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Long-Distance Recreational Travel Behavior and Implications of Autonomous Vehicles

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LONG-DISTANCE RECREATIONAL TRAVEL BEHAVIOR AND IMPLICATIONS

OF

AUTONOMOUS VEHICLES

by

Sailesh Acharya

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ABSTRACT

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by

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Utah State University, 2023

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The study of of long-distance travel has received minimal attention in the travel behavior literature, despite its significant contribution to overall vehicle miles traveled and vehicular emissions. Therefore, this dissertation investigates current travel behavior and anticipated changes that could be brought about by autonomous vehicles (AVs) in the case of long-distance recreational travel. This dissertation has four research objectives: (i) developing a reliable scale to measure long-distance recreational travel satisfaction and identifying the commonality and differences between long-distance and short-distance travel satisfaction, (ii) interconnecting travel behavior and tourism literature by establishing a link between travel satisfaction and tourism satisfaction, (iii) anticipating the acceptance and use of AVs for long-distance recreational travel and understanding the factors affecting such behavior, and (iv) quantifying the impact of vehicle automation, onboard environment, and in-vehicle time use on the choice of AVs and the value of travel time (VOTT) associated. The primary data collection is done through a survey of 696 visitors to the national parks in the US, and several analyses are conducted to address the four research objectives.

The first contribution of this dissertation is the modification of the satisfaction with travel scale in the context of long-distance recreational travel, offering the conceptual strength and the generalizability of the scale. In addition, several differences in long-distance travel behaviors are also revealed compared to commute behaviors, mainly related to the impacts of age, income, and travel duration on travel satisfaction. Second, by establishing the relationships between travel satisfaction and tourism attributes, this dissertation strongly suggests revising the theories adopted in understanding tourists' behaviors by incorporating the travel satisfaction component. This result also offers a managerial implication that the tourism destination management effort also needs to monitor on the tourist experiences on the way between home and destination to improve tourist attractions. Third, the structural model results indicate that the frequency and length of long-distance recreational trips will likely be higher in the AV era. This brings the attention of tourism destination managers not only to manage the tourists' demand at destinations but also to manage the traffic on the roads leading to the tourism destinations. The potential increase in travel demand is linked to the increased potential of in-vehicle activities in AVs. Lastly, the VOTT of human-driven vehicles, autonomous vehicles, and autonomous vehicles with work and leisure interiors are estimated to be $34.70, $31.00, and $30.30 per hour, respectively. Based on the analysis results, it is concluded that vehicle automation will likely benefit individuals by enabling more productive use of travel time, but it could exacerbate the problem of increasing car sizes leading to higher energy consumption and space requirements, necessitating consideration of these negative aspects for the sustainability of the transportation system. Finally, this dissertation identifies the consideration of energy consumption and emissions, the effects of vehicle electrification along with automation, and changes that could be brought by teleworking in long-distance travel behavior and patterns as future research avenues.

(257 pages)

PUBLIC ABSTRACT

Long-distance Recreational Travel Behavior and Implications of Autonomous Vehicles

Sailesh Acharya

Have you ever wondered how people travel long distances and how it could be affected by the emergence of autonomous vehicles (AVs)? This dissertation aims to answer those questions by studying the current behavior of long-distance recreational travelers and their preference in the age of AVs. This dissertation has four main goals. First, it seeks to develop a reliable way to measure people's satisfaction with long-distance recreational trips and understand the similarities and differences between long- and short-distance travel satisfaction. Second, it looks at the connection between how people travel, how satisfied they are with their travel experiences, and how this relates to their overall satisfaction with their destination. Third, it explores how people feel about using AVs for long-distance travel and tries to understand what influences their decisions. Lastly, it looks at the impact of vehicle automation, the interior of AVs, and how people use their time during travel on their choices and preferences. The necessary data is gathered through a survey of 696 people who visited national parks in the US.

The survey responses are analyzed to understand the research objectives, and some interesting insights are obtained. First, a survey instrument (i.e., a list of questions) is developed to accurately measure long-distance travelers' satisfaction. The analysis discovers that the factors that affect satisfaction with long-distance travel differ from those that affect short-distance travel. Second, a strong link is established between people's satisfaction with their travel experiences (on the way) and their overall tourism

experience (at destination). Third, the study suggests people might travel more frequently and for longer distances with the introduction of AVs. This result means that we should not only focus on managing tourism destinations but also consider the impact on traffic and infrastructure leading to these destinations. Finally, the study finds that people are interested in using their travel time more productively in AVs, but we should be mindful of the negative consequences, such as increased energy consumption and space requirements. In conclusion, this dissertation sheds light on long-distance travel behavior and the potential changes that could come with using AVs. It emphasizes the importance of enjoying the journey, the impact on tourism, and the need for sustainable transportation. So, next time you plan a road trip, remember there’s more to consider than just getting to your destination!

Dedicated to my parents
Sabitra Ojha and Devi Prasad Acharya

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Chapter 1

Introduction

1.1 Background

Travel behavior studies mostly revolve around understanding the underlying psychological processes—such as motivations, attitudes, perceptions, beliefs, and preferences—influencing people's travel decision-making, choices, and experiences. This knowledge is crucial for policymakers and practitioners to design interventions and strategies promoting sustainable and desirable travel behaviors. Additionally, studying travel behavior enhances overall travel experiences and individuals' well-being, as the satisfaction resulting from travel is strongly tied to life satisfaction and overall well-being (De Vos et al., 2013). By delving into the psychological aspects of travel, such as motivations, satisfaction, and experiences, researchers can provide valuable insights into city and regional transportation planning, enabling the design of a transportation system that caters to travelers' emotional and psychological needs. It also helps facilitate developing interventions promoting well-being and amplifying the positive impacts of travel on individuals' mental and emotional health.

The study of long-distance travel—where travel distances and durations typically exceed daily commuting ranges, sometimes requiring more planning and time commitments, including overnight stays—has received less attention in the travel behavior literature, possibly because of its relatively smaller share of an individual's trip-making (for example, 2.5% of trips in the US were >50 miles one-way in 2017; McGuckin, 2018). However, it is crucial to transportation planning and policymaking because long-distance trips contribute a significant portion of overall vehicle miles traveled (43.3% of total person-mile travel in the US was contributed by trips >50 miles in 2017; McGuckin, 2018) and thus to total vehicular emissions. Understanding the motivations, preferences, and decision-making processes associated with long-distance travel helps design transportation systems, infrastructure, and services effectively to serve the needs of long-distance travelers. Additionally, it is possible to gain insights into the socio-economic implications of long-distance travel, including its impact on industries like recreation, tourism, and hospitality that mainly rely on long-distance travel. Analyzing the patterns and determinants of long-distance travel also supports developing strategies and policies that foster the sustainability of the transportation system. Moreover, studying long-distance travel behavior contributes to a broader understanding of mobility patterns and overall well-being.

In recent years, the emergence of autonomous vehicles (AVs) has sparked the potential for a significant paradigm shift in travel behavior. With the advancement of self-driving technology, these vehicles can revolutionize how people perceive and engage in travel. The promised convenience, efficiency, safety, and equity associated with AVs (Hwang and Kim, 2023; Mueller et al., 2020; Vahidi and Sciarretta, 2018) have the power to reimagine transportation patterns and choices fundamentally. Travel times could become more productive, allowing passengers to engage in work or leisure activities during their journeys. Thus, this technology not only could change travel decisions, choices, and preferences but could also revolutionize the daily activity patterns of people (Pudane et al., 2019, 2021). Furthermore, adopting AVs could have wide-ranging implications for sustainability, including the potential for reduced emissions through optimized traffic flow and energy-efficient driving (Narayanan et al., 2020; Vahidi and Sciarretta, 2018). However, despite their transformative potential, careful attention must be given to addressing infrastructure, regulations, public acceptance, and ethical and legal challenges (Fagnant & Kockelman, 2015). The impact of AVs on long-distance travel is particularly noteworthy. Extended periods on the road often accompany long-distance travel, and AVs possess the potential to revolutionize this experience. The introduction of autonomous driving systems could significantly enhance the comfort and convenience of long-distance travel by allowing passengers to relax or engage in various work and leisure activities without needing constant driver attention.

1.2 Gaps and research questions

The above background highlighted the importance of understanding long-distance travel behavior and anticipating future changes that could be brought about by vehicle automation. In light of this, this dissertation aims to address some critical theoretical and empirical gaps in the literature, especially in the context of long-distance recreational travel. The following points present the research questions addressed in this dissertation and discuss the gap associated with each question in the literature. (Note the detailed background behind each question is presented in Chapter 2 through Chapter 5.)

1. How is satisfaction with long-distance travel different than with short-distance travel?

Most of the travel behavior literature revolves around understanding commute and short-distance travel behavior potentially because of the higher share of short-distance travel, leaving the long-distance travel behavior unexplored. This research question aims to investigate if and how long-distance travel satisfaction differs from short-distance travel satisfaction. More specifically, there is a need to understand the similarities and differences between the experiences of short- and long-distance travelers, mainly in terms of socio-demographic, attitudinal, and trip-related characteristics, to account for long-distance travel behavior in transportation planning. Developing a reliable scale to measure long-distance travel satisfaction is needed because the commonly used scale for commute or short-distance travel called the Satisfaction with Travel Scale (STS) (developed by Ettema et al., 2011) has been validated in different short-distance travel settings (e.g., De Vos et al., 2015; Singleton, 2019; Smith, 2017; Ye & Titheride, 2017). However, its validation and modification in the long-distance travel setting is still missing. Having a reliable scale to measure long-distance travel satisfaction allows the exploration of long-distance travel behavior, including the differences in commute and long-distance travel behavior. This dissertation addresses this question in the case of long-distance recreational travel.

2. What is the missing link between travel behavior and tourism satisfaction?

This question aims to join the link between travel behavior and tourism literature. Measuring destination satisfaction and revisit intention, and investigating their determinants are the most commonly studied aspects in tourism literature. Tourism studies have considered the role of the transportation services around the destination and associated experiences on these tourism attributes (e.g., Benur & Bramwell, 2015; Loi et al., 2017; Pagliara et al., 2015; Thompson & Schofield, 2007). However, the role of transportation and travel experience (while traveling from home to destination and destination to home) on destination satisfaction and revisit intention has never been investigated. On the other hand, travel behavior literature acknowledges the importance of travel satisfaction in improving life satisfaction and well-being (De Vos, 2019). Still, the literature lacks an investigation of the role of travel satisfaction on tourism, which is an integral part of overall well-being (Smith & Diekmann, 2017). Based on these two gaps in tourism and travel behavior literature, this question evaluates if travel satisfaction has a role in destination satisfaction and revisit intention and, if yes, how they are related. The answer to this question would help transportation planners and destination managers to account for the transportation needs of tourists to improve tourist attractions. This evaluation is possible with the development of the scale to measure long-distance travel satisfaction addressed through the first research question of this dissertation.

3. What changes in long-distance travel behavior can be expected in the autonomous vehicle era?

Autonomous vehicles (AV) are believed to change how people travel once they become widespread in the market. However, similar to studying general long-distance travel behavior, investigating the potential changes in long-distance travel behavior that AVs could bring remains limited in the literature. This question aims to contribute to this gap by investigating the acceptance and demand of AVs for long-distance recreational travel. Since vehicle automation potentially allows travelers to free up their driving time and use it for in-vehicle activities (Pudane et al., 2019) and the value associated with such in-vehicle activities has higher importance on a longer travel duration than on a shorter one (Rhee et al., 2013), the behavioral response of travelers to the acceptance and the use of AVs for long-distance travel could be different than for short-distance (see Dannemiller et al., 2021; Lee et al., 2021 for example). The answer to this question would aid transportation planners and recreational destination managers in preparing well ahead to manage the long-distance recreational demand induced by vehicle automation.

4. What are the roles of vehicle automation, onboard environment, and in-vehicle time use on travel choices and behaviors?

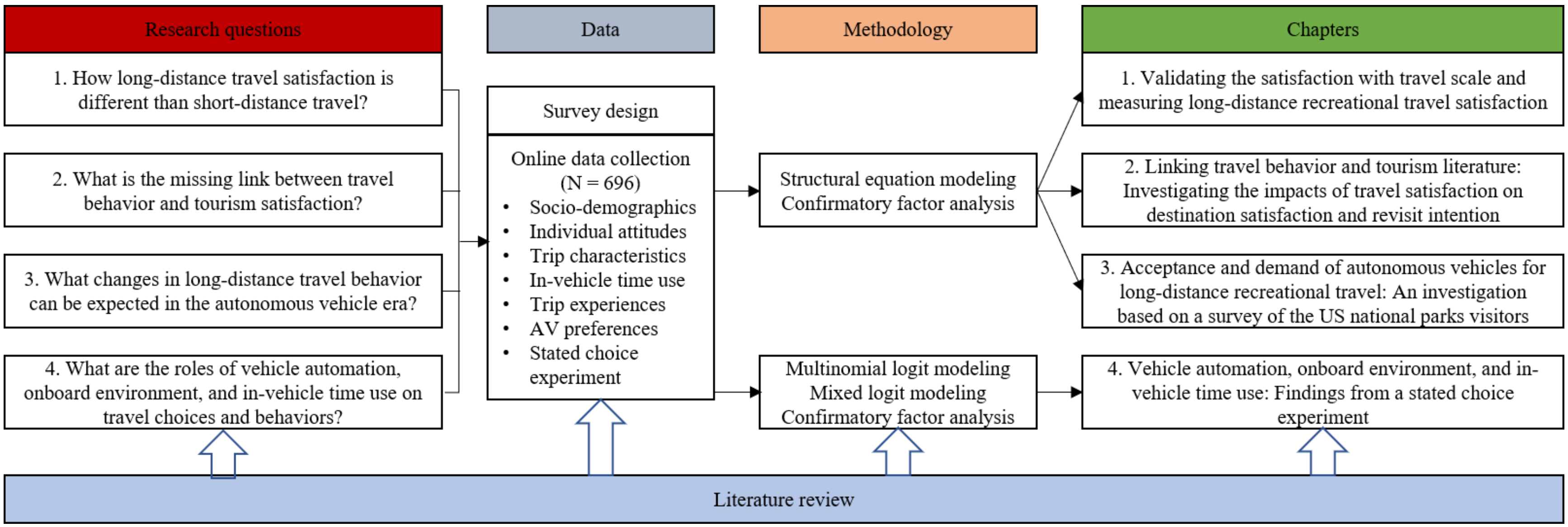
To further investigate the travel behavior changes expected in the autonomous vehicle (AV) era, this question aims to quantify the role of vehicle automation, onboard environment, and in-vehicle time use on travel mode choices and the monetary value of travel time. Having a general expectation of the AVs' self-driving ability to free up travel time for in-vehicle activities and thus on individuals' daily activity patterns (Pudane et al., 2019), a deeper investigation is needed to answer whether changing the current vehicles to self-driving is sufficient or sophisticated larger vehicle interiors are required along with automation for such changes in activity-travel patterns. The answer to this question would help transportation planners to account for the monetary values of automation, onboard interior environment, and in-vehicle activities in transportation planning in the AV era. This question would also help ascertain the future of AVs—if the future AVs would be larger sized to offer a favorable onboard for in-vehicle activities, concerning the problem of emissions and larger road/parking spaces.

1.3 Study Approach

The four research questions of this dissertation are addressed by analyzing the responses collected from a survey of long-distance recreational travelers. **Figure 1.1** presents the dissertation map that shows the flow of the research questions, procedures adopted to answer each question, and the associated outcomes.

Figure 1.1

Dissertation map.



The study approach continuously involves reviewing the literature. The review of literature guides identifying the background information and previous research findings related to each of the questions. It also aids in identifying the data and potential analytical methodology that could be adapted to answer the questions. The extensive literature review concludes the need for primary data collection, given the ubiquity of the research questions. Thus, an online questionnaire survey is designed to collect data on long-distance recreational travel behavior and preferences for autonomous vehicles (AVs). The survey features two parts, including revealed preference and stated preference questions. The revealed part dedicates to ascertaining the current long-distance recreational travel behavior, whereas the stated part assesses travelers' preferences towards different aspects of AVs for future travel. The survey uniquely focuses on understanding how travelers spend travel time in-vehicle and how it will change in the AV era. A stated choice experiment with different vehicle controls and interiors is also featured in the survey. The survey is distributed online to visitors to the national parks in the US.

The data collected is used to address the four research questions of the dissertation. The structural equation modeling framework is implemented to answer the first three research questions, whereas the mixed (and multinomial) logit models are estimated to answer the fourth research question. Several confirmatory factor analyses are also conducted in the several stages of the investigations. Finally, the analysis findings of each research question result in this dissertation's four main chapters (chapters 2-5).

1.4 Overview

This dissertation is structured into six chapters. The general introduction of the dissertation, which includes the need to study long-distance travel behavior, gaps in the literature, and research questions addressed through this dissertation, has been presented in Chapter 1. The remaining chapters are summarized in the following paragraphs.

Chapter 2 deals with validating or modifying the scale to measure travel satisfaction for long-distance recreational travel and using the scale to understand the socio-demographic, attitudinal, and trip-related determinants of travel satisfaction. First, the satisfaction with travel scale, the most popular scale to measure affective and cognitive dimensions of travel satisfaction, is validated after some modifications in the case of long-distance recreational travel. The potential future uses of the validated scale are highlighted. Next, the determinants of different travel satisfaction dimensions are investigated using the validated scale. The findings related to the travel satisfaction determinants are reported. The discussion is made by comparing determinants of long-distance recreational travel satisfaction observed from this study with the determinants of commute travel observed in past studies.

Chapter 3 utilizes the travel satisfaction scale validated in Chapter 2 to understand the relationships between travel satisfaction, destination satisfaction, and revisit intention. Recognizing the well-established relationship between destination satisfaction and revisit intention in tourism literature, a conceptual research model hypothesizes the role of travel satisfaction on destination satisfaction and revisit intention. The proposed model is analyzed using the structural equation modeling framework, and the direct and indirect impacts are estimated. By approving the hypotheses made, the potential implications are discussed, including the need to consider travel attributes (e.g., the quality of the highways, modal alternatives, etc.) by tourism destination managers to maintain and improve the attractions of tourist destinations.

Chapter 4 focuses on understanding the potential impacts of autonomous vehicles (AVs) on long-distance travel behavior. Specifically, the travelers' acceptance and use of AVs for long-distance recreational travel are analyzed using the structural equation modeling approach from the stated preference responses. The socio-demographic, attitudinal, and trip-related determinants of the acceptance and use of AVs are estimated. In addition, the impact of travel-based activities in a self-driving environment on AVs' acceptance and use intention is investigated. The potential implications of the study findings are discussed. The discussion highlights the need to consider the possible increase in the long-distance recreational travel demand from vehicle automation and the number of visitors to recreational destinations.

Chapter 5 features a stated choice experiment among three travel modes: human-driven vehicle, autonomous vehicle, and autonomous vehicle with work and leisure interior, to further understand the travel behavior implications that could be brought by vehicle automation. The role of in-vehicle activities and the need for a favorable onboard environment in the AV era are investigated using the mixed logit modeling approach. In addition, the monetary contributions of automation, onboard environment, and in-vehicle activities on the value of travel time are estimated. The discussion cautions against the role of automation in the problem of increasing vehicle size over decades in need of the larger vehicle interior for work and leisure activities.

Finally, Chapter 6 concludes the dissertation by summarizing the preceding chapters' findings, discussing the study findings' implications, stating the study's limitations, and providing recommendations for future research.

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Chapter 2

Validating the satisfaction with travel scale and measuring long-distance recreational travel satisfaction

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Abstract

The study of long-distance recreational travel is limited, despite its importance in both travel behavior and tourism literature. To aid the literature, this study validates the existing satisfaction with travel scale (STS)—which has been mostly used and validated for commute and daily travel—and investigates the factors affecting travel satisfaction. The data was collected from a questionnaire survey of visitors to US national parks conducted in the Summer of 2022, and a structural equation modeling framework was used for analyses. Confirmatory factor analysis suggested a three-factor structure with two affect-related factors—positive deactivation and positive activation—and a third factor (cognitive evaluation) related to valence and cognitive assessment of travel experience. The proposed measurement scale for long-distance recreational travel satisfaction could be used by tourism studies to investigate the interrelationships between travel satisfaction and tourism satisfaction, which could offer ways to increase the sustainability of tourism destinations. Structural equation model results show that socio-demographics, general travel attributes, trip-specific characteristics, travel-based activities, travel time perception, and attitudes are directly related to travel satisfaction. In addition to these direct effects, socio-demographic and general travel attributes are related to travel satisfaction indirectly through attitudinal characteristics (driving enjoyment and polychronicity). This investigation revealed a few differences in commute and long-distance travel behaviors: mostly the impacts of age, income, and travel duration on travel satisfaction. Based on the study results, it is also speculated that future autonomous vehicles would be a favorable choice for long-distance recreational travelers only if the option of manual driving is possible in those vehicles.

Keywords: travel satisfaction, long-distance recreational travel, travel-based activities, structural equation modeling

2.1 Introduction

The study of ways to improve quality of life and well-being is of keen interest to researchers and policymakers across various disciplines, including transportation, health, sociology, and psychology (Zhang, 2017). Overall life satisfaction and well-being are considered to have bidirectional relationships with satisfaction in each life domain (e.g., travel, work, health, marriage, etc.) (Diener, 2009; Schwanen & Wang, 2014; Zarabi et al., 2019). Looking at the travel domain, the experiences resulting from daily commutes and transportation in general influence other domains of life satisfaction and overall well-being. At the same time, satisfaction in other life domains also impacts one's evaluation of travel satisfaction (De Vos, 2019). With this pivotal role of travel satisfaction in different domains of life satisfaction and overall well-being, research on travel satisfaction and the factors influencing it is important. Realizing that, several existing travel behavior studies have focused on: developing a travel satisfaction measurement scale; measuring levels of travel satisfaction; assessing relationships between travel satisfaction and domain-specific/overall life well-being; and investigating associations of socio-demographic, trip-related, built-environment, and attitudinal factors with travel satisfaction. However, most of these studies are based on commuting or daily travel behavior.

Unlike past research, the present study investigates long-distance recreational travel behavior and satisfaction. This is important for several reasons. First, long-distance recreational travel has received less attention in the travel behavior literature, possibly because of its relatively smaller share of an individual's trip-making—2.5% of trips in the US were >50 miles one-way in 2017 (McGuckin, 2018)—and its role in shaping travel patterns. However, long-distance recreational trips contribute a large share of person-miles traveled: 43.3% of total person-miles traveled in the US came from trips >50 miles in 2017 (McGuckin, 2018). In addition, individuals' travel behaviors do not solely depend on their usual activities (e.g., work and commute), but also on their occasional activities. In fact, an individual's decision to purchase a vehicle not only depends upon the features needed for his/her frequent daily needs but also the features needed for occasional needs (e.g., additional seating, range, cargo, all-wheel drive) (Sprei & Ginnebaugh, 2018). Thus, ignoring long-distance recreational travel (an occasional event for most individuals) in the study of overall travel behavior could lead to biased results. Also, understanding the similarities and differences between long-distance recreational and commute/daily travel behavior could broaden the understanding of people's travel patterns and decisions.

Second, tourism destination managers focus their attention on repeat visitors (who are believed to be more important for sustainability and growth than first-time visitors) by increasing the attraction and loyalty of tourists (Meleddu et al., 2015; Van Dyk et al., 2019). However, existing tourism studies are missing an important aspect in their investigations: the emotions and experiences of tourists on their way to/from destinations. Tourists typically spend a significant portion of their overall journey time traveling to/from the destination, thus the emotions and experiences during this time could presumably impact one's evaluation of destination satisfaction. Considering this aspect in tourism studies could broaden the understanding of tourism satisfaction. Proposing a reliable measurement scale for tourism travel satisfaction could aid researchers in looking at the relationships between tourists' travel and destination satisfaction and suggest to destination managers ways to improve satisfaction and loyalty.

Third, the impact of travel satisfaction on life well-being is widely studied in the literature, and findings agree that travel has a relatively less positive (or even negative) impact on well-being (Morris et al., 2020). This conclusion is drawn mostly from reseach on commute travel satisfaction. However, recreational travel is considered to offer more positive emotions and experiences compared to other purposes (commuting, shopping, daily travel, etc.) (Zhu & Fan, 2018). Also, since most long-distance recreational travel leads to tourism destinations, and tourism activities are linked to higher life satisfaction (Uysal et al., 2016), the impact of recreational travel on well-being could be different from commute travel. Thus, including long-distance recreational trips in travel behavior studies could help ascertain a more accurate contribution of overall travel satisfaction on life well-being.

Fourth, significant changes in travel behavior and travel demand, including increases in the number and distance of travel, are anticipated when autonomous vehicles (AVs) become widespread. This is expected because of the ability to do a wide range of in-vehicle activities (including working and studying) while driving in an AV (Dannemiller et al., 2021; Zmud et al., 2016). Since most future AV trips are considered to be longer than current trips, looking at current long-distance travel behavior could bring insights into how future AV travel behavior might look. More specifically, research on the impacts of activities conducted in-vehicle, travel time perception, and the driving efforts on the satisfaction of current long-distance travel could help anticipate travel behavior and demand in the AV era more accurately.

Motivated by the discussion above, this study first presents a measurement scale for long-distance recreational travel satisfaction by modifying and validating an existing travel satisfaction scale called the satisfaction with travel scale (STS), which has been validated mostly on commute/daily travel. Second, utilizing the validated/modified STS, the associations of long-distance recreational travel satisfaction with socio-demographics, general travel attributes, trip-specific characteristics, travel-based activities, travel time perception, and attitudinal characteristics are investigated. The data for this study is collected from a questionnaire survey of visitors to US national parks, and a structural equation modeling (SEM) framework is used for analyses. The following sections of the paper: summarize the literature and note the study objectives, outline the data collection procedure adopted and the descriptive statistics, describe the methodology adopted, present the analysis results, and discuss the study's findings, implications, and limitations.

2.2 Literature review and study objectives

2.2.1 Measuring travel satisfaction

Two ways of measuring travel satisfaction have been used extensively in the literature. The first method asks travelers to rate a single statement about travel satisfaction (e.g., Mao et al., 2016; Mouratidis et al., 2019; Wang & Loo, 2019). The second way is to ask travelers to rate multiple items related to the travel experience (e.g., Chen et al., 2022; De Vos, 2015; Ettema et al., 2011, 2012, 2017; Shukhov et al., 2021; Singleton 2019a, 2019b; Smith, 2017; Ye & Titheridge, 2017). However, there are both pros and cons in single- and multi-item ways of measurement. A single-item measure is easy to implement with little to no respondent burden, but it mostly captures a summary cognitive evaluation (described below) of the travel only. A multi-item measure may be a little more difficult to implement and could increase respondent burden because multiple items (that are somewhat similar to each other) are involved. But, this measurement can capture more detailed and varied travel experiences and emotions.

One of the most widely accepted multi-item scales for measuring travel satisfaction is the nine-item Satisfaction with Travel Scale (STS) developed by Ettema et al. (2011). The STS is closely related to the concept of subjective well-being (SWB) because the development of STS was based on the measurement of SWB (see Ettema et al., 2011 for details) as travel is a domain of life satisfaction and well-being. SWB is often thought of in two different ways (Ryan & Deci, 2001): hedonic and eudaimonic. Hedonic SWB reflects the mood, preference, and happiness of a person, whereas eudaimonic SWB is related to the happiness achieved through self-actualization (De Vos et al., 2013; Ryan & Deci, 2001). Hedonic SWB is further considered to be composed of two dimensions (Diener, 2009): affective and cognitive. The affective dimension refers to the emotional state of an individual (i.e., the short-term presence of positive or negative emotions), whereas the cognitive dimension is related to the general evaluation of life by an individual (i.e., long-term life satisfaction).

The STS is generally conceived as measuring the hedonic (affective and cognitive) component of travel domain-specific SWB. The original STS scale (Ettema et al., 2011) consists of three components: the first two components—positive deactivation (PD) and positive activation (PA)—are related to the affective dimension, and the third component refers to cognitive evaluation (CE). In total, there are nine items in STS (see **Table 2.1**), with three items per component. The PD and PA names are used specifically because six items in the affective dimension were derived from the Swedish Core Affect Scale (SCAS) (Västfjäll et al., 2002), which represents affect in two dimensions: valence (positive to negative) and arousal (activation to deactivation). An example of PD is "relaxed," while an example of PA is "alert." The other three statements about travel were made to measure CE, for example, "worked well." Altogether, these nine statements were originally measured on a nine-point (-4 to +4) semantic differential scale during STS development, although many later applications employed a seven-point (-3 to +3) scale.

Since the development of STS, there have been a few attempts to validate and modify the STS scale. The summary of such efforts is presented in **Table 2.1**. In 2015, De Vos et al. (2015) fitted a measurement model of STS utilizing data from Ghent, Belgium, and concluded that a two-factor STS fits better than the original three-factor STS. The two factors were affective evaluation (AE) and CE, where the AE was essentially the combination of PD and PA in the original STS. However, interestingly, the authors did not find evidence of measurement invariance across modes, concluding that the modified STS is still not fully applicable to all modes. In 2017, Smith (2017) modified the original nine-item three-factor STS scale to a seven-item two-factor scale based on the responses from commuters in the US. The factors were the same as in De Vos et al.'s (2015) modified STS, but the number of items was reduced to seven from nine. This modification was motivated by the aim of reducing the respondent burden. Again in 2017, Ye and Titheridge (2017) modified Ettema et al.'s (2011) STS to a one-factor structure with seven items after dropping two items—"*fed up – engaged*" and "*low – high standard*"—based on a pilot survey from China. More recently, in 2019, Singleton

(2019a) proposed and validated a three-factor STS where the factors were the same as the original STS, but some of the items were modified to align with the English translations and SWB concepts. Additionally, the author validated the measurement invariance of this modified STS across modes, concluding that the modified STS was generally applicable across all modes. A major limitation of this modified STS is that two valence-related items—"*sad – happy*" and "*displeasing – enjoyable*"—loaded into PA and CE, respectively, contrary to the author's hypothesis of a fourth valence-only factor (Singleton, 2019a).

With these past efforts in developing a measurement structure of STS, none of the studies could come up with a reliable structure of STS that can be used for any study context, trip purpose, and travel mode. The data from different study contexts, trip purposes, and travel modes seem to fit the different structures of the STS: a nine-item three-factor structure for hypothetical travel in Ettema et al. (2011), a nine-item two-factor structure for leisure trips in Belgium in De Vos et al. (2015), a seven-item two-factor structure for commute trips in the US in Smith (2017), and a nine-item three-factor structure for commute trips in the US in Singleton (2019a). In addition to the varying number of items and factors in the structure of STS across these studies, the wording and loadings of the items also vary. Some of the studies also suffer from potential discriminant validity issues because of the high correlation among the factors: 0.79–0.89 in Singleton (2019a), and 0.58–0.66 (moderately high correlations) in De Vos et al. (2015) even after excluding the observations with identical responses for all nine STS items. This demands the validation and modification of the STS scale (and its modified versions) in different study contexts.

Table 2.1

Summary of studies validating and modifying the STS.

Citation	Travel mode	Travel purpose	Data	Method	Factors: items
Ettema et al. (2011)	Bus, car	Hypothetical travel agenda	155 university students from Sweden	Averaging	• PD: time pressed – relaxed, worried – confident, stressed – calm. • PA: tired – alert, bored – enthusiastic, fed up – engaged. • CE: worst – best, low – high standard, worked well – poorly.
De Vos et al. (2015)	Car, transit, bike, walk	Most recent leisure trip	1,411 from Ghent, Belgium	Exploratory factor analysis	• AE: hurried – relaxed, worried – confident, stressed – calm, tired – alert, bored – enthusiastic, fed up – engaged. • CE: worst – best, low – high standard, didn't work well – worked well.
Smith (2017)	Car, transit, carpool, bike, walk	Most recent commute trip	828 commuters from Oregon, US	Confirmatory factor analysis	• AE: tense – relaxed, worried – confident, tired – excited, bored – enthusiastic, not enjoyable – enjoyable. • CE: worst – best, poorly – smoothly.
Ye and Titheridge (2017)	Car, transit, active modes, others	Most recent commute trip	1215 from China	Confirmatory factor analysis	• STS: time pressed – relaxed, worried – confident, stressed – calm, tired – alert, bored – enthusiastic, worst – best, worked well – poorly.
Singleton (2019a)	Car, transit, non-motorized	Most recent commute trip	654 commuters from Oregon, US	Confirmatory factor analysis	• PD: distressed – content, tense – relaxed. • PA: sad – happy, tired – energized, bored – enthusiastic. • CE: displeasing – enjoyable, poorly – smoothly, worst – best, worried – confident.
This study	Car	Most recent long-distance recreational trip	696 US adults	Confirmatory factor analysis	• PD: distressed – content, tensed – relaxed, worried – confident. • PA: tired – energized, bored – enthusiastic. • CE: sad – happy, displeasing – enjoyable, poorly – smoothly, worst – best.

2.2.2 Determinants of travel satisfaction or its dimensions

Several studies in the literature have examined the determinants of travel satisfaction or its dimensions. Based on a brief review of such studies (presented below), we have categorized the possible determinants of travel satisfaction into six categories: socio-demographics, general travel attributes, built environment and spatial attributes, trip-specific characteristics, travel-based activities and travel time perception, and attitudinal characteristics.

There exist differences in travel satisfaction based on the socio-demographics of individuals. By clustering the individuals based on the research of travel satisfaction from six European cities, Susilo and Cats (2014) identified the distinctive determinants of trip satisfaction for women, young, and low-income or unemployed travelers (compared to other groups). Higher travel satisfaction in older adults was reported in several past studies (Chen et al., 2022; Ettema et al., 2017; Wang & Loo, 2019; Ye & Titheridge, 2017). Females were found more satisfied with travel than males (Ettema et al., 2017). In terms of income, Zhao and Li (2019) found the middle-income group individuals more satisfied with their general travel compared to low- and high-income counterparts, whereas Singleton (2019b) and Smith (2017) found higher commute satisfaction in the higher-income individuals. Individuals with good and excellent self-reported health conditions were generally more satisfied with their travel compared to those with poor health conditions (Smith, 2017; Chen et al., 2022).

The most commonly considered travel attribute in the research of travel satisfaction is the travel mode. Some studies have analyzed the modal differences in travel satisfaction, whereas others have investigated travel satisfaction for a specific travel mode. In general, trips with active travel were more satisfying than with other modes (Mao et al., 2016; Singleton, 2019b; Smith, 2017). A U-shaped relationship between modal flexibility and travel satisfaction was reported by Mao et al. (2016): commuters with high modal flexibility were more satisfied with their travel because of the possibility to use the preferred mode, but the higher travel satisfaction of commuters with very low modal flexibility was because of their lower expectations from travel.

Previous studies show a strong link between travel satisfaction and built environment and spatial attributes. Based on the review of existing literature, De Vos and Witlox (2017) noted that the spatial differences in travel satisfaction are explained by the differences in travel context and perceptions. These differences are attributed to the built environment characteristics, which dictate the mode choice, trip characteristics, and experience. Mouratidis et al. (2019) investigated the relationship between travel satisfaction and urban form and found an indirect path of the relationship: urban sprawl, neighborhood density, and distance to the city center affect the choice of travel mode and travel duration, which ultimately affect satisfaction with travel. A study from China (Zhao & Li, 2019) found higher travel satisfaction for city center residents compared to suburban residents overall. Sukhov et al. (2021) conducted a before-and-after comparison of travel satisfaction in public transit and found that public transport service quality attributes (reliability, information, courtesy, comfort, and safety) are strongly linked to travel satisfaction.

Trip-specific attributes are widely acknowledged in the literature to be related to travel satisfaction. Chen et al. (2022) found sports, leisure, recreational, and shopping trips more satisfactory compared to commute trips. Alone trips were identified as less satisfactory than trips with companions by Wang and Loo (2019). In the case of public transit, the quality of service was found to be related to travel satisfaction: the availability of power outlets and cell signal coverage increased satisfaction with high-speed rail travel in China (Wang & Loo, 2019). Ettema et al. (2017) found the strong impact of weather (sunshine, temperature, wind, rain) on travel satisfaction; however, differences in the impacts were identified between the motorized and non-motorized modes. The duration of travel time (Ettema et al., 2012; Singleton, 2019b; Wang & Loo, 2019) and congestion (Smith, 2017) negatively impact travel satisfaction. It is also evident that satisfied travelers are less sensitive to longer travel duration than dissatisfied travelers (Poudel and Singleton, 2022).

A few studies have investigated the impacts of travel-based activities and travel time perceptions on travel satisfaction. Wang and Loo (2019) evaluated the role of travel-based activities on high-speed rail travel satisfaction and found positive impacts of work-related and entertainment-related e-activities on work/business and non-work/business travel satisfaction, respectively. Similarly, in the case of public transport travel, Ettema et al. (2012) ascertained that travel-based activities impact both affective and cognitive dimensions of travel satisfaction, though a few differences were observed in the relationships based on the trip direction (i.e., going or returning trip). Singleton (2019b) identified strong associations between travel time perceptions (satisfaction with travel time and travel time usefulness) and the travel satisfaction dimensions.

Different types of attitudinal characteristics were considered in different past studies. Ye and Titheridge (2017) found that pro-transit, pro-walk, pro-driving, and positive travel attitudes are positively linked to travel satisfaction. Chen et al. (2022)

found positive impacts of pro-transit, pro-walking, and pro-environment attitudes on travel satisfaction in dockless bike sharing. Attitudes related to transition, trip productivity, destination attributes, and the safety of bikes were identified to impact travel satisfaction (Smith, 2017).

Besides these efforts of past studies in investigating the determinants of travel satisfaction, the method of travel satisfaction measurement varies a lot within these studies: most of the studies used a single-item measure of travel satisfaction, while only a handful of studies (summary presented in **Table 2.2**) have used STS or its variants. The way of measuring travel satisfaction likely impacts its relationships with the explanatory variables because the single-item measurement mostly refers to the cognitive evaluation of the travel only, but the STS or its variants measure both the affective and cognitive dimensions of travel satisfaction. Also, the differences in the relationships between explanatory variables and different dimensions of travel satisfaction offer a wider interpretation of the concept of travel satisfaction. For example, a result from Chen et al. (2022)—a pro-walking attitude was related to higher positive activation but not to other dimensions of travel satisfaction—could be interpreted as: the people who were inclined to walk generally had higher positive activation while traveling via dockless bike sharing. However, past studies do not seem to consider these differences in the relationships among travel satisfaction dimensions in their interpretations.

Table 2.2

Summary of studies investigating the determinants of travel satisfaction using the STS.

Citation	Travel mode	Travel purpose	Dependent variables	Independent variables

Ettema et al. (2012)	Public transport	Commute	Three components of STS: PD, PA, CE; derived from 9 items.	• Socio-demographics • Travel-based activities
Ettema et al. (2017)	Car, public transport, active modes	Commute	STS derived from 3 items related to PD, PA, CE.	• Socio-demographics • Weather-related variables
Smith (2017)	Car, transit, walk, bike	Commute	STS derived from 7 items related to AE and CE.	• Socio-demographics • Travel mode • Trip attributes • Work and home satisfaction • Attitudes
Ye and Titheridge (2017)	Car, rail, walk, bike, worker bus	Commute	STS derived from 7 items related to PD, PA, CE.	• Socio-demographics • Built environment • Trip-specific characteristics • Travel mode • Attitudes
Singleton (2019b)	Car, transit, walk, bike	Commute	Three components of STS: PD, PA, CE; derived from 9 items.	• Socio-demographics • Travel mode • Travel time perceptions
Shukhov et al. (2021)	Public transport	All-purpose	STS derived from 3 items related to PD, PA, CE.	• Service attributes (reliability, information, courtesy, comfort, safety)
Chen et al. (2022)	Dockless bike-sharing	All-purpose	Overall STS and its three components: PD, PA, CE; derived from 9 items.	• Socio-demographics • Trip-specific characteristics • Attitudes • Some neighborhood attributes
This study	Car	Long-distance recreational	Three components of STS: PD, PA, CE; derived from 9-items.	• Socio-demographics • General travel attributes • Trip-specific characteristics • Travel-based activities • Travel time perception • Attitudinal characteristics

2.2.3 Study objectives

The summary of the literature review presented in the preceding sections shows that neither a measurement scale consisting of affective and cognitive dimensions of travel satisfaction nor the investigation of the determinants of travel satisfaction exists in the specific context of long-distance recreational travel. To contribute to these research gaps, this study has two objectives: (1) to modify/validate the STS (and its variants) and define its representation (one-factor, two-factor, three-factor, or four-factor) for long-distance recreational travel; and (2) to investigate the determinants of travel satisfaction for long-distance recreational travel.

2.3 Data

The data used in this study was gathered from an online questionnaire survey (see Acharya, 2022) the authors conducted in the Summer of 2022. The survey was part of a larger study designed to assess long-distance recreational travel behavior. In the survey, long-distance recreational travel was defined as travel intended for pleasure and recreation and involving at least 75 miles of travel one-way. Though the US national long-distance passenger travel demand model uses the distance threshold of 50 miles to classify a trip as long-distance (Outwater et al., 2015), we adopted the 75 miles one-way distance threshold (similar to Dannemiller et al., 2021) to screen out the potential inclusion of short-distance trips which are behaviorally different than long-distance trips. Thus, the respondents of the survey were those who had visited one of the national parks of the US in 2022 by driving at least 75 miles one-way, and no air travel was involved in the trip. The detailed information provided by the respondents about their most recent trips to national parks, including their travel experiences, are used in this study. The survey was distributed online using a Qualtrics panel and 696 complete responses were collected. The mean response time for the survey was about 16 minutes. The following sections present the descriptive statistics of the exogenous variables, attitudinal latent variables, and travel satisfaction (the STS) considered in the research model (to be discussed later).

2.3.1 Exogenous variables

The descriptive statistics of the socio-demographic characteristics, general travel attributes, trip-specific characteristics, travel-based activities, and travel time perception of the sample are presented in **Table 2.3**. To assess the representativeness of the sample, **Table 2.3** also presents the statistics of socio-demographic characteristics of the US population obtained from the 2021 American Community Survey (ACS) estimates (US Census Bureau, 2021). The sample and US population distributions look fairly similar for age, gender, race, and income. Compared to the US population, middle-aged (35-64 years) individuals, females, whites, and individuals from middle-income households ($25-100k) were slightly overrepresented in our sample. Since these discrepancies were small, no weighting of the sample was performed before analysis.

Table 2.3

Sample data for socio-demographics, general travel attributes, trip-specific characteristics, travel-based activities, and travel time perception (N = 696).

Variable	Sample				US population
	Mean	SD	#	%	%
Socio-demographic characteristics					
Age					
18-34 years			191	27.44	29.14
35-64 years			404	58.05	49.23
65+ years			101	14.51	21.63
Gender					
Female			359	56.90	49.50
Male/other			337	43.10	50.50 (male)
Race/ethnicity					
White			576	82.76	72.90
Others			120	17.24	
Education					
No college degree			291	41.81	
Undergraduate degree			278	39.94	
Graduate degree or higher			127	18.25	
Student					

No			512	73.56	
Yes, part-time			46	6.61	
Yes, full-time			138	19.83	
Employment					
No			210	30.17	
Yes, part-time			90	12.93	
Yes, full-time			396	56.90	
Household income (annual)					
< $25k			110	15.80	17.40
$25-50k			187	26.87	19.10
$50-75k			155	22.27	16.80
$75-100k			99	14.22	12.80
≥$100k			145	20.83	34.00
# adults in household (age ≥18 years)	2.18	0.98			
# children in household (age <18 years)	0.90	1.15			
General travel attributes					
Driving experience (years)	25.66	16.61			
Traffic citations: no			291	41.81	
Crash experience: no			234	33.62	
# of household vehicles	1.52	0.77			
Travel mode					
Commute: personal car			612	87.93	
Shopping trips: personal car			651	93.53	
Personal business trips: personal car			632	90.80	
Social/recreational trips: personal car			627	90.09	
Typical # of long-distance recreational trips per year	3.32	2.19			
Trip-specific characteristics					
Travel time (hours, one-way)	10.89	12.83			
Travel cost (dollars, one-way)	193.40	202.52			
Travel companion					
Total #	2.36	1.93			
Spouse: present			453	65.09	
Children: present			320	45.98	
Siblings: present			56	8.005	
Other family members: present			109	15.66	
Friends: present			135	19.40	
Ownership of vehicle					
Owned/leased			611	87.79	
Rented			60	8.62	
Borrowed			25	3.59	
Vehicle type					
Sedan/hatchback			262	37.64	
SUV			319	45.83	
Truck			69	9.91	
Electric			21	3.02	
Vehicle feature					
Blind-spot monitoring			219	31.47	
Lane-keep assistance			188	27.01	
Adaptive cruise control			400	57.47	
Automatic emergency braking			192	27.59	
Driver monitoring			132	18.97	
Parking assistance			180	25.86	
Collision warning			259	37.21	
Trip experience					

Rain			343	49.28
Low visibility			95	13.65
Congestion			233	33.48
Involved in a crash			4	0.57
Percentage of time/distance driven in the trip				
0-25%			40	5.75
25-50%			113	16.24
50-75%			150	21.55
75-100%			117	16.81
Whole trip			276	39.66
Travel-based activities				
Listening to music, radio, or other audio			670	96.26
Singing, dancing			174	25.00
Interacting with other passengers			467	67.10
Talking on phone			268	38.51
Texting, emailing, or other messaging; teleconference			185	26.58
Reading newspapers, books, websites, etc.			60	8.62
Using social websites or apps			184	26.44
Watching movies/TV/ other entertainment			105	15.09
Playing games			127	18.25
Working or studying			13	1.87
Caring for or playing with children or pets			87	12.50
Eating food, drinking beverage, smoking			442	63.51
Sleeping or snoozing			153	21.98
Viewing scenery; watching people			362	52.01
Thinking or daydreaming			164	23.56
Watching the road			504	72.41
Travel time perception				
Travel time usefulness (1: Mostly wasted – 5: Mostly useful)	4.14	0.97		

Travel-based activities report the activities conducted by the respondents during their trip. In the questionnaire, the respondents were asked to select the (multiple) activities they conducted during their recent long-distance recreational travel from the list of 16 activities. The question was: "*Which of the following activities did you do in-vehicle during the trip? Consider the activities you did both ways. Select all that apply.*" The distribution of travel-based activities shows that listening to music, radio, or other audio was the most performed activity whereas working or studying was the least.

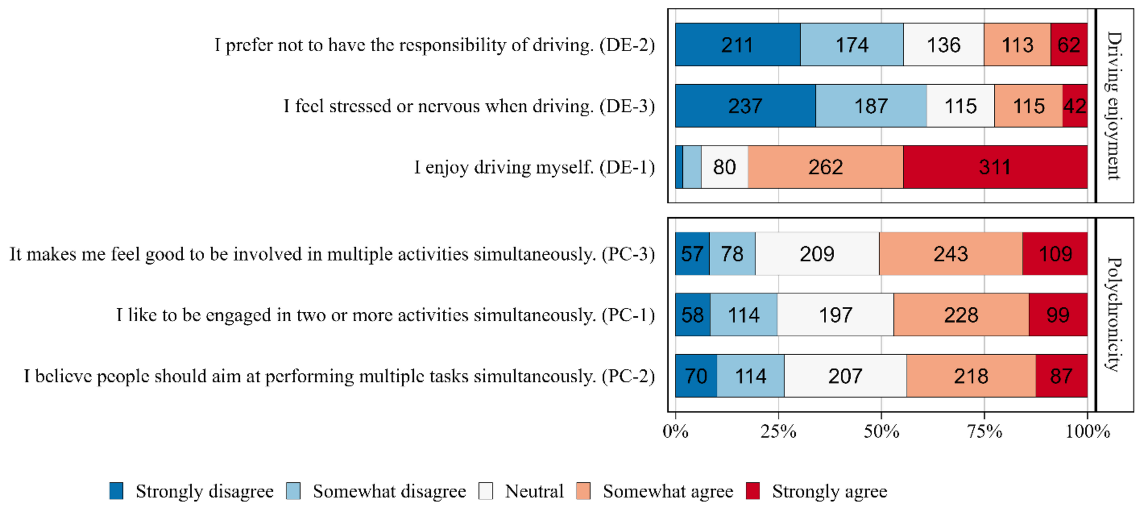
Travel time usefulness is a quality evaluation of the time spent traveling by travelers. This was assessed by asking a question about the usefulness or worthwhileness of the travel time. The question was: "*How useful or worthwhile would you rate the time you spent traveling?*" Respondents had to answer on a five-point Likert-type scale ranging from mostly wasted (1) to mostly useful (5). The distribution of responses shows that most of the respondents rated higher travel time usefulness (mean: 4.14).

2.3.2 Attitudinal latent variables

Driving enjoyment and polychronicity are the attitudinal characteristics considered in this study. Driving enjoyment measures an individual's attitude toward driving a car manually, whereas polychronicity assesses an individual's preference for doing multiple activities/tasks simultaneously. Both of these attitudinal characteristics are latent in nature, meaning that multiple indicators are used to define these unobserved variables. The items/indicators of latent variables driving enjoyment and polychronicity are adopted from Haboucha et al. (2017) and Malokin et al. (2019) respectively. The list of the adopted indicators and the distribution of responses are presented in **Figure 2.1**. The distribution of the indicators shows that roughly two-thirds and half of the sample had positive attitudes (strongly or somewhat agree) about manual driving enjoyment and polychronicity, respectively.

Figure 2.1

Sample data for the indicators of attitudinal characteristics.

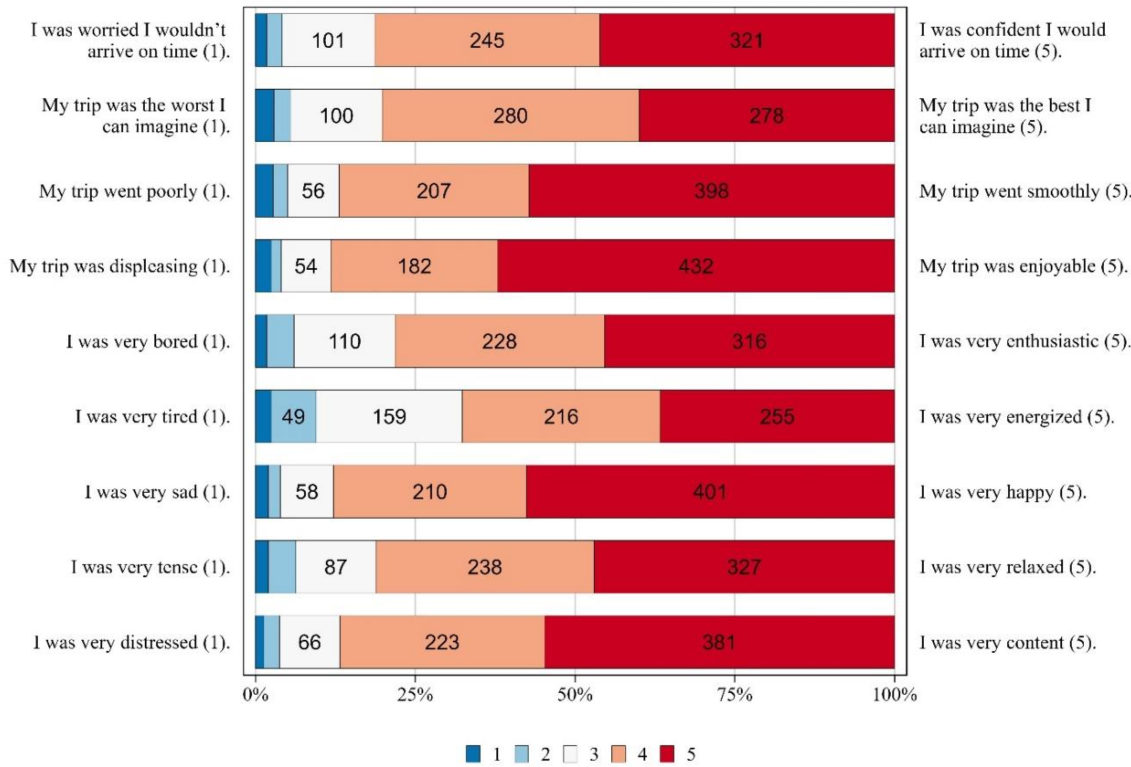


2.3.3 Travel satisfaction

The measurement of travel satisfaction followed the procedure adopted by past studies developing or adjusting the STS scale, with some modifications. Though the past studies had asked the respondents to rate statements about travel statements either on a nine- or seven-point semantic differential scale, we asked the respondents to rate nine statements about how they felt while traveling on a five-point semantic differential scale. The five-point scale was chosen for two reasons: (1) the literature (Norman, 2010; Sullivan & Artino, 2013) suggests that the use of a five-point scale is sufficient to measure the continuous nature of the response; and (2) respondent burden decreases with the use of a lower-point scale. The wording of the statements or items of travel satisfaction was adapted from Singleton (2019a), as it is the most recent study that validated/modified the STS for the US context. The list of the statements asked in the questionnaire and the distribution of responses are presented in **Figure 2.2**. The distribution shows that more than three-quarters of the sample had positive perceptions (ratings 4 and 5, out of 1-5) towards the statements of travel satisfaction.

Figure 2.2

Sample data for indicators of the satisfaction with travel scale.



2.4 Methodology

Data were analyzed using the structural equation modeling (SEM) framework. A SEM model involving latent variables consists of two parts (Kline, 2015): measurement and structural models. A measurement model defines the relationship between the unobserved latent variable(s) and the observed items, whereas a structural model defines the relationships between latent and exogenous variables. Within a SEM framework, the measurement models of latent variables are usually defined by conducting confirmatory factor analysis (CFA).

Since the first study objective was to validate/modify STS for long-distance recreational travel, the CFA technique was adopted. The suitability of the data for factor analysis was checked using the Kaiser, Meyer, Olkin (KMO) measure of sampling adequacy (Kaiser, 1970) and Barlett's test of Sphericity (Barlett, 1951). The measurement model consisted of nine five-point Likert scale items (presented in **Figure 2.2**) as observed items and travel satisfaction dimensions (to be described later) as unobserved latent variables. The specification of the measurement model connecting the observed items and the latent variables is shown in Equation 2-1.

$$v_t = \lambda_t \mathrm{F}_l + \mathrm{e}_l \qquad \text{2-1}$$

where, $l \in \{1, 2, \ldots, L\}$ and $t \in \{1, 2, \ldots, T\}$ are the indexes of latent variables and observed items such that F_l and v_t represent the vector of latent variables and their respective observed items. λ_t is the vector of parameters that link observed items v_t and latent variables F_l. e_l represents the measurement error associated with each latent variable. The measurement errors are assumed to be standard normally distributed. Several configurations linking the latent variables (i.e., travel satisfaction dimensions) and observed items were tested and modified subsequently. (The detailed procedure is explained in Section 2.5.1.) Finally, a reliable measurement model of STS was finalized.

The same procedure was adopted to finalize the measurement structure of attitudinal latent variables: driving enjoyment and polychronicity.

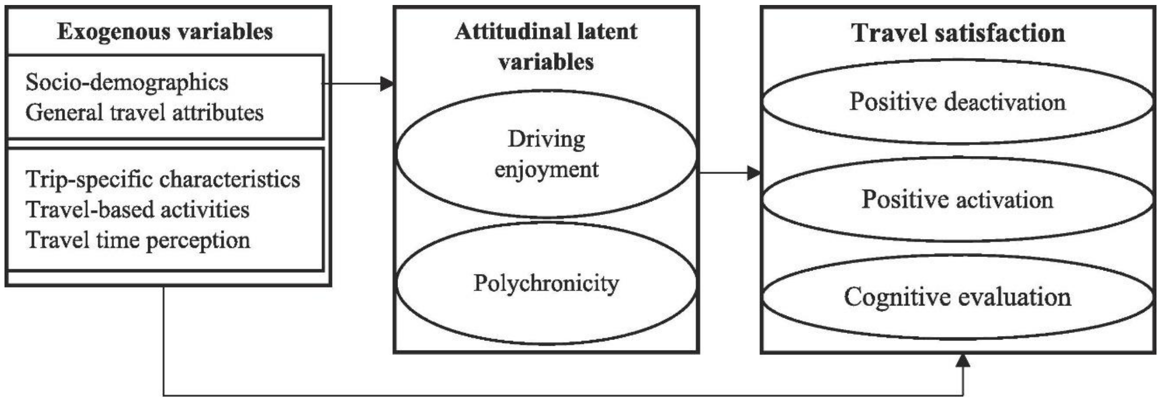
Once the measurement structures of STS and attitudinal latent variables were finalized, a conceptual research model was proposed (shown in **Figure 2.3**) hypothesizing the relationships between travel satisfaction dimensions and exogenous variables (socio-demographics, general travel attributes, trip-specific characteristics, travel-based activities, and travel time perception) and attitudinal latent variables (driving enjoyment and polychronicity). This proposed model was adopted for SEM to attain the second study objective. In addition to the direct impacts of exogenous and latent variables on travel satisfaction dimensions, the model considered the indirect impacts of socio-demographics and general travel attributes on travel satisfaction dimensions through attitudinal latent variables: driving enjoyment and polychronicity. A general specification of the structural equation model is represented by Equation 2-2.

$$\mathrm{F}_l = \mathrm{B}_i X_i + \mathrm{r}_l \qquad \text{2-2}$$

where $i \in \{1, 2, \ldots, I\}$ is the index of predictor variables such that X_i denotes the vector of predictors variables and B_i represents their respective parameters that explain their relationships with outcome variables F_i. r_l is the vector of residuals associated with each outcome variable. This error term is also assumed to be standard normally distributed.

Figure 2.3

Research model.



The goodness-of-fit of measurement and structural models were judged by the combination of a number of indices as recommended by Kline (2015): the ratio of chi-square value to degrees of freedom (χ^2 /df), comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). In general, a model with a higher value of CFI and lower values of χ^2 /df, RMSEA, and SRMR better fit the data. As suggested by the literature (Browne & Cudeck, 1992; Hair et al., 2010; Hooper et al., 2008; Hu and Bentler, 1999; Kline, 2015), the cutoff values of these indices for a good model fit are: χ^2 /df < 2, CFI > 0.95, RMSEA < 0.05, and SRMR < 0.08, and for an acceptable model fit are: χ^2 /df < 5, CFI > 0.90, RMSEA < 0.08, and SRMR < 0.10. All measurement and structural models were fitted using the lavaan package (Rosseel, 2012) in R (R Core Team, 2022). As seen in **Figure 2.2**, the responses to the indicators of travel satisfaction were not normally distributed (negatively skew with positive means); thus, a robust variant of the maximum likelihood estimator developed by Yuan and Bentler (2000) called maximum likelihood estimation with robust standard errors and a Satorra-Bentler scaled test statistics (MLM) was used for estimating measurement and structural models.

2.5 Results

2.5.1 Satisfaction with the travel scale

The sampling adequacy and significant correlation in the data (i.e., the nine indicators of travel satisfaction) for factor analysis were confirmed using the KMO measure of sampling adequacy with the KMO of 0.90 and the result of Barlett's test of sphericity (Chi-square (df = 36) = 2376.38, $p < 0.001$). After verifying the suitability of data for factor analysis, eight different measurement models (models A–H) of travel satisfaction were fitted to validate or modify the STS using the CFA. The factor definition and goodness-of-fit statistics of these models (models A–H) are reported in **Table 2.4**. These models were proposed and tested following the recommendations of past studies examining the STS and the authors' hypotheses supported by SWB theory.

Table 2.4

Factor structure and goodness-of-fit statistics of measurement models of STS.

Model	Factor definition	$\chi 2$ /df	CFI	SRMR	RMSEA	Notes
A	TS: distressed – content, tensed – relaxed, sad – happy, tired – energized, bored – enthusiastic, displeasing – enjoyable, poorly – smoothly, worst – best, worried – confident.	111.21/27 = 4.12	0.928	0.050	0.094	Model defined by authors.
B	AE: tensed – relaxed, tired – energized, bored – enthusiastic, displeasing – enjoyable, worried – confident. CE: poorly – smoothly, worst – best.	81.75/13 = 6.29	0.925	0.051	0.115	Similar to Smith (2017).

C	AE: distressed – content, tensed – relaxed, sad – happy, tired – energized, bored – enthusiastic, displeasing – enjoyable, worried – confident. CE: poorly – smoothly, worst – best.	107.45/26 = 4.13	0.932	0.048	0.094	Similar to De Vos et al. (2015).
D	AE: distressed – content, tensed – relaxed, tired – energized, bored – enthusiastic, worried – confident. CE: sad – happy, displeasing – enjoyable, poorly – smoothly, worst – best.	81.03/26 = 3.12	0.954	0.042	0.077	Model defined by authors.
E	PD: distressed – content, tensed – relaxed, worried – confident. PA: sad – happy, tired – energized, bored – enthusiastic, displeasing – enjoyable. CE: poorly – smoothly, worst – best.	85.26/24 = 3.55	0.950	0.043	0.083	Similar to Ettema et al. (2011).
F	PD: distressed – content, tensed – relaxed. PA: sad - happy, tired - energized, bored – enthusiastic. CE: displeasing – enjoyable, poorly - smoothly, worst – best, worried – confident.	84.428/24 = 2.98	0.954	0.043	0.080	Similar to Singleton (2019a).
G	PD: distressed – content, tensed – relaxed, worried – confident. PA: tired - energized, bored – enthusiastic. CE: sad - happy, displeasing - enjoyable, poorly - smoothly, worst – best.	63.37/24 = 2.64	0.968	0.037	0.067	Model defined by authors.
H	PD: distressed – content, tensed – relaxed, worried – confident. PA: tired – energized, bored – enthusiastic. VL: sad – happy, displeasing – enjoyable. CE: poorly – smoothly, worst – best.	62.13/21 = 2.85	0.967	0.037	0.072	Model defined by authors.

First, the one-factor model (A) with nine items was fitted considering its simple structure and discriminant validity issues (because of the high correlation between the dimensions of travel satisfaction) in past studies. The model was unacceptable because of a higher RMSEA value (0.094). Second, three two-factor models (B, C, D) were fitted where models B and C were the replications of Smith (2017) and De Vos et al. (2015) models (though the wording of items varies) and model D was proposed based on the authors' hypothesis. Model B (similar to Smith (2017)) consisting of seven items had unacceptable goodness-of-fit statistics, particularly the values of χ^2 /df > 5.00 (6.29) and RMSEA > 0.080 (0.115). When following De Vos et al. (2015) recommendations in model C, the value of χ^2 /df came out as acceptable, but the model suffered from a higher RMSEA value (0.094). Next, model D was proposed by switching two valence-related items (“sad – happy” and “displeasing – enjoyable”) as indicators of cognitive evaluation (CE) instead of affective evaluation (AE) in model C. As a result, the goodness-of-fit statistics improved and reached an acceptable range.

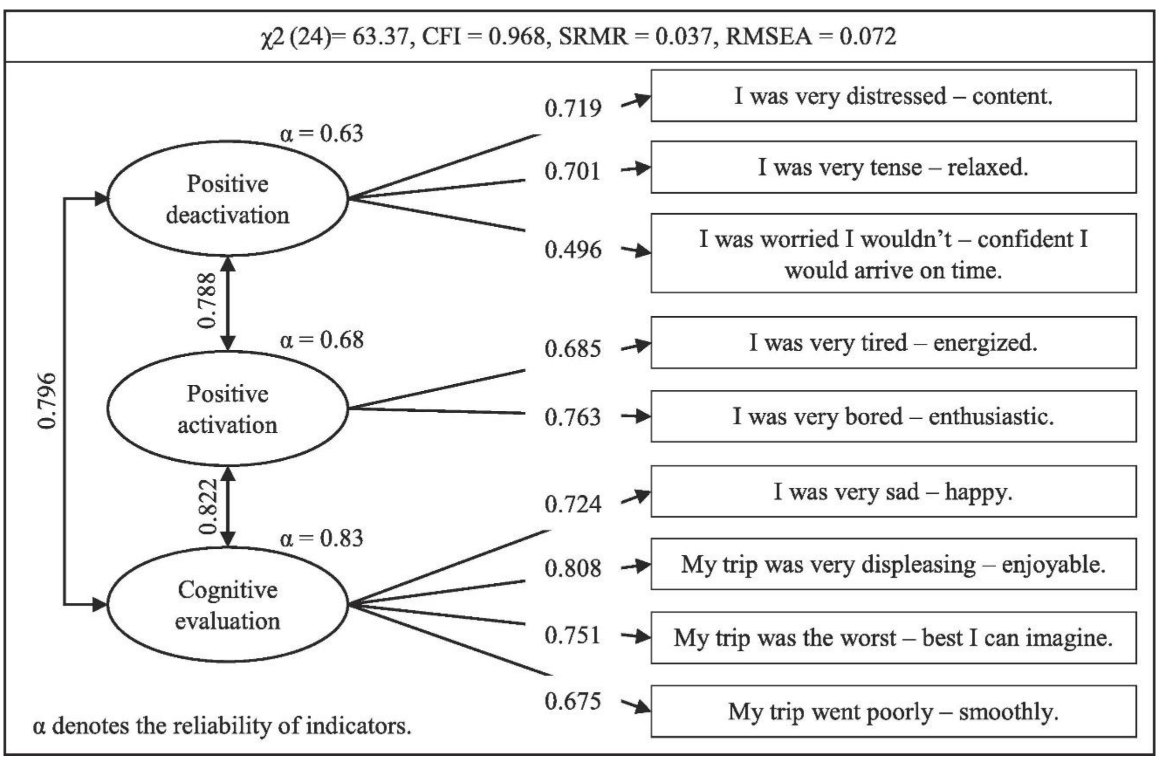
Third, three three-factor models (E, F, G; all with nine items) were fitted where models E and F were the replications of the Ettema et al. (2011) and Singleton (2019a) models, respectively, and model G was proposed based on the authors’ hypothesis. Models E and F both had RMSEA values outside of the acceptable range (0.083 and 0.080, respectively). Model G was proposed by switching two valence-related items (“sad – happy” and “displeasing – enjoyable”) as indicators of CE instead of positive activation (PA) in model E. As a result, goodness-of-fit statistics were found to be within acceptable ranges.

Finally, a four-factor model (H) was proposed by distinguishing two valence-related items (“sad – happy” and “displeasing – enjoyable”) and considering them as a new factor called valence (VL). The goodness-of-fit statistics of this model also came within acceptable ranges.

Overall, among eight models (A–H), three models (D, G, and H) were found to have acceptable goodness-of-fit statistics. Realizing all these three models were nested into each other, the best model was selected by conducting likelihood-ratio tests. (A likelihood-ratio test between two nested models, constrained and unconstrained, checks whether the improvement in the chi-square value in the constrained model is worth losing degree(s) of freedom.) Compared to model D, there was a significant decrease in the chi-square value in model G (diff in χ^2 = 17.66, diff in df = 3). When comparing models G and H, there was not a significant difference in chi-square values (diff in χ^2 = 1.24, diff in df = 3). Additionally, models D and H had higher correlations between the factors (0.875 and 0.763–0.962, respectively), indicating potential overlapping constructs, compared to model G (0.788–0.822). Thus, based on the results of likelihood-ratio tests and the correlations among the factors, model G was considered to be the best model representing STS. The CFA results of this model (model G) are presented in **Figure 2.4**.

Figure 2.4

CFA results of proposed STS.



2.5.2 Determinants of travel satisfaction

Once the measurement structure of the STS was finalized, the simultaneous relationships of the variables proposed in the research model (shown in **Figure 2.3**) were tested using SEM, and the results are presented in **Table 2.5**. The results show both the impacts of socio-demographics and general travel attributes on attitudinal latent variables and the impacts of all exogenous and attitudinal latent variables on three dimensions of travel satisfaction estimated jointly. Having both direct and indirect impacts of socio-demographics and general travel attributes on travel satisfaction dimensions, the discussion/interpretation of the results presented in Sections 2.5.2.1 and 2.5.2.2 were made based on the total impacts (combination of both direct and indirect impacts/effects). The calculation and values of total effects are not presented here; contact authors if needed. However, for other exogenous variables, the discussion/interpretation presented in Sections 2.5.2.3, 2.5.2.4, and 2.5.2.5 relied on their direct impacts on travel satisfaction dimensions. By jointly estimating the factors affecting travel satisfaction dimensions, the correlations of error components were computed, and higher correlation values (>0.8) suggest that common unobserved factors jointly increase or decrease all three dimensions. The model development process started by considering all variables presented in **Table 2.3** and two latent variables, but the model was finalized by gradually dropping the insignificant predictors. Thus, only the (marginally) statistically significant estimates (at a 90% confidence interval) are presented in **Table 2.5**. One thing to note is the measurement structures of the attitudinal latent variables (i.e., of driving enjoyment and polychronicity) were defined using CFA (same process as that of the STS definition) before plugging them into the SEM. Those results are presented in **Table 2.6** in the Appendix.

Table 2.5

Results of the structural portion of SEM.

Variables	Driving enjoyment		Polychronicity		Travel satisfaction					
					Positive deactivation		Positive activation		Cognitive evaluation	
	Coeff.	z-stat	Coeff.	z-stat	Coef.	z-stat	Coef.	z-stat	Coef.	z-stat
Socio-demographic characteristics										
Age										
35-64 years	0.073	1.869								
65+ years					-0.084	-2.131				
Gender: Female	-0.140	-3.387					-0.074	-2.240		
Education: Graduate degree or higher			0.091	2.450						
Student										
Yes, part-time	-0.078	-1.960								
Yes, full-time	-0.092	-2.164								
Employment										
Yes, part-time					0.072	2.117				
Yes, full-time			0.172	4.294						
Household income (annual)										
$25-50k			-0.091	-2.306	0.097	2.413			0.087	2.477
$50-75k					0.084	1.998			0.096	2.774
# children in household (age <18 years)			0.095	2.431						
General travel attributes										
Driving experience (years)	0.210	5.081	-0.233	-5.385	0.180	3.539				
Traffic citations: no			-0.065	-1.710	0.089	2.633				
# of household vehicles									0.073	2.776
Travel mode: personal car										
Personal business trips	0.096	2.245					-0.056	-1.609		
Social/recreational trips							0.116	3.120		
Typical # of long-distance recreational trips per year	0.124	3.021							-0.074	-2.429
Trip-specific characteristics										
Travel time (hours, one-way)					-0.074	-1.796	0.089	2.707		
Travel companion										
Total #									-0.093	-1.919
Spouse: present					-0.059	-1.657				

Children: present					0.145	3.634	0.122	3.181
Other family members: present			-0.121	-3.326				
Friends: present					0.073	2.172		
Vehicle type								
Truck							0.080	2.724
Vehicle feature								
Lane-keep assistance							0.051	1.889
Driver monitoring			0.081	2.520				
Trip experience								
Rain			-0.106	-2.423	-0.115	-2.634	-0.157	-3.938
Congestion					-0.059	-1.696		
Percentage of time/distance driven								
25-50%			-0.117	-2.178				
50-75%			-0.134	-2.334				
75-100%			-0.125	-2.359				
Whole trip			-0.159	-2.457				
Travel-based activities								
Listening to music, radio, or other audio							0.068	2.669
Interacting with other passengers							0.049	1.612
Using social websites or apps					-0.068	-1.946		
Sleeping or snoozing					-0.067	-1.826		
Thinking or daydreaming							0.066	2.350
Travel time perception								
Travel usefulness			0.348	7.524	0.363	7.557	0.281	6.366
Attitudinal characteristics								
Driving enjoyment			0.267	4.909	0.136	2.806	0.145	3.284
Polychronicity			0.136	2.841	0.164	3.414	0.116	2.522
Error correlations								
Positive activation					0.815	7.946	0.841	7.733
Positive deactivation							0.806	6.515
Goodness-of-fit statistics								
Chi-square value (degree of freedom)	846.871 (598)							
CFI/SRMR/RMSEA	0.944/0.028/0.025							
R-squared value	0.140	0.181	0.271		0.262		0.171	

Note: All coefficients are standardized.

2.5.2.1 Socio-demographics

Middle-aged travelers (35–65 years old) had a higher driving enjoyment and travel satisfaction (indirect effect) compared to younger and older travelers. Being an older traveler (65+ years) was related to lower travel satisfaction, mostly on the deactivation dimension, compared to younger counterparts. This result is opposed to the results of past studies (e.g., Chen et al., 2022; Ettema et al., 2017; Ye & Titheridge, 2017) and could signify the difference in travel behavior among different travel purposes and settings. Having a lower deactivation satisfaction for older individuals could be because of their inability to tolerate a longer travel duration (mean 10+ hours in our sample) as opposed to relatively lower travel duration (in the order of 30 minutes or 1 hour) in past studies. However, in line with past studies (e.g., Ettema et al., 2017; Singleton 2019b), females were found to have lower travel satisfaction indirectly (also directly on the positive activation dimension) through lower driving enjoyment attitudes. Individuals with relatively more education (graduate degree or higher), non-students, full-time employees, and those from households with more children had a higher preference for polychronicity and thus were related to higher travel satisfaction. Also, part-time employees were reported to have a more relaxed travel experience compared to their unemployed and full-time counterparts. Our model results differ from past studies in terms of the relationship between income and travel satisfaction: Smith et al. (2017) and Singleton (2019b) reported higher commute satisfaction for high-income group individuals (annual household income $75k+ and $150k+ respectively) whereas we found a higher travel satisfaction for middle-income individuals ($25–75k) compared to those from lower and higher income groups; although, this group did not have differences in satisfaction with the activation dimension (except individuals with $25–75k annual household income). Perhaps the more time middle-income individuals dedicate to planning long-distance recreational trips (because of budget constraints) (Humagain and Singleton, 2021) makes their trips and associated travel more enjoyable and satisfying compared to high-income individuals (who are frequent recreationists (Karl et al., 2020)) and low-income individuals (who make a very few trips and are more worried about the trip expenses (Karl et al., 2020)).

2.5.2.2 General travel attributes

Individuals with more driving experience had higher driving enjoyment and were more monochronic. Considering both direct and indirect impacts, travelers with more driving experience had a higher positive deactivation and cognitive evaluation but lower positive activation during travel. Similarly, individuals with at least one traffic citation in the past were more polychronic and had higher positive activation and cognitive evaluation dimensions but a lower positive deactivation. The number of household vehicles was positively related to the cognitive evaluation of travel. Higher driving enjoyment was observed for individuals with a car as the primary travel mode for personal business trips; thus, they had higher travel satisfaction (except for lower positive activation). However, individuals with a personal car as the primary mode of travel for social and recreational trips had higher positive activation during travel. Individuals who make more long-distance recreational trips typically had a higher driving enjoyment. They had higher ratings in affect-related dimensions but not in cognitive assessment of travel. These relationships were rarely investigated/discovered in past studies.

2.5.2.3 Trip specific characteristics

Travel duration was negatively and positively associated with deactivation and activation dimensions of travel satisfaction, respectively. In other words, travelers' deactivated emotions (distressed and tense) grew with an increase in travel duration but, at the same time, their level of activation (energized and enthusiastic) increased. Usually, the duration of travel is viewed as a negative influencer of travel satisfaction for commute travel (Ettema et al., 2012; Singleton, 2019b; Wang & Loo, 2019), and the same relationship existed for deactivation dimension in our model, but an opposite relationship was observed for the activation dimension. A finding from tourism literature—distant travelers generally have a higher excitement to visit and participate in the activities at recreational destinations (Nyaupane et al., 2003; Larsen & Guiver, 2013, Yang et al., 2017)—could explain this opposing relationship, such that increased activation in recreational travel is because of the increased excitement and enthusiasm to visit the destination.

The presence of a child or friend as a travel companion made the travel more satisfying (positive activation); however, surprisingly, the presence of a spouse or other family member lowered the travel satisfaction with a more distressed and tense experience (negative deactivation). Overall, having more travel companions lowers the cognitive evaluation of travel. Perhaps this is because the presence of other passengers disrupts what could otherwise be a peaceful and relaxing experience driving alone. Driving a truck was associated with a higher cognitive evaluation of travel. This is probably because of the larger trunk space and flexibility of off-road driving in trucks (which are important in US national park visits) compared to sedans and hatchbacks.

Advanced vehicle features like driver monitoring and lane-keeping assistance features made the travel more satisfying with a higher positive deactivation experience and cognitive evaluation. Driving through rain lowered all dimensions of travel satisfaction (as in Ettema et al., 2012), whereas congestion lowered the activation dimension only (as in Smith, 2017). Those who drove more (by the percentage of time/distance) during the trip had lower travel satisfaction with a less activated travel experience.

2.5.2.4 Travel-based activities and travel time perception

Few travel-based activities were found to be significantly related to travel satisfaction. Using social media and sleeping or snoozing during the travel reduced travel satisfaction by lowering the activation experience, but listening to music, interacting with other passengers, and thinking or daydreaming while traveling increased the cognitive evaluation of travel and travel experience. These findings are somewhat similar to past studies (Ettema et al., 2012; Wand & Loo, 2019), but the significance of a more productive activity like working was not reported by our model, possibly because of the discretionary nature of recreational travel (and fewer observations with such activities). Similar to Singleton (2019b), travel time perception measured by an evaluation of travel time usefulness was positively associated with travel satisfaction, indicating that effective utilization of travel time (possibly by doing in-vehicle activities of interest) improves the travel experience.

2.5.2.5 Attitudinal characteristics

Both attitudinal latent variables considered in the study, driving enjoyment and polychronicity, had a significant positive impact on all travel satisfaction dimensions.

Given the discretionary nature of recreational travel and only vehicle drivers as the respondents of the survey, we expected to see a positive impact of preference for manual driving on travel satisfaction. A past study (Ye & Titheridge, 2017) also reported higher satisfaction with the commute (made with multi-modes) for individuals with pro-driving attitudes. Similarly, we found a positive impact of polychronicity preference on travel satisfaction. It could be explained by a higher preference for doing multiple activities for polychronic individuals (Keseru & Macharis, 2018) making the travel time more productive and satisfying. The significance of these attitudinal variables not only improved our understanding of how individual attitudes are related to travel satisfaction directly but also mediated the indirect effects of socio-demographic and general characteristics on travel satisfaction dimensions (as described in Sections 2.5.2.1 and 2.5.2.2).

2.6 Discussion and conclusion

With the necessity of a reliable scale for measuring long-distance recreational travel satisfaction, we modified and validated the existing STS (that is mostly used for commute and daily travel) as an effective measure of hedonic subjective well-being for long-distance recreational travel based on the empirical data collected from the recent visitors of US national parks. Though we adopted the items (and their wordings) recommended by Singleton (2019a) based on the items recommended in the original STS (by Ettema et al., 2011) and its modified versions (De Vos et al., 2015; Smith, 2017) in the US context, our data supported a different three-factor structure (positive deactivation, positive activation, and cognitive evaluation) of STS. The item "worried – confident" was loaded as an indicator of the positive deactivation factor similar to Ettema et al. (2011) (also De Vos et al. 2015; Smith, 2017), instead of cognitive evaluation in Singleton (2019a). It is to be noted that this item had a relatively low loading (0.496) compared to past studies, probably because of the recreational travel purpose adopted in this study, where reaching the destination exactly on time is not as important as for commute travel. A more-valence-related item ("sad – happy") came out to be an indicator of cognitive evaluation instead of positive activation in Singleton (2019a). Additionally, our investigation of the STS measurement structure distinguished two valence-related items ("sad – happy" and "displeasing – enjoyable") from the rest, but the factor valence had a very high correlation with factor cognitive evaluation, suggesting the three-factor structure that merged them. Thus, the cognitive evaluation factor in our measurement model more or less captures both valence and cognitive assessment of travel. Overall, this study concludes that the STS is a reliable way to measure travel satisfaction, and a slightly modified STS structure (shown in **Figure 2.4**) can be used as a tool to measure long-distance recreational travel satisfaction. The proposed scale can be utilized by tourism researchers to measure tourist travel satisfaction and evaluate its relationships with destination satisfaction and loyalty. A follow-up study has been conducted in this direction (Acharya et al., 2023).

After defining the measurement structure of the STS for long-distance recreational, we investigated the determinants of travel satisfaction dimensions by considering a wide set of exogenous variables related to socio-demographics, general travel attributes, trip-specific characteristics, travel-based activities, travel time perception, and attitudes. Results show that these exogenous variables explain the differences in travel satisfaction (and among the dimensions of travel satisfaction).

Unlike past studies, we investigated the indirect impacts of socio-demographic and general travel attributes on travel satisfaction dimensions through attitudinal latent variables, which increased our explanation and interpretation of differences in travel satisfaction. Most of the results were consistent with past studies, whereas some discrepancies (mostly on the impacts of socio-demographics on travel satisfaction) were observed particularly because of the recreational travel purpose and the consideration of the indirect impacts through attitudinal latent variables.

The role of advanced vehicle features, travel-based activities, travel time perception, and attitudes in travel satisfaction dimensions offer implications for the autonomous vehicle (AV) era. With self-driving capabilities, AVs allow travelers to spend their time as they like with a wide range of possible in-vehicle travel-based activities (Moore et al., 2020; Singleton, 2019c). Our results—showing the positive impacts of travel usefulness (or effective utilization of travel time), doing more active in-vehicle activities while traveling, and driving vehicles with advanced features (that potentially reduce driving efforts) on travel satisfaction—indicate that the satisfaction of long-distance recreational travel will likely increase when these trips are made with AVs. Conversely, the positive impact of driving enjoyment on travel satisfaction indicates that travelers might miss manual driving in AVs, particularly during recreational travel where the driving environment is different than daily commute travel. Also, our results show that driving a greater percentage of time/distance in the trip leads to lower travel satisfaction. Combining all these results, it could be concluded that long-distance recreational travelers enjoy manual driving but probably for a shorter duration only; thus, AVs seem to be a favorable choice for long-distance recreational travelers if the option of manual driving is possible in those vehicles.

Finally, we identify four shortcomings in this study that could be addressed through additional research. First, the validation of the STS in the present study context (i.e., long-distance recreational travel by car in the US) doesn't indicate the universal validity of the scale. Demonstrating the measurement invariance of the STS structure across different geographical locations (with different language translations) and travel modes is necessary for such validity. Future studies should continue in this direction. Second, people may confound their liking/satisfaction of destination attributes and activities conducted at the destination with their satisfaction of travel to the destination. This could have impacted the responses to the indicators of STS in this study. Future studies could address this issue by adopting an intercept survey, where the travelers are intercepted and surveyed on the way to their destinations. Third, despite claiming the travel purpose adopted in the study was recreational, respondents were limited to national park visitors only. This was done to make the survey sizable; however, it could have impacted the study results. The study sample also underrepresents the higher-income US population. Fourth, though this study briefly discussed the possible impacts of AVs on travel satisfaction based on the study results, further research should be continued in this domain given AVs as the future of transportation. Particularly, it would be interesting to see how travelers will spend their travel time freed up in an AV instead of actively driving in a human-driven vehicle, and its possible impact on travel satisfaction.

CRediT author statement

Sailesh Acharya: Conceptualization, Study design, Data collection, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review and editing. **Michelle Mekker**: Supervision, Funding acquisition, Writing – review and editing. **Patrick A. Singleton**: Supervision, Writing – review and editing.

Declaration of Interest: None.

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Appendix

Table 2.6

CFA results of the measurement structures of attitudinal latent variables.

	Driving enjoyment		Polychronicity	
Variables	Coeff.	z-stat	Coeff.	z-stat
Driving enjoyment				
DE-1	0.488	n/a		
DE-2	-0.838	-8.806		
DE-3	-0.729	-9.358		
Polychronicity				
PC-1			0.807	n/a
PC-2			0.817	23.515
PC-3			0.888	24.216
Goodness-of-fit indices				
$\chi 2$ /df	21.350/8 = 2.668			
CFI/SRMR/RMSEA	0.990/0.043/0.149			

Note: Before fitting the CFA, the KMO value of 0.71 and the Chi-square value of 1584.35 (df = 15, p-value = < 0.001) resulting from the KMO test of sampling adequacy and Barlett's test of sphericity respectively confirmed the suitability of data for factor analysis.

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Chapter 3

Linking travel behavior and tourism literature: Investigating the impacts of travel satisfaction on destination satisfaction and revisit intention

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Abstract

This study aims to link two closely related domains in literature – travel behavior and tourism. Travel behavior studies partly aim to improve travel satisfaction by exploring its relationships with overall and domain-specific life satisfaction. Tourism studies, on the other hand, focus on improving the attraction and sustainability of tourism destinations and often investigate the factors affecting destination satisfaction and revisit intention. The present study uncovers the interconnections between travel behavior and tourism by investigating the impacts of travel satisfaction on destination satisfaction and revisit intention. An online survey of 696 visitors to national parks in the US conducted in the Summer of 2022 was analyzed using a structural equation modeling approach. Analysis results show that travel satisfaction has a direct impact on destination satisfaction and both direct and indirect (through destination satisfaction) impacts on revisit intention. Also, interestingly, results reveal that travel satisfaction has a stronger impact on revisit intention than destination satisfaction. These results offer an important implication to the tourism destination managers that investing in destination attributes alone might not be sufficient to attain the desired level of tourism for the destination. Thus, an area to be focused on is improving the satisfaction and experiences of travelers on the way to their destination. This could be achieved by investing in transportation infrastructures, networks, facilities, and services connecting major tourism destinations and city centers.

Keywords: destination satisfaction, revisit intention, tourism, travel behavior, travel satisfaction, structural equation modeling

3.1 Introduction

The study of ways to improve quality of life is of keen interest to researchers and policymakers across various disciplines, including travel, tourism, health, sociology, and psychology (Zhang, 2017). Both travel behavior (De Vos, 2019) and tourism (Smith & Diekmann, 2017) literature acknowledge the respective roles of daily travel or commute experiences and tourism activities on life satisfaction and overall well-being. Realizing these relationships, travel behavior studies have suggested transportation agencies minimize congestion (Ye & Titheridge, 2017), reduce travel time (Higgins et al., 2018), develop and promote advanced and safer vehicles (e.g., autonomous vehicles), design leisure- and work-friendly vehicle interiors (de Almeida Correia et al., 2019), etc. as ways to offer pleasant and satisfying travel experiences to the travelers. Tourism studies, on the other hand, have recommended tourism destination managers develop infrastructures in the destination and area around it (Sangpikul, 2018), offer affordable tour packages to the visitors (Ghose & Johann, 2018), arrange convenient transportation services around destinations (Loi et al., 2017; Thompson & Schofield, 2008), offer good food and accommodation facilities around the destination (Heung & Qu, 2020), etc. for exceptional tourism experience and sustained and repeated tourism. However, an important part of tourism travel—that is the emotions and experiences of travelers when traveling from home to destination—is seldom considered in either tourism or travel behavior literature, which therefore will be the focus of this study.

A plethora of existing studies (summarized in the literature review presented in Section 3.2) has somehow considered and found the significant impacts of transportation services, facilities, and experiences on tourism satisfaction. These studies conclude that accessibility, service quality, perceived value, and image of the transport system influence tourism satisfaction (Virkar & Mallya, 2018). However, they lack looking at a potentially important dimension of tourism travel: emotions experienced by the visitors when traveling from home to tourism destinations. The only relatable study that has considered this aspect is De Vos (2019), which asserted that there is a significant impact of affective and cognitive dimensions of travel emotions and experiences on the satisfaction with leisure activities conducted at the destination. In a country like the US, where the travel time and distance of tourism or recreational trips are relatively high (see NHTS, 2022), the investigation of the role of travel experiences and emotions on tourism destination satisfaction can be considered more important. Thus, deriving the data from US national park visitors, this study investigates the impact of travel satisfaction, a measure of affective emotions and cognitive evaluations of travel experience while traveling between home and destination, on destination satisfaction and revisit intention. Study findings are expected to offer important policy implications to the tourism destination managers, including the answer to the questions of whether they should take care of transportation infrastructures beyond the destination premises to improve visitors' travel experiences and attraction of destinations.

The remainder of this paper is organized as follows. Section 3.2 presents the review of tourism and travel behavior literature and conceptualizes the research model. Section 3.3 outlines the data collection procedure adopted and the descriptive statistics of the data. Section 3.4 describes the methodology adopted to attain the study objective. Section 3.5 presents the analysis results and related discussion. And lastly, study conclusions, implications, and limitations are presented in Section 3.6.

3.2 Literature review and research model

3.2.1 Destination satisfaction and revisit intention

The quality and performance of tourism destinations are often judged by the combination of two attributes: destination satisfaction and revisit intention. First, destination satisfaction refers to the aggregate feeling experienced by an individual after and/or during a visit to a destination (Cole & Scott, 2004). Destination satisfaction is measured either in the form of attribute satisfaction or overall satisfaction. Attribute satisfaction assesses the satisfaction level of the visitor on various attributes of the destination whereas overall satisfaction measures the visitors' level of satisfaction holistically. Depending upon the type of destination studied, common destination attributes considered by existing studies are nature, culture, service, infrastructure, accommodation, and food. Additionally, research has shown that individual attribute satisfaction leads to overall destination satisfaction (e.g., Chi & Qu, 2009; Hall et al., 2017; Yuan et al., 2018). Knowing the direct impacts of destination satisfaction on the destination's popularity, revisit intention, word-of-mouth publicity, consumption of products and services, and loyalty (Kozak et al., 2005), the monitoring of destination satisfaction and investigation of its influencers are crucial to destination managers to enhance visitors' overall destination experience and develop an effective destination marketing strategy.

Second, revisit intention is defined as the behavioral intention of a visitor to visit the destination again in the future. It is often called the strongest indicator of destination loyalty. The measurement of revisit intention is common because it is closely related to the concept of repeat tourism, which states that the sustainability and growth of a tourism destination rely (and should aim) on the tourists who repeat their visits rather than on the first-time visitors only (Meleddu et al., 2015; Van Dyk et al., 2019). Realizing this, a plethora of studies in the literature have investigated the factors affecting revisit intention and concluded that destination satisfaction is one of the strongest factors affecting revisit intention (e.g., Campo-Martinez et al., 2010; Humagain & Singleton, 2021; Lee et al., 2020; Pai et al., 2020).

3.2.2 Role of transportation services and experiences in tourism

While looking at the role of transportation services and experiences in tourism, two concepts, i.e., ‘transport as tourism’ and ‘transport for tourism’ need to be understood first (Page and Connell, 2014). First, the ‘transport as tourism’ concept states that transportation itself could be a tourism activity; for example, driving on a scenic route, sailing on a cruise or taking a cruise, riding in a gondola, etc. Transportation services and facilities being the major attraction of these ‘transport as tourism’ destinations, destination managers aim to provide exceptional transportation services and experiences to visitors. Past studies have investigated the impact of transportation facilities, services, and visitors’ experiences on overall destination satisfaction and revisit intention. Findings show that self-drive visitors (visitors who drive on routes for tourism) value the availability of road facilities (Wu et al., 2018), roadside facilities (Denstadli & Jacobsen, 2011), and scenery (Wu et al., 2018) on the route as important determinants of tourism satisfaction. Similarly, cruise tourists were found to consider the duration and cost of cruising (Kawasaki & Lau, 2020), the facilities available onboard (such as Wi-Fi, currency exchange, and shopping) (De Vaio et al., 2021), and crowding in the cruise (Sanz-Blas et al., 2019) as influencers of cruising satisfaction and loyalty. Overall, managers of 'transport as tourism' destinations acknowledge the significant role of transportation facilities, services, and experiences for sustained and repeated tourism and put forward their efforts in investing in transportation facilities and services to improve visitors' transportation experience. Also, some travel behavior studies believe in the existence of what they call 'undirected travel' or 'travel for its own sake' whereby trips have no destination, or the destination is ancillary to the travel (e.g., Hook et al., 2022; Mokhtarian and Salomon, 2001). These trips (e.g., recreational walking, cycling, jogging) show that travel can have positive utilities in itself (e.g., the sensation of speed, exposure to the environment), and may therefore be perceived as more positive than other types of trips (Hook et al., 2021).

Second, the concept of 'transport for tourism' emphasizes the importance of transportation facilities and services in tourism destinations that are not specialized for 'transport as tourism'. Any tourism destinations not meant primarily for transportation activities, such as national parks, fall under this category. These destinations mostly focus on providing exceptional tourism services by investing in infrastructures (within the destination and the area around), offering several accommodations and entertainment packages, and offering easy parking and transportation services (Benur & Bramwell, 2015). Within this list, the necessity of convenient transportation and parking services in the tourism destination and the area around it falls under the concept 'transport for tourism'. However, tourism literature only started realizing this concept more recently, such that only a few studies have investigated the role of transportation facilities, services, and experiences on destination satisfaction and revisit intention. Thompson and Schofield (2007) found a positive impact of ease of use of public transit facilities on destination satisfaction and revisit intention for Manchester, UK visitors. The quality of the tourist shuttle, measured from experiences with staff hospitality, punctuality of service, travel efficiency, and safety while traveling, was found to impact the satisfaction of the visitors of Macao city, China (Loi et al., 2017). Similarly, the choice of tourism destinations in Spain was influenced by the availability of convenient high-speed rail transportation (Pagliara et al., 2015). Apart from the transit services in destinations, Seetanah and Nunkoo (2020) found a positive role of visitors' satisfaction with airport services on their destination revisit intention. Overall, studies have concluded that the availability of convenient transportation services and facilities within the destination and the area around it plays a significant role in improving destination satisfaction and loyalty.

3.2.3 Travel satisfaction

Travel satisfaction is a measure of a traveler's experienced emotions and cognitive evaluation of travel resulting either from a specific trip or general daily travel (De Vos & Witlox, 2017). It is generally measured either by asking the travelers to rate a single statement about their travel (example question: *how would you rate your overall satisfaction level while traveling from origin to destination?*) or by asking the travelers to rate multiple statements about the travel experience. Among these two ways, travel behavior literature agrees that measurement by multiple items, which covers both affective emotions and cognitive evaluation of travel, is superior to single-item measurement, which mostly captures the cognitive evaluation of travel only. The most widely adopted multiple-item measurement scale of travel satisfaction is the satisfaction with travel scale (STS), where travelers are asked to indicate to what extent they experienced certain emotions and evaluated their travel. Original STS (Ettema et al., 2011) had nine items measuring three travel satisfaction dimensions: (1) positive deactivation (*time-pressed – relaxed*, *worried – confident*, *stressed – calm*), (2) positive activation (*tired – alert*, *bored – enthusiastic, fed up – engaged*), and (3) cognitive evaluation (*worst – best*, *low – high standard*, *worked well – poorly*). The STS has been modified in different research settings (Acharya et al., in progress; see also De Vos et al, 2015; Smith, 2017; Singleton, 2019a).

In the travel behavior literature, the measurement of travel satisfaction is considered a top priority because of its relationships with satisfaction with different life domains and overall life satisfaction or well-being (Mokhtarian & Pendyala, 2018). Research has shown a strong connection between commute satisfaction and work satisfaction (About-Zeid & Ben-Akiva, 2011), leisure travel satisfaction and activity satisfaction at the destination (De Vos, 2019), and daily travel satisfaction and overall well-being (Friman et al., 2017). Also, some studies (e.g., De Vos & Witlox, 2017; Mouratidis, 2020) suggest that daily travel satisfaction affects the choice of travel mode and residential location (in the long term) or vice versa. Realizing the importance of travel satisfaction, a plethora of studies have investigated the factors affecting travel satisfaction in search of ways to improve travel satisfaction (e.g., Acharya et al., in progress; Chen et al., 2022; Ettema et al., 2012, 2017; Singleton, 2019b; Shukov et al., 2021; Smith, 2017; Ye and Titheridge, 2017). Results of these studies show that socio-demographic characteristics, travel mode, travel time (perception), built environment and spatial attributes, travel-based activities, and individual attitudes affect one’s evaluation of travel.

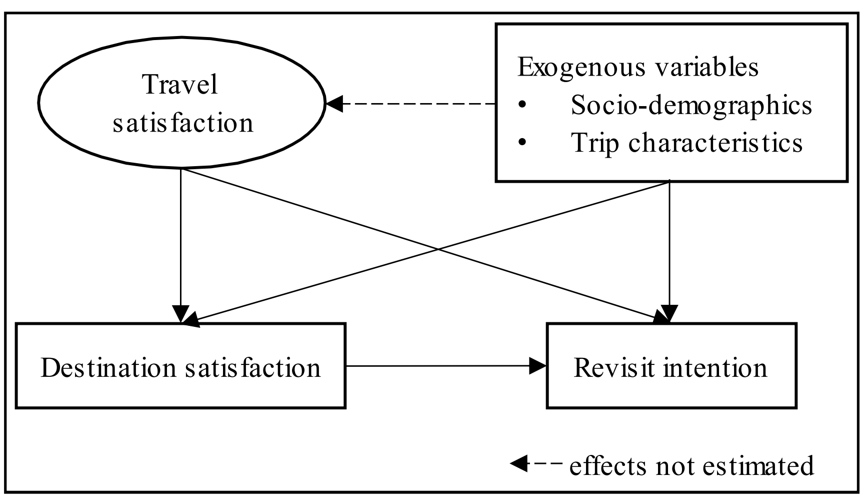
3.2.4 Summary and research model

The review of tourism and travel behavior literature presented above shows that studies linking these two domains are lacking. On the one hand, tourism literature focuses on enhancing the attraction of tourism destinations and has considered the role of transportation services and experiences in destination satisfaction and revisit intention. However, the transportation services and experience looked at in these studies are limited to the transportation facilities within the destination or area around it. To our knowledge, none of the studies in the tourism literature have investigated the role of transportation and travel experience (while traveling from home to destination and destination to home) on destination satisfaction and revisit intention. On the other hand, travel behavior literature acknowledges the importance of travel satisfaction in improving life satisfaction and well-being, but the literature lacks analysis of the role of travel satisfaction on tourism destination satisfaction and revisit intention. Thus, the primary objective of this study is to link tourism and travel behavior literature by investigating the impact of travel satisfaction (experiences of travel between home and destination) on destination satisfaction and revisit intention.

To attain the study objective, we propose a research model, shown in **Figure 3.1**, that hypothesizes the connections between travel satisfaction, destination satisfaction, and revisit intention. With the literature precedence on the significant impact of transportation services/experiences within the destination and the area around it (including airport services) on destination satisfaction and revisit intention, we hypothesize that travel satisfaction has a significant impact on destination satisfaction and revisit intention. Also, in line with existing tourism literature, we hypothesize a direct positive impact of destination satisfaction on revisit intention. With these two hypotheses, destination satisfaction is considered to mediate the impact of travel satisfaction on revisit intention. The impacts of travel satisfaction on destination satisfaction and revisit intention are controlled by the socio-demographic and trip characteristics of the respondents. The proposed model also hypothesizes the effects of socio-demographic and trip characteristics on travel satisfaction, but these effects are not estimated in this paper since a companion paper (Acharya et al., in progress) has calculated and presented these effects. Travel satisfaction is measured from a modified STS scale consisting of nine items whereas destination satisfaction and revisit intention are measured as single items. Utilizing the data collected from US national park visitors, the proposed research model is analyzed using the structural equation modeling (SEM) framework.

Figure 3.1

Proposed research model.



3.3 Data

The data used in this study was gathered from an online survey the authors conducted in the Summer of 2022 (see Acharya, 2022). The survey was part of a larger study designed to assess long-distance recreational travel behavior and preferences toward autonomous vehicles. In the survey, long-distance recreational travel was defined as travel intended for pleasure and recreation and involving at least 75 miles of travel one-way. Thus, the respondents of the survey were those who had visited one of the national parks of the US in 2022 by driving at least 75 miles one way, and no air travel was involved in the trip. The detailed information provided by the respondents about their most recent trips to national parks, including their travel experiences and destination satisfaction, are used in this study. The survey was distributed online using Qualtrics and 696 complete responses were collected. The following sections present the descriptive statistics of destination satisfaction and revisit intention, indicators of travel satisfaction, and the socio-demographic and trip characteristics of the sample along with their measurement.

3.3.1 Destination satisfaction and revisit intention

The destination satisfaction of national park visitors and their intention to revisit the destination are two outcome variables considered in the study, which are referred to as **destination satisfaction** and **revisit intention**, respectively. Both destination satisfaction and revisit intention were measured from single 5-point Likert scale questions. Though measuring revisit intention using a single question is common in literature, there exist two common ways to measure destination satisfaction – by measuring either individual attribute satisfaction or overall satisfaction. We adopted a single overall satisfaction question to measure destination satisfaction given the direct impact of attribute satisfaction on overall satisfaction found in the literature. The wording of questions, choice categories, and the distribution of responses for both variables, destination satisfaction and revisit intention, are presented in **Table 3.1**. The response distributions are negatively skewed with positive means as most of the respondents had positive perceptions towards destination satisfaction and revisit intention. While comparing the responses on destination satisfaction and revisit intention, visitors were found to have a slightly higher destination satisfaction (mean: 4.649) than revisit intention (mean: 4.427).

Table 3.1

Sample data for destination satisfaction and revisit intention (n = 696).

Variable	Question	Descriptive statistics		
		Response category	#	%
Destination satisfaction	How would you rate your overall satisfaction with this visit to [destination]?	Extremely dissatisfied	4	0.57
		Somewhat dissatisfied	6	0.86
		Neither satisfied nor dissatisfied	14	2.01
		Somewhat satisfied	182	26.15
		Extremely satisfied	490	70.40
		On average	4.649 (mean)	0.624 (s.d)
Revisit intention	How likely do you think that you would visit [destination] again in the future?	Extremely unlikely	9	1.29
		Somewhat unlikely	18	2.59
		Neutral	43	6.18
		Somewhat likely	223	32.04
		Extremely likely	403	57.90
		On average	4.427 (mean)	0.824 (s.d.)

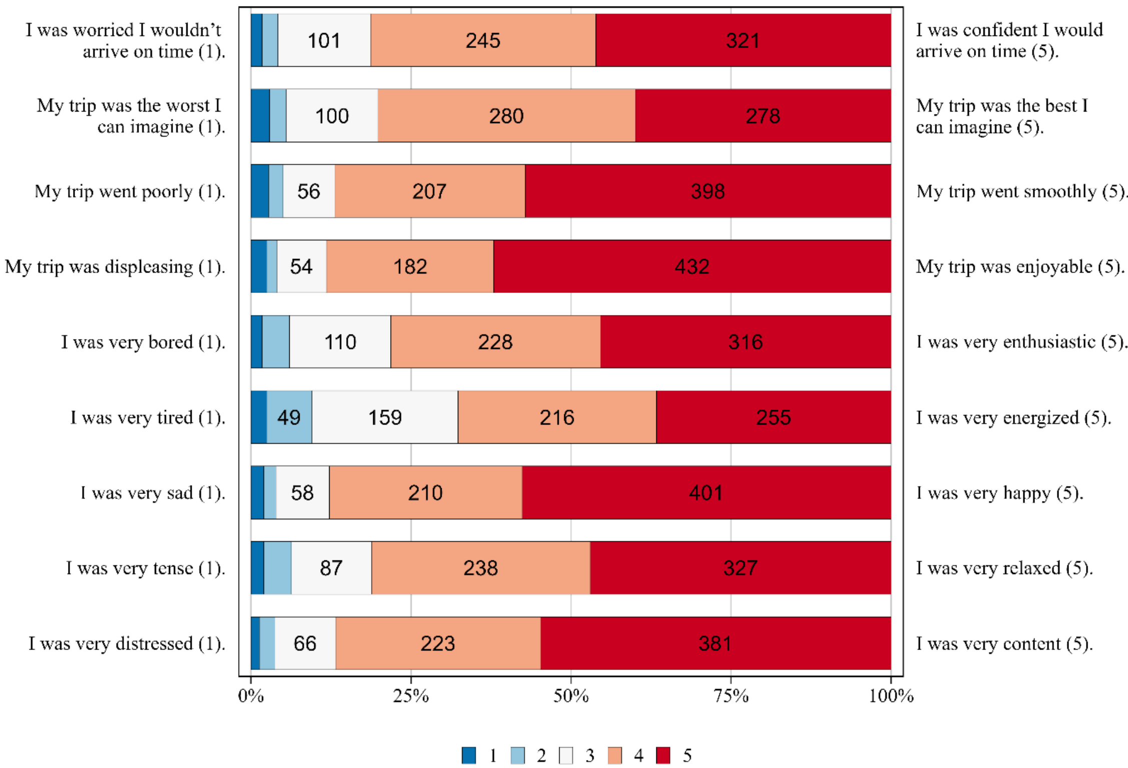
3.3.2 Indicators of travel satisfaction

Being the primary variable of interest in the study, travel satisfaction was measured from a comprehensive multi-item scale of travel satisfaction measurement called the Satisfaction with Travel Scale (STS) which assesses both affective and cognitive dimensions of travel experience. Thus, in the questionnaire, respondents were asked to rate nine statements about how they felt while traveling on a five-point semantic differential scale. The wording of the statements/items of STS was adapted from

Singleton (2019a), which modified/validated the STS developed by Ettema et al. (2011) (and later modified by De Vos (2015)) for the US context. The list of the statements asked in the questionnaire and the distribution of responses are presented in **Figure 3.2**. The distribution shows that more than three-quarters of the sample had positive perceptions (ratings 4 and 5, out of 1-5) towards the statements of travel satisfaction.

Figure 3.2

Sample data for travel satisfaction indicators (n = 696).



3.3.3 Socio-demographic and trip characteristics

To control for the impacts of travel satisfaction on destination satisfaction and revisit intention, several socio-demographic and trip characteristics of the respondents are considered in the study. The variables considered, and their descriptive statistics are presented in **Table 3.2**.

The sample consisted of adults only such that the age was at least 18 years. Among them, more than half (58.85%) belonged to the 35-64 years age category. The proportion of females (56.90%) was slightly higher than that of males (43.10%). In terms of race, more than three-quarters of respondents were white. More than half of the sample had at least an undergraduate degree (58.19%). The proportions of students (26.44%) and unemployed individuals (30.17%) in the sample were almost equal. The annual household income of almost half of the sample (49.14%) lay between $25k and $75k. The average number of adults (age >18 years) and children (age <18 years) in the household of the sample were 2.18 and 0.98, respectively. All respondents had a driving license, and the average driving experience reported was 25.66 years. The average number of household vehicles in the sample was 1.52. Respondents reported that they typically make 3.32 long-distance recreational trips in a year, on average.

The socio-demographic characteristics of the US population (obtained from the American Community Survey Data (US Census Bureau, 2021)) are compared with the respondents' characteristics to assess the representativeness of the sample (**Table 3.2**). The sample and US population distribution look fairly similar for age, gender, race, and income. Compared to the US population, middle-aged (35-64 years) individuals, females, whites, and individuals from middle-income households ($25-100k) were slightly overrepresented in our sample. Since these discrepancies were small, no weighting of the sample was performed before analysis.

Based on the characteristics of the recent long-distance recreational trip made by the respondents, the average one-way travel time and travel cost in the sample were found to be 10.89 hours and $193.30 respectively. During the travel, there were 2.36 travel companions on average in the sample, out of which travelers' spouses account for 65.09%. Around one-third of the sample (38.65%) were first-time visitors to the destination. Slightly less than half of the sample (47.12%) stayed at the destination for at least two nights.

Table 3.2

Sample data for socio-demographic and trip characteristics (n = 696).

Variable	Sample				US population
	#	%	Mean	SD	%
Socio-demographics					
Age					
18-34 years	191	27.44			29.14
35-64 years	404	58.05			49.23
65+ years	101	14.51			21.63
Gender					
Female	359	56.90			49.50
Male/Other	337	43.10			50.50 (male)
Race/ethnicity					
White	576	82.76			72.90
Others	120	17.24			
Education					
No college degree	291	41.81			
Undergraduate degree	278	39.94			
Graduate degree or higher	127	18.25			
Student					
No	512	73.56			
Yes, part-time	46	6.61			
Yes, full-time	138	19.83			
Employment					
No	210	30.17			
Yes, part-time	90	12.93			
Yes, full-time	396	56.90			
Household income (annual)					
< $25k	110	15.80			17.40
$25-50k	187	26.87			19.10
$50-75k	155	22.27			16.80
$75-100k	99	14.22			12.80
≥$100k	145	20.83			34.00
# adults in the household (age ≥18 years)			2.18	0.98	
# children in the household (age <18 years)			0.90	1.15	

Driving experience (years)			25.66	16.61
# of household vehicles			1.52	0.77
Typical # of long-distance recreational trips per year			3.32	2.19
Trip characteristics				
Travel time (hours, one way)			10.89	12.83
Travel cost (dollars, one way)			193.40	202.52
Travel companion				
Total #			2.36	1.93
Spouse: present	453	65.09		
Children: present	320	45.98		
Siblings: present	56	8.01		
Other family members: present	109	15.66		
Friends: present	135	19.40		
Length of stay at the destination				
Less than 1 hour	6	0.86		
1-4 hours	104	14.94		
4-8 hours	119	17.10		
1 night	139	19.97		
2 nights	180	25.86		
More than 2 nights	148	21.26		
# of past visits to the destination				
None	269	38.65		
1	184	26.44		
2	119	17.10		
3	43	6.18		
More than 3	81	11.64		

3.4 Methodology

We used confirmatory factor analysis (CFA) and structural equation modeling (SEM) techniques in this study. The measurement structure of travel satisfaction was defined using CFA. A measurement model defines the relationship between unobserved latent factors and observed items. Here, travel satisfaction was considered the second-order factor measured from three first-order factors: positive deactivation, positive activation, and cognitive evaluation (to be described later), derived from nine observed five-point Likert scale items (presented in **Figure 3.2**).

The specification of the measurement model that shows the connections between observed items and three first-order latent factors is shown in Equation 3-1.

$$v_t = \lambda_t F_l^* + e_l \tag{3-1}$$

where, $l \in \{1, 2, 3\}$ and $t \in \{1, 2, \ldots, 9\}$ are the indexes of first-order latent factors (representing positive deactivation, positive activation, and cognitive evaluation respectively) and observed items (presented in **Figure 3.2**) such that F_l^* and v_t represent the vector of first-order latent factors and their respective observed items. λ_t is the vector of parameters that link observed items v_t and latent factors F_l^*. e_l represents the measurement error associated with each factor. The measurement errors are assumed to be standard normally distributed.

Similarly, the specification of the measurement that shows the connections between first- and second-order latent factors is shown in Equation 3-2.

$$F_l^* = \lambda_l F + e \tag{3-2}$$

F represents the second-order factor (i.e., travel satisfaction) which is related to the first-order factors by the vector of parameters λ_l. e represents the measurement error associated with the second-order factor which is assumed to be standard normally distributed. The procedure adapted to finalize the configuration of the second-order factor structure of travel satisfaction is presented later.

Once the measurement model of travel satisfaction was defined, SEM was used to investigate the impacts of travel satisfaction on destination satisfaction and revisit intention as per the research model defined in **Figure 3.1**. A structural equation model assesses the simultaneous relationships between latent and exogenous variables of interest. In the structural model, destination satisfaction and revisit intention were outcome variables whereas travel satisfaction (i.e., the second-order latent factor), socio-demographics, and trip characteristics were considered possible predictors. Also, the model considered the simultaneous direct impact of destination satisfaction on revisit intention. A general specification of the structural equation model is represented by Equation 3-3.

$$Y_l = B_i X_i + r_l \tag{3-3}$$

where $i \in \{1, 2, \dots, I\}$ is the index of predictor variables such that X_i denotes the vector of predictor variables (travel satisfaction (F), socio-demographics, and trip characteristics; also destination satisfaction in the case of revisit intention as outcome variable) and B_i represents their respective parameters that explain their relationships with the outcome variable (destination satisfaction and revisit intention) Y_j. r_l is the vector of residuals associated with each outcome variable. This error term is also assumed to be standard normally distributed.

As recommended by Kline (2015), the goodness-of-fit of measurement and structural models were judged by the combination of a number of indices: the ratio of chi-square value to degrees of freedom (χ^2 /df), comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). In general, a model with a higher value of CFI and lower values of χ^2 /df, RMSEA, and SRMR better fit the data. As suggested by the literature (Browne & Cudeck, 1992; Hair et al., 2010; Hooper et al., 2008; Hu and Bentler, 1999; Kline, 2015), the cutoff values of these indices for a good model fit are: χ^2 /df < 2, CFI > 0.95, RMSEA < 0.05, and SRMR < 0.08, and for an acceptable model fit are: χ^2 /df < 5, CFI > 0.90, RMSEA < 0.08, and SRMR < 0.10. All measurement and structural models were fitted using the lavaan package (Rosseel, 2012) in R (R Core Team, 2022). As seen in **Table 3.1** and **Figure 3.2**, the responses to outcome variables (destination satisfaction and revisit intention) and indicators of the latent factor (travel satisfaction) were not normally distributed (negatively skew with positive means); thus, a robust variant of the maximum likelihood estimator developed by Yuan and Bentler (2000) called maximum likelihood estimation with robust standard errors and a Satorra-Bentler scaled test statistics (MLM) was used for estimating measurement and structural models.

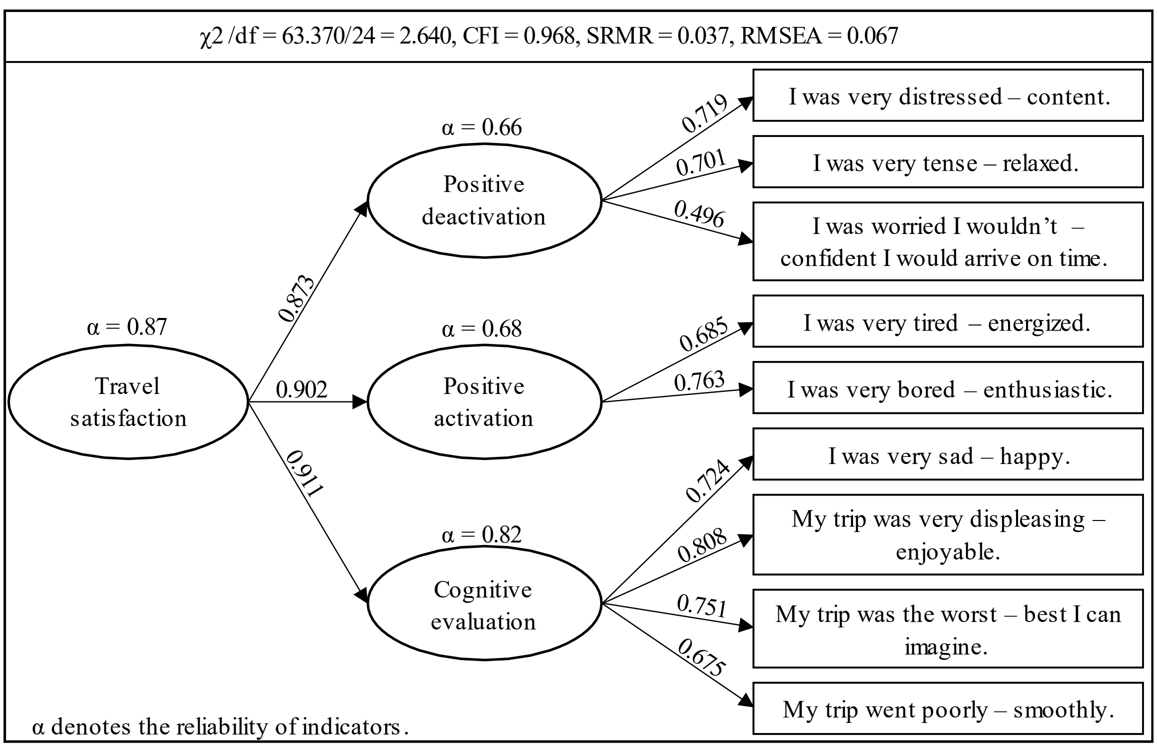
3.5 Results and discussions

3.5.1 Confirmatory factor analysis results: measurement structure of travel satisfaction

The measurement structure of travel satisfaction was defined from nine scale items assessing travel experience using CFA. Travel satisfaction, being a domain of overall life satisfaction and wellbeing, is believed to be composed of three dimensions: the first two dimensions – positive deactivation (PD) and positive activation (PA) – are related to the affective experience of travel whereas the third dimension refers to cognitive evaluation (CE) of travel. A separate companion paper (Acharya et al., in progress) defined the relationships between nine observed items and these three dimensions of travel satisfaction where items "*distressed – content*", "*tense – relaxed*", and "*worried – confident on time*" defined PD, items "*tired – energized*", and "*bored – enthusiastic*" defined PA, and items "*sad – happy*", "*displeasing – enjoyable*", "*worst – best*", and "*poorly – smoothly*" defined CE. For this paper, we defined the second-order factor called "travel satisfaction" which essentially captures the commonality between these three travel satisfaction dimensions (PD, PA, and CE). This definition of the second-order factor was supported by higher correlations between PD, PA, and CE (0.788-0.822). Finally, CFA was conducted for the proposed second-order measurement structure of travel satisfaction and the results are resented in **Figure 3.3**. The acceptable goodness-of-fit statistics (χ^2 /df = 2.640 < 5, CFI = 0.968 > 0.90, RMSEA = 0.037 < 0.08, and SRMR = 0.067 < 0.10) of the measurement model confirm that the second-order measurement structure of travel satisfaction is viable and can be used for further analysis. With this, the overall impact of travel satisfaction on destination satisfaction and revisit intention, rather than the individual impacts of the three travel satisfaction dimensions, can be assessed.

Figure 3.3

Measurement model of travel satisfaction.



3.5.2 Structural equation modeling results

The research model proposed in **Figure 3.1** was analyzed using SEM and the results are presented in **Table 3.3**. In the research model, travel satisfaction was the only latent variable that was measured as defined in Section 3.5.1, and the rest of the variables were directly measured as discussed in Section 3.3. In terms of variables related to socio-demographic and trip characteristics, all variables presented in **Table 3.2** were first considered in the model but the model was finalized by gradually dropping the insignificant effects. Thus, only the (marginally) statistically significant estimates (at a 90% confidence interval) are presented in **Table 3.3**. Since, the proposed model conceptualized the inter-relationship between the outcome variables, both direct and indirect impacts of predictor variables on outcome variables exist. To maintain brevity, only the direct effects of socio-demographic and trip characteristics on outcome variables were computed; however, travel satisfaction being the variable of interest in the study, both direct and indirect effects as well as total effects of travel satisfaction on revisit intention were computed and are presented in **Table 3.3**. The goodness-of-fit statistics of the final model (χ^2 /df = 1.428 < 2, CFI = 0.968 > 0.95, RMSEA = 0.033 < 0.05, and SRMR = 0.027 < 0.08) lay under good range. Finally, the interpretations of the results presented in the following sub-sections are based on the final model outcomes (shown in **Table 3.3**).

3.5.2.1 Relationships between travel satisfaction, destination satisfaction, and revisit intention

The model results show that travel satisfaction had a direct impact on both destination satisfaction and revisit intention. Also, since destination satisfaction had a significant direct positive impact on revisit intention, travel satisfaction had an indirect impact on revisit intention through destination satisfaction. Looking at the direct effects, the direct effect of destination satisfaction (0.260) on revisit intention was higher than that of travel satisfaction (0.205). However, when accounting for the indirect effect of travel satisfaction on revisit intention through destination satisfaction (0.117), the total effect of travel satisfaction (0.322) surpassed the direct effect of destination satisfaction (0.260). Also, the direct effect of travel satisfaction on destination satisfaction alone (0.448) was higher than the total effect (0.322) on revisit intention.

First, the direct positive impact of destination satisfaction on revisit intention, found in this study, aligns with past studies (Campo-Martinez et al., 2010; Humagain & Singleton, 2021; Lee et al., 2020; Pai et al., 2020). This confirms how crucial the satisfaction of the visitors to the destination is for them to develop destination loyalty and a positive intention to revisit the destination. Second, results showing the positive impacts of travel satisfaction on destination satisfaction (direct effect only) and revisit intention (both direct and indirect effects) support our prior hypothesis that travel satisfaction is an important indicator of destination satisfaction and loyalty. Thus, it is suggested that travel satisfaction should not be ignored when discussing ways to improve destination loyalty and revisit intention. Third, a higher effect size of travel satisfaction on destination satisfaction than on revisit intention indicates that travel satisfaction has a stronger immediate impact on destination experience than on intention to revisit in the future. Thus, based on the joint model results, it could be concluded that travel satisfaction has a significant role in shaping travelers’ perception of destination satisfaction and revisit intention.

When looking closely at the results, the effect of travel satisfaction on revisit intention was higher compared to that of destination satisfaction. This finding is surprising since tourism studies have always considered destination satisfaction as the strongest influence of revisit intention or destination loyalty, neglecting the emotions experienced on the way to destinations. However, the difference in the magnitudes of these effects could have been amplified by the survey strategy adopted. Most of the respondents have probably responded to the survey shortly after their visits, as this retrospective survey was conducted in the Summer when most people visit national parks in the US. Since the size of the effect of longer-term remembered destination experiences on revisit intention is usually higher than that of shorter-term remembered experiences (Barnes et al., 2016), it could have been too short for the respondents to reveal their stable destination satisfaction and revisit intention in the survey. In terms of travel satisfaction, the affection and evaluation of the travel for an individual can be assumed to decrease over time with the strongest effect during or just after the travel. Based on these reasons, we speculate that the size of the effects of travel satisfaction and destination satisfaction on revisit intention calculated in this analysis might represent the short-term impacts.

3.5.2.2 Socio-demographic and trip-specific determinants of destination satisfaction and revisit intention

The model results show that several socio-demographic and trip characteristics were associated with destination satisfaction and revisit intention. Older-aged individuals (65+ years of age) had lower revisit intention than their younger counterparts. Undergraduate degree holders were less interested in revisiting the destination compared to individuals with other educational backgrounds. Part-time students had overall lower ratings on destination satisfaction than non- and full-time students whereas full-time employees had higher revisit intention. Belonging to a household with income > $100k was linked to having lower revisit intention. An increase in the number of household vehicles was related to the increase in destination satisfaction. These results show that some socio-demographic characteristics explain the heterogeneity in destination satisfaction and revisit intention.

An increase in travel companions was linked with an increased destination revisit intention in our data. This finding aligns with past studies (e.g., Vada et al., 2022) and empirically supports the idea that the presence of travel companion/s improves tourism experiences and satisfaction. Also, looking specifically at the type of companion, trips made with spouse and friends were found to have higher revisit intention and destination satisfaction, respectively. Though past studies had contradictory findings on the impact of length of stay on tourism experiences (e.g., Kim & Lee, 2016 (positive impact) vs. Feitosa & Silva, 2022 (negative impact)), the length of stay was associated positively with destination satisfaction and revisit intention in our model: visitors who stayed for more than one and two nights had significantly higher revisit intention and destination satisfaction, respectively. Finally, the visitors who had visited the destination at least three times in the past unsurprisingly had significantly higher revisit intentions for the future too compared to those who have visited the destination less than three times in the past.

Table 3.3

Structural equation modeling results.

Variables	Destination satisfaction		Revisit intention	
	Coeff.	z-stat	Coeff.	z-stat
Travel satisfaction				
Direct effect	0.448	7.272	0.205	3.908
Indirect effect			0.117	4.446
Total effect			0.322	5.974
Destination satisfaction				
Direct/total effect			0.260	4.567
Socio-demographics (direct effects only)				
Age				
65+ years			-0.187	-4.124
Education: Undergraduate degree			-0.063	-1.830
Student				
Yes, part-time	-0.121	-2.651		
Employment				
Yes, full-time			0.099	2.726
Household income (annual)				
More than $100k			-0.094	-2.606
# of household vehicles	0.073	2.221		
Trip characteristics (direct effects only)				
Travel companion				
Total #			0.065	2.192
Spouse: present			0.083	2.365
Friends: present	0.063	1.997		
Length of stay at the destination				
2 nights	0.174	5.568		
More than 2 nights	0.099	2.603	0.069	2.928
# of past visits to the destination				
3			0.069	2.928
More than 3			0.179	5.335
Goodness-of-fit statistics				
$\chi2$ /df	241.348/169 = 1.428			
CFI/SRMR/RMSEA	0.968/0.033/0.027			
R-squared value	0.253		0.278	

Note: All coefficients are standardized.

3.6 Conclusion

With the primary aim to link two closely related domains of literature – travel behavior and tourism, we applied a structural equation modeling approach to investigate the impact of travel satisfaction on destination satisfaction and revisit intention. First, results show that affective and cognitive experiences while traveling between home and destination have a significant impact on one's evaluation of destination satisfaction and revisit intention. This has implications for both travel behavior and tourism literature. Tourism literature seeks to the factors that affect the sustainability of tourism destinations (Meleddu et al., 2015; Van Dyk et al., 2019), and this result informs tourism destination managers to consider travel emotions and evaluations of visitors when searching for ways to improve the attraction of tourism destinations. Thus, we recommend tourism destination managers develop ways to improve travel satisfaction to tourism attractions. For this, the results of travel behavior studies could be utilized: trip characteristics, road network features, vehicular attributes, individual attitudes and perceptions, and socio-demographics have significant associations with travel satisfaction (Acharya et al., in progress; Chen et al., 2022; Ettema et al., 2012, 2017; Singleton, 2019b; Shukov et al., 2021; Smith, 2017; Ye and Titheridge, 2017). Travel behavior studies aim to investigate the connections between travel domain-specific life satisfaction and satisfaction with other domains of life (Mokhtarian & Pendyala, 2018), and this result confirms a clear relationship between travel satisfaction and tourism satisfaction. This finding embraces the attention paid to examining travel satisfaction by travel behavior studies that aim to improve life satisfaction and well-being.

Second, results reveal that the impact of travel satisfaction on revisit intention is stronger than the impact of destination satisfaction on revisit intention. This remarkable finding again highlights the importance of travel satisfaction in maintaining sustained and repeated tourism for a destination but also suggests that investing in destination attributes alone might not be sufficient to attain the desired level of tourism for the destination. Other study results such as the relationships between travel satisfaction, trip characteristics, and socio-demographics with destination revisit intention are in line with the existing tourism studies. Overall, this study aims to uncover an important aspect of tourism destination satisfaction, i.e., travel satisfaction, while keeping other factors the same. Thus, this study first aligns with the recommendations put forward by tourism studies that sustained and repeated tourism of a destination can be maintained by regularly investing in infrastructures in the destination and area around it, developing affordable tour packages, offering good food and accommodations, managing good transportation facilities around the destination, etc. and second presents a novel recommendation to the destination managers that travel experiences of the visitors while traveling between home and destination should also be taken care of. Being significant indicators of travel satisfaction, investment in transportation networks, facilities, and services connecting major tourism destinations and city centers could boost the travel satisfaction of the visitors of tourism destinations. Specifically, creating high-capacity road infrastructure (resulting in limited congestion) and reliable travel time information on the way to tourism destinations, in combination with sufficient and cheap parking facilities, may stimulate travel satisfaction (Ettema et al., 2013; Susilo & Cats, 2014). Developing more rest areas and combining them with service plazas, restaurants, and other entertainment options as well as scenic viewpoints/landscapes on the way to destinations could help offer positive experiences to travelers. An environmentally sustainable strategy could be offering public transit services to the visitors which could be dedicated to the tourism destination and have different entertainment options (e.g., bars, restaurants, casinos, etc.) in-vehicle. This option is essentially the addition of the 'transport for tourism' concept to conventional destination attraction strategies.

Being the first study to conceptualize and empirically prove the relationships between travel satisfaction and destination satisfaction and revisit intention, this study has several limitations that could offer several future research opportunities. First, people may confound their liking/satisfaction for the destination, destination attributes, or activities conducted at the destination with their liking of travel to reach that destination (people being happy with their travel because they are going to a recreational or fun destination) (see De Vos, 2019 for reasonings). This would mean that not only travel satisfaction can affect destination satisfaction, as hypothesized in this study, but also the other way around to a certain extent. This opposing relationship was not investigated in this study and could be a future research opportunity. Second, as tourism studies (e.g., Loi et al., 2017) agree that overall destination satisfaction and loyalty are mediated by designation image, future studies should aim at investigating the mediation by destination image and other possible variables to broaden the understanding of the role of travel satisfaction in tourism. Third, as discussed earlier, the relationships between travel satisfaction, destination satisfaction, and revisit intention estimated in this study mostly represent the short-term impacts. Thus, estimating the same relationships based on long-term remembered experiences could help understand the phenomena more precisely. Fourth, this study measured destination satisfaction and revisit intention from single items to maintain the brevity of the questionnaire. Future studies could consider destination satisfaction measured through several attributes (such as nature, people and culture, hospitality, food, accommodation, transportation, infrastructure, etc.) and investigate the relationships of travel satisfaction with each destination attribute satisfaction. Also, a question on only revisiting intention might not represent destination loyalty completely. Thus, including the recommendation intention could strengthen the measurement of destination loyalty. Fifth, the survey used in this study included the responses of the US national park visitors who visited by driving only. These inclusion criteria were selected purposefully to attain multiple objectives of the survey which are beyond this study's objectives but limit the generalizability of this study's findings. The examination of the same relationships (i.e., impacts of travel satisfaction on destination satisfaction and loyalty) for different research settings, including destinations other than national parks, the visitors using different travel modes (e.g., public transit, air travel, etc.), the visitors and destinations from different geographical scope, etc., could be a future research avenue.

Declaration of Interest: None.

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Chapter 4

Acceptance and demand of autonomous vehicles for long-distance recreational travel

Abstract

The study of anticipated changes in travel behavior that could be brought by autonomous vehicles (AVs) has been widely studied for commuting and short-distance daily travel, but little attention has been given to long-distance travel. To fill this research gap, this study presents an analytic framework that estimates the public preference towards the adoption and use (in terms of frequency and length of trips) of AVs for the specific case of long-distance recreational travel (LDRT), which is behaviorally and structurally different than commute travel, using the data collected from a survey of US national park visitors conducted in Summer 2022. Numerous exogenous factors (socio-demographics, general travel behavior, trip-specific characteristics, in-vehicle time use-related factors) and attitudinal latent variables (AV usefulness, AV concern, driving enjoyment) were considered as potential influencers of AV acceptance and demand in the model, which was analyzed using the structural equation modeling (SEM) technique. The results indicate that the frequency and length of long-distance recreational trips will likely be higher in the AV era. This brings the attention of tourism destination managers not only to manage the tourists' demand at destinations but also to manage the traffic on the roads leading to the destinations. In addition, the results show that the LDRT demand will continue to rise with the increase in AV acceptance because of the usefulness and the potential for several in-vehicle activities offered by vehicle automation despite the system safety, data privacy, and legal liability concerns associated. The study results also reveal

that some travelers will likely miss manual driving enjoyment in AV driving, especially in a novel travel environment like tourism travel, and thus might opt for manual driving options. Based on the study findings, we advocate for the timely consideration of induced LDRT and tourism travel demand generated by AVs—for example by provisioning sustainable public transport options to recreational and tourism destinations.

Keywords: autonomous vehicles, public acceptance, travel demand, in-vehicle activities, time use, long-distance travel, tourism

4.1 Introduction

Over the last few years, transportation studies have widely focused on understanding the public preferences towards the adoption of autonomous vehicles (AVs) including their several forms (as privately-owned vehicles, shared vehicles, public transport, etc.) as a top research priority, given the future of AVs. Most of these studies have evaluated the heterogeneity in different forms of AV adoption based on socio-demographics, individual attitudes, and existing travel behavior (see review papers: Gkartzonikas and Gkritza, 2019; Narayanan et al., 2020; Othman, 2021), while some (e.g., LaMondia et al., 2016; Perrine et al., 2020) have predicted the travel demand in different scenarios of AVs' market penetration. However, these efforts either mostly revolve around AV adoption/demand for commutes/daily trips or rely on some hypothetical assumptions that do not fully capture users' perceptions leaving the realistic investigation of AV preferences/demand for long-distance travel a less studied topic, as highlighted by a recent literature review by Thomopoulos et al. (2021). The relatively less focus on the study of long-distance travel behavior and associated implications of AV adoption in the existing literature could be attributed to a small share of long-distance trips in total trips: 2.5% of trips in the US were >50 miles one-way in 2017 (McGuckin, 2018). However, the study of long-distance travel behavior is important because these trips contribute a large share of total person-mile travel: 43.3% of total person-mile travel in the US was contributed by trips >50 miles in 2017 (McGuckin, 2018).

Realizing this, the present study is dedicated to understanding the public perception of the adoption and use of AVs for long-distance travel. More specifically, the case study is made for the "recreational" purpose only within the broad spectrum of long-distance recreational travel. The choice of recreational travel purpose comes with two reasons: (1) recreational trips contribute a large share of long-distance trips, especially in a country like the US where popular recreational destinations like national parks require a significant amount of travel, and (2) the study of recreational travel is important from a life satisfaction and well-being perspective as the activity participation at recreational destinations is considered a top contributor to individuals' life satisfaction and overall well-being (Smith and Diekmann, 2017). This study defines long-distance recreational travel (LDRT) as the trips made to national parks by driving (partially or fully) at least 75 miles one-way. With this definition, we introduce a conceptual model to study the public preferences towards the adoption and use of AVs for the LDRT. The model jointly estimates the preference to adopt an AV (instead of a human-driven vehicle (HV)), using AVs for more trips, and using AVs for longer trips among several socio-demographic, individual travel behavior, trip-specific, in-vehicle time use-related, and attitudinal characteristics. In addition, the model uniquely estimates the impacts of AV adoption preference and AV use preference in terms of frequency and length by allowing the preferences for more AV trips and longer AV trips to correlate with each other. The data to analyze the proposed model was collected from a survey of visitors to US national parks conducted in 2022 Summer.

The remainder of this paper is organized as follows. Section 4.2 presents a review of the relevant existing studies and concludes with specific study objectives. Section 4.3 outlines the procedure adopted and the instruments used in data collection along with the descriptive statistics of the data. Section 4.4 proposes the conceptual research model and discusses the methodology adopted to analyze the proposed research model. Section 4.5

presents the model results and associated discussions. And lastly, study conclusions, implications, and limitations are presented in Section 4.6.

4.2 Related works and current study

With several years of research on AV adoption interest, studies have concluded that the public's interest in AV adoption varies based on several factors, ranging from socio-demographics and individual attitudes/perceptions to built environment characteristics (see reviews by Gkartzonikas & Gkritza, 2019; Golbabaei et al., 2020; Keszey, 2020; Zhang & Kamargianni, 2023). In addition to these factors, an individual's interest in adopting or using an AV also varies based on the form of AV (privately owned, shared service, public transit, etc.) (Acharya 2023; Wang et al., 2020) and trip characteristics (travel time, travel cost, trip purpose, etc.) (Tu et al., 2022). Furthermore, it is commonly accepted that the adoption and demand for AVs for long-distance trips will vastly differ from that for short-distance trips (Dannemiller et al., 2023). This consensus hypothesizes that AV adoption interest for long-distance travel will be higher than for usual short-distance travel (e.g., commute and other daily travel) with two assumptions: (1) the time freed up in AV travel because self-driving could be utilized for other activities of interest, and (2) the stress/tiredness of manual driving will be released in AV travel. Both advantages are considered to have a pronounced effect on long-distance travel compared to short-distance because of the longer travel time spent in long-distance travel.

There have been a few empirical research studies to understand how time use in AV travel will change and its impact on the adoption and use of AVs. By time use, we refer to the utilization of travel time for in-vehicle activities, hereafter referred to as travel-based activities (TBAs), such as listening to music, using social media, talking on the phone or with other passengers, reading, sleeping or snoozing, etc. Based on a survey of the Austin population, Dannemiller (2023) discovered that individuals who like to do more in-vehicle activities are more likely to use AVs for more and longer trips. They also identified that the magnitude of the impact of TBA on AV demand is higher for long-distance trips compared to short-distance trips. Kim et al. (2020) identified the segments of Georgians based on their interests in different in-vehicle activities they like to do during AV travel and analyzed the correlation of segments with the frequency and length of AV trips. They concluded that AVs would increase both the frequency and length of trips, but they would have a stronger impact on increasing trip length compared to increasing trip frequency. Besides these, some studies have looked at the choice preferences between automated and conventional travel modes. Ashkrof et al. (2019) conducted a stated choice experiment in the Netherlands to analyze the choice between conventional car, public transport, and automated driving transport service (ADTS) and found ADTS as an attractive mode for long-distance leisure trips compared to short-distance commuting trips. A similar finding in terms of a higher preference for AVs for long-distance trips compared to short-distance trips was asserted from a survey of the South Korean population (Lee et al., 2021). The results of these studies embrace the hypothesis that the interest in the adoption and use of AVs would be higher for long-distance trips compared to short-distance trips. Conversely, the discussions related to concerns on the effective utilization of in-vehicle travel time during AV travel have been growing since Singleton (2019) noted that the propensity of increase in TBAs during AV travel would likely be modest compared to HV travel because of vehicle designs and road alignments. However, empirical evaluation of the changes in TBA participation in-vehicle during AV travel compared to HV travel (and other conventional modes) is lacking despite its high importance (e.g., to calculate the change in the value of travel time that is used for the economic evaluation of highway projects).

The analysis of in-vehicle time use during AV travel compared to HV travel will be complete only when the manual driving enjoyment is incorporated. This is because the propensity of utilizing travel time for TBAs is limited depending on whether the individual is manually driving the vehicle or not (Keseru and Macharis, 2018). The wide discussion on higher TBAs in AV travel (compared to HV travel) assumes that people do not like to manually drive vehicles (because it is a stressful job); instead, they like to do other activities in-vehicle. However, there is a notion that some people love manually driving vehicles, probably because the sensation of the engine and acceleration (Bjorner, 2017) has been ingrained in the human experience for centuries. Past empirical studies have shown that manual driving enjoyment is associated with lower interest in using and adopting AVs (e.g., Haboucha et al., 2017), but manual driving enjoyment is also likely to decrease when the trip distance or time increases because of the increased driving efforts (or stress). The role of manual driving enjoyment is more important in our study context (i.e., LDRT) because of the novel travel environment associated (to be discussed in the next paragraph) with longer travel.

Since tourism trips are parallel to long-distance recreational trips, the dynamics involved in tourism travel need to be considered when talking about LDRT. Tourism travel is unique from daily travel (e.g., commuting, shopping, etc.) because it usually involves new routes (probably scenic routes as well), offers freedom from the daily schedule, and is related to the excitement for destination activities creating a novel travel environment. This necessitates the understanding of AV implications in tourism travel behavior. Realizing this, tourism studies have started discussing the importance of the integration of AVs in tourism research (e.g., Burcher et al., 2018; Cohen and Hopkin, 2019). They have a common consensus that AVs could change the way people travel to tourism destinations because of the flexibility offered by AVs (e.g., night-time traveling where travelers can sleep in-vehicle). A few empirical studies have investigated the potential impacts of AVs on tourism. For instance, Ribeiro et al. (2022) found that public trust in technology plays a vital role in the adoption of AVs for tourism. Similarly, Tussyadiah et al. (2017) concluded that the reliability and functionality of automation could boost AV acceptance in tourism. These findings are not new when referring to travel behavior literature. However, the critical need in tourism literature is to empirically analyze the behavioral changes in tourism travel with the introduction of AVs. This will essentially inform the anticipated changes in tourism demand and potential behavioral changes in activity participation at destinations such that destination managers can prepare well ahead to act on such changes.

Based on the discussion presented above, the following points discuss how the present study departs from the existing studies and contributes to the knowledge base:

- The existing empirical studies looking at the impact of TBAs on AV adoption/uses haven’t considered the change in TBAs compared to existing modes. In fact, the propensity of TBAs for a travel mode has always been linked positively to the choice of that mode (Keseru and Macharis, 2018), and it is not surprising to see the same finding for AVs. However, an important aspect that is lacking in the literature is whether TBAs will increase in AVs compared to HVs or not, and, if yes, how this increase will impact AV adoption and use interest. This study compares the TBAs between HV and AV scenarios and estimates the impact of change in TBAs on AV adoption and use (for more and longer trips) interests. The finding will help anticipate the value of AV travel time for LDRT and potential changes in travel demand.

- The release of driving stress has always been considered a top advantage of AV travel—with a more pronounced effect on long-distance travel. However, based on the rich discussion on the dynamics associated with manual driving enjoyment made above, it would be interesting to see how manual driving enjoyment plays role in individuals' interest in adopting and using AVs for LDRT given the novel travel environment associated but with a longer travel time.
- Adopting the study limited to the visitors of national parks, this study contributes to tourism literature by investigating how tourists are likely to adopt AVs when they are available, and how in-vehicle time use will likely impact the demand of tourists at destinations. This will inform the destination managers to prepare well ahead not only to manage the tourist demand at destinations but also to manage the traffic on the way to destinations to maintain a high level of visit experience for the visitors (see Acharya et al., 2023 to see how tourism destination satisfaction and travel experiences are related). In addition, importantly, this effort attempts to update the tourism literature by utilizing the recent research progress from the travel behavior literature in terms of the behavioral implications of AVs.

4.3 Data

The data used in this study was gathered from an online questionnaire survey the authors conducted in the Summer of 2022. The survey was part of a larger study designed to assess long-distance recreational travel behavior and preferences toward AVs. In the survey, long-distance recreational travel was defined as travel intended for pleasure and recreation and involving at least 75 miles of travel one-way. Thus, the respondents of the survey were those who had visited one of the national parks of the US in 2022 by driving at least 75 miles one-way, and no air travel was involved in the trip. The questionnaire consisted of questions of two broad categories: revealed and stated preference. The revealed preference portion was dedicated to ascertaining respondents' experiences of their recently made long-distance recreational travel including travel satisfaction. The stated portion was about their future preference toward autonomous vehicles for long-distance recreational travel. Before asking the questions related to AVs, a brief introduction of an AV was presented in the questionnaire: "*An autonomous vehicle (AV) is a vehicle having full self-driving capabilities such that no driver is needed to drive. The vehicle uses various in-vehicle technologies and sensors to drive itself*." The survey was distributed online using a Qualtrics panel and 696 complete responses were collected. Among the several questions asked in the survey, only the questions or variables relevant to this study are described here. The complete questionnaire can be found in an online repository (Acharya, 2022).

4.3.1 Socio-demographic and trip characteristics

The descriptive statistics of the socio-demographic and trip characteristics of the sample are presented in **Table 4.1**. Most of the respondents (~90%) reported using a car as a travel mode for all travel purposes, as expected. Notably, the sample has an average LDRT per year of 3.32.

The descriptive statistics of the trip characteristics of the respondents are discussed here. Given the screening criteria used, the sample has an average travel time of ~10 hours and a travel distance of ~193 miles one-way. Most of the respondents (87%) reported using their own vehicle for the trip. Regarding vehicle types used by respondents, SUVs had the highest share (45%). The share of different advanced vehicle features in the trip vehicles of the sample lies in the range of 18-57%. The average number of travel companions for the sample is 2.36, out of which 65% of the respondents reported having their spouse as a travel companion. Around three-quarters of respondents reported driving for more than 50% of the time/distance in the trip. About half and one-third of the total respondents experienced rain and congestion respectively during the trip.

Table 4.1

Descriptive statistics of socio-demographic and trip characteristics of the sample.

Variable	Categorical		Continuous	
	#	%	Mean	SD
Socio-demographics				
Age				
18-34 years	191	27.44		
35-64 years	404	58.05		
65+ years	101	14.51		
Gender: Female	359	56.90		
Race/ethnicity: White	576	82.76		
Education				
High school or below	291	41.81		
Undergraduate degree	278	39.94		
Graduate degree or higher	127	18.25		
Student				
No	512	73.56		
Yes, part-time	46	6.61		
Yes, full-time	138	19.83		
Employment				
No				
Yes, part-time	210	30.17		

Yes, full-time	396	56.90		
Race/ethnicity: White	576	82.76		
# adults in the household (age ≥18 years)			2.18	0.99
# children in the household (age <18 years)			0.90	1.15
Annual household income				
< $25k	110	15.80		
$25-50k	187	26.87		
$50-75k	155	22.27		
$75-100k	99	14.22		
≥$100k	145	20.83		
Driving experience (years)			25.66	16.61
# household vehicles			1.52	0.77
Travel mode				
Commute: car	612	87.93		
Shopping trips: car	651	93.53		
Personal trips: car	632	90.80		
Social/recreational trips: car	627	90.09		
Past traffic citations: no	291	41.81		
Past crash experience: no	234	33.62		
Typical # of long-distance recreational trips per year			3.32	2.19
Trip characteristics				
Travel time (hours, one way)			10.89	12.83
Travel cost (dollars, one way)			193.40	202.52
Vehicle ownership: Own	611	87.79		
Vehicle type				
Sedan/hatchback	262	37.64		
SUV	319	45.83		
Truck	69	9.91		
Vehicle feature				
Blind-spot monitoring	219	31.47		
Lane-keep assistance	188	27.01		
Adaptive cruise control	400	57.47		
Automatic emergency braking	192	27.59		
Driver monitoring	132	18.97		
Parking assistance	180	25.86		
Collision warning	259	37.21		
Travel companion				
Total #			2.36	1.93
Spouse: present	452	64.94		
Children: present	320	45.98		
Siblings: present	56	8.01		
Other family members: present	109	15.66		
Friends: present				
Percentage time/distance driven				
0-25%	40	5.75		
25-50%	113	16.24		
50-75%	150	21.55		
75-100%	117	16.81		
Whole trip	276	39.66		
Trip experience				
Rain	343	49.28		
Low visibility	95	13.65		
Congestion	233	33.48		

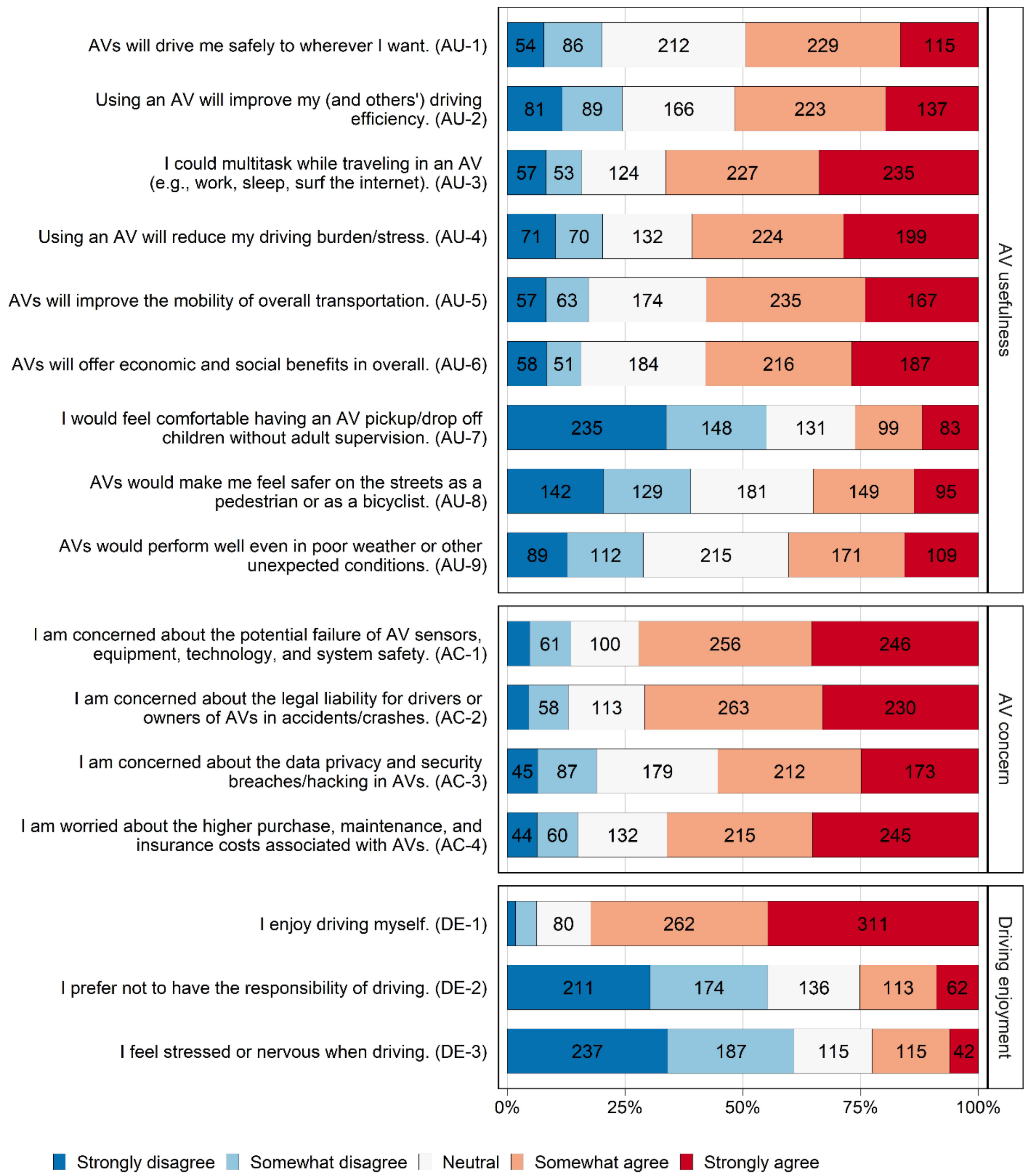
4.3.2 Attitudinal characteristics

This study considers six different attitudinal characteristics of the respondents, which are: AV usefulness, AV concern, technology savviness, driving enjoyment, polychronicity, and environmental concern. Out of these, three characteristics—AV usefulness, AV concern, and driving enjoyment—are only discussed here since the rest of them were dropped from the final model (to be explained later).

AV usefulness is defined as an indication of an individual's perception of the advantages, benefits, and uses of AVs. A higher value of this variable indicates more positive sentiment toward AVs. AV concern is defined as an indication of an individual's perception of the worries and concerns related to the adoption and use of AVs. A higher value of this variable indicates more negative sentiment toward AVs. Driving enjoyment is defined as a measure of how an individual enjoys or gets stressed while driving the vehicle manually. A higher value of this variable indicates positive sentiment towards manual vehicle driving. Based on these definitions, each attitudinal characteristic represents different but related facets of individual attitudes. For example, AV concern is formed by an individual's perception of data privacy and security, uncertainty about legal liabilities in accidents, design of AV sensors, etc. Thus, these attitudinal characteristics were measured as latent variables. Referring to these variables as latent means they were unobserved and estimated from several measured indicators. The list of the indicators of each latent variable and their distribution of the responses are presented in **Figure 4.1**. (The methodology adopted to define the relationships and the associated results are presented later.) All indicators were measured on a 5-point Likert scale ranging from strongly disagree to strongly agree.

Figure 4.1

Distribution of the responses to the indicators of significant attitudinal latent variables.



4.3.3 TBA and TU difference scores between AVs and HVs

The time spent traveling is either spent on driving tasks only (in case of manual driving) or/and is dedicated to some other in-vehicle activities simultaneously. To assess the potential impacts of travel-based activities (TBAs) on intentions to adopt and use AVs (for more and longer trips), the questionnaire asked the respondents to (multiple) select the activities conducted while traveling among a set of 17 distinct activities, both in HV and AV scenarios. The questions were worded as: "*Which of the following activities did you do in-vehicle during the trip? Consider the activities you did both ways. Select all that apply*." and "*Hypothetically, consider that you drove in an autonomous vehicle instead of your vehicle during the last trip so that you didn't have to drive. In this scenario, which of the following activities would you do while traveling? Consider the trip both ways. Select all that apply*.". Thus, TBAs for the HV scenario represent the activities a traveler participated in while on his/her recent trip whereas TBAs for the AV scenario represent the activities that a traveler would have participated in if that trip was made on an AV.

Among these 17 activities, only 15 activities were considered in this study as most of the respondents (~90%) reported listening to music and very few respondents (~1%) reported "other" activities in both HV and AV scenarios. Then, the remaining 15 activities were merged into seven groups depending upon the nature of the activity and conceptual compatibility, which are:

- Use social media (one): Using social websites or apps (Facebook, Instagram, Twitter, LinkedIn, etc.)

- Work/study/read (three): Working or studying; Texting, emailing, other messaging, teleconference; Reading newspapers, books, websites, etc.
- Interact (two): Interacting with other passengers; Talking on phone.
- Entertain (except music) (three): Singing, dancing; Watching movies/TV/other entertainment; Playing games.
- Eat/care (two): Eating food, drinking beverage, smoking; Caring for or playing with children or pets.
- Relax (three): Sleeping or snoozing; Viewing scenery, watching people; Thinking or daydreaming.
- Watch road (one): Watching the road.

The scores for these newly constructed activities were calculated as the sum of the number of activities selected in each group. Finally, for these seven groups of activities, the descriptive statistics of each activity score for both HV and AV scenarios and their differences (AV-HV) were calculated and are presented in **Table 4.2**. A higher positive value of the difference score for an activity indicates a higher preference for that activity in an AV compared to a HV. Activity difference scores (between AV and HV) were positive for all activities except watch road, as expected, and the highest difference was observed for the Work/study/read activity.

In addition, this study considers travel time usefulness (TU) as a potential factor that influences public preferences toward adopting and using AVs. TU is defined as an indicator of one's evaluation of how productively the travel time was spent. The questionnaire asked two questions to assess TU in HV and AV scenarios respectively, which were worded as "*How useful or worthwhile would you rate the time you spent* *traveling?*" and "*How useful or worthwhile would you rate the time you spent traveling in an autonomous vehicle for this hypothetical trip scenario?*" respectively. These questions were asked on a 5-point Likert scale ranging from mostly wasted (1) to mostly useful (5). The descriptive statistics of TU scores for HV and AV scenarios and their differences (AV-HV) were calculated and are presented in **Table 4.2**. A negative mean value of the TU difference score indicates that, on average, respondents considered HVs better than AVs in terms of TU or effective utilization of travel time.

Table 4.2

Descriptive statistics of TBA and TU scores in HV and AV.

Variable	HV		AV		(AV – HV)	
	Mean	SD	Mean	SD	Mean	SD
TBA score						
Use social media (min = 0, max = 1)	0.26	0.44	0.43	0.50	0.17	0.52
Work/study/read (min = 0, max = 3)	0.37	0.64	0.78	0.91	0.41	0.90
Interact (min = 0, max = 2)	1.06	0.69	1.20	0.76	0.15	0.71
Entertain (except music) (min = 0, max = 3)	0.58	0.84	0.93	1.03	0.35	0.93
Eat/care (min = 0, max = 2)	0.76	0.63	0.83	0.72	0.07	0.68
Relax (min = 0, max = 3)	0.98	0.96	1.22	1.10	0.24	1.06
Watch road (min = 0, max = 1)	0.72	0.45	0.65	0.48	-0.07	0.49
TU score (min = 1, max = 5)	4.13	0.97	4.02	1.06	-0.11	1.26

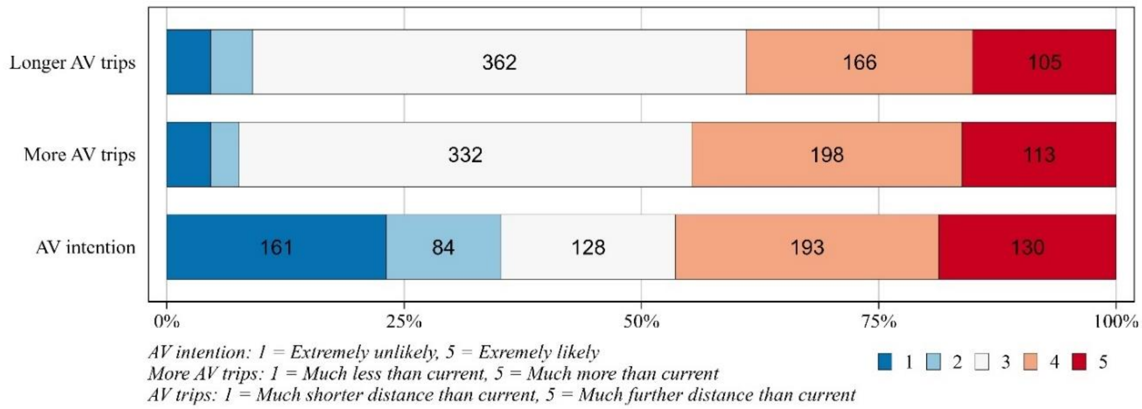
4.3.4 Intentions to adopt AVs and potential demand

This section discusses three primary variables of interest in this study: AV intention, more AV trips, and longer AV trips. AV intention is defined as an indication of an individual's preference for using AVs for future long-distance recreational trips. To assess this, respondents were asked to answer a question worded as "*Consider you had the option of using an autonomous vehicle instead of the current vehicle for your trip to [DESTINATION]. In this situation, how likely is it that you would use the autonomous* *vehicle instead of the current vehicle?*" on a 5-point Likert scale ranging from extremely unlikely (1) to extremely likely (5). The distribution of the responses is presented in **Figure 4.2**. The distribution shows that the sample is almost equally divided on the positive (46%) and negative (35%) intentions to adopt AVs for long-distance recreational travel.

To get an idea of potential travel demand when AVs are available, the respondents were asked whether they would go on more long-distance recreational trips or trips with farther destinations when AVs become available to them. The questions were worded as "*In the future, when autonomous vehicles are available, how would the number of long-distance recreational trips you make in a typical year change?*" and "*In the future, when autonomous vehicles are available, your long-distance recreational trips would most likely be …*", such that they represent the variables "More AV trips" and "Longer AV trips" respectively. The choice categories for these variables and their sample distribution are presented in **Figure 4.2**. Around half of the respondents (47% and 52%) predicted having the same number of and same distance trips in the future as currently whereas slightly less than half of the respondents (44% and 38%) reported having longer distances and a higher number of trips when AVs become available. This distribution indicates that a significant portion of people desires to visit more recreational destinations even by spending more time traveling probably in search of novelty.

Figure 4.2

Distribution of the intentions to adopt and use AVs.



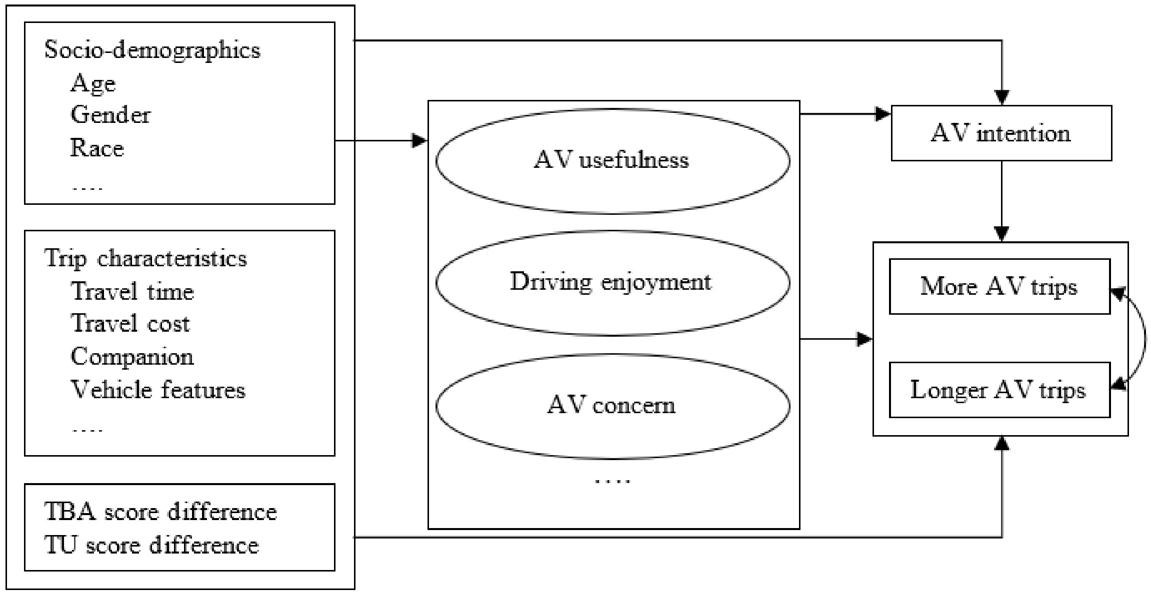
4.4 Conceptual model and methodology

4.4.1 Conceptual model

To attain the study objectives, we proposed a conceptual research model, which is shown in **Figure 4.3**. The model conceptualized the relationships between exogenous variables (socio-demographics, trip characteristics, TBA and TU difference scores), attitudinal variables (AV usefulness, AV concern, driving enjoyment, and others), and outcome variables (AV intention, more AV trips, and longer AV trips). Since individual attitudes are usually stochastic and contingent upon socio-demographics, the model considered the indirect impact of socio-demographics on outcome variables. In addition, we hypothesized that the intention to adopt AV affects using AV more and for longer trips, thus the model consisted of the effects of AV intention on more and longer AV trips. Finally, the residuals of two outcome variables (more AV trips and longer AV trips) were considered to be correlated due to some unobserved variables they have in common.

Figure 4.3

Conceptual research model.



4.4.2 Methodology

We adopted the structural equation modeling (SEM) framework to analyze the proposed conceptual research model because of its capability to model the simultaneous relationships between directly observed and unobserved latent variables. A SEM model consists of two parts (Kline, 2015): a measurement model and a structural model. A measurement model defines the relationships between unobserved latent variables and their observed/measured indicators whereas a structural model defines the relationships between the directly observed and latent variables. The structural model could consist of a series of simultaneous relationships between the variables. Within the SEM framework, the measurement models of latent variables are usually defined by conducting confirmatory factor analysis (CFA).

In our research model, six latent variables: AV usefulness, AV concern, technology savviness, driving enjoyment, polychronicity, and environmental concern were considered. Since these latent variables were not directly observed and needed to be approximated from their respective measured indicators, measurement structures of these latent variables were required. The measurement model showing the connections between latent variables and their respective measured indicators was first set up and then estimated using CFA. The specification of a typical measurement model that shows the connections between latent variables and their measured indicators is shown in Equation 4-1.

$$v_t = \lambda_t \mathrm{F}_l + \mathrm{e}_l \quad \text{4-1}$$

where, $l \in \{1, 2, \ldots, L\}$ and $t \in \{1, 2, \ldots, T\}$ are the indexes of latent variables and measured indicators such that F_l and v_t represent the vector of latent variables and their respective measured indicators. λ_t is the vector of parameters that link measured indicators v_t and latent variables F_l. e_l represents the measurement error associated with each latent variable. The measurement errors are assumed to be standard normally distributed.

Once the measurement structures of latent variables were finalized, the structural relationships between the directly observed variables (exogenous and outcome variables) and latent variables (approximated from their measured indicators) were estimated in accordance with the relationships proposed in **Figure 4.3**. A general specification of the structural equation model is represented by Equation 4-2.

$$Y_l = B_i X_i + r_l \quad \text{4-2}$$

where $i \in \{1, 2, \ldots, I\}$ is the index of predictor variables such that X_i denotes the vector of predictors variables and B_i represents their respective parameters that explain their relationships with outcome variables Y_i. r_l is the vector of residuals associated with each outcome variable. This error term is also assumed to be standard normally distributed. In the equations of the structural model, outcome variables and predictors of this equation varied depending upon the relationships hypothesized in **Figure 4.3**. For example, one equation of the structural model consisted of exogenous and latent variables as predictors of AV intention whereas the other consisted of exogenous variables, latent variables, and AV intention as predictors of more AV trips and longer AV trips. Because of these simultaneous relationships between variables, both direct and indirect associations between the variables can be estimated from the SEM model.

Both measurement and structural models were estimated in the lavaan package (Rosseel, 2012) in R (R Core Team, 2022). For estimation, a robust variant of the weighted least square estimator that uses a scaling factor to adjust the chi-square to approximate the mean and variance of chi-square distribution called WLSMV (Asparouhov & Muthen, 2006) was used. This estimator is generally preferred when the responses to the indicators of latent variables are ordered categorical and not normally distributed, as in our case (see **Figure 4.1** for the distribution of the indicators of latent variables). Goodness-of-fit of the models was judged by the combination of a number of indices as recommended by Kline (2015): the ratio of chi-square value to degrees of freedom (χ^2 /df), comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). In general, a model with a higher value of CFI and lower values of χ^2 /df, RMSEA, and SRMR better fit the data. As suggested by the literature (Browne & Cudeck, 1992; Hair et al., 2010; Hooper et al., 2008; Hu and Bentler, 1999; Kline, 2015), the cutoff values of these indices for a good model fit are: χ^2 /df < 2, CFI > 0.95, RMSEA < 0.05, and SRMR < 0.08, and for an acceptable model fit are: χ^2 /df < 5, CFI > 0.90, RMSEA < 0.08, and SRMR < 0.10.

4.5 Results and discussion

4.5.1 Model estimation and fit

Following the SEM methodology presented earlier, two models were estimated: (1) the measurement model of latent variables, and (2) the SEM model based on the conceptualized research model. The measurement model definition started by linking six latent variables with their respective measured indicators. The model was run using CFA and acceptable goodness of fit indices ($\chi 2$ (df = 237) = 1298.68, CFI = 0.957, TLI = 0.949, RMSEA [90% CI range] = 0.080 [0.076, 0.085], and SRMR = 0.061) was observed for the model. After finalizing the measurement model of latent variables, a SEM model consisting of both the measurement model (finalized earlier) and structural model (based on conceptualized research model) was estimated. Since three of the latent variables considered in the measurement model (technology savviness, polychronicity, and environmental concern) had insignificant relationships with any of the outcome variables, they were dropped from the final SEM model. (Thus, these insignificant latent variables are neither discussed in the paper nor the distribution of their measured indicators are presented in **Figure 4.1**). The goodness-of-fit indices of the final SEM model were $\chi 2$ (df = 1043) = 1758.80, CFI = 0.952, TLI = 0.992, RMSEA [90% CI range] = 0.031 [0.029, 0.034], and SRMR = 0.064. These indices lie within the good range as discussed above and thus confirm the reliability of model estimates. Subsequent sections detail the estimates of the final SEM model.

4.5.2 Measurement and structural models of latent variables

This section reports the measurement structure of the latent variables and their structural relationships with socio-demographics from the final SEM model. A portion of the final SEM model showing the measurement model of latent variables and the structural relationships between socio-demographics and latent variables are shown in **Table 4.3**. All measured indicators are significantly linked with their respective latent variables and have standardized loadings > |0.60|. This again confirms the suitability of the measurement model.

The effects of socio-demographics on latent variables were considered in the model, and the model results show the significance of this consideration. Graduate or higher degree education, full-time employment, and car as commute modes were linked with a higher AV usefulness, whereas driving experience and car as travel modes for personal trips were linked with a lower AV usefulness. Females, white individuals, and individuals from a larger household size had a higher AV concern than their counterparts. Individuals with a higher driving experience and those who typically make a higher number of LDRT were found to have a higher driving enjoyment whereas females had lower driving enjoyment than males on average. Other variables explaining heterogeneity in driving enjoyment include annual household income of $50-75k and no past traffic citation. As indicated by the R-squared values, socio-demographic variables explained about 12% of the variance in attitudinal latent variables. Overall, the results confirm that attitudinal latent variables are stochastic with a portion of their variances explained by individual socio-demographics.

Table 4.3

Results of measurement and structural models of latent variables.

Variables	AV usefulness	AV concern	Driving enjoyment
Measurement model			
AV usefulness			
AU-1	0.840*		
AU-2	0.843*		
AU-3	0.696*		
AU-4	0.839*		
AU-5	0.870*		
AU-6	0.836*		
AU-7	0.717*		
AU-8	0.807*		
AU-9	0.727*		
AV concern			
AC-1		0.908*	
AC-2		0.852*	
AC-3		0.673*	
AC-4		0.733*	
Driving enjoyment			
DE-1			0.611*
DE-2			-0.941*
DE-3			-0.710*
Structural model			
Age (base: 18-34 years)			
35-64 years	0.034	0.053	0.050
65+ years	0.019	-0.010	-0.030
Gender: Female	-0.064	0.089~	-0.083~
Education (base: High school or below)			
Undergraduate degree	-0.017	0.029	-0.032
Graduate degree or higher	0.101~	-0.053	-0.057
Student (base: No)			
Yes, part-time	0.054	0.010	-0.045
Yes, full-time	0.048	0.020	-0.050
Employment (base: No)			
Yes, part-time	0.049	0.017	-0.006
Yes, full-time	0.149*	0.012	-0.010
Race/ethnicity: White	-0.015	0.083~	0.003
# adults in the household (age ≥18 years)	0.007	0.130*	0.021
# children in the household (age <18 years)	-0.063	-0.097	0.017

Annual household income (base: <$25k)			
$25-50k	-0.043	0.073	0.039
$50-75k	0.024	0.089	0.127~
$75-100k	-0.002	-0.042	0.087
≥$100k	0.036	-0.019	0.122
Driving experience (years)	-0.160*	0.113	0.202*
# household vehicles	-0.035	0.022	-0.026
Travel mode			
Commute: car	0.118*	0.040	-0.008
Shopping trips: car	-0.048	0.024	0.015
Personal trips: car	-0.073~	0.022	0.079
Social/recreational trips: car	0.009	-0.024	0.051
Past traffic citations: No	0.059	-0.061	-0.093~
Past crash experience: No	-0.028	-0.009	0.061
Typical # of long-distance recreational trips per	-0.018	-0.044	0.103*
R-squared value	0.122	0.110	0.126

Notes: Number of observations = 696, ***** indicates significance at 95% confidence interval, and ~ indicates (marginal) significance at 90% confidence interval.

4.5.3 Structural models of outcome variables

This section reports the structural relationships between exogenous, latent, and outcome variables estimated from the SEM model. Since the research model consisted of a series of simultaneous relationships, all direct, indirect, and total effects of predictor variables on outcome variables were estimated and are presented in **Table 4.4**. The direct impact of a predictor variable on an outcome variable is reported as a direct effect, whereas its indirect impact through another variable (called the mediator) is reported as an indirect effect.

There lies confusion in the interpretation of indirect or mediation effects in the literature as different rules exist. Out of which, the most popular rule is the four-step approach proposed by Baron and Kenny (1986) which essentially requires all the path coefficients contributing to an indirect effect to be significant to have the indirect effect to exist. This rule has been highly criticized recently because of several flaws (see Zhao et al., 2010 for the summary). Thus, the current practice is to look at the significance of the overall indirect effect (i.e., multiplication of the path coefficients contributing to the indirect effect) rather than the significance of the individual coefficients of the paths of indirect effect. On this line, the significance of indirect effects reported in **Table 4.4** is based on the overall indirect effects.

Table 4.4

Results of structural models of outcome variables.

	AV intention		More AV trips			Longer AV trips		
Variables	IE-L	DE	IE-L	IE-A	DE	IE-L	IE-A	DE
Socio-demographic characteristics								
Age (base: 18-34 years)								
35-64 years	0.016	0.019	0.027	0.003	0.082~	0.021	0.003	0.107*
65+ years	0.009	-0.028	0.006	-0.005	0.141*	0.004	-0.005	0.099
Gender: Female	-0.031	0.004	-0.032	0.001	0.024	-0.032~	0.001	0.049
Education (base: High school or below)								
Undergraduate degree	-0.008	0.024	-0.009	0.004	-0.021	-0.009	0.004	-0.034
Graduate degree or higher	0.048~	0.010	0.041	0.002	-0.014	0.033	0.002	0.050
Student (base: No)								
Yes, part-time	0.026	0.049~	0.024	0.008	0.015	0.018	0.008	-0.003
Yes, full-time	0.023	0.039	0.022	0.006	0.028	0.015	0.007	-0.042
Employment (base: No)								
Yes, part-time	0.023	0.006	0.026	0.001	0.050	0.020	0.001	-0.038
Yes, full-time	0.071*	-0.039	0.076*	-0.006	0.015	0.060*	-0.007	0.004
Race/ethnicity: White	-0.007	0.026	0.000	0.004	-0.013	-0.003	0.005	-0.019
# adults in the household (age ≥18 years)	0.003	0.010	0.017	0.002	0.029	0.010	0.002	-0.069~
# children in the household (age <18 years)	-0.030	0.090*	-0.040	0.015~	0.025	-0.028	0.015~	-0.040
Annual household income (base: <$25k)								
$25-50k	-0.021	-0.011	-0.012	-0.002	-0.058	-0.011	-0.002	-0.040
$50-75k	0.011	0.015	0.032	0.003	-0.02	0.027	0.003	-0.012
$75-100k	-0.001	-0.025	0.003	-0.004	-0.043	0.007	-0.004	-0.073
≥$100k	0.017	0.006	0.027	0.001	-0.045	0.027	0.001	-0.013
Driving experience (years)	-0.077*	-0.158*	-0.053	-0.026*	-0.177*	-0.040	-0.027~	-0.160~
# household vehicles	-0.017	-0.049	-0.018	-0.008	-0.010	-0.016	-0.008	-0.043
Travel mode								
Commute: car	0.057*	0.033	0.063*	0.005	0.008	0.049*	0.006	0.047
Shopping trips: car	-0.023	-0.047	-0.021	-0.008	-0.003	-0.017	-0.008	0.019
Personal trips: car	-0.035~	0.003	-0.028	0.001	-0.120*	-0.021	0.001	-0.065
Social/recreational trips: car	0.004	0.035	0.007	0.006	0.049	0.008	0.006	0.021
Past traffic citations: No	0.028	0.034	0.016	0.006	-0.048	0.012	0.006	-0.061
Past crash experience: No	-0.013	-0.026	-0.010	-0.004	0.021	-0.005	-0.004	-0.049
Typical # of long-distance recreational trips per year	-0.008	0.013	-0.004	0.002	0.069~	0.002	0.002	0.132*
Trip characteristics								

Travel time (hours, one way)	-0.038	-0.006*		-0.007*	
Travel cost (dollars, one way)	0.061	0.010*		0.010*	
Vehicle ownership: Own	0.020	0.003*		0.003*	
Vehicle type					
Sedan/hatchback	-0.017	-0.003*		-0.003*	
SUV	-0.069	-0.011*		-0.012*	
Truck	-0.052	-0.009*		-0.009*	
Vehicle feature					
Blind-spot monitoring	0.031	0.005*		0.005*	
Lane-keep assistance	0.023	0.004*		0.004*	
Adaptive cruise control	0.070~	0.012*		0.012*	
Automatic emergency braking	0.064	0.011*		0.011*	
Driver monitoring	0.057	0.009*		0.010*	
Parking assistance	0.041	0.007*		0.007*	
Collision warning	0.001	0.000*		0.000*	
Travel companion					
Total #	-0.090	-0.015*		-0.015*	
Spouse: present	-0.007	-0.001*		-0.001*	
Children: present	0.083	0.014*		0.014*	
Siblings: present	-0.027	-0.004*		-0.005*	
Other family members: present	0.035	0.006*		0.006*	
Friends: present	0.031	0.005*		0.005*	
Percentage time/distance driven (base: 0-50%)					
50-75%	0.030	0.005*		0.005*	
75-100%	0.073~	0.012*		0.013*	
Whole trip	0.022	0.004*		0.004*	
Trip experience					
Rain	-0.029	-0.005*		-0.005*	
Low visibility	-0.020	-0.003*		-0.003*	
Congestion	-0.008	-0.001*		-0.001*	
TBA and TU					
TBA score difference					
Use social media	-0.023	-0.004	0.023	-0.004	0.005
Work/study/read	0.027	0.004	0.145*	0.005	0.046
Interact	0.108*	0.018*	0.088*	0.018~	0.071
Entertain (other than music)	0.073~	0.012	0.125*	0.012	0.115*
Eat/care	0.018	0.003	-0.035	0.003	0.022
Relax	-0.019	-0.003	0.010	-0.003	0.031
Watch road	0.009	0.001	0.002	0.002	0.055
TU score difference	0.368*	0.060*	0.179*	0.063*	0.119*

Latent variables					
AV usefulness	0.479*	0.079*	0.430*	0.082*	0.325
AV concern	-0.063*	-0.010~	0.103*	-0.011~	0.048
Driving enjoyment	0.009	0.002	0.088*	0.002	0.105
AV intention			0.164*		0.171*

Notes: Number of observations = 696, **bold** indicates significance at 95% confidence interval, and *italics* indicates (marginal) significance at 90% confidence interval. IE-L: Indirect effect through latent variables, IE-A: Indirect effect through AV intention, DE: Direct effect.

4.5.3.1 AV intention

The model conceptualized the direct impact of AV intention on the preference for more and longer AV trips. The estimated result proves our hypothesis that those who are inclined to adopt AVs for long-distance recreational trips have a higher interest in using AVs for more and longer trips. This result brings an important issue for consideration: travel demand will surge when more and more AVs come to the market. Transportation agencies should be well prepared to accommodate the travel demand generated by AVs along with working on the development of AVs and enhancing the public attitudes towards AVs. Though the discussion on shared AVs is pronounced as a solution to lower induced travel demand because of vehicle automation (Golbabaei et al., 2021; Narayanan et al., 2020), this might not be true, especially in recreational travel where people usually desire a calm, peaceful, and familiar travel environment.

Policies to reduce recreational travel are impractical as participating in recreational activities (which offers freedom and escape from daily activities) is believed to have a positive role in one’s life satisfaction and overall well-being. In addition, tourism destinations aim to have a high number of visitors for the sustainability of their tourism business. With the introduction of AVs, the number of visitors to recreational destinations (e.g., national parks) will likely increase but there comes a challenge to accommodate the increased travel demand. As it is undesirable environmentally and economically to increase the capacity of road networks connecting popular recreational destinations, alternative solutions are needed to accommodate the travel demand induced because of AVs. Since most of the US national parks are accessible via driving only, this might be a good time to work on developing sustainable public transit systems that connect popular recreational destinations (including national parks) and major city centers.

4.5.3.2 Socio-demographics

The model estimated the direct and indirect influences of socio-demographics on the intention to adopt an AV and use it for more and longer AV trips. The indirect effects were considered through attitudinal latent variables for AV intention, more AV trips, and longer AV trips, and also through AV intention for more AV trips and longer AV trips as shown in the research model. Individuals aged >34 years had a higher intention to use AVs for more recreational trips compared to individuals of age 18-34 years. Middle-aged individuals (35-64 years) showed a greater preference for longer AV trips compared to younger individuals (18-34 years). Graduate or higher degree holders had a higher intention to adopt AVs because of their higher confidence in AV usefulness. Part-time students had a higher intention to adopt AVs compared to non-students. Full-time employed individuals had a higher intention to adopt AVs and make more and longer trips in the future because of their higher confidence in AV usefulness. Individuals having a larger number of adults in the household were shown to have a lower preference for longer AV trips whereas individuals from a household with more children had a higher preference for AVs instead of HVs. The driving experience was found negatively related to AV intention, more AV trips, and longer AV trips. The higher the number of household vehicles, the lower the preference to adopt AVs.

Daily travel behavior, especially mode choice for different purposes of travel, had different associations with AV intention, more AV trips, and longer AV trips. On average, individuals who use a car for daily commutes had a higher preference for adopting and using an AV for long-distance recreation travel. Because of lower confidence in AV usefulness, car users for personal trips were found to have a lower preference to adopt AVs for long-distance recreational trips. This group also stated that they would use AVs less than the current in terms of the number of trips. Individuals who typically travel more for recreation were found to intend to make a higher number of and longer AV trips when they are available, but they didn't show preferences to replace HVs with AVs for long-distance recreational trips.

4.5.3.3 Trip characteristics

Trip-specific characteristics were considered as the predictors of intention to adopt only, but they could have indirect effects on the intentions for more and longer AV trips in accordance with the research model. When looking at the direct effects, only two variables—having adaptive cruise control in the trip vehicle and driving 75-100% of the trip time/distance—had (marginally) significant effects on the intention to replace the current trip vehicle with an AV. Higher interest in adopting an AV for those who had adaptive cruise control indicates that as people get used to advanced vehicle features they prefer trying for more advanced and probably autonomous driving features. The tiredness and fatigue as a result of driving for a longer period of time could have resulted in the interest in AVs for those who drove 75-100% of the trip. Interestingly, those who drove the whole trip alone were no different than those who drove less (0-50% of the trip) in AV adoption interest.

Turning to the indirect effects of trip-specific characteristics on intentions to more and longer AV trips through AV adoption interest, all variables considered had significant effects. Though we stick with the practice of not looking at the significance of individual paths contributing to the indirect effects in this paper, here we consider Baron and Kenny's (1986) criteria because of the significance of the indirect effects of trip-specific criteria on more and longer AV trips were dominated by the higher path coefficients of AV adoption interest with intentions to make more and longer AV trips compared to the lower path coefficients between trip-specific characteristics and AV adoption interest. Following Baron and Kenny's (1986) criteria, the only trip-specific characteristics indirectly associated with more and longer AV trips were having adaptive cruise control in the trip vehicle and driving 75-100% of the trip time/distance.

4.5.3.4 Differences in TBA and TU scores

The model estimated the influences of TBA and TU score differences on the intention to adopt and use AVs. Higher TBA difference scores (AV-HV) for interaction and entertainment activities were linked with a higher intention to adopt AVs for long-distance recreational trips. Individuals expecting more working/studying/reading, interaction, and entertainment activities on an AV than on a HV had a higher likelihood to travel more in an AV. Similarly, higher TBA scores for work/study/read and entertainment were linked to a higher propensity for longer AV trips. These results indicate that a favorable environment to conduct a wide range of in-vehicle activities in an AV compared to a HV might attract consumers to adopt AVs for long-distance recreational trips and use them for more and longer trips in the future.

It can be expected that people's preference for a travel mode is contingent upon how effectively or productively they can spend the time in-vehicle. The effects of TU score differences on intention to adopt and use AVs shown by the model align with our expectations. When combining this result with the sample distribution of responses on

TU (i.e., lower TU in an AV compared to a HV on average), it could be concluded that people aren't certain if they will be able to effectively utilize the time freed up by autonomous driving if they adopt and use an AV. Conducting different in-vehicle activities of interest is usually viewed as a way to spend the travel time productively, but it could have been hard for the respondents to comprehend if they could do in-vehicle activities without boredom in an AV especially when they are on long-distance travel. This result aligns with Singleton's (2019) note that the change in the propensity of doing in-vehicle activities in AVs and its contribution to travel time productivity is likely to be modest compared to that of HVs. Nevertheless, model results confirm that AV adoption and use interests are linked with the effective utilization of travel time in AVs compared to HVs.

4.5.3.5 Latent variables

Model results show that attitudinal latent variables have significant effects on the intention to adopt and use AVs for long-distance trips in the future. Individuals having a higher positive sentiment towards AV usefulness had a higher intention to adopt AVs and use them for more and longer long-distance recreational trips in the future when they are available. Since AV usefulness is an indication of the perceived efficiency, productivity, and convenience of an AV in fulfilling an individual's driving needs (Xiao & Goulias, 2022), this result is expected because it is plausible for individuals to desire a more efficient and useful mode of travel.

Individuals having a higher AV concern were found to have a lower intention to use AVs for long-distance recreational trips, as expected. Believing that the concerns towards a technology lower the trust and hence the behavioral acceptance of the technology (Acharya & Mekker, 2022a), several past studies have also concluded a similar finding: issues such as equipment safety (Acharya & Humagain, 2022), data privacy and security (Acharya & Mekker, 2022b), and legal liability (Fagnant & Kockelman, 2015) are barriers to the acceptance of AVs. However, interestingly, this group of individuals stated that they would use AVs for more recreational trips in the future even if they have a higher AV concern. This is an indication that even though the acceptance of AVs will be contingent upon the concerns associated, their use or demand will be higher once they are accepted by the public. This highlights that transportation agencies should also be proactive in managing the travel demand that could be induced by vehicle automation.

An individual's driving enjoyment was found unrelated to his/her intention to accept AVs. This insignificant relationship could be attributed to the balance between some people not preferring AVs as they prioritize the sense of control and automotive emotions attached to manual driving (Bjorner, 2017) whereas others consider the safety benefits offered by autonomous driving worth losing the driving pleasure in HVs (Shammut et al., 2023). However, driving enjoyment had a positive impact on the intention to reach more recreational destinations using AVs. This could be probably because of the intrinsic intention to travel and visit more recreational destinations by those who enjoy driving. Also, this group of people might expect to enjoy AV driving especially during recreational travel because of scenes, nature, and novel travel environments (compared to daily travel) even though they wouldn't not be controlling the steering manually. However, as shown by the result, the choice of farther recreational destinations is not motivated by vehicle automation for people who enjoy controlling vehicles manually.

4.6 Conclusion

With the necessity to understand the acceptance and demand of AVs for LDRT, we estimated the interest in adopting AVs (by replacing HVs) and using them for more and longer trips in the future by conducting a survey of US national park visitors. The analysis accounted for numerous exogenous (socio-demographics, general travel behavior, trip-specific characteristics, in-vehicle time use-related factors) and attitudinal latent (AV usefulness, AV concern, driving enjoyment) variables, which provides a richer discussion on the factors influencing AV adoption and uses. Using the SEM framework, we explicitly accounted for the impact of AV adoption interest on the intentions to use AVs for more and longer LDRT trips and also allowed the model to estimate the correlation between intentions to use AVs for more and longer trips (the estimated residual correlation between the residuals—standardized coefficient: 0.378, z-value: 10.510—confirms that common unobserved factors affect these interests jointly.). In addition, we disentangled the direct and indirect relationships between the variables to better understand the behavior process behind the public interest in adopting and using AVs for long-distance recreational trips. The following are the key findings of this paper:

- The propensity of doing in-vehicle activities increases in AV travel compared to HV travel. And this increase has a significant role in developing the public intention to adopt and use AVs for LDRT.
- Individuals with higher manual driving enjoyment have a lower interest in adopting AVs for LDRT, but they will use AVs more frequently once they adopt them.

Similarly, AV concerns will likely limit AV adoption interest but won't limit AV-induced travel demand. AV usefulness is viewed as a positive contributor to both AV adoption and use (in terms of higher trip frequency and longer trip length).

- When AVs come to the roads, the demand for travel leading to recreational and tourism destinations likely increases. Also, the travel demand keeps increasing with an increase in AV adoption rate. This brings the attention of the recreational and tourism destination managers to manage the increased demand at destinations and the roads leading to destinations.

This study has several limitations that can be addressed through further research. First, the paper discusses the decrease in TU in AV travel compared to HV based on descriptive statistics without statistical analyses. This is our next step to extend this research. It would be interesting to see the interplay between increased TBAs and decreased TU in AV travel compared to HV travel. Second, with known empirical evidence of an increased TBAs in AV travel compared to HV travel, it is necessary to quantify the contribution to the value of travel time savings. The calculated value can be used for evaluating the justifications of highway projects leading to recreational destinations. It would also be interesting to see if and how travelers value the role of different vehicle configurations (e.g., work-friendly or leisure-friendly design) to create a favorable environment for conducting in-vehicle activities.

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Chapter 5

Vehicle automation, onboard environment, and in-vehicle time use: Findings from a stated choice experiment

Abstract

This study aims to investigate the roles of the onboard environment and in-vehicle time use on travel experiences in the age of automation. With this goal, a stated choice experiment was conducted involving 696 long-distance recreational travelers (visitors to US national parks) to analyze mode preferences among human-driven vehicles (HV), autonomous vehicles (AVs), and autonomous vehicles with work and leisure interiors (AV-WL), along with the associated value of travel time (VOTT). Several multinomial and mixed logit models with different specifications were employed to achieve the study objective. The estimated VOTT values for HV, AV, and AV-WL were \$34.70, \$31.00, and \$30.30 per hour, respectively. The sequential reduction in VOTT values from HV to AV and AV to AV-WL suggests a monetary association with vehicle automation and the onboard environment. While there was no significant contribution of in-vehicle activity participation on VOTT for HV and AV, texting/emailing/teleconference activity contributed to VOTT for AV-WL. Furthermore, a higher preference for activity participation in automated driving compared to manual driving was related to a stronger preference for AV and AV-WL. Additionally, the study found that the usefulness of travel time was associated with the mode choice decision and the VOTT of the modes. Taking all these results into consideration, we conclude that vehicle automation, onboard environment or interior design, and the propensity for in-vehicle activities and their usefulness are critical factors in mode choice decisions in the AV era. Based on the study findings, we discuss that vehicle automation is likely to benefit individuals by enabling a more productive use of travel time, but it could exacerbate the problem of increasing car sizes, leading to higher energy consumption and space requirements. Thus, it is necessary to consider these negative aspects for the sustainability of the transportation system.

Keywords: autonomous vehicle, time use, travel-based activities, onboard environment, value of travel time.

5.1 Introduction

Autonomous vehicles (AVs) with self-driving capabilities have become a foreseeable future of the transportation system thanks to the researchers and developers who made it possible. The primary motivation behind introducing this cutting-edge technology is to eradicate human errors in manual driving and make the transportation system safer (Mueller et al., 2020). Other reasons include making transportation equitable and accessible to everyone (e.g., mobility to disables and people who can't drive themselves; Hwang and Kim, 2023), ensuring efficient mobility (e.g., through traffic signal optimization, optimizing flows and trajectories for fuel efficiency, efficient vehicle routing, etc.; Narayanan et al., 2020; Vahidi and Sciarretta, 2018), etc. However, at the same time, several concerns exist with the introduction of this technology: equipment and system safety performance (Acharya and Humagain, 2022), higher cost (Emory et al., 2022), data privacy and security (Acharya and Mekker, 2022), and legal liabilities (Alawadhi et al., 2020).

From the economic perspective, the introduction of AVs is considered beneficial (compared to current vehicles referred to as human-driven vehicles or HVs) even though they will likely have a higher initial cost. In this line of thought, the monetary benefits of AVs are believed to come from their self-driving abilities because the time spent driving HVs can be substituted by other activities (that could earn money) while driving/riding in AVs. If AV travel time becomes less onerous (or economically more beneficial) than HV travel time because of the possibilities of in-vehicle activities, it would not only impact the public choice of travel modes but also a considerable shift in travel behavior could be expected because of the changes in individual activity patterns (Pudane et al., 2019, 2021). In econometrics, one way to measure this is by calculating the so-called value of travel time (VOTT), which is the people's willingness to pay to avoid having to spend a unit time traveling (Jara-Diaz, 2000). As discussed in the Background section below, several studies have conducted stated choice experiments and concluded that AVs would likely have lower VOTT than HVs. They have speculated the potential of AVs for a wide range of TBAs as the primary source of reduced VOTT. However, a thorough investigation of in-vehicle time use in AVs and its contribution to VOTT is lacking in the literature. The present study investigates the roles of vehicle automation, onboard environment, and in-vehicle activities possibilities on the VOTT to contribute to this gap.

This study features a stated choice experiment between different vehicle controls and vehicle interiors to attain this broad objective. Specifically, the experiment tests the choice of automated control of vehicles over human control and the regular vehicle interior (like current cars) over a sophisticated work- and leisure-friendly in-vehicle environment. As a result, three alternatives—human-driven vehicle (HV), autonomous vehicle (AV), and work- and leisure-friendly vehicle (AV-WL)—are presented in the choice experiment. In addition to explicitly discerning the choice alternatives based on vehicular control and interior (or onboard environment), the impacts of the preferences for different in-vehicle travel-based activities (TBAs) and the perception of the utilization of travel time, measured as travel-time usefulness (TU), on various choice alternatives are analyzed. The data necessary for this study, including the stated choice experiment, were collected from a survey of 696 long-distance recreational travelers conducted in 2022 summer. Since in-vehicle time use becomes more important in a longer travel duration than a shorter one (Rhee et al., 2013), considering only long-distance travelers in the survey makes it more suitable to elicit the economic valuation of automation and in-vehicle time use.

The remainder of this paper is organized as follows. Section 5.2 presents a review of the relevant existing studies and concludes with the focus of the study. Section 5.3 outlines the procedure adopted in the stated choice experiment and in collecting other necessary data. It also presents the descriptive statistics of the sample. Section 5.6 illustrates the methodology adopted to attain the study objective. Section 5.7 outlines the model results and their interpretations. And lastly, study conclusions, implications, and limitations are presented in Section 5.8.

5.2 Background

Travel-based activities (TBAs) (sometimes also referred to as “travel-based multitasking”) refer to the in-vehicle activities travelers perform while traveling. These include activities ranging from so-called productive (e.g., working, reading) to unproductive (e.g., sleeping or snoozing) activities (Keseru & Macharis, 2018). The consideration of the role of TBAs in travel behavior literature became popular once Mokhtarian and Salomon (2001) conceptualized that the activities conducted while traveling are a component of the travel experience utility. This concept is supported by the fact that people have limited time (e.g., 24 hours a day) to do a fixed set of activities, and performing some of those activities in-vehicle while traveling frees up time for other activities of interest. This positive role of TBAs on travel experience or the utility of travel has been verified in some empirical settings (e.g., Ettema & Verschuren, 2007; Malokin et al., 2019; Molin et al., 2020; Sun and Wong, 2022).

The propensity of doing several TBAs varies based on the onboard environment, such as travel mode, vehicle interior, onboard connectivity, travel companion/s, travel duration, travel purpose, etc. (Keseru & Macharis, 2018; Pawlak, 2020). For example, suppose a traveler is actively participating in driving the vehicle. In that case, a limited set of activities (e.g., listening to music, talking on the phone, and talking with other passengers) could be conducted in addition to the driving task (Circella et al., 2012). However, while using public transit (e.g., bus, train), there are more options for activities that vary from listening to music, working, watching a movie, sleeping, watching the scenery, or talking with other passengers (Krueger et al., 2019a). The availability of ICT devices (smartphones, tablets, laptops, etc.) and onboard Wi-Fi in the vehicle increases the options for watching videos/movies, internet surfing, working, etc., while traveling (Pawlak, 2020). Walking and biking could be considered as the activity of exercising along with traveling (Keseru & Macharis, 2018). In the case of ride-hailing, the activities conducted vary whether (or with whom) the ride is shared (Krueger et al., 2019a). Among the existing modes of travel, the train can be considered to be the mode that offers the highest level of TBA potential because it involves a gradual change in speed, acceleration, and direction as opposed to other modes (Singleton, 2019).

Now turning to this study's focus—TBAs in AVs. Since manual control is not required in AVs, sometimes it is argued that AV travelers can do TBAs as much as train travelers or even more in the case of private AVs (because of the privacy and travelers' "own" onboard). But, there is also a counterargument that the TBAs in AV travel couldn't match that of train travel because of the vehicle designs and operations (e.g., trajectory, speed, acceleration, etc.) (Singleton, 2019). Nevertheless, a few empirical studies have attempted to study how in-vehicle activities will change in the AV era and their impact on the preferences for AVs. Wudud and Huda (2020) identified that the willingness to conduct TBAs is higher in AVs compared to HVs, and this increase contributes to the usefulness of travel time. Acharya and Mekker (in progress) ascertained that though the propensity of most in-vehicle activities increases in AVs compared to HVs, working, studying, interaction, and entertainment activities have a pronounced impact on the acceptance and use of AVs. Similarly, Lethtonen et al. (2022) identified that the willingness to perform leisure activities in AVs promotes traveling more in AVs, whereas Dannemiller et al. (2023) concluded that almost all types of TBAs contribute to traveling more and longer in AVs. Opposingly, some empirical studies have concluded that changes in TBAs in AVs will likely be modest (or even no change) compared to HVs. For example, Lee et al. (2021) asserted that productive TBAs rarely occur in long-distance AV travel. Waded and Huda (2020) investigated the reasoning behind such a result, which found that motion sickness in AVs hinders the willingness to conduct productive TBAs. These studies (Lee et al., 2021; Wadud and Huda, 2020) have advocated for the need for work- and leisure-friendly vehicle interior design in AVs to justify the potential of increased TBAs.

Several studies (e.g., Correia et al., 2019; Kolarova et al., 2019; Zhong et al., 2020 and many more; see Harb et al. (2021) for review) have conducted stated choice experiments to evaluate the potential VOTT of AV travel. Most of those have found a reduced VOTT in AVs but with a lot of variabilities (ranging from 5% to 90% decrease in VOTT compared to HVs as summarized by Harb et al., 2021) not only based on the different forms of AVs (e.g., private, shared, etc.) but also based on the design and presentation of the choice experiment. For example, explicit mentioning of TBAs or multitasking (Gao, 2019), using animated videos to introduce AVs (Huda et al., 2023), and replacing "AV" wording with "chauffeur-driven vehicle" (Correia et al., 2019; Huda et al., 2023) in the choice experiment reduced the VOTT estimates for AVs. However, a few of those studies (e.g., Krueger et al., 2019b) have reported no reduction (or even increase) in VOTT in AVs compared to HVs (see Rashidi et al. (2020) for a summary of these studies). These conflicting findings are likely attributed to the lack of real-world experience with AVs (necessitating the analyses to rely on stated behavior rather than on revealed behavior) and also the spatial (Edelmann et al., 2021) and temporal (Acharya and Humagain, 2022) variations in AV sentiments. The studies reporting reduced VOTT for AVs have interpreted the TBA potential and reduced driving stress in AVs as contributors to reduced VOTT. In contrast, others have interpreted the manual driving enjoyment or the lack of economic value of TBAs in AVs (by doing unproductive activities only) as reasons behind the constant or increased VOTT. These interpretations are primarily based on speculation rather than on empirical grounds. An exception is Correia et al. (2019), which conducted a choice analysis between HV, AV with work interior, and AV with leisure interior to evaluate the importance of the onboard environment for TBAs and found the reduced VOTT for work-AV compared to HV and leisure-AV. This result justifies the monetary value of work activities conducted in-vehicle but not leisure activities.

In summary, the preceding discussion demonstrates that a category of studies has investigated the impact of TBAs on the acceptance and use of AVs for more and longer travel, whereas the other category has evaluated the VOTT of AV travel. However, a joint understanding of how vehicle automation will impact the propensities for TBAs and, ultimately, the VOTT is lacking in the literature, which is the focus of this study. Correia et al. (2019) have contributed to this subject by incorporating different onboard environments in the choice experiment. However, their analysis lacks other crucial in-vehicle time use aspects such as TBA, TU, etc. Thus, the present study analyzes the choice decisions among HVs, AVs, and work and leisure interior AVs and also quantifies the contribution of time use variables (TBAs and TU) on the VOTT estimates.

5.3 Study design and data collection

This study draws data from the authors' online questionnaire survey in the Summer of 2022. The survey was part of a larger study designed to assess long-distance recreational travel behavior and preferences toward different aspects of AVs. The survey defined long-distance recreational travel as travel intended for pleasure and recreation and involving at least 75 miles of travel one-way. Thus, the survey respondents were those who had visited one of the US national parks in 2022 by driving at least 75 miles one-way, and no air travel was involved in the trip. Data collected from two sections of the survey are used in this study. The first section asked about the socio-demographic details of the respondents along with their attitudes and behaviors and the characteristics of their recently made long-distance recreational trip. The second section featured a stated choice experiment in which the respondents were asked to indicate whether they would switch to different configurations of AVs (to be discussed later) on the trip they recently undertook if those options were available. Before asking the questions related to AVs, a brief introduction of an AV was presented in the questionnaire: *"An autonomous vehicle (AV) is a vehicle having full self-driving capabilities such that no driver is needed* *to drive. The vehicle uses various in-vehicle technologies and sensors to drive itself.”*. The survey was distributed online using a Qualtrics panel, and 696 complete responses were collected. Among the several questions asked in the survey, only the questions or variables relevant to this study are described here. The full questionnaire can be found in an online repository (Acharya, 2022).

5.4 Stated choice experiment

The stated choice experiment followed a sequence of steps. First, the definitions of the alternatives to be presented in the choice task were defined in the survey as:

- **Current vehicle** refers to the vehicle you used to get to [DESTINATION] and return. This mode is hereafter referred to as “**HV**” since all current vehicles require human-driving effort.
- **Autonomous vehicle with current vehicle interior** refers to a self-driving vehicle with an interior vehicle design the same as that of your current vehicle. Thus, consider this vehicle option as same as your current vehicle but with the self-driving ability so that you don’t have to drive. This mode is hereafter referred to as “**AV**” for simplicity.
- **Autonomous vehicle with work and leisure interior** refers to a self-driving vehicle where the interior vehicle design is friendly for work and leisure activities. In this vehicle option, the seats are comfortable for sleeping or relaxing, Wi-Fi is available for leisure or work, a table can be pulled for work, charging ports are available for laptops and smartphones, etc. You can expect to do work or leisure activities inside this vehicle without the responsibility of driving. This mode is hereafter referred to as “**AV-WL**”.

Second, after defining the alternatives, the survey introduced the choice task: "Consider all three vehicle options were available for you to choose for your last trip to [DESTINATION], which option would you prefer? Each vehicle option had different travel time and cost associated. The values of the travel time and travel cost in the options presented below are around the values you experienced one-way on the last trip which are [TT] and [TC] respectively.". Here [DESTINATION] refers to the national park the respondent had visited on the last trip, and [TT] and [TC] reflect the one-way travel time and travel cost experienced on that trip. The information regarding the destination, travel time, and travel cost was obtained from the revealed part of the survey.

Third, four choice tasks were presented to each respondent, where the respondent had to choose a travel mode (among HV, AV, and AV-WL) based on the travel time and cost associated with the mode. The travel time and cost associated with each mode were pivoted around the reference values the respondent experienced on the last trip to ensure the realism of the choice task (Hess and Rose, 2009). The attributes and their levels used to design the choice tasks are presented in **Table 5.1**. Various techniques to design the choice tasks range from orthogonal to efficient designs (Rose et al., 2008). We adopted the orthogonal design strategy here, given its simplicity and performance (Walker et al., 2018). As a result, 12 orthogonal designs were generated using the Ngene software (ChoiceMetrics, 2018). These 12 scenarios were divided into three blocks so that each respondent had to face a randomly selected block consisting of four scenarios. **Figure 5.1** shows an example choice scenario presented to the respondents in the survey. With 696 respondents and 4 choice scenarios per respondent, we obtained a total of 2784 choice observations. In the experiment, the HV, AV, and AV-WL were chosen 1115 (40%), 677 (24%), and 992 (36%) times, respectively.

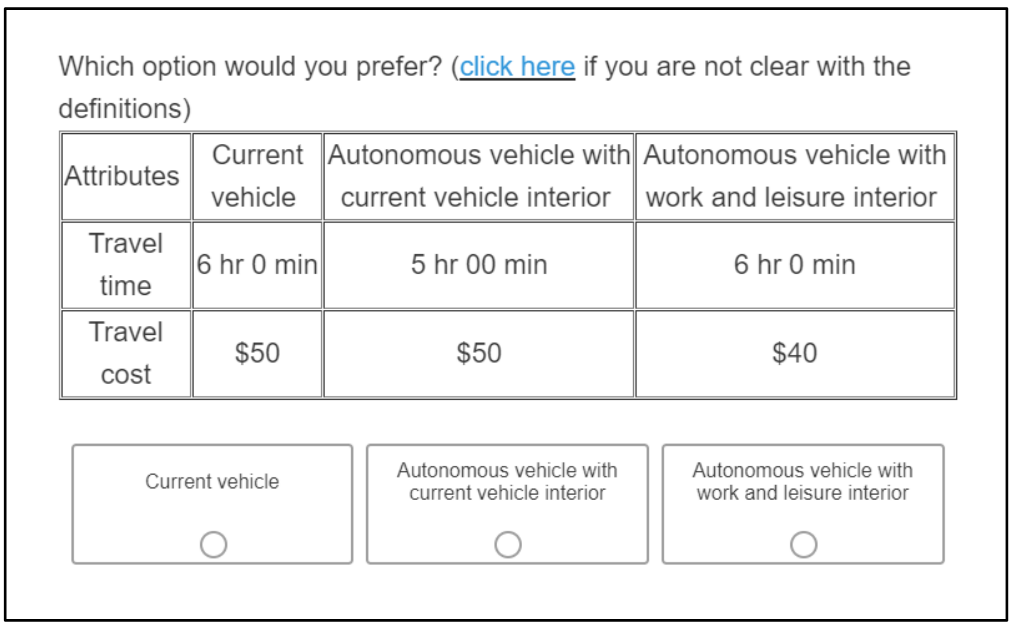
Table 5.1

Mode attributes and levels used in the stated choice experiment.

Attribute	HV	AV	AV-WL
Travel time	0.8*TT, TT, 1.2*TT	0.8*TT, TT, 1.2*TT	0.8*TT, TT, 1.2*TT
Travel cost	0.8*TC, TC, 1.2*TC	0.8*TC, TC, 1.2*TC	0.8*TC, TC, 1.2*TC

Figure 5.1

Example choice scenario presented in the survey.



Which option would you prefer? (click here if you are not clear with the definitions)

Attributes	Current vehicle	Autonomous vehicle with current vehicle interior	Autonomous vehicle with work and leisure interior
Travel time	6 hr 0 min	5 hr 00 min	6 hr 0 min
Travel cost	$50	$50	$40

Current vehicle

Autonomous vehicle with current vehicle interior

Autonomous vehicle with work and leisure interior

5.5 Sample statistics

This section reports the statistics related to the study sample characteristics and the stated choice experiment. The descriptive statistics of the socio-demographics and general travel behavior of the sample are presented in **Table 5.2**. It also reports the average one-way travel time and cost experienced by the sample on their last long-distance recreational trips, which are 10.89 hours and $193.40, respectively.

Table 5.2

Descriptive statistics of the sample (n = 696).

Variable	Categorical		Continuous	
	#	%	Mean	SD
Age				
18-34 years	191	27.44		
35-64 years	404	58.05		
65+ years	101	14.51		
Gender: Female	359	56.90		
Race/ethnicity: White	576	82.76		
Education				
High school or below	291	41.81		
Undergraduate degree	278	39.94		
Graduate degree or higher	127	18.25		
Student				
No	512	73.56		
Yes, part-time	46	6.61		
Yes, full-time	138	19.83		
Employment				
No				
Yes, part-time	210	30.17		
Yes, full-time	396	56.90		
Race/ethnicity: White	576	82.76		
# adults in the household (age ≥18 years)			2.18	0.99
# children in the household (age <18 years)			0.90	1.15
Annual household income				
< $25k	110	15.80		
$25-50k	187	26.87		
$50-75k	155	22.27		
$75-100k	99	14.22		
≥$100k	145	20.83		
Driving experience (years)			25.66	16.61
# household vehicles			1.52	0.77
Travel mode				
Commute: car	612	87.93		
Shopping trips: car	651	93.53		
Personal trips: car	632	90.80		
Social/recreational trips: car	627	90.09		
Past traffic citations: no	291	41.81		
Past crash experience: no	234	33.62		
Typical # of long-distance recreational trips per year			3.32	2.19
AV familiarity (1: unf – 5)				
One-way travel time (hours)			10.89	12.83
One-way travel cost (dollars)			193.40	202.52

This study considers six attitudinal characteristics of the sample: AV usefulness, AV concern, technology savviness, driving enjoyment, polychronicity, and environmental concern, measured as latent variables to increase the interpretability of the mode choice. AV usefulness refers to an individual's perception of the advantages and benefits of using AVs, with higher scores indicating a more favorable attitude towards AVs. Conversely, AV concern assesses the individual's worries and apprehensions about adopting and using AVs, with higher scores indicative of a more unfavorable stance. Driving enjoyment measures the individual's enjoyment or stress associated with manual driving, with higher scores representing a positive sentiment towards driving manually. Polychronicity refers to the individual's preference for multitasking and relaxed attitude towards time. Individuals with a higher level of polychronicity likely enjoy engaging in multiple activities or tasks simultaneously. Moreover, technology savviness assesses the individual's familiarity and proficiency in using various technological devices and their ability to adapt to new technological advancements and innovations. Lastly, environmental concern pertains to the individual's awareness, interest, and willingness to take action in protecting and preserving the natural environment and its resources. In the questionnaire, respondents were asked to rate several statements (related to these latent variables) on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5). The lists of statements or indicators related to each latent variable and the sample distribution of their response are presented in **Table 5.3**.

Table 5.3

Latent variable indicators and their sample distribution.

Latent variables and their indicators	Reference[a]	Distribution [Response category 1, 2, 3, 4, 5]

AV usefulness	Acharya and Mekker (2022); Dannemiller et al. (2021)	
AVs will drive me safely to wherever I want. (AU-1)		[8%, 12%, 30%, 33%, 17%]
Using an AV will improve my (and others') driving efficiency. (AU-2)		[12%, 13%, 24%, 32%, 20%]
I could multitask while traveling in an AV (e.g., work, sleep, surf the internet). (AU-3)		[8%, 8%, 18%, 33%, 34%]
Using an AV will reduce my driving burden/stress. (AU-4)		[10%, 10%, 19%, 32%, 29%]
AVs will improve the mobility of overall transportation. (AU-5)		[8%, 9%, 25%, 34%, 24%]
AVs will offer economic and social benefits in overall. (AU-6)		[8%, 7%, 26%, 27%, 31%]
I would feel comfortable having an AV pick up/drop off children without adult supervision. (AU-7)		[34%, 21%, 19%, 14%, 12%]
AVs would make me feel safer on the streets as a pedestrian or as a bicyclist. (AU-8)		[20%, 19%, 26%, 21%, 14%]
AVs would perform well even in poor weather or other unexpected conditions. (AU-9)		[13%, 16%, 31%, 25%, 16%]
AV concern	Dannemiller et al. (2021)	
I am concerned about the potential failure of AV sensors, equipment, technology, and system safety. (AC-1)		[5%, 9%, 14%, 37%, 35%]
I am concerned about the legal liability for drivers or owners of AVs in accidents/crashes. (AC-2)		[5%, 8%, 16%, 38%, 33%]
I am concerned about the data privacy and security breaches/hacking in AVs. (AC-3)		[6%, 12%, 26%, 30%, 25%]
I am worried about the higher purchase, maintenance, and insurance costs associated with AVs. (AC-4)		[6%, 9%, 19%, 31%, 35%]
Technology savviness	Dannemiller et al. (2021)	
I like to be among the first to have the latest technology. (TS-1)		[12%, 16%, 20%, 26%, 25%]
Having internet connectivity everywhere I go is important to me. (TS-2)		[3%, 7%, 18%, 32%, 41%]
Driving enjoyment	Haboucha et al. (2017)	
I enjoy driving myself. (DE-1)		[2%, 4%, 11%, 38%, 45%]
I prefer not to have the responsibility of driving. (DE-2)		[30%, 25%, 20%, 16%, 9%]
I feel stressed or nervous when driving. (DE-3)		[34%, 27%, 17%, 17%, 6%]
Polychronicity	Ettema and Verschren (2007)	
I like to be engaged in two or more activities simultaneously. (PC-1)		[8%, 16%, 28%, 33%, 14%]
I believe people should aim at performing multiple tasks simultaneously. (PC-2)		[10%, 16%, 30%, 31%, 12%]
It makes me feel good to be involved in multiple activities simultaneously. (PC-3)		[8%, 11%, 30%, 35%, 16%]
Environmental concern	Haboucha et al. (2017)	
I am concerned about current environmental pollution and its impact on health. (EC-1)		[4%, 7%, 16%, 35%, 38%]
I don't change my behavior based solely on concern for the environment. (EC-2)		[17%, 25%, 22%, 22%, 13%]
I rarely worry about the effects of pollution on myself and my family. (EC-3)		[24%, 27%, 18%, 19%, 12%]

[a]The referenced studies motivated deriving the statements of the latent variable indicators in the survey.

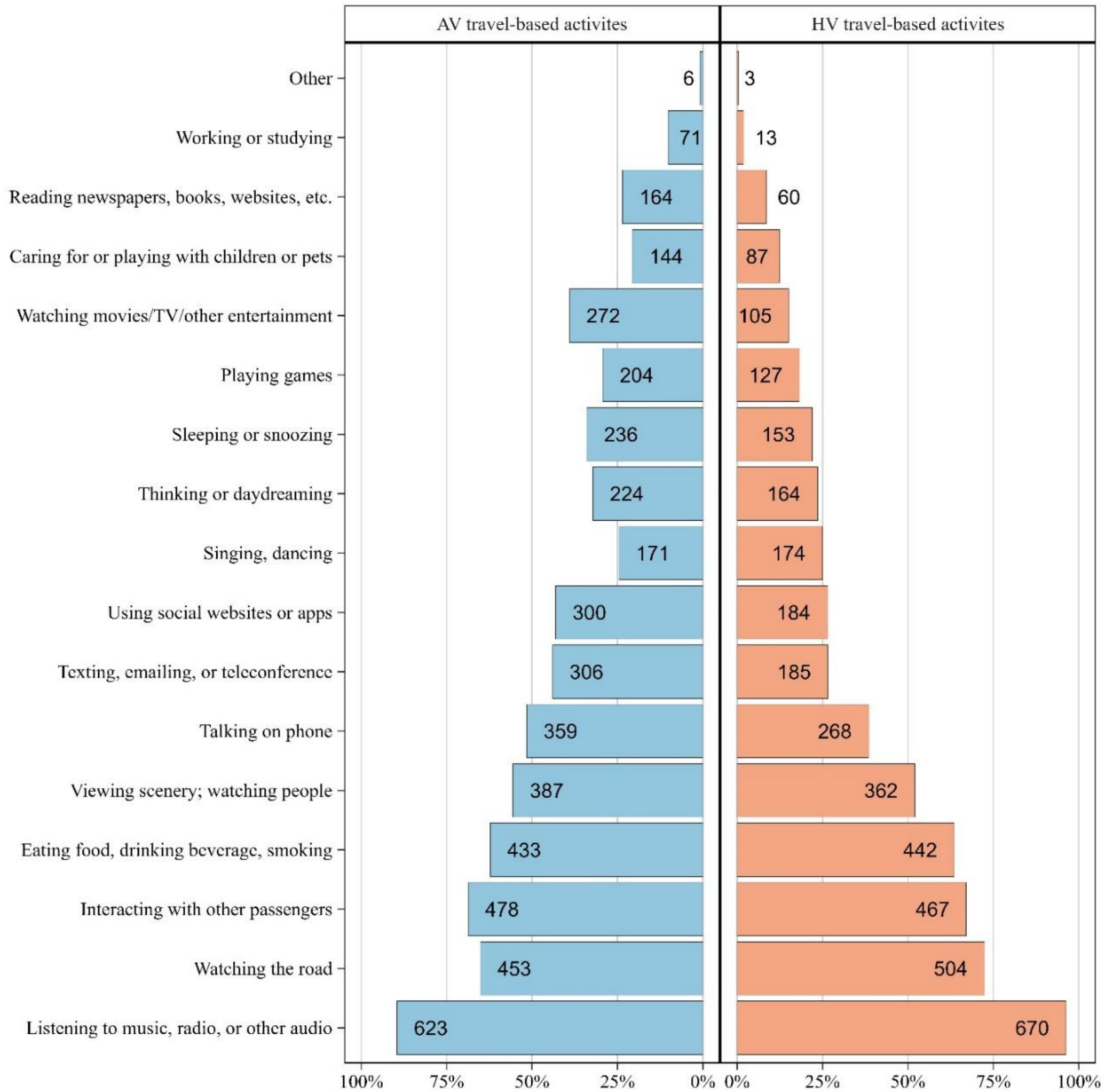
The survey respondents were asked to reveal the TBAs they participated in during their last trip and their preferred TBAs if the vehicle in the last trip was an AV to assess how individuals spend time in-vehicle and its impact on the mode choice between HV, AV, and AV-WL. The questions were worded as follows:

1. Which of the following activities did you do in-vehicle during the trip? Consider the activities you did both ways. Select all that apply.
2. Hypothetically, consider that you drove in an autonomous vehicle instead of your vehicle during the last trip so that you didn't have to drive. In this scenario, which of the following activities would you do while traveling? Consider the trip both ways. Select all that apply.

In these questions, respondents had to (multiple) select the activities conducted in-vehicle from the set of 17 activities in both HV and AV scenarios. The list of the TBAs and their distributions in both scenarios are presented in **Figure 5.2**. The modeling exercise (to be presented later) uses individual TBAs in HV and AV scenarios as dichotomous variables and the difference in the total number of TBAs between AV and HV scenarios (AV-HV) as a continuous variable.

Figure 5.2

Distributions of HV and AV travel-based activities (n = 696).



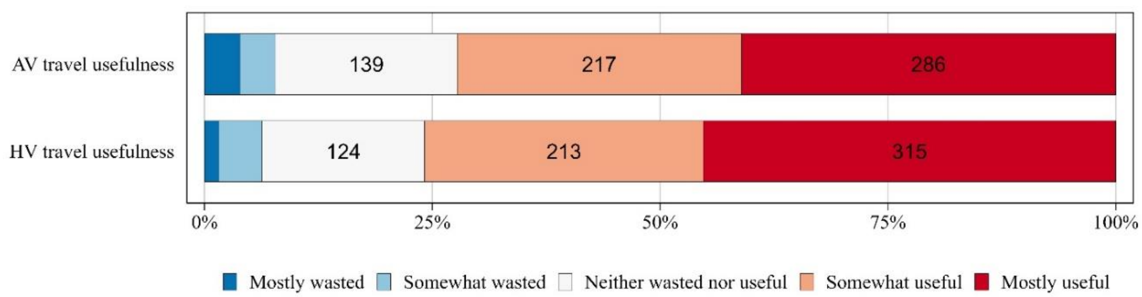
Next, travel usefulness, an indicator of an individual's evaluation of how productively the travel time was spent, was assessed for both HV and AV scenarios. For this, the following two 5-point Likert scale questions ranging from mostly wasted (1) to mostly useful (5) were asked to the respondents:

1. How useful or worthwhile would you rate the time you spent traveling?
2. How useful or worthwhile would you rate the time you spent traveling in an autonomous vehicle for this hypothetical trip scenario?

The distribution of the responses to these two questions is presented in **Figure 5.3**. The modeling exercise (to be presented later) uses individual TU in HV and AV scenarios and the difference in TU between AV and HV scenarios (AV-HV) as continuous variables.

Figure 5.3

Distribution of responses of HV and AV travel usefulness (n = 696).



5.6 Methodology

5.6.1 Modeling approach

The random utility maximization (RUM) framework (McFadden, 1974) was adopted to analyze the stated choice experiment data. In this framework, the decision-makers are assumed to make rational decisions by choosing the alternatives having the highest utility (utility can be defined as the overall satisfaction a decision-maker receives after choosing the alternative) among a set of alternatives (Marshak, 1960). In this study, travelers (or survey respondents) are the decision-makers, and the travel modes (HV, AV, and AV-WL) are the alternatives. Consider *n* ε {1, 2, …, *N*} travelers have options to choose *m* ε {1, 2, …, *t*} travel modes. Then, according to RUM, the probability that an individual *n* chooses an alternative *t* is represented by Equation 5-1 (McFadden, 1974; Train 2009).

$$P_n^t = \text{Prob}(U_n^t > U_n^m) \text{ for all } m \neq t \qquad 5\text{-}1$$

where, U_n^m is the utility experienced by traveler *n* when choosing mode *m*, which can be expressed as in Equation 5-2.

$$U_n^m = V_n^m + \varepsilon_n^m \qquad 5\text{-}2$$

V_n^m and ε_n^m are the deterministic and indeterministic parts of the utility equation from the analyst's perspective. However, the decision-makers make their choice considering both V_n^m and ε_n^m. Thus, properly representing the utility equation's deterministic and indeterministic parts is necessary to model the choice accurately. The deterministic part V_n^m depends upon the parameter estimates of covariates and are estimated statistically. However, as the indeterministic part ε_n^m cannot be estimated directly, different specifications are made to model the choice decision accurately.

In Equation 5-1, P_n^t is the cumulative probability that the traveler *n* chooses mode *t*. Thus, this cumulative probability can be expressed using the density of the indeterministic part, i.e., $f(\varepsilon_n)$ as shown in Equations 5-3 and 5-4.

$$P_n^t = \int I(U_n^t > U_n^m) f(\varepsilon_n) d(\varepsilon_n) \text{ for all } m \neq t \qquad 5\text{-}3$$

$$P_n^t = \int I(\varepsilon_n^m < \varepsilon_n^t + V_n^t - V_n^m) f(\varepsilon_n) d(\varepsilon_n) \text{ for all } m \neq t \quad \text{5-4}$$

where the integral $I(.)$ takes the value of 1 if the condition inside is true; otherwise, 0. Different specifications of the indeterministic term (ε_n) lead to different models that vary from logit to probit to mixed models. However, for brevity, only the specifications of multinomial logit (MNL) and mixed logit (ML) models, which are used in this paper, are explained here.

The MNL model is obtained when the indeterministic term ε_n^m is assumed to be an independently, identically, extreme value (i.e., ε_n^m follows Gumbel distribution). Thus, the density function and cumulative density function of ε_n^m in this model are shown in Equations 5-5 and 5-6 respectively.

$$f(\varepsilon_n^m) = e^{-\varepsilon_n^m} e^{-e^{-\varepsilon_n^m}} \quad \text{5-5}$$

$$F(\varepsilon_n^m) = e^{-e^{-\varepsilon_n^m}} \quad \text{5-6}$$

Since ε_n are independent across the alternatives, the integral $I(.)$ in Equation 5-4 is the product of the cumulative distribution over all $m \neq t$. Thus, when plugging Equations 5-5 and 5-6 into Equation 5-4, Equation 5-7 is obtained.

$$P_n^t = \int (\prod e^{-e^{-(\varepsilon_n^t + V_n^t - V_n^m)}}) e^{-\varepsilon_n^m} e^{-e^{-\varepsilon_n^m}} d(\varepsilon_n) \text{ for all } m \neq t \quad \text{5-7}$$

After some algebraic manipulations, Equation 5-7 can be expressed in the closed form as in Equation 5-8.

$$P_n^t = \frac{e^{V_n^t}}{\sum_m e^{V_n^m}} \quad 5\text{-}8$$

It is worth noting that, as the deterministic part V_n^m is assumed to depend on parameters (say β's), the parameters are assumed to be the same for all travelers *n* in the formulation of MNL probability. To relax this assumption, the β's are assumed to vary across travelers in the ML probability formulation (McFadden & Train, 2000). This assumption is considered superior to that of standard logit probability (where β's are considered constant across all travelers) as it captures the random taste variations across travelers (Train, 2009). To start the formulation of ML probability, let's represent the utility equation, shown in Equation 5-2, in the form of β's as in Equation 5-9.

$$U_n^m = \beta_n^{m\,\prime} X_n^m + \varepsilon_n^m \quad 5\text{-}9$$

where, X_n^m are the covariates that explain the deterministic part of the utility and β_n^m are the respective parameter estimates. Again, the indeterministic part ε_n^m is assumed to have a Gumbel distribution. Thus, the probability of choosing an alternative *t* by a traveler *n* is the same as that of Equation 5-8 except that the deterministic part of the utility equation V_n^t varies across travelers, which essentially captures the random taste variation. As a result, the choice probability in the ML model is expressed in Equation 5-10.

$$P_n^t = \int L_n^t(\beta) f(\beta) d\beta \quad 5\text{-}10$$

where, $L_n^t(\beta)$ represents the logit choice probability obtained by considering the variation in β's over travelers in Equation 5-8, which is shown in Equation 5-11.

$$L_n^t(\beta) = \frac{e^{V_n^t(\beta)}}{\sum_m e^{V_n^m(\beta)}} \quad \text{5-11}$$

The ML probability is thus obtained by plugging Equation 5-11 into Equation 5-10, which is shown in Equation 5-12.

$$P_n^t = \int \frac{e^{V_n^t(\beta)}}{\sum_m e^{V_n^m(\beta)}} f(\beta) d\beta \quad \text{5-12}$$

The choice probability as represented in Equation 5-12 is very flexible compared to the specification in Equation 5-8 in the case of the MNL model. First, different functional distributions of β can be assumed: normal, lognormal, uniform, triangular, or any other distribution based on the type and characteristics of associated covariate X_n^m (Train, 2009). Second, the specification of β's can be accommodated to capture the panel effects if multiple-choice experiments are conducted for the same individual, as in this study. However, this flexibility in the ML model comes at the cost of multi-dimensional integrals with no closed-form solution as in the MNL model, meaning that simulations are required to solve this model.

5.6.2 Model specification and estimation

Based on the methodology discussed above, four different logit models (one MNL: MNL-I, and three ML: ML-II, ML-III, and ML-IV) were specified to achieve the study objective, and the summary of the specifications of the models is reported in **Table 5.4**. To ease the discussion on different model specifications, let's rewrite the utility equation, i.e., Equation 5-9, in a simple form without mode and traveler indices, which is shown in Equation 5-13.

$$U = ASC + \beta * X + \varepsilon \qquad 5\text{-}13$$

Where U represents the utility associated with a mode for a traveler, ASC is the alternative specific (or mode-specific) coefficient, X and β represent the covariates and their respective coefficients, and ε represents the error term. The choice experiment explicitly considered travel time and cost, aiming to understand the impacts of travel time and cost on mode choice decision. Consequently, travel time and cost can be taken as covariates in Equation 5-13 such that their respective β parameters can be estimated. Additionally, the sensitivities of travel time and travel cost on mode choice can be understood by estimating the value of travel time (VOTT), defined as the marginal rate of substituting travel time for the cost. The VOTT can be obtained as a ratio of parameter estimates of travel time and travel cost from the utility equation (i.e., $VOTT = \frac{\beta_{time}}{\beta_{cost}}$). To ease the interpretation of mode choice models, the utility equations were specified in the VOTT space (similar to Gaker et al., 2011; Krueger et al., 2016) in all four models without changing the functional form of the models, which is shown in Equation 5-14.

$$U = ASC + \beta_{cost} * \beta_{VOTT} * X_{time} + \beta_{cost} * X_{cost} + \varepsilon \qquad 5\text{-}14$$

The four models differ based on the specification of the ASC and VOTT parameters in Equation 5-14. The ASC and VOTT parameters were kept fixed for all individuals in the first model (MNL-I) such that the model was multinomial. This assumption was relaxed in the second model (ML-II) by considering the randomness in the ASC and VOTT parameters such that the model resulted in a mixed logit. The random ASC and VOTT parameters were imposed to have normal and triangular distributions. Since the value of VOTT should be non-negative from the behavioral standpoint (Hensher and Green, 2003), this could be achieved by imposing its distribution as log-normal or triangular (Hess et al., 2005). The long tail of the log-normal distribution (see Poudel, 2021, for example) usually overestimates the value of the VOTT; thus, a symmetrical triangular distribution (ranging between -1 and 1) with *mean* = *spread* (see Hensher and Green, 2003) was imposed on the VOTT parameters. In the third model (ML-III), the ASC was specified to be explained by covariates (i.e., socio-demographic, attitudinal, and time-use variables) (such that ASC for a mode is $ASC = ASC_{base} + \beta_X * X$) keeping all other parameters as same as in ML-II. Lastly, in the fourth model, the VOTT parameter was specified to be explained by the covariates (time-use variables) such that $VOT = VOT_{base} + \beta_X * X$. The consideration of covariates in the ASC and VOTT parameters in ML-III and ML-IV aids in investigating the heterogeneity in mode choice decisions and the VOTT across modes, respectively.

Since the attitudinal variables were latent, these needed to be estimated from the measured indicators. Though the simultaneous estimation of the latent variables and choice probability is possible in the choice model framework, called the hybrid choice model (Ben-Akiva et al., 2002), the computation cost of such a model is very high. Thus, a sequential estimation strategy was adopted such that latent variable scores were first estimated from the measured indicators, and these latent scores were taken as input in the choice models. The choice models were estimated using the Pandas Biogeme package (Bierlaire, 2020), whereas the definition of the latent variables and their score estimation were performed in the semopy package (Igolkina and Meshcheryakov, 2020) in Python.

Table 5.4

Summary of different model specifications.

	Models			
	MNL-I	ML-II	ML-III	ML-IV
Distribution of ASCs	Fixed	Random: normal	Random: normal	Random: normal
VOTT space specification	✔	✔	✔	✔
Distribution of VOTT coefficients	Fixed	Random: triangular	Random: triangular	Random: triangular
Distribution of cost coefficients: Fixed and same across modes	✔	✔	✔	✔
Covariates of ASCs	✘	✘	✔	✘
Covariates of VOTT parameters	✘	✘	✘	✔
Panel effect	✘	✔	✔	✔

5.7 Results and discussion

5.7.1 Key sample statistics

The travelers' preferences for several TBAs and evaluation of TU are the primary variables of interest to the study objective. Thus, here we discuss the sample distribution of these variables. The distributions of in-vehicle activities travelers participated in the last trip (i.e., TBAs in HV) and the activities travelers would like to participate in an AV travel (i.e., TBAs in AV), presented in **Figure 5.2**, depict that travelers' preferences for TBAs were different in AV travel than in HV travel. Though the ranking of the activities remained almost the same, the proportion of choice of activities varied. On average, four out of 17 activities – listening to music, watching the road, eating, and singing – were preferred lower in AV travel than in HV travel. Of the remaining activities, some notable activities having a higher preference in AV than in HV were texting/emailing/teleconference (n = 306 vs. 185), using social media (n = 300 vs. 184), watching movies/TV (n = 272 vs. 105), reading newspaper/books (n = 164 vs. 60), and working or studying (n = 71 vs. 13). The average number of TBAs (out of 17) in HV and

AV travel were found to be 5.70 and 6.94 respectively. The mean and standard deviation of the difference in the number of TBAs between AV and HV travel (AV – HV) were 1.24 and 3.31, respectively. These statistics conclude that in-vehicle activity participation will likely increase in AV travel compared to HV travel. The next question is how worthwhile these TBAs are in choosing AVs over HVs and their monetary contributions to VOTT, which is discussed in the next section.

The distributions of TU (i.e., the evaluation of the utilization of in-vehicle travel time) in HV and AV travel, presented in **Figure 5.3**, show that around three-quarters of the sample had rated their travel time as (somewhat or mostly) useful in both HV and AV travel. When closely looking at the distribution, the usefulness of AV travel time (mean = 4.02, on a scale of 1-5) was lower than that of HV (mean = 4.13, on a scale of 1-5), on average. The mean and standard deviation of the difference in TU between AV and HV travel (AV – HV) were -0.11 and 1.26, respectively. This finding is quite surprising (and opposed to that of Wadud and Huda, 2020) as it is commonly hypothesized that AV travelers can do a wide range of in-vehicle activities making their travel time more productive than HV travelers. Leaving the detailed investigation of the reduced TU in AV travel than in HV travel for further research, the contributions of the TU scores on the choice of AVs over HVs and on the VOTT are evaluated next.

5.7.2 Estimation results

The results of the four models: MNL-I, ML-II, ML-III, and ML-IV, with model specifications as discussed in Section 5.6.2, are presented in **Table 5.5**. With 696 individuals and 4 choice scenarios per individual, we had a total of 2784 choice observations. The first model (MNL-I) was the simple multinomial model that didn't consider the random effects of the parameters and the panel effects, whereas the rest of the models (ML-II, ML-III, and ML-IV) were the improvement over the first model (by considering panel effects and random effects of interest). Given these forms of model specifications, the null log-likelihood values of all models were the same (-3058.54), and the final log-likelihood of the MNL-I was the poorest (-2946.54) compared to that of other mixed logit models (ML-II: -2491.30, ML-III: -2263.30, ML-IV: -2379.65) as expected. ML-II was the mixed logit model with random ASC and VOTT parameters, whereas ML-III improved over ML-II by considering socio-demographics, latent variables, and time-use variables as covariates of ASCs to uncover the heterogeneity in the mode choice. As discussed earlier, the latent variables were first estimated separately (these results are presented in **Table 5.6** in the appendix), and their predicted scores were plugged into the choice model. Finally, ML-IV improved over ML-II by considering time-use variables as the covariates of VOTT parameters to reveal the systematic preference heterogeneity in VOTT. Though the initial specifications of ML-III and ML-IV consisted of several covariates, insignificant covariates (at a 90% confidence interval) were gradually dropped to obtain the final models shown in **Table 5.5**.

Table 5.5

Estimation results of the choice models.

	MNL-I		ML-II		ML-III		ML-IV	
Variables	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Alternative-specific attributes								
HV (reference level)								
AV								
Constant	-0.479	-6.85	-0.789	-4.46	-0.461	-2.31	0.255	1.44
Standard deviation			0.229	0.36	-0.489	-2.28	2.200	8.22
Socio-demographics								
# children in the household					0.146	2.41		
Income: $25-50k					-0.448	-2.33		
Income: $50-75k					-0.413	-2.18		
Income: ≥$100k					-0.605	-2.92		
Student: Yes, part-time					0.911	3.86		
Time-use variables								
Diff. in # of TBAs (AV-HV)					0.082	2.83		
Diff. in TU (AV-HV)					0.287	3.64		
Latent variables								
AV usefulness					1.320	9.45		
Environmental concern					0.486	2.42		
Polychronicity					-0.184	-1.91		
AV-WL								
Constant	-0.069	-1.18	-0.584	-3.14	-0.298	-0.83	0.061	0.264
Standard deviation			1.54	10.70	-1.540	-10.90	3.520	10.50
Socio-demographics								
Age: 65+ years					-0.493	-1.83		
AV familiarity					-0.195	-2.22		
Past traffic citations: no					0.211	2.72		
Student: Yes, full-time					-0.414	-1.72		
Time-use variables								
Diff. in # of TBAs (AV-HV)					0.125	3.39		
Diff. in TU (AV-HV)					0.305	2.86		
Latent variables								

AV usefulness					1.82	10.20		
Environmental concern					0.862	3.47		
Travel cost ($)	-0.00304	-5.59	-0.00585	-5.53	-0.0053	-5.66	-0.00568	-5.72
VOTT ($/hr.)								
HV								
Base	24.70	4.32	48.90	4.50	34.70	4.08	77.50	3.74
Standard deviation			171	4.43	57.60	3.61	40.20	2.25
Time-use variables								
Travel time usefulness							-10.30	-3.09
AV								
Base	25.90	4.03	34.00	8.88	31.00	3.74	97.50	2.96
Standard deviation			-21.60	-3.70	13.80	2.91	24.00	3.02
Time-use variables								
Travel time usefulness							-14.60	-2.46
AV-WL								
Base	26.30	4.42	32.10	4.05	30.30	3.80	103.0	2.79
Standard deviation			-13.90	-2.59	5.090	0.201	-16.20	-2.30
Time-use variables								
Texting, emailing, or teleconference							-10.20	-3.22
Travel time usefulness							-15.10	-2.17
Goodness-of-fit statistics								
Null model log-likelihood	-3058.54		-3058.54		-3058.54		-3058.54	
Final model log-likelihood	-2946.54		-2491.30		-2263.30		-2379.65	
Akaike information criterion	5905.07		5004.61		4584.59		4789.30	
Bayesian information criterion	5940.66		5054.61		4716.41		4857.48	
# of estimated parameters[a]	6		11		29		15	
Number of observations	2784 (696*4)		2784 (696*4)		2784 (696*4)		2784 (696*4)	

[a]These figures refer to the # of parameters estimated in the final models (i.e., models with significant covariates only).

5.7.2.1 Value of travel time (VOTT)

Having all models specified and estimated in the VOTT space, the VOTT values can be obtained directly from the model results. The VOTT values estimated from only the first three (MNL-I, ML-II, and ML-III) models are discussed here because the fourth model (ML-IV) considered the preference heterogeneity, which didn’t directly give the average VOTT estimates. The model specifications allowed different modes to have different VOTT values by considering mode-specific travel time parameters but fixed cost parameters.

The first model (MNL-I) estimated the VOTT values to be $24.70, $25.90, and $26.30 per hour for HV, AV, and AV-WL, respectively. Next, the second model (ML-II) reported the VOTT values to be $48.90, $34.00, and $32.10 per hour for HV, AV, and AV-WL, respectively. We reckon the increase in the VOTT values for all modes in ML-II compared to that in MNL-I is expected because ML-II constrained the individual VOTT parameters to be only positive following the behavioral assumptions. All VOTT estimates in ML-II had significant standard deviations suggesting the heterogeneity in the VOTT. Also, ML-II considered the panel effect, which changed the rank of VOTT values across modes: AV-WL and HV had the lowest and highest VOTT based on ML-II, but this ranking was exactly the opposite in MNL-I. Finally, the VOTT values reduced slightly in the third model (ML-III): $34.70, $31.00, and $30.30 per hour for HV, AV, and AV-WL, respectively, but the ranking remained the same as in ML-II. Since ML-III was superior to MNL-I and ML-II from behavioral (by constraining the VOTT estimates to be positive), model specification (by considering panel effects and heterogeneity in the mode choice), and the fit statistics (lowest final log-likelihood, AIC, and BIC values) standpoints, we recognize the VOTT estimates from the ML-III as the most accurate.

5.7.2.2 Time-use variables

The impacts of time-use variables on the mode choice decisions were estimated from ML-III. Automated modes (AV and AV-WL) were more favored when the difference in the number of TBAs between AV and HV increased. This result suggests that AVs can attract individuals having higher TBA preferences. When closely looking at the estimates, the difference in the total number of TBA between AV and HV had a higher impact on the choice of AV-WL than AV. It clearly shows that the AV-WL was perceived to be a more favorable choice for in-vehicle activities. When combining this result with the discussion on descriptive statistics of TBAs in HVs and AVs made in Section 5.7.1, it can be concluded that people are interested in doing more TBAs in AVs compared to HVs, and this increase has a significant impact on the adoption of AVs. In addition, the preference for AVs will rise if the vehicle interiors are designed for work and leisure activities. Next, the increase in TU between AV and HV was significantly associated with the choice of AV and AV-WL, meaning that the modes having higher TU is preferred. However, since using AVs decreases TU on average (based on the discussion made in Section 5.7.1), the preference for AVs over HVs cannot be expected as of now because of the possibility of effectively utilizing in-vehicle travel time.

Time-use variables’ contributions to the VOTT were estimated in ML-IV by considering TBAs and TU as covariates of VOTT parameters. In the final model, only texting/emailing/teleconference activity appeared to be a significant TBA that explained heterogeneity in VOTT of AV-WL, but TU seemed significant for all modes. Those interested in texting/emailing/teleconference activity in an automated vehicle had a $10.20/hour lower VOTT for AV-WL compared to those who weren't interested. Having an insignificant monetary value of TBAs in HV is somewhat understandable because the traveler must dedicate substantial effort and energy to the driving task, and the activities conducted simultaneously with driving could be perceived as having no monetary value. However, the result showing no contribution of most of the TBAs in VOTT for AV and AV-WL travel is beyond our expectation, but it could be attributed to the study design that it was hard for the respondents to perceive if they would do economically valuable activities while riding in an automated vehicle given the uncertainty and concerns associated. In terms of TU, an increase in the TU score by one unit decreased the VOTT for HV, AV, and AV-WL by $10.30, $14.60, and $15.10 per hour, respectively. This result supports the notion that if the travel time is utilized effectively in-vehicle, it will decrease the VOTT. TU's contribution order in VOTT for HV, AV, and AV-WL indicates the monetary value of automation and the onboard environment.

5.7.2.3 Socio-demographics and latent variables

The impacts of socio-demographics and latent variables on the mode choice decisions were estimated in ML-III. The results show heterogeneity in the mode choice decisions based on some socio-demographic characteristics. The individuals with a higher number of children in the household favored the choice of AV. Higher-income individuals appeared to have less preference for AV. Part-time students had a higher preference for AV, whereas full-time students had a lower preference for AV-WL. Older aged individuals (65+ years old) showed less preference for AV-WL. Individuals with no past traffic citations were more inclined towards AV-WL. An increase in familiarity with autonomous technology lowered the preference for AV-WL.

The results show that some attitudinal variables significantly influenced mode choice decisions. Higher AV usefulness was significantly associated with the choice of automated modes, with a higher impact on AV-WL than AV. Since AV usefulness indicates an AV's perceived efficiency, productivity, and convenience in fulfilling an individual's driving needs (Xiao and Goulias, 2022), this result is expected because it is plausible for individuals to desire a more efficient and useful mode of travel. Similarly, environmental concern was associated with a higher preference for automated options (AV and AV-WL). It could be attributed to the understanding that the future AVs would most likely be electric (see Singh et al. (2023) for reasoning) and more environmentally beneficial than current vehicles, though this information wasn't explicitly mentioned in the survey instructions. Lastly, polychronic individuals were less inclined towards AV. It probably explains their multitasking preference: driving and doing other activities simultaneously in HV or multiple activities at a time in an AV-WL where the onboard is suitable for work and leisure activities. In other words, polychronic individuals might have realized that automated vehicles with interiors similar to current cars would not suit economically meaningful in-vehicle multitasking.

5.8 Conclusion

In this study, we made an effort to investigate the role of automation, onboard environment, and in-vehicle time on the choice of AVs and their monetary value. For this, we surveyed 696 US national park travelers, featuring a stated choice experiment between HV, AV, and AV-WL modes. Based on the results of several multinomial and mixed logit models fitted, we conclude that the vehicle automation, onboard environment or vehicle interior design, and the propensity of doing in-vehicle activities and their usefulness are critical in mode choice decisions. To quantify the importance of these factors, we estimated the heterogeneity in both mode choice decisions and the VOTT associated with each mode.

The study estimated the VOTT of HV, AV, and AV-WL to be $34.70, $31.00, and $30.30 per hour, respectively. These values are within a plausible range given the long-distance travel (sample mean one-way travel time = 10+ hours) pursued in this case study since a slightly higher VOTT can be expected for a longer duration of travel (Lee et al., 2021; Mackie et al., 2003). These values show vehicle automation lowered the VOTT by 10.66% from current HVs, and adding a favorable onboard environment (by introducing work- and leisure-friendly vehicle interiors) further reduced the VOTT by 2.26%. These reductions not only indicate that the automated options would be more favorable to travelers when these vehicles come to the market, but the travelers would most likely prefer the automated vehicles with larger and sophisticated vehicle interiors that offer onboard for work and leisure activities. The direction and the size of the impacts of the difference in the number of TBAs and TU between AV and HV travel on the utilities of the travel modes also support this interpretation.

Since driving is the primary task for HV travelers, other in-vehicle activities can sometimes be thought to be conducted to pass the time or get rid of boredom. However, when AVs replace these HVs, the driving activity will no longer be required, which means the travelers have options to or need to spend time on other in-vehicle activities. Along this line, our result also shows that people are interested in doing more TBAs in

AVs than in HVs. However, regarding the effective utilization of in-vehicle travel time or TU, the result shows that people are not hopeful they could spend travel time more effectively in AVs than in HVs. It could be attributed to the thought that automated vehicles without favorable interiors for TBAs could lead to boredom instead of favoring productive in-vehicle activities. The insignificance of TBAs contribution on VOTT for both HV and AV options in the choice model also reflects that it is unlikely to do productive activities (e.g., using a laptop for work) inside current cars traveling. These results and discussions lead to the conclusion that freeing up driving tasks in the current vehicles might not be sufficient to get the monetary values of TBAs in VOTT; instead, a favorable onboard environment is needed. This conclusion is also supported by the result that texting/emailing/teleconferencing lowered the VOTT in AV with work and leisure interiors by $10.20 per hour. Finally, this concludes that when AVs come to the market, the consumers would most likely prefer the option of having for onboard environment favorable for work and/or leisure activities (e.g., with Wi-Fi coverage, charging ports, table for work, flexible seats, TV, etc.).

The future of automated vehicles being driven toward having sophisticated larger interior designs could be beneficial from an individual perspective in that people can use travel time more productively and free the time for other activities of interest. However, from a societal standpoint, these sophisticated interior designs lead to larger vehicle sizes such that the problem of the continuous increase in the size of cars in the last few decades (Meyer, 2023) will most likely be worsened by vehicle automation. Thus, the AVs would not only induce more travel demand (Acharya and Mekker, in progress; Dannemiller et al., 2023) but also consume more energy and require more road and parking space because of the larger vehicle designs. Finally, these negative aspects that could be brought about by automation should be considered while discussing the ways towards the sustainability of the transportation system.

5.8.1 Study limitations

This study considered the impact of different TBAs on the mode choice decision and the VOTT of each mode. Since the survey listed the TBAs for HV and AV scenarios, we ascertained the roles of TBA participation on the mode choice and VOTT associated, but the role of the duration of TBA participation is missing. Considering activity participation duration could help ascertain a clearer picture of the roles of TBAs in mode choice decisions. It could be a future research avenue. Next, TBA and TU questions asked for an automated vehicle scenario without distinguishing the vehicle interior were considered as the attributes of both AV and AV-WL modes in the choice models. This limitation could be rectified by distinguishing the TBA participation and TU in AV and AV-WL. Even with the primary aim to explore the current topic in the setting of all-purpose long-distance travel, we limited our study to long-distance recreational travel because of the resources. Thus, extending this topic for other purposes, such as business, visiting friends and families, etc., with different travel companion scenarios could help ascertain the importance of automation, onboard environment, and in-vehicle activities in more detail.

Appendix

Table 5.6

Results of confirmatory factor analysis of latent variables.

Variables	Coeff.	t-stat	Variables	Coeff.	t-stat
AV usefulness			Technology savviness		
AU-1	1.000	n/a	TS-1	1.000	n/a
AU-2	1.093	28.79	TS-2	0.661	14.84
AU-3	0.934	23.16	Driving enjoyment		
AU-4	1.112	28.84	DE-1	1.0000	n/a
AU-5	1.057	30.21	DE-2	-2.417	-10.62
AU-6	1.055	29.60	DE-3	-2.026	-11.11
AU-7	0.942	19.68	Polychronicity		
AU-8	1.049	24.66	PC-1	1.000	n/a
AU-9	0.911	22.11	PC-2	1.026	23.34
AV concern			PC-3	1.080	24.88
AC-1	1.000	n/a	Environmental concern		
AC-2	0.981	20.56	EC-1	1.000	n/a
AC-3	0.792	15.84	EC-2	-1.557	-10.56
AC-4	0.893	17.79	EC-3	-1.402	-10.74
# of observations	696				
Estimator	MLW: Wishart log-likelihood				
Goodness-of-fit indices					
χ^2 /df	909.36/237 = 3.84				
CFI/TLI/RMSEA	0.924/0.913/0.063				

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Chapter 6

Summary and conclusions

This dissertation aimed to better understand the multiple facets of long-distance travel behavior. Specifically, this dissertation looked at the current long-distance travel behavior and the anticipated changes in the long-distance travel behavior that could be brought about by autonomous vehicles (AVs) shortly. First, it reviewed the existing knowledge about long-distance travel behavior and identified four important research questions that need to be answered. Second, primary data collection was done by surveying 696 travelers to the national parks in the US. Finally, data analyses were conducted using several techniques, including the structural equation and mixed logit modeling frameworks, to answer the research questions. The findings of the analyses offer several theoretical and practical implications.

This concluding section first highlights the key findings, contributions, and implications of the dissertation by revisiting the research questions asked. Then, the limitations of the dissertation and the potential future research direction are discussed.

6.1 Key findings, contributions, and implications

The analyses contained within this dissertation produced numerous findings related to current and future long-distance travel behavior. The following paragraphs discuss the key findings of each research question, their contributions to the literature, and the theoretical and practical implications.

1. How is satisfaction with long-distance travel different than with short-distance travel?

The answer to this question first required a reliable instrument or scale to measure long-distance travel satisfaction. Thus, the commonly used travel scale for commute and daily travel—called the satisfaction with travel scale (STS), developed initially by Ettema et al. (2011) and later validated by others (e.g., De Vos et al., 2015; Singleton, 2019; Smith, 2017; Ye & Titheride, 2017)—was modified and validated to develop as a reliable instrument to measure long-distance travel satisfaction. The modified STS was presented as a three-factor structure composed of positive deactivation, positive activation, and cognitive evaluation dimensions. The scale identified that the indicator capturing the travelers' concern over reaching the destination on time is no longer critical in long-distance travel satisfaction (in the context of recreational travel purposes) than commute and daily travel satisfaction. Also, the scale distinguished the valence-related emotions associated with travel satisfaction and merged them as a component of the cognitive evaluation dimension. Note that the indicators of valence-related emotions had no consistent loadings to a travel satisfaction dimension in the previous versions of the STS (see De Vos et al., 2015; Ettema et al., 2011; Singleton, 2019; Smith, 2017; Ye & Titheride, 2017). Overall, this modification of the STS improved the conceptual strength and validity of the original STS scale. The modified scale can be used in many settings, such as to evaluate the travel satisfaction of tourists, where the travel is usually long-distance, which is valuable to recreational destination managers.

After modifying the scale, the socio-demographic, general travel-related, trip-specific, in-vehicle time-use-related, and attitudinal determinants of different travel satisfaction dimensions were investigated to determine if and how long-distance travel behavior differs from short-distance or commute behavior. The investigation revealed a few differences in the role of some socio-demographic (age and income) and trip (travel duration) characteristics on travel satisfaction between long-distance and short-distance travel. In addition, the analysis showed that travel usefulness (or effective utilization of travel time), doing more active in-vehicle activities, and driving vehicles with advanced features (that potentially reduce driving efforts) positively impacted different travel satisfaction dimensions. This result indicates that the satisfaction of long-distance recreational travel will likely increase when these trips are made with AVs. Conversely, manual driving enjoyment negatively affected travel satisfaction, meaning travelers might miss manual driving in AVs, particularly during recreational travel, where the driving environment differs from daily commute travel. Also, the results showed that driving a greater percentage of time/distance in the trip led to lower travel satisfaction. Based on these results, it is concluded that long-distance recreational travelers enjoy manual driving but probably for a shorter duration only; thus, AVs seem to be a favorable choice for long-distance recreational travelers if manual driving is possible in those vehicles.

2. What is the missing link between travel behavior and tourism satisfaction?

The modification of the STS scale for long-distance travel in Chapter 2 offered ways to further investigate long-distance travel behavior. This research question was framed as a modified STS scale use case. This question aimed to investigate the interconnections between travel behavior and tourism literature by analyzing the impacts of travel satisfaction on two critical tourism attributes—destination satisfaction and revisit intention. Travel satisfaction was measured using the modified STS scale, and its direct and indirect impacts on destination satisfaction and revisit intention were estimated. As a result, travel satisfaction significantly impacted both destination satisfaction and revisit intention. An important theoretical implication can be drawn from this result that the analysis of tourist behavior needs to consider the travel satisfaction component, given that the tourists spend a significant duration of their overall trip time between their home and the destination. This also necessities revisiting the theories used in tourism literature, such as the theory of planned behavior, goal-directed behavior, etc., and modifying them by considering travel satisfaction as an indicator of tourist behavior.

Estimation of the direct and indirect effects revealed that the impact of travel satisfaction on revisit intention was more substantial than the impact of destination satisfaction on revisit intention. This remarkable finding highlights the importance of travel satisfaction in maintaining sustained and repeated tourism for a destination. It also suggests that investing in destination attributes alone might not be sufficient to attain the desired level of tourism for the destination. In summary, the results from this analysis first support the recommendations put forward by tourism studies that sustained and repeated tourism of a destination can be maintained by regularly investing in infrastructures in the destination and area around it, developing affordable tour packages, offering good food and accommodations, managing good transportation facilities around the destination, etc. and second present a novel recommendation to the destination managers that travel experiences of the visitors while traveling between home and destination should also be taken care of. Being significant indicators of travel satisfaction, investment in transportation networks, facilities, and services connecting major tourism destinations and city centers could boost the travel satisfaction of the visitors of tourism destinations. Specifically, creating high-capacity road infrastructure (resulting in limited congestion) and reliable travel time information on the way to tourism destinations, in combination with sufficient and cheap parking facilities, may stimulate travel satisfaction (Ettema et al., 2013; Susilo & Cats, 2014). Developing more rest areas and combining them with service plazas, restaurants, and other entertainment options, as well as scenic viewpoints/landscapes on the way to destinations, could help offer positive experiences to travelers. An environmentally sustainable strategy could be offering public transit services, having different entertainment options (e.g., bars, restaurants, casinos, etc.) in-vehicle, connecting tourist attractions and the city/population centers. This option adds the 'transport for tourism' concept to conventional destination attraction strategies.

3. What changes in long-distance travel behavior can be expected in the autonomous vehicle era?

This research question aimed to anticipate the changes in long-distance travel behavior that could be brought about by autonomous vehicles (AVs) in the near future. First, the long-distance travelers' perceptions towards the acceptance and use of AVs for long-distance recreational travel were studied. The results showed that the respondents were almost equally divided on the positive (46%) and negative (35%) intentions to adopt AVs for long-distance recreational travel. Around half of the respondents (47% and 52%) predicted having the same number of and same distance trips in the future as currently. In contrast, slightly less than half of the respondents (44% and 38%) reported having longer distances and more trips when AVs become available. These statistics indicate that the demand for long-distance recreational travel will likely rise due to AVs necessitating the preparation and planning to accommodate the induced travel demand. An environmentally viable solution to this increased travel demand could be provisioning public transport modes, including shared AV options, to connect popular recreational destinations (including national parks) and major city centers.

To better understand the factors affecting the acceptance and use of AVs for long-distance recreational travel, the analysis considered numerous exogenous (socio-demographics, general travel behavior, trip-specific characteristics, in-vehicle time use-related factors) and attitudinal latent (AV usefulness, AV concern, driving enjoyment) variables as potential influencers of the acceptance and use of AVs in addition to considering the impact of the acceptance on the use of AVs for more and longer trips. First, it was found that those inclined to adopt AVs for long-distance recreational trips had a higher interest in using AVs for more and longer trips. This result suggests that AV-induced travel demand will keep increasing as AVs become more widespread and publicly accepted. Second, AV acceptance and use intentions heterogeneity was observed based on several socio-demographic, general travel-related, and trip-specific characteristics. Third, model results confirmed that AV adoption and use interests were linked with the use of in-vehicle travel time. That means the potential to conduct a wide range of travel-based activities in AVs and effectively utilize travel time for activities other than driving were the factors influencing the higher acceptance and use of AVs. Fourth, AV usefulness, AV concerns, and driving enjoyment were significantly related to the acceptance and use of AV. The directionality of the impacts of these attitudinal variables was as expected, except that the AV concerns positively impacted having more long-distance recreational trips in the future. This result indicates that even though the acceptance of AVs will be contingent upon the associated concerns, their use or demand will be higher once the public adopt these vehicles. In summary, this analysis first predicted that the long-distance recreational travel demand would likely surge when AVs become widespread, suggesting transportation planners and destination managers consider these near-future changes to manage the flow of tourists efficiently and second investigated the factors associated with such changes that could help planners formulate the plans to address the AV-induced travel demand.

4. What are the roles of vehicle automation, onboard environment, and in-vehicle time use on travel choices and behaviors?

This question aimed to make a deeper investigation of the traveler's motivations towards the adoption of AVs. Specifically, the idea was to ascertain the weightage of the vehicle automation, onboard environment, and in-vehicle time use people consider when deciding to adopt an AV and, thus, the monetary values associated. Therefore, a stated choice experiment was conducted to understand the preferences of automated vehicle control over human control and the regular vehicle interior (like current cars) over a sophisticated work- and leisure-friendly interior by featuring three alternatives—human-driven vehicle (HV), autonomous vehicle (AV), and work- and leisure-friendly vehicle (AV-WL)—that vary by travel time and cost. The choice decisions were analyzed, and the travel time (VOTT) values for HV, AV, and AV-WL were $34.70, $31.00, and $30.30 per hour, respectively. These results showed that automation alone lowered the VOTT by 10.66% from current HVs, and adding a favorable onboard environment (by introducing work- and leisure-friendly vehicle interiors) further reduced the VOTT by

2.26%. These reductions indicate that the automated options would be more favorable to travelers when these vehicles come to the market; however, travelers would most likely seek the options with larger and more sophisticated interiors that could offer favorable onboard for work and leisure activities in-vehicle.

To further investigate this question, travelers' preferences for several in-vehicle travel-based activities and their evaluation of utilization of travel time (i.e., travel time usefulness) were measured in both HV and AV scenarios. Results revealed that travelers were interested in more travel-based activities in AVs than in HVs, but they were not confident that the travel time would be effectively utilized in the AV environment. Next, the analysis considered the role of travel usefulness and in-vehicle activities on the mode choice and VOTT associated with each mode. The mode choice results showed that the increase in travel-based activities and travel usefulness between AV and HV environments (AV – HV) had significant roles in the choice of automated modes (AV and AV-WL). However, when looking at the monetary value of travel-based activities on the VOTT of each mode, only texting/emailing/teleconferencing activity significantly lowered the VOTT in AV with work and leisure interior by $10.20 per hour. In contrast, travel usefulness had a significant monetary contribution in the VOTT of all modes. Based on all these results, it could be concluded that the drivers of the current cars cannot potentially conduct travel-based activities with monetary worth because of the primary driving task required. Regarding AVs having the same interior as the current cars, travelers would be interested in conducting more travel-based activities, but they are not confident that the vehicle interior would be favorable to perform those activities meaningful to have a monetary value associated. Finally, this leads to the conclusion that when AVs come to the market, consumers would prefer vehicles with an onboard environment favorable for work and leisure activities (e.g., Wi-Fi coverage, charging ports, a table for work, flexible seats, TV, etc.).

The future of automated vehicles being driven toward having sophisticated larger interior designs could be considered beneficial from an individual perspective in that people can use travel time more productively and free the time for other activities of interest. However, from a societal standpoint, these sophisticated interior designs lead to larger vehicle sizes such that the problem of the continuous increase in the size of cars in the last few decades (Meyer, 2023) will most likely be worsened by vehicle automation. Thus, the AVs would not only induce more travel demand (Acharya and Mekker, in progress; Dannemiller et al., 2023) but also consume more energy and require more road and parking space because of the larger vehicle designs. Finally, these negative aspects that could be brought about by automation should be considered while discussing the ways towards the sustainability of the transportation system.

6.2 Limitations and recommendations for future studies

This dissertation is not without limitations. The specific limitations and recommendations associated with each chapter have already been presented at the end of the chapters; however, the following points discuss the overall limitations of this dissertation and recommendations for future research.

1. Survey Instrument

This dissertation collected the data by conducting an online questionnaire survey of the targeted respondents. Since the survey asked about the respondents' revealed experiences and stated preferences, several limitations are associated with this approach. Recalling the past travel experience is always retrospective and could pose differences between actual and revealed behavior. For example, the survey asked the respondents to reveal their travel experience by rating several indicators (e.g., happy – sad) of the travel satisfaction scale, and revealing such experience is challenging because it is likely that the activity participation at the destination would hide such experience. The survey asked the respondents to state their preference for several aspects of autonomous vehicle technology, which are difficult to answer because such technology is non-existent. The actual behavior might vary significantly from the stated when such technology comes to the real world. A more hypothetical question in the survey asked the respondents to state the preferred in-vehicle activities they would like to do if the vehicle they used on the trip was autonomous. The answers to these hypothetical questions indicated the future scenario but could pose some discrepancies. Though we acknowledge the limitations of this survey approach, it is always hard to suggest an alternative approach that is relatively easy to implement. The revealed portion of the survey could be made more realistic by surveying the respondents as soon as after the experience. Also, an interview approach could help get more accurate data. The stated portion of the survey could be made more realistic by designing a more interactive survey (e.g., using video animation to show what autonomous vehicles are). Also, a costly but accurate approach could be a simulator-based study where a hypothetical travel environment (e.g., in an autonomous vehicle) could be set up, and the subject's behavior could be observed and analyzed.

2. Targeted respondents

This dissertation primarily wanted to look at the behaviors of long-distance travelers as opposed to short-distance travelers (i.e., commuters), which are believed to be structurally different. However, the dissertation was limited to long-distance recreational travelers only to ease the data collection effort. As a result, a comparison of the behaviors of long-distance travelers with different travel purposes (e.g., business, social, recreation, etc.) is absent in this dissertation, which could be pursued by future studies. Not only will this reveal the differences in long-distance travel behaviors among different travel purposes, but this will also help anticipate the acceptance and demand of AVs for different long-distance travel purposes. Ultimately, this will show the holistic picture of the changes in travel behavior that AVs could bring.

Additionally, this dissertation limited the recreational destinations to national parks in the US only, which limits the generalizing of the dissertation results. An analysis from Chapter 3 of this dissertation shows that destination satisfaction is influenced by the travel experience on the way to the destination. There could be another way around where the destination type (or its characteristics) affects the travel experience. Future studies should relax this limitation covering various destinations and geographical areas. The survey also didn’t allow the response from travelers involving air travel, which is also a study limitation that could be relaxed in future studies. Long-distance recreational trips involving air travel can be assumed to differ from those involving driving only because of the associated dynamics such as travel cost, travel time, connections, and other travel itineraries. The survey also collected data from those who drove the vehicle at least partially, mainly to understand the preferences for travel-based activities. Future studies could also collect data from the passengers to understand the preferences for several TBAs. It allows not only comparing the changes in TBAs between HVs and AVs as in this dissertation, but also corroborating if TBA preferences in AVs would be the same as those of passengers in HVs. Lastly, in light of multiple definitions of long-distance travel in the existing literature that mainly vary by travel distance (e.g., one-way distance ranging from 50 to 150 miles), this dissertation adopted a distance threshold of 75 miles one-way. It could also pose some limitations when comparing the results of this study with past studies.

3. In-vehicle time use

One primary focus of this dissertation was understanding how travelers use time in-vehicle, especially during long-distance travel. With this aim, the survey asked the respondents to reveal the activities they conducted in-vehicle during the trip and also asked them to rate the usefulness or worthwhileness of travel time spent. The respondents were asked the same questions after asking to pretend the vehicle was an AV instead of a HV to see the changes in in-vehicle time-use that AVs could bring about. This approach has successfully revealed the existing and potential future (i.e., in AVs) in-vehicle time-use behavior, as seen from the results in the preceding chapters. However, the current approach ignores the duration travelers participated in different TBAs. Including activity participation duration in analyzing the in-vehicle time use behavior could bring additional insights. This dissertation suggests future studies consider this aspect. Next, the choice experiment presented in Chapter 5 didn’t consider the in-vehicle time use variables directly but considered time-use perceptions asked from different questions. A further limitation was that the time-use variables collected for a general AV scenario were considered the same for two alternatives: autonomous vehicles with current interiors and autonomous vehicles with work and leisure interiors. These limitations could be relaxed either by considering time-use variables as attributes of choice experiment itself or by considering the differences in the responses to time-use variables in different alternatives with different characteristics. Additionally, based on the several trial analyses (not presented in any chapters because of inconclusive findings) of the responses to the travel time usefulness or worthwhileness question, this dissertation speculates the use of this question to understand the effectiveness of travel time usefulness needs to be revisited. This dissertation suggests conducting focus groups and Delphi surveys to refine the use of the travel time usefulness question in the travel behavior survey.

6.3 Future research direction

This dissertation contributes to the knowledge of the current long-distance travel behavior and AV-induced long-distance travel behavior changes from the behavioral standpoint. The study of long-distance travel behavior can be continued in the following direction.

1. The analysis of energy consumption and emissions is required to achieve the goal of energy-efficient and sustainable travel. However, long-distance travel has received minimal attention in analyzing transportation energy consumption and emission, similar to the study of travel behavior, despite a large share of long-distance trips on overall vehicle miles traveled. Thus, estimating and considering the energy and emissions associated with long-distance travel is necessary for the plans and policies for transportation sustainability. It could be a future research direction.
2. This dissertation investigated the implications of autonomous vehicles on long-distance travel behavior and demand. Since the future autonomous vehicles will likely

be electric, the anticipated travel behavior changes must be looked at from an autonomous electric vehicle viewpoint. Future long-distance travel behavior studies should incorporate the uncertainties in electric vehicle driving range and charging infrastructure in addition to uncertainties with autonomous technology. As a result, an extension to this dissertation could be estimating potential changes in long-distance travel patterns and demand because of the automation and electrification of vehicles and their impact on energy consumption and emissions.

3. Teleworking or working from home has always been considered a top strategy for reducing travel demand, and it has gained popularity more recently due to the global COVID-19 pandemic. While teleworking can be assumed to reduce overall travel demand, it has secondary impacts on home location choice and travel behavior (e.g., increase in city center trip length, increase in errands travel, need for recreational travel, etc.) (Macias et al., 2022). The changes brought by teleworking on long-distance (recreational) travel behavior, demand, and associated energy consumption could be another promising future research direction.

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Appendices

Appendix A. Survey Questionnaire

Screening Questions:

This part of the questionnaire assesses whether you qualify for this study or not. You will be offered to participate in the study only if you qualify.

1. Are you a resident of the United States?
   a. Yes
   b. No

2. Are you 18 years or older?
   a. Yes
   b. No

3. In 2022, have you been to any of the following national parks? Please select the most recent one you visited. Also, select the primary destination ONLY if multiple destinations were involved in the trip.
   a. Acadia National Park (Maine)
   b. National Park of American Samoa (American Samoa)
   c. Arches National Park (Utah)
   d. Badlands National Park (South Dakota)
   e. Big Bend National Park (Texas)
   f. Biscayne National Park (Florida)
   g. Black Canyon of the Gunnison National Park (Colorado)
   h. Bryce Canyon National Park (Utah)
   i. Canyonlands National Park (Utah)
   j. Capitol Reef National Park (Utah)
   k. Carlsbad Caverns National Park (New Mexico)
   l. Channel Islands National Park (California)
   m. Congaree National Park (South Carolina)
   n. Crater Lake National Park (Oregon)
   o. Cuyahoga Valley National Park (Ohio)
   p. Death Valley National Park (California, Nevada)
   q. Denali National Park and Preserve (Alaska)
   r. Dry Tortugas National Park (Florida)
   s. Everglades National Park (Florida)
   t. Gates of the Arctic National Park and Preserve (Alaska)
   u. Gateway Arch National Park (Missouri)
   v. Glacier National Park (Montana)
   w. Glacier Bay National Park and Preserve (Alaska)
   x. Grand Canyon National Park (Arizona)
   y. Grand Teton National Park (Wyoming)
   z. Great Basin National Park (Nevada)
   aa. Great Sand Dunes National Park and Preserve (Colorado)
   bb. Great Smoky Mountains National Park (North Carolina, Tennessee)
   cc. Guadalupe Mountains National Park (Texas)

dd. Haleakala National Park (Hawaii)
ee. Hawai'i Volcanoes National Park (Hawaii)
ff. Hot Springs National Park (Arkansas)
gg. Indiana Dunes National Park (Indiana)
hh. Isle Royale National Park (Michigan)
ii. Joshua Tree National Park (California)
jj. Katmai National Park and Preserve (Alaska)
kk. Kenai Fjords National Park (Alaska)
ll. Kings Canyon National Park (California)
mm. Kobuk Valley National Park (Alaska)
nn. Lake Clark National Park and Preserve (Alaska)
oo. Lassen Volcanic National Park (California)
pp. Mammoth Cave National Park (Kentucky)
qq. Mesa Verde National Park (Colorado)
rr. Mount Rainier National Park (Washington)
ss. New River Gorge National Park and Preserve (West Virginia)
tt. North Cascades National Park (Washington)
uu. Olympic National Park (Washington)
vv. Petrified Forest National Park (Arizona)
ww. Pinnacles National Park (California)
xx. Redwood National and State Parks (California)
yy. Rocky Mountain National Park (Colorado)
zz. Saguaro National Park (Arizona)
aaa. Sequoia National Park (California)
bbb. Shenandoah National Park (Virginia)
ccc. Theodore Roosevelt National Park (North Dakota)
ddd. Virgin Islands National Park (Virgin Islands)
eee. Voyageurs National Park (Minnesota)
fff. White Sands National Park (New Mexico)
ggg. Wind Cave National Park (South Dakota)
hhh. Wrangell-St. Elias National Park and Preserve (Alaska)
iii. Yellowstone National Park (Wyoming, Montana, Idaho)
jjj. Yosemite National Park (California)
kkk. Zion National Park (Utah)
lll. None of the above

[The answer to this question (QN. 3) is referred to as [DESTINATION] in the rest of the questionnaire.]

4. Did you drive a vehicle yourself (partially/fully) to get to [DESTINATION] and return?

a. Yes
b. No

5. Which of the following best matches the average one-way distance of your trip to [DESTINATION]?

a. <50 miles

b. 50-75 miles
c. 75-100 miles
d. >100 miles

6. Did any part of your travel to [DESTINATION] involve air travel?
a. Yes
b. No

7. [If option (a) in QN. 1, option (a) in QN. 2, not option (f) in QN. 3, option (a) in QN. 4, options (c) or (d) in QN. 5, option (b) in QN. 6] Congratulations you qualify for this survey. Please proceed ahead.

8. [If option (b) in QN. 1, option (b) in QN. 2, option (f) in QN. 3, option (b) in QN. 4, options (a) or (b) in QN. 5, option (a) in QN. 6] Sorry you do not qualify for this survey. To qualify for this survey, you need to be a US adult (age ≥ 18 years) and have visited at least one of the national parks of the US in 2022 by driving at least 75 miles one way without the involvement of air travel.

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Letter of Information:

Long-distance recreational travel experience and autonomous vehicles

You are invited to participate in a research study conducted by Sailesh Acharya, a Ph.D. student supervised by Dr. Michelle Mekker in the Department of Civil and Environmental Engineering at Utah State University, for his Ph.D. dissertation.

The purpose of this research is to understand how people experience traveling long-distance to recreational destinations. Specifically, we are interested in learning about travelers' moods, attitudes, and overall experience of long-distance recreational travel along with their preference for autonomous or self-driving vehicles. You are being asked to participate in this research because you are an adult (18 years or older) living in the US and have visited one of the US national parks in 2022 by driving at least 75 miles one way.

Your participation in this study is voluntary and you may withdraw your participation at any time for any reason.

If you take part in this study, you will be asked to complete one survey, which should take up to 15 minutes.

The possible risks of participating in this study include loss of confidentiality. Although you will not directly benefit from this study, it has been designed to understand the travel experience of long-distance recreational travelers which informs transportation agencies for transportation planning efforts and investment decisions.

We will make every effort to ensure that the information you provide remains confidential. We will not be collecting personally identifiable information. However, it may be possible for someone to recognize the specifics you share with us.

We will collect your information through Qualtrics. Online activities always carry a risk of a data breach, but we will use systems and processes that minimize breach opportunities. This survey will be securely stored in a restricted-access folder on Box.com, an encrypted, cloud-based storage system.

For your participation in this study, you will receive compensation equal to the amount you agreed upon before you entered into the survey. Compensation will occur upon completion of the survey.

You can decline to participate in any part of this study for any reason and can end your participation at any time.

If you have any questions about this study, you can contact Sailesh Acharya (student investigator, sailesh.acharya@usu.edu, 435-557-6198), or Dr. Michelle Mekker (principal investigator, michelle.mekker@usu.edu, 315-447-4151). Thank you again for your time and consideration. If you have any concerns about this study, please contact Utah State University's Human Research Protection Office at (435) 797-0567 or irb@usu.edu.

By continuing to the survey, **you agree that you are 18 years of age or older and wish to participate**. You agree that you understand the risks and benefits of participation and that you know what you are being asked to do. You also agree that if you have contacted the research team with any questions about your participation and are clear on how to stop your participation in this study if you choose to do so. Please be sure to retain a copy of this form for your records.

Main Survey:

Letter of Information: Letter of information (Click to download)

9. Please select "Accept" if you have read the letter of information and agree to participate in this study.
    a. Accept
    b. Decline

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We anticipate that this survey will take around 15 minutes to complete. You will be asked questions in five sections (Parts 1-5). You can track your progress with the bar at the top of the screen.

In the rest of the survey, you will be asked several questions related to the last trip. You should refer to your recent trip to [DESTINATION] as the last trip.

Part 1: Travel experience

This part of the questionnaire is related to expressing the details of the trip you made to [DESTINATION] and related travel experiences.

10. Where did you start your trip to [DESTINATION]? Please enter the name of state and zip code.
    State: [short answer]
    Zip code: [short answer]

11. On average, what was the **one-way travel time** of this trip?
    Hours: [short answer]
    Minutes: [short answer]

12. In dollars, approximately, how much did you spend on gas **one-way**? If your vehicle was electric, please input the cost incurred to charge the vehicle. You can input half of the total cost you paid for the gas/electricity during the whole trip.
    [short answer]

13. What vehicle did you drive for the trip?
    a. A vehicle owned/leased by your household
    b. A rented vehicle
    c. A vehicle borrowed from family, friend, or peer

14. Which of the following are true about the vehicle you drove for the trip? Select all that apply.
    a. Was a sedan or hatchback.
    b. Was an SUV.
    c. Was a truck.
    d. Was a recreational vehicle (e.g., RV)
    e. Was an electric vehicle.
    f. Other (please specify):

15. Which of the following features did the vehicle you drove for the trip have? Check all that apply.
    a. Blind-spot monitoring.
    b. Lane departure warning or lane-keep assistance.
    c. Adaptive cruise control.
    d. Automatic emergency braking.
    e. Driver monitoring.
    f. Parking assistance.
    g. Forward/backward collision warning.
    h. None of the above.
    i. Don’t know.

16. Who were your travel companions? Input the number of other people present in your vehicle based on your relationship with them.

a. Spouse
b. Children
c. Siblings
d. Other family members
e. Friends
f. Other (please specify):

17. What percentage of time or distance did you drive yourself on the overall trip? Consider both the trip to [DESTINATION] and the return trip to home.

a. I didn't drive at all.
b. 0-25 %
c. 25-50%
d. 50-75%
e. 75-100%
f. I was the only one who drove for the whole trip.

18. Did you experience any of the following during the trip? Select all that apply.

a. Rain
b. Snow
c. Low visibility
d. Congestion
e. Witnessed a crash
f. Involved in a crash
g. Other (please specify): ……
h. None of the above

19. Which of the following activities did you do in-vehicle during the trip? Consider the activities you did both ways. Select all that apply.

a. Listening to music, radio, or other audio
b. Singing, dancing
c. Interacting with other passengers
d. Talking on phone
e. Texting, emailing, or other messaging; teleconference
f. Reading newspapers, books, websites, etc.
g. Using social websites or apps (Facebook, Instagram, Twitter, LinkedIn, etc.)
h. Watching movies / TV / other entertainment
i. Playing games
j. Working or studying
k. Caring for or playing with children or pets
l. Eating food, drinking beverage, smoking
m. Sleeping or snoozing
n. Viewing scenery; watching people
o. Thinking or daydreaming
p. Watching the road

q. Other (please specify): …………..

20. How useful or worthwhile would you rate the time you spent traveling?
    a. Mostly wasted
    b. Somewhat wasted
    c. Neither wasted nor useful
    d. Somewhat useful
    e. Mostly useful

21. For each of the following pairs, select the choice that best corresponds to your overall experience on your trip to [DESTINATION]. Consider the trip both ways.
    a. I was very distressed – content.
    b. I was very tense – relaxed.
    c. I was very sad – happy.
    d. I was very tired – energized.
    e. I was very bored – enthusiastic.
    f. My trip was displeasing – enjoyable.
    g. My trip went poorly – smoothly.
    h. My trip was the worst – best I can imagine.
    i. I was worried I wouldn't – confident I would arrive on time.

22. How long did you stay in [DESTINATION]?
    a. Stayed for less than 1 hour, without night stay.
    b. Stayed for 1-4 hours, without night stay.
    c. Stayed for 4-8 hours, without night stay.
    d. Stayed for 1 night.
    e. Stayed for 2 nights.
    f. Stayed for more than 2 nights.

23. How would you rate your overall satisfaction with this visit to [DESTINATION]?
    a. Extremely dissatisfied
    b. Somewhat dissatisfied
    c. Neither satisfied nor dissatisfied
    d. Somewhat satisfied
    e. Extremely satisfied

24. Including this visit, how many times have you visited [DESTINATION]?
    a. 1
    b. 2
    c. 3
    d. 4
    e. 5+

25. How likely do you think that you would visit [DESTINATION] again in the future?
    a. Extremely unlikely
    b. Somewhat unlikely

c. Neutral
d. Somewhat likely
e. Extremely likely

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Part 2: Autonomous vehicle scenario

This is the second part of the survey. Here you will be asked several questions involving autonomous vehicles.

26. Before we start, we would like to know your familiarity with autonomous vehicle technology. How familiar are you with autonomous vehicles and/or their technologies?
    a. Not familiar at all
    b. Slightly familiar
    c. Moderately familiar
    d. Very familiar
    e. Extremely familiar

27. Please read the definition of an autonomous vehicle below before proceeding forward.

An a**utonomous vehicle (AV)** is a vehicle having full self-driving capabilities such that no driver is needed to drive (SAE level 5, click here to learn more). The vehicle uses various in-vehicle technologies and sensors to drive itself.

28. Consider if you had the option of using an autonomous vehicle instead of the current vehicle for your trip to [DESTINATION]. In this situation, how likely is it that you would use the autonomous vehicle instead of the current vehicle?
    a. Extremely unlikely
    b. Somewhat unlikely
    c. Neutral
    d. Somewhat likely
    e. Extremely likely

29. Hypothetically, consider that the vehicle you drove on the last trip was an autonomous vehicle having self-driving capability, but you also had an option of driving that autonomous vehicle in manual mode (i.e., you can drive the autonomous vehicle like a human-driven vehicle). In that scenario, what percentage of the trip would you switch to manual drive mode? You must select 0% if you don't want to switch to manual mode and 100% if you want to drive manually for the complete trip. Select your preference for both going and returning trips separately below.
    a. On going trip (one-way)
    b. On returning trip (one-way)
        i. 0%
        ii. 25%
        iii. 50%
        iv. 75%
        v. 100%

30. Hypothetically, consider that you drove in an autonomous vehicle instead of your vehicle during the last trip so that you didn't have to drive. In this scenario, which of the

following activities would you do while traveling? Consider the trip both ways. Select all that apply.

a. Listening to music, radio, or other audio
b. Singing, dancing
c. Interacting with other passengers
d. Talking on phone
e. Texting, emailing, or other messaging; teleconference
f. Reading newspapers, books, websites, etc.
g. Using social websites or apps (Facebook, Instagram, Twitter, LinkedIn, etc.)
h. Watching movies / TV / other entertainment
i. Playing games
j. Working or studying
k. Caring for or playing with children or pets
l. Eating food, drinking beverage, smoking
m. Sleeping or snoozing
n. Viewing scenery; watching people
o. Thinking or daydreaming
p. Watching the road
q. Other: …………..

31. How useful or worthwhile would you rate the time you spent traveling in an autonomous vehicle for this hypothetical trip scenario?

a. Mostly wasted
b. Somewhat wasted
c. Neither wasted nor useful
d. Somewhat useful
e. Mostly useful

32. In the future, when autonomous vehicles are available, how would the number of long-distance recreational trips you make in a typical year change?

a. Much less than current
b. Somewhat less than current
c. About the same as current
d. Somewhat more than current
e. Much more than current

33. In the future, when autonomous vehicles are available, your long-distance recreational trips would most likely be ...

a. … much shorter distance than current.
b. … somewhat shorter distance than current.
c. … about the same distance as current.
d. … somewhat further distance than current.
e. … much further distance than current.

34. Suppose you had two additional mobility options (along with your current mode) to travel for your trip to [DESTINATION] and cost wouldn't be the issue. First was an

autonomous vehicle having the self-driving ability, and second was teleportation where you could snap your fingers or blink your eyes and be instantly transported to wherever you want. In this scenario, which option would you choose for your last trip to [DESTINATION]? Please rank these three options based on your preference such that the first ranked option (1) is the most preferred and the last ranked (3) is the least preferred.

a. The same vehicle you drove for the last trip.
b. An autonomous vehicle with self-driving capability.
c. Instantaneous teleportation.

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Part 3: Stated choice experiment

35. For the following four questions, you will be given the following three vehicle options to choose from:
    1. Current vehicle.
    2. Autonomous vehicle with current vehicle interior.
    3. Autonomous vehicle with work and leisure interior.

1. Current vehicle refers to the vehicle you used to get to [DESTINATION] and return.

2. Autonomous vehicle with current vehicle interior refers to the self-driving vehicle with interior vehicle design same as that of your current vehicle. Thus, consider this vehicle option as same as your current vehicle but with the self-driving ability so that you don't have to drive.

3. Autonomous vehicle with work and leisure interior refers to the self-driving vehicle where the interior vehicle design is friendly for work and leisure activities. In this vehicle option, the seats are comfortable for sleeping or relaxing, Wi-Fi is available for leisure or work, a table can be pulled for work, charging ports are available for laptops and smartphones, etc. You can expect to do work or leisure activities inside this vehicle without the responsibility of driving.

Consider all three vehicle options were available for you to choose for your last trip to [DESTINATION], which option would you prefer? Each vehicle option had different travel time and cost associated. The values of the travel time and travel cost in the options presented below are around the values you experienced one-way on the last trip which are [TT] and [TC] respectively.

[Only one block among the following three will be presented to each respondent randomly. TT and TC refer to the one-way travel time and cost experienced by the respondent respectively.]

Block I

36. Which option would you prefer? (click here if you are not clear with the definitions)

Attributes	Current vehicle	Autonomous vehicle with current vehicle interior	Autonomous vehicle with work and leisure interior
Travel Time	TT	1.2 * TT	TT
Travel Cost	TC	1.2 * TC	1.2 * TC
Choice			

37. Which option would you prefer? (click here if you are not clear with the definitions)

Attributes	Current vehicle	Autonomous vehicle with current vehicle interior	Autonomous vehicle with work and leisure interior
Travel Time	1.2 * TT	TT	1.2 * TT
Travel Cost	TC	TC	0.8 * TC
Choice			

38. Which option would you prefer? (click here if you are not clear with the definitions)

Attributes	Current vehicle	Autonomous vehicle with current vehicle interior	Autonomous vehicle with work and leisure interior
Travel Time	TT	0.8 * TT	TT
Travel Cost	1.2 * TC	0.8 * TC	1.2 * TC
Choice			

39. Which option would you prefer? (click here if you are not clear with the definitions)

Attributes	Current vehicle	Autonomous vehicle with current vehicle interior	Autonomous vehicle with work and leisure interior
Travel Time	0.8 * TT	TT	0.8 * TT
Travel Cost	0.8 * TC	TC	0.8 * TC
Choice			

Block II

40. Which option would you prefer? (click here if you are not clear with the definitions)

Attributes	Current vehicle	Autonomous vehicle with current vehicle interior	Autonomous vehicle with work and leisure interior
Travel Time	TT	1.2 * TT	TT
Travel Cost	TC	0.8 * TC	0.8 * TC
Choice			

41. Which option would you prefer? (click here if you are not clear with the definitions)

Attributes	Current vehicle	Autonomous vehicle with current vehicle interior	Autonomous vehicle with work and leisure interior
Travel Time	TT	0.8 * TT	TT
Travel Cost	1.2 * TC	1.2 * TC	0.8 * TC
Choice			

42. Which option would you prefer? (click here if you are not clear with the definitions)

Attributes	Current vehicle	Autonomous vehicle with current vehicle interior	Autonomous vehicle with work and leisure interior
Travel Time	1.2 * TT	0.8 * TT	1.2 * TT
Travel Cost	0.8 * TC	TC	1.2 * TC
Choice			

43. Which option would you prefer? (click here if you are not clear with the definitions)

Attributes	Current vehicle	Autonomous vehicle with current vehicle interior	Autonomous vehicle with work and leisure interior
Travel Time	0.8 * TT	1.2 * TT	0.8 * TT
Travel Cost	TC	TC	1.2 * TC
Choice			

Block III

44. Which option would you prefer? (click here if you are not clear with the definitions)

Attributes	Current vehicle	Autonomous vehicle with current vehicle interior	Autonomous vehicle with work and leisure interior
Travel Time	1.2 * TT	TT	0.8 * TT
Travel Cost	0.8 * TC	0.8 * TC	TC
Choice			

45. Which option would you prefer? (click here if you are not clear with the definitions)

Attributes	Current vehicle	Autonomous vehicle with current vehicle interior	Autonomous vehicle with work and leisure interior
Travel Time	0.8 * TT	TT	1.2 * TT
Travel Cost	0.8 * TC	1.2 * TC	TC
Choice			

46. Which option would you prefer? (click here if you are not clear with the definitions)

Attributes	Current vehicle	Autonomous vehicle with current vehicle interior	Autonomous vehicle with work and leisure interior
Travel Time	1.2 * TT	TT	0.8 * TT
Travel Cost	1.2 * TC	1.2 * TC	TC
Choice			

47. Which option would you prefer? (click here if you are not clear with the definitions)

Attributes	Current vehicle	Autonomous vehicle with current vehicle interior	Autonomous vehicle with work and leisure interior
Travel Time	0.8 * TT	TT	1.2 * TT
Travel Cost	1.2 * TC	0.8 * TC	TC
Choice			

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<u>Part 4: Perception of autonomous vehicles and other attributes</u>

You completed more than two-thirds of the survey! You will be finished soon. In this fourth part of the survey, you will be asked to rate several statements about autonomous vehicles and general attributes.

48. To what extent do you agree or disagree with the following statements about autonomous vehicles (AVs)?

a. AVs will drive me safely to wherever I want.
b. Using an AV will improve my (and others') driving efficiency.
c. I could multitask while traveling in an AV (e.g., work, sleep, surf the internet).
d. Using an AV will reduce my driving burden/stress.
e. AVs will improve the mobility of overall transportation.
f. AVs will offer economic and social benefits overall.

49. To what extent do you agree or disagree with the following statements about autonomous vehicles (AVs)?

a. I would feel comfortable having an AV pickup/drop off children without adult supervision.
b. I am concerned about the potential failure of AV sensors, equipment, technology, and system safety.
c. I am concerned about the legal liability for drivers or owners of AVs in case of accidents/crashes.
d. AVs would make me feel safer on the streets as a pedestrian or as a bicyclist.
e. AVs would perform well even in poor weather or other unexpected conditions.
f. I am concerned about the data privacy and security breach/hacking in AVs.
g. I am worried about the higher purchase, maintenance, and insurance costs associated with AVs.

50. To what extent do you agree or disagree with the following statements about yourself?

a. I like to be among the first to have the latest technology.
b. Learning how to use new technology is often frustrating for me.
c. Having internet connectivity everywhere I go is important to me.

51. To what extent do you agree or disagree with the following statements about yourself in general?

a. I enjoy driving myself.
b. I feel safer driving myself rather than others driving me.
c. I prefer not to have the responsibility of driving.
d. I feel stressed or nervous when driving.
e. I enjoy driving during recreational travel.

52. To what extent do you agree or disagree with the following statements about yourself?

a. I like to be engaged in two or more activities simultaneously.

b. I believe people should aim at performing multiple tasks simultaneously.
c. It makes me feel good to be involved in multiple activities simultaneously.

53. To what extent do you agree or disagree with the following statements about yourself?
a. I am concerned about current environmental pollution and its impact on health.
b. I don't change my behavior based solely on concern for the environment.
c. I rarely worry about the effects of pollution on myself and my family.

54. When autonomous vehicles (AVs) are available in the market, how likely do you think that you would …?
a. … ride in an AV
b. … purchase an AV
c. … recommend your family member, friends, and peers to purchase an AV
d. … purchase and/or use an AV if it is electric

55. Suppose autonomous vehicles (AVs) are available in the market now, how long would your household wait to purchase an AV?
a. My household won't purchase an AV.
b. Within less than 1 year from now.
c. Within 1-2 years from now.
d. Within 2-5 years from now.
e. Within 5-10 years from now.
f. After more than 10 years from now.

______________________________Page Break______________________________

Part 5: Sociodemographic and travel characteristics

In this last part of the survey, you will be asked to provide your socio-demographic and individual travel characteristics.

56. What is your age?
    a. 18 to 24 years
    b. 25 to 34 years
    c. 35 to 44 years
    d. 45 to 54 years
    e. 55 to 64 years
    f. 65 to 74 years
    g. 75 to 84 years
    h. 85 years and above
    i. Prefer not to answer

57. How do you describe yourself? Check all that apply.
    a. White
    b. Black or African American
    c. American Indian or Alaska Native
    d. Asian
    e. Native Hawaiian or Pacific Islander
    f. Hispanic or Latino
    g. Other (please specify): …
    h. Prefer not to answer

58. How do you describe your gender?
    a. Female
    b. Male
    c. Prefer to self-describe (please specify): …
    d. Prefer not to answer

59. What is the highest degree or level of school you have completed?
    a. Not a high school graduate, grade 12 or less
    b. High school diploma or equivalent (e.g., GED)
    c. Bachelor’s or associate degree
    d. Graduate degree or higher
    e. Prefer not to answer

60. Are you currently enrolled in any type of school?
    a. Yes, full-time
    b. Yes, part-time
    c. No

61. How many people of 18 years or older (including yourself) live in your household?
    a. 1 (just me)
    b. 2

c. 3
d. 4
e. 5
f. 6
g. 7
h. 8+

62. How many people of below 18 years live in your household?
a. 0
b. 1
c. 2
d. 3
e. 4+

63. What is your approximate total household income (before taxes)?
a. Less than $10,000
b. $10,000 to $14,999
c. $15,000 to $24,999
d. $25,000 to $34,999
e. $35,000 to $49,999
f. $50,000 to $74,999
g. $75,000 to $99,999
h. $100,000 to $149,999
i. $150,000 or more
j. Don’t know
k. Prefer not to answer

64. Are you currently employed?
a. Yes, full-time
b. Yes, part-time
c. No

65. What is your occupation?
[short answer]

66. Do you have a driver’s license?
a. Yes
b. No

67. How many years have you held your driver’s license?
[short answer] years

68. Have you ever received any traffic citations?
a. No, I haven’t got any traffic citations to date.
b. Yes, 1.
c. Yes, 2.

d. Yes, 3-5.
e. Yes, 5+.

69. Have you ever witnessed or been involved in any traffic crashes in the past?
a. No, never.
b. Yes, 1.
c. Yes, 2.
d. Yes, 3-5.
e. Yes, 5+.
f. Yes, 10+.

70. How many vehicles are available to you at your home? Only count those in working conditions that are privately owned or leased by you or your household.
a. 0
b. 1
c. 2
d. 3
e. 4
f. 5+

71. What transportation mode do you typically use for the following purposes?
a. Work/school trips
b. Grocery and Shopping trips
c. Personal Business trips
d. Social/Recreational trips
i. Walk
ii. Bike, scooter, skateboard
iii. Personal car (driving yourself)
iv. Carpool, taxi, Uber, Lyft, UTA on-demand, etc.
v. Public transit (bus, train, light rail)

72. In a typical year, how many times do you drive long-distance for recreational purposes (e.g., visiting national and state parks, and other tourist destinations)? Consider trips of distance more than 75 miles one-way as long-distance.
a. 0
b. 1
c. 2
d. 3
e. 4
f. 5
g. 6-9
h. 10+

Page Break

[If option (b) Decline in QN. 1]

Your response has been recorded.

We thank you for your time spent taking this survey. If you have any questions, suggestions, or recommendations regarding this survey, please fill free to send an email at sailesh.acharya@usu.edu.

______________________________Survey Ends_______________________________

Appendix B. Curriculum Vitae

Sailesh Acharya **CV**

Graduate Research Assistant
Dept. of Civil and Envt. Engineering
Utah State University
Logan, Utah, 84322
(435)557-6198 | sailesh.acharya@usu.edu

Modeling and Metrics Intern
Center for Integrated Mobility Sciences
National Renewable Energy Laboratory
Golden, Colorado, 80401
(303)630-5666 | sailesh.acharya@nrel.gov

Employment

Utah State University, Logan, UT (2020 Jan – Running)
(Role: *Graduate Research Assistant*)

- Collaborating in preparing proposals for research project funding.
- Leading and conducting several funded and unfunded research projects.
- Presenting and publishing research findings in conferences and academic journals.
- Teaching undergraduate and graduate students through formal lectures and informal guidance.

National Renewable Energy Laboratory, Golden, CO (2023 Jan – Running)
(Role: *Transportation Modeling and Metrics Intern*)

- Using Google Transit Feed Specification (GTFS) data to assess accessibility and mobility of city/region.
- Using the existing Mobility Energy Productivity (MEP) tool to understand the quality of the transportation system and working to advance the tool.
- Developing the long-distance travel demand model and using it to model the spread of the virus (e.g., COVID-19) through domestic and international long-distance travel.

Education

Ph.D. Doctor of Philosophy in Civil and Envt. Engineering (2020 Jan – Running)
Utah State University, Logan, UT

- Transportation Engineering specialization
- GPA: 4.00 *(till date)*
- Advisor: Dr. Michelle Mekker
- Dissertation (proposed): *"Long-distance Recreational Travel Behavior and Choice of Autonomous Vehicles"*

M.Sc. Master of Science in Transportation Engineering (2017 Jun – 2019 Jul)
Institute of Engineering, Pulchowk Campus
Tribhuvan University, Nepal

- Percentage: 83.20 %
- Advisor: Anil Marsani

- Thesis: "*Modelling the relationship between the pedestrian illegal mid-block crossings with traffic and geometric parameters*"

B.E. Bachelor of Civil Engineering (2012 Nov – 2016 Nov)
Institute of Engineering, Pulchowk Campus
Tribhuvan University, Nepal

- Percentage: 73.47 %

Skills

- Statistical analysis – probabilistic modeling, (non-)linear regression, ANOVA, time-series regression, spatial analysis, discrete choice modeling, latent class analysis, logit/probit models.
- Psychometrics – factor analysis, path analysis, structural equation modeling, longitudinal/growth analysis.
- Machine learning – clustering, principal component, decision trees, random forest, KNN, SVM.
- Statistical visualization – ggplot, BaseR, Microsoft packages.
- Data collection – design of stated and revealed preference surveys, choice experiment design.
- Transportation – travel behavior analysis, travel demand modeling, safety analysis.
- Technical writing and presentation.

Software

R-programming | ArcGIS | Python | SPSS | AutoCAD | VISSIM | CUBE | Synchro | Microsoft office

Publications

Peer-reviewed journal articles

1. Acharya, S., Mekker, M., & Singleton, P. A. (2023). Validating the satisfaction with travel scale and measuring long-distance recreational travel satisfaction. *Transportation Research Part F: Traffic Psychology and Behaviour*, *95*, 1-17. https://doi.org/10.1016/j.trf.2023.03.015.
2. Acharya, S., Mekker, M., & De Vos, J. (2023). Linking travel behavior and tourism literature: Investigating the impacts of travel satisfaction on destination satisfaction and revisit intention. *Transportation Research Interdisciplinary Perspectives*, *17*, 100745. https://doi.org/10.1016/j.trip.2022.100745.
3. Acharya, S., & Mekker, M. (2022). The verbiage in variable message signs and traffic diversion during crash incidents. *Journal of Intelligent and connected vehicles*, *5*(3), 333-344. https://doi.org/10.1108/JICV-06-2022-0022.
4. Acharya, S., & Mekker, M. (2022). Measuring data sharing intention and its association with the acceptance of connected vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *89*, 423-436. https://doi.org/10.1016/j.trf.2022.07.014.

5. Acharya, S., & Singleton, P. A. (2022). Associations of inclement weather and poor air quality with non-motorized trail volumes. *Transportation Research Part D: Transport and Environment*, *109*, 103337. https://doi.org/10.1016/j.trd.2022.103337.
6. Acharya, S., & Mekker, M. (2022). Public acceptance of connected vehicles: An extension of the technology acceptance model. *Transportation Research Part F: Traffic Psychology and Behaviour*, *88*, 54-68. https://doi.org/10.1016/j.trf.2022.05.002.
7. Acharya, S., & Mekker, M. (2022). Importance of the reputation of data manager in the acceptance of connected vehicles. *Communications in Transportation Research*, *2*, 100053. https://doi.org/10.1016/j.commtr.2022.100053.
8. Acharya, S., & Humagain, P. (2022). Public Interest in Autonomous Vehicle Adoption: Evidence from the 2015, 2017, and 2019 Puget Sound Travel Surveys. *Journal of Transportation Engineering, Part A: Systems*, *148*(4), 04022003. https://doi.org/10.1061/JTEPBS.0000655.
9. Acharya, S., & Poudel, N. (2019). Optimal Location of Administrative Center: A Case Study of Province No. 1, Nepal. *International Journal of Advanced Engineering, Management and Science*.
10. Acharya, S., & Marsani, A. (2019). Modelling the Relationship between Pedestrian Illegal Mid-Block Crossings with Traffic and Geometric Parameters. *International Journal of Advanced Engineering and Management*.

Research project reports

1. Acharya, S. & Mekker, M. (2022). Evaluating the impact of detour messaging on actual driver detour behavior. Utah Department of Transportation (UDOT). https://rosap.ntl.bts.gov/view/dot/61158.
2. Acharya, S. & Mekker, M. (2021). Public Perception of the Collection and Use of Connected Vehicle Data. Mountain-Plains Consortium. MPC-21-439. https://rosap.ntl.bts.gov/view/dot/58951.

Datasets and software

1. Sailesh Acharya. (2023). saileshacharya1/trail-volumes-air-quality: trail-volumes-air-quality. Zenodo. https://doi.org/10.5281/zenodo.7498242.
2. Acharya, S. (2022). autonomous-vehicle-interests-multivariate-modeling. Zenodo. https://doi.org/10.5281/zenodo.6795556.
3. Acharya, S. (2022). long-distance-recreational-travel-survey. Zenodo. https://doi.org/10.5281/zenodo.7319988.

Newspaper articles

1. Acharya, S. & Acharya, S. (2020). Incentivising electric car buyers in Nepal can be a risky affair, economically. Onlinekhabar. https://english.onlinekhabar.com/incentivising-electric-car-buyers-in-nepal-can-be-a-risky-affair-economically.html.

Presentations

1. Acharya, S., Mekker, M., & Singleton, P. A. (2023 January). Validating the Satisfaction with Travel Scale and Measuring Long-distance Recreational Travel Satisfaction. Presented at the 102^{nd} Annual Meeting of the Transportation Research Board, Washington DC.
2. Acharya, S. & Mekker, M. (2023 January). Measuring Intentions to Ride, Own, or Recommend Connected Vehicles Using a Multivariate Model. Presented at the 102^{nd} Annual Meeting of the Transportation Research Board, Washington DC.
3. Acharya, S. & Mekker, M. (2023 January). How Does the Reputation of Data Manager Affect the Public Acceptance of Connected Vehicles?: Findings from a Questionnaire Survey in the United States. Presented at the 102^{nd} Annual Meeting of the Transportation Research Board, Washington DC.
4. Acharya, S. & Mekker, M. (2022 December). Long-distance recreational travel experience and choice of autonomous vehicles. Presented at the 16^{th} International Conference on Travel Behaviour Research, Santiago, Chile.
5. Acharya, S. & Mekker, M. (2022 August). Behavioral response of drivers towards different verbiage of crash-related message in variable message sign – Findings from a real-field data of Utah**.** Presented at the 2022 Institute of Transportation Engineers (ITE) Annual Meeting and Exhibition, New Orleans, LA.
6. Acharya, S. & Mekker, M. (2022 June). Can connected vehicles be a source of data for traffic operation and planning? Findings based on public perception. Presented at the 2022 Institute of Transportation Engineers (ITE) Western District Annual Meeting, Palm Springs, CA.
7. Acharya, S. & Mekker, M. (2022 June). Variable Message Signs' Verbiage and Drivers' Response during Crash Incidents. Presented at the 2022 Institute of Transportation Engineers (ITE) Western District Annual Meeting, Palm Springs, CA.
8. Acharya, S. & Mekker, M. (2022 June). Public acceptance of connected vehicles: an extension of the technology acceptance model. Presented at the 2022 Institute of Transportation Engineers (ITE) Mountain District Annual Meeting, Boise, ID.
9. Acharya, S. & Mekker, M. (2022 June). Are Data Issues the Barriers to the Acceptance of Connected Vehicles? Evidence from a Questionnaire Survey in the US. Presented at the International Conference on Transportation & Development 2022, Seattle, WA.
10. Acharya, S. & Mekker, M. (2022 April). Behavioral response of drivers towards different verbiage of crash-related message in variable message sign – Findings from a real-field data of Utah**.** Presented at the Student Poster Competition 2022 organized by Utah State University College of Engineering.
11. Acharya, S. & Mekker, M. (2022 January). Exploring Associations between Variable Message Signs' Verbiage and Traffic Diversion During Crash Incidents. Presented at the 101^{st} Annual Meeting of the Transportation Research Board, Washington DC.
12. Acharya, S. & Mekker, M. (2022 January). Are We Ready to Share Data for Connected Vehicles? Evidence from a Questionnaire Survey in the US. Presented at the 101^{st} Annual Meeting of the Transportation Research Board, Washington DC.

13. Acharya, S. & Singleton, P. A. (2022 January). Exploring Associations of Inclement Weather and Poor Air Quality on Non-motorized Trail Volumes Using a Time Series Framework. Presented at the 101st Annual Meeting of the Transportation Research Board, Washington DC.
14. Acharya, S. & Humagain, P. (2022 January). Public Interest in Autonomous Vehicle Adoption: Evidence from the 2015, 2017, and 2019 Puget Sound Travel Surveys. Presented at the 101st Annual Meeting of the Transportation Research Board, Washington DC.
15. Acharya, S., (2021 November). Safety evaluations of diverging diamond interchanges in Utah. Presented at the Utah Institute of Transportation Engineers (UTite) best student paper competition, Salt Lake City, UT.
16. Acharya, S., & Mekker, M. (2021 September). Investigating data sharing intention in connected vehicle technology. Presented at the 14th International Conference of Eastern Society of Transportation Studies (EASTS), Hiroshima, Japan (Virtual).
17. Acharya, S., (2020 November). Exploring the associations of inclement weather and poor air quality with non-motorized travel using time series framework. Presented at the Utah Institute of Transportation Engineers (UTite) best student paper competition, UT (Virtual).
18. Acharya, S., & Poudel, N. (2019 September). Optimal location of administrative center: a case study of province no. 1, Nepal. Presented at the 13th International Conference of Eastern Society of Transportation Studies (EASTS), Colombo, Sri Lanka.

Funded research projects

Utah State University, Logan, UT (as a graduate research assistant; Principal Investigator: Dr. Michelle Mekker)

1. Validating the collection of skid data by assessing correlation with crash data
   - Funding: $35,000 (UDOT)
   - Start date: September 19, 2022; Status: Running
2. State of the practice of crash reporting in the US and implications for CAV safety assessment
   - Funding: $80,000 (MPC), $70,910 (USU), $9,090 (UDOT)
   - Start date: August 24, 2021; Status: Running
   - Link: https://www.mountain-plains.org/research/details.php?id=557
3. Evaluating the impact of detour messaging on actual driver detour behavior
   - Funding: $35,000 (UDOT)
   - Start date: March 16, 2020; Status: Completed
   - Link: https://drive.google.com/file/d/1aa12EnD7JuYr9jXRV-_X-4wSeaHkHNGz/view
4. Public perception of the collection and use of connected vehicle data (MPC-621)
   - MPC funding: $49,958.20 (MPC), $49,958.20 (Utah LTAP)
   - Start date: February 19, 2020; Status: Completed
   - Link: https://www.mountain-plains.org/research/details.php?id=518

Teaching

Utah State University, Logan, UT

2018 CEE5230 Geometric Design of Highways

- *Guest lecturer:* Vertical alignment, design of vertical curves.

National College of Engineering, Lalitpur, Nepal

2018 CE653 Transportation Engineering
CE703 Transportation Engineering II

Himalayan College of Geomatics Engineering, Kathmandu, Nepal

2020 BEG474GE Engineering Survey I
BEG475GE Engineering Survey II
2019 BEG474GE Engineering Survey I
BEG475GE Engineering Survey II
2018 BEG474GE Engineering Survey I
BEG475GE Engineering Survey II

Aryan School of Engineering and Management, Kathmandu, Nepal

2018 ECO411 Engineering Economics
CVL411 Estimation and Costing

Janakpur Engineering College, Bhaktapur, Nepal

2018 CE653 Transportation Engineering
CE703 Transportation Engineering II
2017 CE704 Hydropower Engineering
CE606 Engineering Hydrology
CE754 Construction Management
CE653 Transportation Engineering

Awards

- "Outstanding Ph.D. Scholar" award (with a $500 cash prize) for the academic year 2022-2023 by the College of Engineering, Utah State University.
- Winner of the student poster competition 2022 organized by the College of Engineering, Utah State University ($200 cash prize).
- Runner-up in the Institute of Transportation Engineers, Utah chapter (UTite) student paper competition 2021 ($150 cash prize).
- Runner-up in the Institute of Transportation Engineers, Utah chapter (UTite) student paper competition 2020 ($150 cash prize).

Professional Activities, Memberships, and Certifications

Peer-review

- Journal articles
  - *Transportation Research Part F: Traffic Psychology and Behaviour*
  - *Transportation Research Interdisciplinary Perspectives*
  - *Journal of Transportation Engineering Part A: Systems*

- *Transportation Research Record*

- Conferences
  - *102nd Annual Meeting of the Transportation Research Board (2023)*
  - *101st Annual Meeting of the Transportation Research Board (2022)*
  - *100th Annual Meeting of the Transportation Research Board (2021)*

Memberships

- Utah State University Institute of Transportation Engineers Student Chapter
- Nepal Engineers Association

Certifications

- FE Civil (NCEES)
- Civil Engineer (Nepal Engineering Council)

Student Activities/Leadership

- Graduate Director of Engineering Council USU (Aug 2021 – Apr 2022)
- President of USU Nepalese Students Association (Dec 2021 – Aug 2022)

Media Mentions

- Mortensen, M. (2022, Jan 24). Transportation Engineering Student Presents Four Papers at Annual Research Meeting. https://www.usu.edu/today/story/transportation-engineering-student-presents-four-papers-at-annual-research-meeting.
- Mortensen, M. (2021, Nov 23). USU Civil and Environmental Engineering Students win Best Paper Awards. https://engineering.usu.edu/news/main-feed/2021/usu-civil-and-environmental-engineering-students-win-best-paper-awards.
- Pennington, A. (2021, Feb 1). Engineering Grad Students Win Research Paper Competition. https://www.usu.edu/today/story/engineering-grad-students-win-research-paper-competition.

Past Employment

National College of Engineering (Lalitpur, Nepal)

- Lecturer, CE Department (Transportation-related subjects) (2019 Apr – 2019 Dec)

Mannings Consult Pvt. Ltd. (Lalitpur, Nepal)

- Transport specialist (resource person) (2018 Mar – 2019 Dec)

Janakpur Engineering College (Bhaktapur, Nepal)

- Asst. Lecturer, CE Department (Transportation related subjects) (2017 Jan – 2018 Mar)

References

Dr. Michelle Mekker
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