg-Roanoke, VA, Washington, DC, and Minneapolis, MN metropolitan areas from fall 2016 to spring 2018. Respondents answered an entry survey, tracked their travel for 7 days, and answered a trip survey associated with each trip. The dataset provides opportunities to examine travel and activities with a very refined spatio-temporal resolution.

In Chapter 2, I reviewed the literature on the positive utility of travel, satisfaction with travel, travel-based multitasking, mode choice modeling, smartphone data collection, and other relevant literature. Chapter 3 described the overall research design and data collection effort, as well as providing a description of the sample characteristics. Chapters 4, 5, and 6 explored three research topics (1) desirability of trip making, (2) willingness to spend time traveling, and (3) the role of satisfaction in the mode choice decision. Then, I constructed three sets of models to explore the three research topics. Discussion of the results, as well as comparisons with previous studies and practice were presented. This chapter highlights the results and contributions of this dissertation in research and practice. It addresses the limitations, as well as the potential directions for future research.

7.2 Key findings

Three studies in this dissertation examined three measures of the positive utility of travel and their relationship with travel behavior. I quantified (1) the desirability of trip making, (2) the ideal travel time related to different travel characteristics, and (3) the effect of satisfaction on commute mode choice. The first study (Chapter 4) examines the patterns of travel affinity with various travel modes, trip purposes, and activities during the trip. Travel affinity was measured by asking the willingness to forgo a trip when there is an opportunity to do so. Although this measure has not been used widely in transportation research, I found it a valid and strong measure of the positive utility of travel. This study found that travelers were more willing to make trips when they traveled on foot or bicycle, talked with someone during the trip, and took shorter trips. Additionally, commute trips are less likely to be enjoyed as compared to other, non-commute trips.

The second study (Chapter 5) focused on (1) testing the validity of the "ideal travel time" measurement and (2) measuring factors associated with the willingness to spend time traveling. I found that although ideal travel time was a strong measure of the positive utility of travel, it was very weakly associated with the desirability of trip making and satisfaction with trips. Although few people wanted zero commute time (3%), the number of trips that had zero ideal travel time was much higher (16%), indicating that the desired travel amount may vary across different trip and environmental characteristics and purpose. Ideal travel time was longer for active travel trips, leisure trips, when conducting activities during trips (e.g., talking, using the phone, looking at the landscape), when traveling with companions and during weekend.

The third study (Chapter 6) investigated the role of travel satisfaction and attitude in mode choice behavior. This is one of very few studies that have considered the role of these psychological factors in multimodal mode choice based on revealed preference data. I found that satisfaction and attitude toward modes and travel played a significant role in the choice model; it also modified the role of travel time in the models. However, the perception of travel time usefulness was insignificant in the model. Scenario analyses based on the model results showed that it is optimal to invest in active transportation and public transit at the same time in order to shift car drivers to these sustainable modes.

7.3 Research implications

This dissertation has several implications for research in terms of measurement and modeling. First, it calls for better measurements of mood and satisfaction. Previous studies in this area of research usually rely on a single time point, which results in a less accurate measure of mood and satisfaction, whose nature is transient. A smartphone survey (e.g., as in this study) allows for a better measure of psychological factors. Standardized psychometric scales, such as the Travel Mood Scale (TMS) or Satisfaction with Travel Scale (STS) are reliable scales to be applied in smartphone surveys, in which brevity is essential.

My study is one of very few early attempts to incorporate satisfaction into mode choice models for commute trips. It suggests the need for continued research in mode choice models, as well as other travel demand models (e.g., departure time choice, activity choice, route choice). The question of whether and how to measure satisfaction with non-chosen modes and the accuracy of such measurement deserves more exploration in the future.

This study also highlights the difficulty of and potential solutions for conducting smartphone surveys. Common problems in survey research are recruiting participants and attrition. These problems are particularly serious in smartphone surveys due to privacy concerns, technical issues, and long tracking periods. I found that having accessible technical support helps overcome these issues, especially in-person and over the phone. Building trust is essential for smartphone surveys, as privacy concerns have been the primary issue in recent years. Further, framing the study in a way that is connected to participants' concerns about transportation (e.g., congestion relief, improving safety and health, reducing air pollution, improving transit service) is helpful. Researchers may consider partnering with public entities and/or community-based groups to conduct studies and gain trust from local residents.

7.4 Policy implications

The main outcomes of this dissertation are mode choice, [hypothetical] trip generation, and [hypothetical] time use models that incorporate various psychological factors to more realistically resemble actual travel behavior. These models contribute to travel demand modeling practice, as they modified the current knowledge in the activity-travel relationship. Better mode choice and trip generation models will generate more reliable predictions of future infrastructure use and investment.

Studies of travel affinity (positive utility of travel) have implications for demand modeling and management practice. As travelers are willing to spend time on traveling or make trips regardless of alternative options, practitioners should reevaluate the effectiveness of travel demand management strategies aimed at reducing travel time and trips, such as congestion pricing (e.g., tolls), online shopping, and telecommuting. As long distance and long duration trips may be desirable, travelers may be willing to accept or desire longer commute

times, and choose to live in suburban areas that contribute to urban sprawl. Latent demand for travel should also be considered, as people may be willing to make unnecessary trips even when no-trip options are available (e.g., telecommuting, virtual meetings). Trips can be longer as travel time is more enjoyable – simply by choosing farther destinations or taking longer routes.

This dissertation also highlights the importance of satisfaction in mode choice decision. Including satisfaction in the choice model changes the coefficient of travel time (and potentially cost), which modifies the value of travel time savings. This value of travel time savings is often incorporated into benefit-cost analyses of infrastructure investment. If travel time is incorrectly estimated, so is the benefit. This deserves further study in the future.

The results also suggest several policy tools that increase transport users' satisfaction and promote sustainable transport modes. Such policies should focus on providing satisfactory travel environments for pedestrians, bicyclists, and transit riders. These are also low cost interventions with high benefits, such as increasing subjective well-being and physical activity among urban residents. Furthermore, I found that socializing during trips can improve affinity for travel (and potentially increase satisfaction, as found in other studies). Public transit and carpooling are sustainable modes of transport that may enhance social connections and well-being of users.

Travel satisfaction and multitasking research also informs the adoption of commercial ridesharing service and autonomous vehicles (AVs) (Malokin et al., 2019; Mokhtarian, 2018b; Singleton, 2018a). AVs and commercial ridesharing may provide an unprecedented experience for its users, such as higher autonomy, privacy, and sense of control over one's environment – similar to car driving. At the same time, it has the potential to release users from driving

tasks, allowing multitasking and more productive use of travel time, as found in public transit. In the future, these two modes may converge (e.g., shared AVs) and become more affordable, which can compete with public transit service. Understanding how satisfaction affects mode choice will be essential to predict the adoption rate of AVs and to recommend policies to handle its favorable outcomes and unfavorable consequences on urban planning.

Furthermore, this study supports the previous findings of the negative impact of parking subsidy at work on non-automobile modes. A study at MIT by Rosenfield et al. (2019) shows that the cost for building and maintaining parking in Cambridge, MA exceeds the cost of subsidizing monthly transit passes for faculty and students.

7.5 Limitations

This dissertation suffers from limitations pertaining to sampling, measurement, data coverage, and methods.

First, this study relies on a non-probabilistic sample of Android users. A major difficulty in this study is recruiting and retaining users; those who remained in the study may have been self-selected. This situation adds more uncertainty for the generalizability of this study. The employment of a smartphone app is a barrier to recruit a general population, including those who are not as tech-savvy. However, the results may not substantially differ from this study, as approximately 77% of the US population uses smartphones (Pew Research Center & Inquiries, 2018). No studies have found a difference in socio-demographics of users who use Android and iPhone, the two phone types that account for the majority of the mobile phone market. Several non-refereed studies found no differences between these two user groups. Nonetheless, it is ideal for generalizability purpose to use a probability sample.

Second, although using an app provides significant advantages to the study, it comes with several trade-offs due to occasional failures of the app and phone. I found several minor glitches in the app during the study, but quickly notified users and helped them to retrieve the data; however, there is a small chance that this affected the data set. Further, the app reportedly crashed for some users, which made some users lose their data or extend their tracking period. Battery drain and cold start (i.e., the delay between activating GPS and when the first location point is recorded) are other common issues with phone GPS and GPS devices. This resulted in missing trips or trip segments.

GPS did not work well in certain conditions, for example, around skyscrapers (i.e., urban canyons), underground, or on running trains at high speeds. Train trips (mostly underground) were broken and thus were excluded from analyses in Chapters 4 and 5. In the future, I plan to reconstruct these trips and incorporate in future analyses using this dataset.

This dissertation was based on the premise that the psychological factors were measured instantaneously or shortly after each trip. This might not be the case for some of the surveys that I received where respondents answered the trips surveys when they received the notification (at 7 pm every day). Nonetheless, the measurement in this study (i.e., experience sampling method) is still more accurate than the traditional method (e.g., day reconstruction method).

This study also used imputed satisfaction for the non-chosen travel mode instead of measuring it directly. Satisfaction with non-chosen modes was measured in another study (Singleton, 2017), which overcame this difficulty of imputing, yet it is not without issues. This approach adds much burden on respondents. At the same time, it might not always be accurate as respondents did not experience these non-chosen modes themselves. Imputation is also

subject to other limitations, however it provides an efficient way to survey and account for satisfaction in the choice models.

My models did not control for many variables (e.g., habit, norms, perceived behavioral control), mostly due to (1) small person sample size (e.g., habit, norms, perceived behavioral control), (2) the absence of these variables in the entry survey (e.g., personality, residential self-selection). Previous studies showed that norms and perceived behavioral control are less influential as compared to attitude (Bamberg et al., 2003; Van Acker et al., 2010). While residential self-selection can be confounded when studying the effect of the built environment on the usage of certain transport modes (e.g., amount of walking), evidence for its effects on commuting mode choice is still rare. Moreover, the built environment variables were not included in my models, thus the confounding effect is absent.

7.6 Future research

These research implications and limitations inform several directions for future research. Incorporating other psychological factors (e.g., habit, norms, perceived behavioral control) and built environment variables would be helpful to illuminate travel choice. At the same time, this dataset is rich in both spatial and temporal dimensions and could be used for many additional analyses, such as route choice modeling, satisfaction with activity and life, mode choice for other trip purposes, the usefulness of commute time, as well as for modeling activity patterns based on the GPS data.

Several related questions are left unanswered and deserve more exploration in future projects, such as neighborhood satisfaction and its relationship with activity-travel patterns and overall subjective well-being. A longer tracking period is more desirable to study the activity patterns of different socio-demographic groups.

Finally, a new framework for decision making is desirable to account for satisfaction. The question of accommodating satisfaction in mode choice deserves more attention because (1) the current utility maximization framework may be only able to accommodate some predictable irrationality, (2) endogeneity of satisfaction and travel behavior, and (3) measurement issues when measuring satisfaction and travel experience of hypothetical (non-chosen) modes.

There has been a trade-off between having a long and comprehensive survey with response rate, attrition, and population coverage. Indeed, most long surveys have lower response rates and are very unlikely to be adopted in general practice. However, advances in statistical learning and modeling allows researchers to match detailed survey data to a large, generalizable dataset (Malokin, Mokhtarian, & Circella, 2017). Simulation results could also aid in testing the robustness of the results when changing model parameters. Crowdsourced data would be useful to generate a training data set to build predictive models for statistical matching and data fusion purposes. This work deserves more attention in the future.

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Appendix

PART 1: ENTRY QUESTIONNAIRE

(To be completed <u>once</u> on Qualtrics, embedded in the Daynamica app)

<u>I. Travel information</u>

1. Do you own a bike in working condition?

Yes

No

2. Do you have a monthly public transit pass?

Yes

No

3. Do you have access to a car on a regular basis?

Yes

No

4. Do you have a driver's license?

Yes

No

5. Do you currently have a parking permit or free parking at work or school?

Yes

No

6. What is your current on-way commute time, on average?

____ minutes

7. What is your ideal one-way commute time?

____ minutes

8. How many trips did you make using each mode of transportation <u>last week</u>?

By car (as driver) ____

By car (as passenger) _____

By bike: _____

By walking: _____

By transit: _____

9. What is your monthly cost for transportation, on average, in US dollars?

____

10. Please check all the events that have happened to you in the <u>last three months</u>.

Move to a different neighborhood
Start a new job or change workplace
Retire or cease working
Have a newborn
Acquire a driver's license
Purchase the first car
Purchase a bicycle
Start cohabiting (with family member(s) or partner)
Stop cohabiting (with family member(s) or partner)
Be affected by SafeTrack (for DC area participants)
None of the above.

11. What was your <u>primary</u> method of commute <u>three months ago</u>?

Driving
Carpooling
Walking
Bicycling
Public transit
Other

12. During a typical work week, do you work at home?

Yes
No

13. (If selected "Yes" in Question 11) How many days per week do you usually work at home?

1
2
3
4
5
6
7

14. Overall, what is your current health status?

Excellent
Very good
Good
Fair
Poor

15. Please read each of the following statements and indicate how much you agree or disagree with each statement.

(1 = strongly disagree, 4 = neither agree or disagree, 7 = strongly agree)

My neighborhood has good bike infrastructure.

My neighborhood has good sidewalks.

My neighborhood has good car parking.

I can bike safely to where I want to go.

I can bike conveniently to where I want to go.

I don't know how to get around by bike or how to use a bike.

My destinations are too far away to bike.

I can walk safely to where I want to go.

I can walk conveniently to where I want to go.

My destinations are too far away to walk.

I feel comfortable getting on the bus or train.

Bus stops or train stations are accessible from my home.

The bus or train schedule is convenient for me.

The bus or train takes me to where I want to go.

I don't know enough about the transit system to use it.

Driving and parking a personal vehicle is convenient for me.

Commuting by car is costly for me.

It is/would be difficult to get everything done without a personal vehicle.

Environmental concerns affect the choices I make about my daily travel.

I want more physical activity.

I want to use my commute time productively.

My family and friends would support me if I drive less and use alternative travel modes more often.

Many people in my social network walk, bike, or ride transit frequently.

Investing in bike and transit infrastructure is necessary no matter if I use it or not.

I enjoy the process of traveling.

The only good thing about traveling is arriving at your destination.

My commute trip is a useful transition between home and work.

I want to participate more in out-of-home activities.

My travel time is a wasteful.

I like driving.

I like walking.

I like bicycling.

I like riding transit.

When I drive to my frequent destinations, I do it automatically (i.e., without thinking about my decision).

When I walk to my frequent destinations, I do it automatically (i.e., without thinking about my decision).

When I bike to my frequent destinations, I do it automatically (i.e., without thinking about my decision).

When I take transit to my frequent destinations, I do it automatically (i.e., without thinking about my decision).

The conditions of my life are excellent.

I am satisfied with my life.

I lead a purposeful and meaningful life.

My social relationships are supportive and rewarding.

I actively contribute to the happiness and well-being of others.

I am engaged and interested in my daily activities.

I am optimistic about my future.

I am in charge of the situation in which I live.

If you are feeling anxious, depressed, and/or suicidal, you may wish to contact your local mental health clinic or hotline for assistance. The Access HelpLine at 1(888)7WE-HELP or 1-888-793-4357 is provided by the Department of Behavioral Health in DC. This 24-hour, seven-day-a-week telephone line is staffed by behavioral health professionals who can refer a caller to immediate help or ongoing care.

16. Imagine you wanted to visit a bookstore 1.5 miles away from home, and all travel options were available. Which option comes to your mind first?

Driving

Biking

Walking

Riding transit

17. Do you own a dog?

Yes

No

II. Demographics

1. **What is your age?**

____

2. What is your gender?

Male

Female

Other

3. Do you live alone or with other people?

Live alone

Live with roommate(s), housemate(s), or in a dorm

Live with family, a partner, or others with whom I share some income

Other

4. Only appears to those who live with family, a partner, or others with whom they share some income: **Please indicate how many other members of your household are in each age category.**

Age under 6: _____

Age 6-15: _____

Age 16-17: _____

Age 18-64: _____

Age 65 or older: _____

5. [Only appears to those who live with family, a partner, or others with whom they share some income.] **Please check the category that contains your approximate annual *household* income before taxes.**

Less than $10,000

$10,000 -$19,999

$20,000 -$29,999

$30,000 -$39,999

$40,000 -$49,999

$50,000 -$59,999

$60,000 -$79,999

$80,000 -$99,999

$100,000 -$119,999

$120,000 or more

6. [Only appears to those who live alone or with only roommate(s) or housemate(s).] **Please check the category that contains *your own* approximate annual income before taxes, or allowance.**

Less than $10,000
$10,000 -$19,999
$20,000 -$29,999
$30,000 -$39,999
$40,000 -$49,999
$50,000 -$59,999
$60,000 -$79,999
$80,000 -$99,999
$100,000 -$119,999
$120,000 or more

7. Do you have any physical disability?

Yes
No

8. Which race or ethnicity best describes you?

White
Hispanic or Latino
Black or African American
Native American or American Indian
Asian/Pacific Islander
Two or more races

9. What is the highest level of education you have completed?

Less than high school graduate
High school graduate, include GED
Some college or associate's degree (Vocational)
Bachelor's degree
Master's degree
Doctoral or professional degree (PhD, MD, JD)

10. What is your employment status?

Full-time student
Full-time employee

Part-time employee

Work at home (including homemaker)

Unemployed

Retired

Other

12. How long have you been living in the United States? Enter "0" if you have been in the US for less than a year.

_____ years

13. Would you like to be contacted for future travel studies?

Yes

No

PART 2: TRIP QUESTIONAIRRE

(To be completed for each trip in Daynamica app)

1. What is the purpose of this trip?

Home

Work

Education

Shopping

Eating Out

Personal Business

Leisure & Recreation

Socialization

Other

2. Who did you travel with?

Significant other(s) or family member(s)

Friend(s) or colleague(s)

Acquaintance(s)

Stranger(s)

Dog(s)

3. If it were possible, would you like to arrive at the destination immediately without making the trip?

Yes

No

Neutral

4. For each pair of words please report how you felt after the trip by using the slider. (-5 = Extremely [negative word], 0 = Neutral, 5 = Extremely [positive word])

Stressed	- - - - - - - - - -	Relaxed
Sad	- - - - - - - - - -	Happy
Bored	- - - - - - - - - -	Interested
Irritated	- - - - - - - - - -	Pleased
Unsociable	- - - - - - - - - -	Sociable
Unsafe	- - - - - - - - - -	Safe
Pessimistic	- - - - - - - - - -	Optimistic
Depressed	- - - - - - - - - -	Cheerful
Pressured	- - - - - - - - - -	Calm
Much worse than expected	----------	Much better than expected

5. Overall, were you satisfied with <u>the trip</u> itself?

(-5 = Extremely [negative word], 0 = Neutral, 5 = Extremely [positive word])

Very dissatisfied - - - - - - - - - - Very satisfied

6. Overall, were you satisfied with <u>the activity</u> that you had at the destination?

(-5 = Extremely [negative word], 0 = Neutral, 5 = Extremely [positive word])

Very dissatisfied - - - - - - - - - - Very satisfied

7. What activity did you perform while traveling today? *Check all that apply.*

Talking with people
Making a phone call or texting
Working
Reading
Looking at the landscape
Listening to music/radio
No activity
Other

8. What would be the ideal travel time for this trip, in minute?

___ minutes