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Commercial Short-Haul Flight or Autonomous Mobility-On-Demand: Modeling Air Passengers' Modal Choice

by

Agatha Kessler Fentress

A Dissertation Submitted to the College of Aviation
in Partial Fulfillment of the Requirements for the Degree of
Doctor of Philosophy in Aviation

Embry-Riddle Aeronautical University
Daytona Beach, Florida
September 2022

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Commercial Short-Haul Flight or Autonomous Mobility-On-Demand: Modeling Air Passengers' Modal Choice

By

Agatha Kessler Fentress

This dissertation was prepared under the direction of the candidate's Dissertation Committee Chair, Dr. Dothang Truong , and has been approved by the members of the dissertation committee. It was submitted to the College of Aviation and was accepted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Aviation.

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Abstract

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Title: Commercial Short-Haul Flight or Autonomous Mobility-On-Demand: Modeling Air Passengers' Modal Choice

Institution: Embry-Riddle Aeronautical University

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Commercial short-haul flights (SF) are vital to airports and airlines because they account for one-third of hub traffic and have higher profit margins than the long-haul market. While U.S. commercial air passenger travel has increased steadily over the past decades, SF has been declining and was doing so before the unprecedented decrease in air travel caused by restrictions related to the COVID-19 global pandemic. Once autonomous mobility-on-demand (aMoD) is more viable than the human-driven car, demand for SF could be negatively impacted. Although there is published research on SF and aMoD, studies on factors influencing the choice between SF and aMoD are missing. Based on goal framing theory (GFT) variables, contextual trip attributes, COVID-19 items, and demographics, this study used a quantitative survey design to answer two research questions. The first question sought to identify factors that most influence U.S. air travelers' modal choice for inter-regional travel. The second question aimed to identify distinct passenger clusters for SF and aMoD and evaluate the similarities and differences within these passenger segments. An online questionnaire of 69 items was developed based on extant literature and the theoretical foundation of the GFT. The survey was administered online with an air passenger sample in October 2021 via Amazon's MTurk.

Results from 1,388 air passenger respondents qualified for data analyses, including exploratory factor analysis (EFA), multinomial logistic regression (MNL), two-step cluster analysis (CA), and multivariate analysis of variance (MANOVA).

The findings support the GFT as a theoretical framework for modeling future mode choice and SF and aMoD clusters. The *current primary transport mode* was the most critical predictor for future mode choice. *Self-efficacy*, *value of time, trust*, and *habit* are new variables added to the GFT framework. The first two were useful in predicting future mode choice; *trust* and *habit* were not. Two-thirds (66%) of the current SF passengers intend to shift to other transport modes once aMoD is available; 31% of the current SF market share could be lost to aMoD and 20% to conventional driving. More than half of the current most-traveled air passengers intend to use aMoD as their main transport choice. The potential significant shifts in the ground- and air-mode shares revealed in this study may have crucial impacts on airlines, airports, infrastructure, future air/land-use planning, and the travel and hospitality industries.

Keywords: Short-haul flights, autonomous mobility-on-demand, goal framing theory, cluster analysis, EFA, MANOVA, multinomial logistic regression

Dedication

Aviation is the magic of man defying gravity. Our limitless imagination continually shapes this highway in the sky. In the hopes that this work may contribute even a minute degree to our aerial future, this is dedicated to those who dare to dream. And to …

… my parents, who first put me on a plane at thirteen to fly the 6,000 miles from Hong Kong to England to attend boarding school. Since then, I have flown millions of miles and visited hundreds of airports and their cities,

… my husband, who champions a better passenger experience in airport design,

… Dr. Truong, whose brilliance and generosity guided me to my dream of earning a Ph.D. in Aviation,

… autonomous mobility-on-demand, on the ground and in the air.

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My deepest gratitude goes to Dr. Dothang Truong, my dissertation committee chair, and the committee members – Dr. Jing Yu Pan, Dr. David Cross, and Dr. Joshua Sperling. Their generous support and insightful guidance have made all the difference in my Ph.D. journey. A special thank you goes to Thomas Pellegrin, my study-mate who inspires me with his intellect and sustains me with his humor.

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Chapter I: Introduction

Since the first paying passenger a century ago, commercial aviation has been the highway in the sky for transporting people and cargo, and, with them, ideas igniting globalization. Rapid improvements in aviation technologies have democratized commercial aviation and stimulated passenger growth. However, the commercial aviation industry suffers from low-profit margins, intense competition, and external risks (Chao et al., 2019). Airlines strive to improve the passenger experience, lower costs and operational inefficiencies, decrease CO_2 emissions, and optimize revenues for the industry to thrive (Dobruszkes et al., 2017). In addition to airline competition, they routinely compete with alternative transport modes such as cars and trains, especially on short-haul routes (Pan & Truong, 2019). America's resilient car culture already poses a unique challenge to the airline industry, black swan events such as the COVID-19 pandemic and technological advances may further strengthen the car and other types of ground transportation as a preferred mode of transportation (Cutler & Summers, 2020; Linden, 2020; Rossi et al., 2020).

Subsequent waves of change to impact commercial aviation negatively may come from three primary ground transportation innovations: ground vehicle automation, vehicle electrification, and on-demand platforms. *Autonomous mobility-on-demand* (aMoD) is defined as door-to-door, on-demand mobility service using electric self-driving cars (Fulton et al., 2018; Manfreda et al., 2019; Sheppard et al., 2019). Once aMoD is more viable than the human-driven car (with potentially improved safety, convenience, and cost), demand for commercial aviation, especially short-haul flights, could be negatively impacted (Fagnant & Kockelman, 2018; Meyer et al., 2017). For the purpose of this research, *commercial short-haul flight* (SF) is defined as a flight time of 1 hr or less. *Inter-regional travel* is defined as a flight time of 1 hr or less or a driving distance of 500 mi (800 km) or less. Although there is research on various aspects of SF, aMoD, and inter-regional travel, there is limited identifiable research exploring aMoD as a competing mode to SF. This study seeks to expand the understanding of air passengers' modal choice in inter-regional travel in the context of SF and aMoD.

This chapter begins with background on commercial aviation before and after the onset of the COVID-19 pandemic, SF, alternative transport modes, and the influence of America's car dominance on commercial aviation. This section is followed by a brief description of the literature gaps, statement of the problem, purpose statement, significance of the study, research questions, delimitations, and limitations and assumptions.

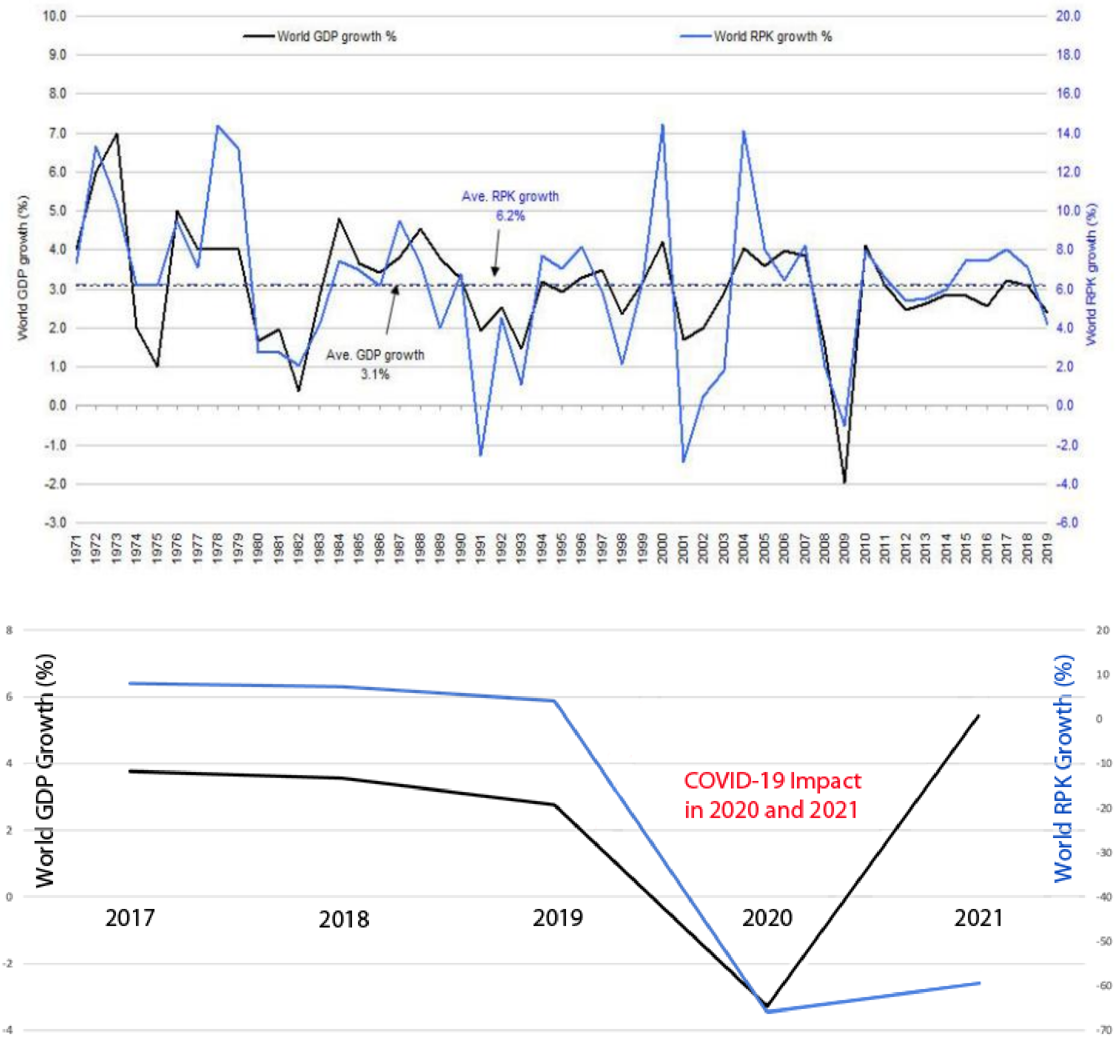
Background

Commercial Air Travel

Commercial aviation connects cities and drives economic and social development through the movement of people and products (De Vos, 2019). Since the first flight in 1903, commercial air transportation has grown into a multi-billion-dollar industry with an annual average growth rate of 6.2% (International Civil Aviation Organization [ICAO], 2020). Figure 1 depicts the annual percentage of worldwide growth in gross domestic product (GDP) and revenue passenger kilometers (RPK) from 1971 to 2021. The top graph in Figure 1 presents the long-term data trends and the lower graph shows the sharp decline in both RPK and GDP coinciding with the global COVID-19 pandemic.

Figure 1

World GDP and World Airline RPK Growth Trends



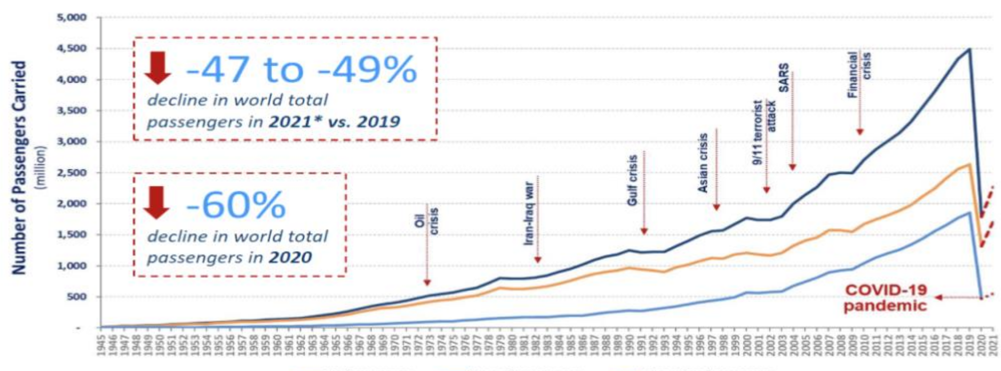
Note. GDP = gross national product; RPK = revenue passenger kilometers. RPK is the sum of the number of paid passengers multiplied by the total distance traveled. Adapted from "CAPA Airline Profit Outlook" by Coalition of Airline Pilots Associations, 2021. Copyright 2021 by Coalition of Airline Pilots Associations.

The rapid growth in global air travel pre-COVID has been attributed to three main reasons (International Air Transport Association [IATA], 2020c). First, an increase in low-cost carriers (LCCs) offering lower ticket prices stimulates demand. In turn, the LCC's market share nearly doubled from 2006 to 2019 (IATA, 2020b). Second, the rise of the middle class, particularly in Asia, means more disposable income for traveling (Ye & Titheridge, 2017). Third, airports have increased infrastructure spending, led by Asia Pacific and the Middle East (Schlumberger, 2017). In 2019, seven of the world's 10 busiest air routes were in the Asia Pacific region (IATA, 2020d). In the same year, the number of scheduled passengers transported by airlines worldwide reached 4.54 billion, doubling from a decade ago (IATA, 2020b). As shown in Figure 1, the general growth trend of RPK mirrors that of the GDP. Figure 1 also shows that RPK and GDP had been trending down even before the start of the pandemic, suggesting the pandemic might be a catalyst and not the sole cause in driving down air travel. According to IATA, year-on-year world RPK contracted by 86.6% in June 2020 (IATA, 2020c). The Coalition of Airline Pilots Associations Centre for Aviation (CAPA, 2020a) reported unprecedented drops in RPK of 65.9% in 2020 and 58.4% in 2021, a grim negative profit margin for the world airline industry.

Although most of the global commercial air traffic growth came from Asia, domestic U.S. air traffic has led the commercial air market, contributing 14% of the global RPK in 2018 (IATA, 2019a). The continued strength in the U.S. commercial air market comes from higher living standards, relatively inexpensive airfares, and business travel (IATA, 2020c). Despite the growth of the commercial airline industry, it is a low-margin business fraught with asymmetrical risks (Vasigh et al., 2008). Airlines worldwide realized a net profit of $27.3 billion in 2018, one of their most profitable years (IATA, 2019b). However, just one company, Apple, made $59.3 billion in the same year, more than double the combined profit of over 200 airlines (Odhise, 2018). U.S. airlines' capital and operating expenses make up 99% of the average annual income, with only a 1% average profit margin for the entire industry from 1950 to 2018 (Chao et al., 2019; IATA, 2019b). In addition to thin and volatile profit margins, the profitability of U.S. airlines cycles up and down, with the long-term trend being downward. The air passenger trends illustrated in Figure 2 show that the airline industry is susceptible to various risks, including financial, political, market, terrorism, resources, supplier, social, and health (IATA, 2021). Market fluctuations and economic difficulties have caused several airlines to declare bankruptcy or merge (Jayanti & Jayanti, 2011; Majid et al., 2016). Airlines for America (A4A, 2020) estimates over 50 airline mergers and 100 bankruptcy fillings from 1930 to 2020; large U.S. airlines such as PAN AM, TWA, and US Airways were among them.

Figure 2

Air Passenger Trends 1945–2021



Note. IATA = International Air Transport Association; SARS = severe acute respiratory syndrome. From “Effects of Novel Coronavirus (COVID-19) on Civil Aviation: Economic Impact Analysis” by IATA, 2021, p. 4. Copyright 2021 IATA. In the public domain.

Despite the cost savings of using new technology, larger aircraft, and more fuel- and crew-efficient operations, airline net revenues have continued downward since 1960 (Bachwich & Wittman, 2017). To make matters worse, while the number of U.S. air passengers had grown by 5% per year pre-pandemic, inflation-adjusted ticket prices have been declining by an average of 2% per year since 1990 (Saxon & Weber, 2017). Intense competition following the 1978 Airline Deregulation Act has consistently driven fares lower. Travel booking websites have democratized information, allowing consumers to compare airline prices and offerings (Dobruszkes et al., 2017); consequently, LCCs have thrived partly because of the Internet (Bachwich & Wittman, 2017). However, competition has become so intense that profit margins have continued their downward trend even with a 27% increase in load factors on U.S. flights over the last two decades (Bachwich & Wittman, 2017).

Short-Haul Flight in the United States

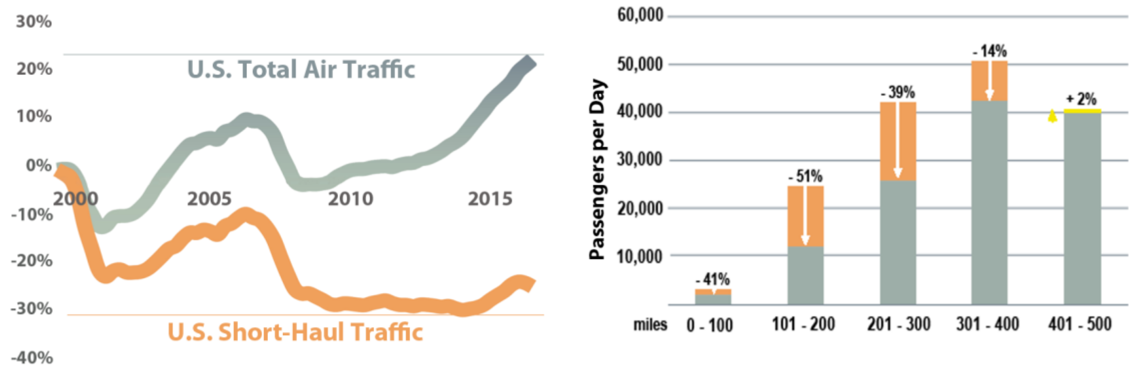
The definition of short-haul flight varies by carrier, country, and organization. Although IATA does not provide a flight-duration or flight-distance definition of short haul, it defines trip length based on the value of travel time savings and the availability of substitutes (IATA, 2010, p. 26). Typically, airlines define short-haul trips differently depending on their market focus. For example, Southwest defines it as 500 mi (800 km) or less, while United Airlines considers a flight within 800 mi (1,200 km) as short (Elking & Windle, 2014; Silk, 2018). A review of the extant literature defined SF as a flight time of between 1 and 2 hr (Hess et al., 2018; Sallinen et al., 2017) or a travel distance of up to 800 mi (1,200 km) (Elking & Windle, 2014; National Academy of

Sciences, Engineering, and Medicine [NAS], 2019). This research defines *SF* as a flight time of 1 hr or a one-way travel distance of 500 miles (800 km) or less.

Evolution of the U.S. Commercial Short-Haul Market. Since the U.S. Interstate Highway System was built in the 1950s, transportation by car has replaced the train in connecting cities across the country. Commercial flight, however, accelerated economic developments by minimizing distances and travel time (Vasigh et al., 2008). The 1978 Airline Deregulation Act removed the U.S. federal government control on barriers to entry, fares, and routes; thus, stimulating free-market innovations and growth (Marien et al., 2018). During the 1980s and 1990s, the U.S. commercial aviation industry experienced significant market growth, primarily in the short-haul sector, propelled by lower fuel costs, a vibrant economy, and cheaper ticket prices (Marien et al., 2019; Sigala, 2014). One of the essential factors in driving short-haul air traffic growth was an advancement in aircraft technology, such as regional jets. These 50-seat carriers competed in operational costs and passenger acceptance, allowing airlines to add new scheduled service between regional airports, which in turn increased passenger choice and reduced travel times (Marien et al., 2019). Nevertheless, while overall air transportation demand has continued to increase since the 1990s, many short-haul markets have seen a dramatic decline in flights since 2000 due to higher operating costs, higher fares, flight delays, post 9/11 airport stresses, and new business communication technologies (Elking & Windle, 2014; NAS, 2019; Millan et al., 2016). The left image in Figure 3 shows that between 2000 and 2017, the total U.S. air passenger market expanded by 25%, but short-haul traffic under 500 mi (800 km) shrunk by 30% (Miller, 2017).

Figure 3

U.S. Air Passenger and SF Markets: 2000–2017



Note. Left: Annual growth rate of the U.S. air passenger and SF markets. Right: Inter-regional air passenger reduction/growth by travel distance. Adapted from "What Caused Short-Haul Traffic Decline in the U.S.? The $34B Question" by C. Miller, 2017, para. 1.

Shorter routes are expected to account for less air traffic than longer ones due to the availability of alternative transportation modes such as cars, buses, and trains. However, the reduction in air traffic for shorter routes is more significant than for longer ones (Miller, 2017). The right image in Figure 3 shows that within the inter-regional travel distance, most passengers travel between 200 and 500 mi. While the total U.S. market rose 25% between 2000 and 2017, the 401 to 500 mi segment rose only 2%. Air passenger traffic in the segments under 400 mi fell by 14% to 51% in those 17 years. Collectively, these trends have created strategic and operational challenges. The number of profitable markets is shrinking. To minimize operating costs on a per-seat-mile basis and to synergize the fixed costs, airlines have resorted to using larger aircraft and reducing the frequency of short-haul routes.

Short-Haul Flight is Vital to Airlines and Airports

Even though the short-haul market has been shrinking, short-haul traffic is vital to U.S. airlines and airports for three reasons: (1) One-third of air traffic from major U.S. hub airports is within 500 mi (800 km) (Marien et al., 2019); (2) Airlines funnel passengers to their hubs to improve load factors for longer trips. If airlines have to lose money on some of these feeder flights, they can make it up by consolidating traffic onto long-haul segments, and by doing so, retain their loyal customers (Achenbach & Spinler, 2018; Soyk et al., 2018); (3) Short-haul air traffic yields a greater margin for the airlines by having a higher percentage of business travelers (NAS, 2019; Vasigh et al., 2008). With a projected loss of $34 billion in revenues from the reduction in short-haul traffic between 2000 and 2017 (Miller, 2017), it is critical that airlines protect their short-haul routes from current and future competing modes.

Transport Modes Competing with Short-Haul Flight

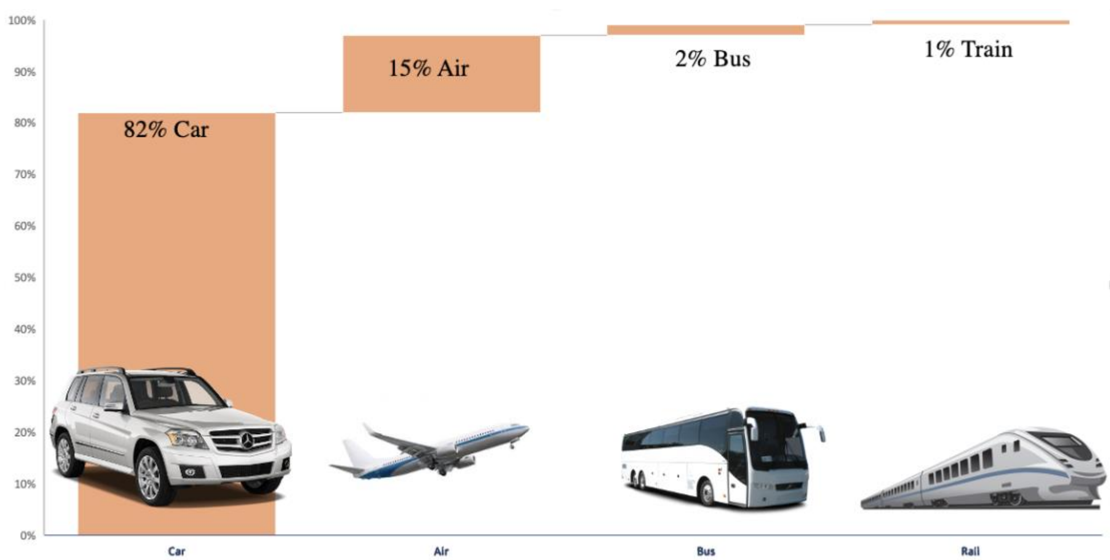
Short-haul air transport is a challenging business because airlines that serve such routes must compete with substitute transportation modes, such as the car, inter-regional train, or inter-regional bus, in addition to other airlines.

Car. As shown in Figure 4, the U.S. has a robust car culture. Of the 3.1 billion annual trips over 100 mi (160 km), 82% are made by car while only 15% are made by air (Bureau of Transportation Statistics [BTS], 2016). Apart from some city-pairs with dense urban centers, the bus (2%) and the train (1%) are not serious competition for the airlines. In fact, for trips between 100 to 500 mi (160 km to 800 km), the car's dominance increased from 82% to 91% of total trips in 2016 (BTS, 2018). The sharp decline in SF is further supported by the Airport Cooperative Research Program (ACRP) (NAS, 2019

[NAS]) Report 204 which investigated the extent the car has diminished the role of SF and concluded that the role of planes and cars has changed since 2000. For inter-regional travel, NAS research in 2019 showed a 30% decrease in airline seat-miles per capita and a 30% reduction in origin-to-destination trips, while the driving miles per capita have increased since 2000 (NAS, 2019, p. xi).

Figure 4

U.S. Trips Over 100 mi (160 km) by Transport Mode in 2016



The city-pair of Houston–Dallas, which are 240 mi (386 km) apart, serves as a good illustration for the increase in driving. Since 2000, the population of these cities has grown by 45% and 39%, respectively (U.S. DoT, 2016), while air traffic between Houston and Dallas has dropped by 60% (Miller, 2017). As two major aviation hubs, they are served by American, Southwest, and United, three of the largest U.S. airlines.

Nevertheless, the dominant substitute is the car, as many people prefer to drive than fly post-9/11 (Hess et al., 2018).

Inter-regional Train and High-Speed Rail. With approximately 150,000 mi (241,400 km) of rail, the U.S. is home to one of the world's largest rail networks (DoT, 2020). Unlike Europe, Asia, and other parts of the world where rail and high-speed rail (HSR) have become a formidable competition to commercial flight (Pan & Truong, 2019), the U.S. has a uniquely different transport infrastructure and travel culture. The convenience provided by the Interstate Highway System and the growth in commercial aviation have contributed to the decline in passenger train transport in most of the U.S. Less than 20% of the country's rail system is used for passenger transport (DoT, 2020), accounting for only 1% of trips over 100 mi (160 km) (BTS, 2016).

One of the regions where rail is beginning to compete with commercial flights is Florida. Virgin's privately-funded HSR began operation in early 2018, servicing passengers between West Palm Beach, Fort Lauderdale, and Miami, a distance of only 62 mi (99.8 km) (Leigh, 2020). By late 2022, the plan is for Virgin's Brightline to expand its diesel-electric rail service to include the Orlando–Tampa route. Once service begins, Virgin will compete with the five scheduled airline routes in Florida that carried 2.3 million annual air passengers in 2019 (Leigh, 2020). Each of these city-pairs is within 300 mi (480 km), a market segment where trains, cars, and planes compete. Another region where rail may compete with commercial flights is California. With its success in Florida, Virgin plans to build a fully-electric HSR to connect Las Vegas to Southern California by the late 2020s (Cogley, 2020; NAS, 2016). At a top speed of 180 mph (290 kph) with few stops along the way, the 170 mi (274 km) journey will take 90 min. In

2020, 17 airlines flew this route with 3.25 million passengers annually (BTS, 2020).

A potential ground-based transport system in the future is the Hyperloop, a scheme in which passengers or cargo travel in pods through a vacuum tube at speeds up to 700 mph (1,130 kph) (Shinde et al., 2017). Currently, Hyperloop is in an experimental phase in the United States and globally. Once operational, travel between San Francisco and Los Angeles, a distance of 382 mi (614.8 km), could be completed in 35 min (Voltes-Dorta & Becker, 2018). Silling (2019) proposed the Hyperloop as a potential alternative to commercial flight, particularly for the short- and medium-haul markets.

Inter-regional Bus. As the most widespread form of public transportation in America, buses operate in more areas than trains and planes and are often used by passengers to travel between places not served by commercial airlines (Merkert & Beck, 2020; Schwieterman, 2016). According to the U.S. DoT, there are 1,200 transit bus systems in the United States, operating 5.3 billion trips every year (U.S. DoT, 2020). While there is no recent scholarly research comparing inter-regional bus travel with flights in the United States, CAPA (2020) reports that Volaris, Mexico's largest domestic airline, benchmarks its cost performance against bus companies as opposed to other airlines. Similarly, Yasar (2017) analyzed the competitive views of managers from different transport modes and found that bus companies regard airlines as competition, but the reverse is not true. Incidentally, operators of all transport modes recognize that price reduction in commercial aviation introduced by LCCs has intensified the competition (Yasar, 2017). While the U.S. commercial aviation industry is dominated by four large airlines, the bus industry is fragmented, with no individual bus companies dictating market prices (BTS, 2020). Like inter-regional trains, inter-regional buses in the

United States are minor competition for commercial air travel.

aMoD. With more short-haul travel choices, air passengers routinely evaluate the time and hassle required for airport security screening, price, convenience, and comfort between air and other transport modes, particularly the car. At precisely the same time airlines and airports are experiencing multiple financial challenges, the threat of substitutes is increasing with the rapid development of vehicle automation, vehicle electrification, and on-demand platforms. While flying is still the preferred mode of transportation for long-distance travel in the United States, the possibility of a threat to SF from emerging ground transport systems such as aMoD should be considered. Disruptors typically come from outside the industry. Christensen (1997, 2011) contends new technologies can displace great firms and even an entire industry by providing consumers with a more accessible or better product/service regardless of how well managed or successful these companies are. A germane real-world example is Apple's iPhone. When Apple launched its first iPhone in 2007, it immediately threatened and ultimately caused structural changes to five industries: personal computer, music, film, camera, and communications (Odhise, 2017). On-demand features paved the way for consumer adoption a few years later of the ride-hailing/sharing model popularized by Uber and Lyft. As the latest multidisciplinary paradigm for personal mobility, aMoD is the confluence of three revolutions in transportation: On-demand platform, vehicle automation, and electrification (Sperling, 1991, 2018). Autonomous vehicles (AVs) refer to all driverless vehicles, including privately-owned AVs. aMoD refers to the service provided by electric AVs on an on-demand ride-hailing platform (Gurumurthy & Kockelman, 2020).

Even though aMoD is a potentially formidable competition to flight, a review of extant literature reveals that despite the considerable number of research studies related to commercial flight and aMoD, there are only five identifiable studies that explore passengers' transport mode choice between commercial flight and aMoD: Ashkrof et al. (2019), LaMondia et al. (2016), NAS (2019), Perrine et al. (2020), and Rice and Winter (2018). None of these studies framed the research from the commercial airlines' perspective, particularly SF; therefore, few findings are directly relevant or easily applicable to the U.S. short-haul air transport market. Furthermore, none researched the key predictors for SF and aMoD; consequently, the main factors influencing air passengers' potential aMoD decisions and how they may differ from SF are still unknown. Additionally, no identifiable studies explored passenger clusters to understand their characteristics; therefore, similarities and differences within distinct aMoD and SF groups are still undetermined. Lastly, the ACRP Research Report 204 (NAS, 2019) was the only study of the five that used a theoretical framework. This research uses the goal framing theory (GFT) as a grounding theory, which is discussed in Chapter II.

Statement of the Problem

SF is a large and critical market to airlines, airports, travelers, and regional and local economies (Marien et al., 2019). External shocks such as the pandemic in 2020 reduced U.S. air demand by an unprecedented 66% (CAPA, 2021), which has accelerated the erosion of this already under-stress air passenger market. The human-driven car has been taking over SF's market share (NAS, 2019; Perrine et al., 2020). Once aMoD is operational, air passengers will have more inter-regional transportation options, which may negatively impact SF's revenue sources and the financial sustainability of airlines and airports. While there is a body of research on various aspects of SF and aMoD individually, there is no identifiable research that explores SF and aMoD as competing modes from the perspective of U.S. air passengers. In addition, there is a lack of knowledge in air passenger segmentation of aMoD. Cluster knowledge of SF and aMoD will aid airlines and airports in understanding these diverse groups of passengers to better communicate and serve them.

Purpose Statement

To fill the research gaps, this study considers differences in modal choice across travel distances and population segments by lending a deeper understanding of U.S. air passengers' modal choice for inter-regional travel. The purpose of this research is twofold: It seeks to develop a model to identify factors that most influence U.S. air passengers' modal choice, principally SF and aMoD; and it seeks to identify distinct SF and aMoD passenger clusters and evaluate the similarities and differences within these passenger segments. While this research considers the potential influence of COVID-19, the primary focus is on travel choices in general, not just during the pandemic.

Significance of the Study

Theoretical Significance

There are five theoretical contributions to the literature on air transportation and inter-regional travel, with each one the first in its category. GFT is a relatively new social sciences theory that has been validated by studies in different fields, including ground transportation. However, this study is the first application of GFT to air transportation research. Second, while there have been increasing studies on aMoD in the past few years, there is no identifiable aMoD research on SF and inter-regional travel. This study is the first exploratory model examining SF and aMoD clusters in the context of inter-regional transportation in the United States. Third, this research presents the first novel multimodal model using SF, aMoD, and the full array of current transport modes to gain a more realistic set of transportation options for inter-regional travel. Fourth, with the increasing popularity of aMoD, prolific research has explored various perspectives. Nevertheless, this study is the first to examine the perspectives of air passengers in aMoD research, thus gaining needed insight into the potential competing role aMoD may pose for SF. Lastly, the drive-time decision between SF, driving, and aMoD has not been studied previously. Therefore, findings from this study add to the scholarly knowledge of both ground and air transportation.

Practical Significance

Transportation planning, policy-making, and infrastructure design take time. This study provides actionable insights to airports, commercial airlines, the general aviation industry, and governments on how air passengers may make modal choices in the short-haul market in the future once aMoD is available. There are four practical contributions. First, knowledge of the factors influencing air passengers' future mode decisions once aMoD is available can inform aviation operators and planners to develop service and communications strategies necessary to keep and grow their customer base. Second, even though this study concerns a future challenge, there is no known scholarly research on air passenger segmentation of SF and aMoD based on GFT variables and contextual trip attributes. This research provides critical input to airlines and airports regarding infrastructure planning and capital evaluations, which are long lead-time decisions. Third, understanding the similarities and differences of early air passenger adopters of aMoD and SF provides aviation operators with the details needed to create critical business and communication strategies for passenger retention. Lastly, this research adds to the limited knowledge of inter-regional travel of 100–500 mi (160–800 km), where three-quarters of all out-of-town trips are made.

Research Questions

This study aims to answer the following two research questions (RQ).

RQ_1. *Based on goal framing theory variables, contextual trip attributes, COVID-19 variables, and demographics, what factors most influence air passengers' modal choice for inter-regional travel of distances under 500 mi (800 km)*?

RQ_2. *What distinct passenger clusters exist for SF and aMoD? How are these clusters similar/different within the SF and aMoD segments*?

Delimitations

Six delimitations set the boundaries for this research.

Focus on the United States. This research is conducted using a quantitative survey method with an online questionnaire focusing on air passengers who have flown in the United States within the last 24 months. The choice of surveying only air passengers in the United States is because transportation choices are influenced by the availability of transportation modes, costs, and distances between cities, among others. Countries may differ significantly in these factors. Therefore, it is crucial to focus on one country or region where the transport infrastructure is relatively homogeneous.

Air Passengers as the Sampling Frame. This study aims to examine the perspectives of air passengers to gain insights into aMoD as a potential competing mode to SF; therefore, novel models using air passengers, not the general population, were developed for data input. Consequently, this study screened for air passengers who have flown commercially within 24 months (October 2019 to October 2021), accounting for the normal flight conditions prior to and during the onset of the pandemic.

Focus on Inter-Regional Travel. For this study, inter-regional travel refers to travel distances of 500 mi (800 km) or a flight time of 1 hr or less. Depending on traffic, assuming an average driving speed of 70 mph (113 kph) on the highway, 500 mi (800 km) is roughly equivalent to 7 to 8 hr of driving time.

aMoD as a Service. Depending on context and publication, AV and aMoD could be interchangeable. For this study, AV is a product (the autonomous car) and aMoD is an on-demand service using an AV. When a privately-owned AV performs an on-demand for-fee service, it is considered aMoD. This study excludes on-demand AVs for cargo transportation (trucking), AVs that run on a track (driverless shuttle-on-a-track or driverless train), and AVs in a closed environment (closed-loop campus and inside airfields).

COVID-19 Variables. Considering the COVID pandemic was ongoing at the time of this research, the influencing COVID factors for air passengers' modal choice are fluid. In addition, cluster analysis provides more valid results when the models have few variables. Therefore, only five COVID variables are included: COVID-19 fear, COVID-19 variants, change in disposable income, air travel during the pandemic, and perception of the economy. All other COVID-related factors are excluded from consideration.

English Language. English was the only language used in the questionnaire because this research was conducted in the United States for domestic travel. Respondents who do not read or write in English were excluded.

Limitations and Assumptions

There are three limitations to this study. First, while survey research is an indirect method of evaluating air passengers' modal choice, it is a generally accepted methodology for determining key factors influencing their behavioral intentions. Every effort was utilized in the research design and execution to enhance the generalizability of results and external validity. A non-response bias test and a comparison of demographics in the air passenger population were conducted to strengthen external validity. Second, data were collected at a single point in time using a single web-based platform. This cross-sectional survey offers the researcher a snapshot in time which is a typical problem that can be solved using longitudinal surveys (which is a recommendation for future research in this study). Third, during the pandemic, air passengers' perceptions may not be the same as in normal times. Therefore, the five COVID variables listed above were included in the study to address possible confounds and enhance external validity.

This research has five assumptions. Assumption 1: Technology and regulatory approvals will not impede the launch of aMoD. Therefore, the topic of regulation is not addressed in this study. Assumption 2: The study participants are able and willing to respond to such projective questions. Considering aMoD is not currently available in most people's daily lives, people may have varying degrees of ability to imagine and answer aMoD-related questions. Pretest and pilot studies were conducted to ensure respondents' ability to answer aMoD questions. Assumption 3: Survey respondents are competent, honest in their opinions, accurate in their responses, and familiar with the terms used in the survey. Pretest and pilot studies led to improvements in respondents' understanding. Assumption 4: Respondents are able and willing to answer the questions truthfully regardless of their fear of the unknown. Assumption 5: Once aMoD becomes available in everyday life, perception of trust and safety will not inhibit aMoD adoption.

Summary

The purpose of this quantitative study is to explore air passengers' multimodal transportation choices for inter-regional travel once aMoD is available and to understand passenger perceptions and characteristics regarding the use of SF and aMoD. This chapter provides a concise introduction to the challenges facing commercial airlines, including industry economic trends and competition from other modes of transportation in the United States. It briefly discusses the extant literature on U.S. transport modes and identifies gaps in the literature related explicitly to SF and aMoD.

The research questions seek to identify predictive factors associated with the goal framing theory that influence air passengers' modal choice for inter-regional travel and classify air passenger segmentation of SF and aMoD and similarities and differences within the clusters. The results from this study have significance to airlines, airports, travelers, and, ultimately, to the regional and local economies. The next chapter reviews the relevant literature, identifies the research gaps, provides justification and support for the chosen research model and variables, and explains the theoretical framework of this study.

Definitions of Terms

Autonomous vehicle (AV)	A fully autonomous Level 5 vehicle is an unmanned ground vehicle that "senses" its environment and navigates without human input (Cook et al., 2019; Menon, 2017).
Autonomous mobility-on-demand (aMoD)	A combination of vehicle automation + vehicle electrification + on-demand business platform.
Driverless cars	Fully automated robotic vehicles designed to travel without human operators (synonymous with autonomous vehicles and robot cars). Driverless cars denote full automation, whereas self-driving cars can have various levels of autonomy (Wen et al., 2019).
Goal framing theory (GFT)	The GFT theory concerns the power of goals to drive cognitive processes and motivation. (Lindenberg, 2016; Steg et al., 2016). There are three overarching GFT goals: hedonic (to feel good), gain (to optimize resources), and normative (to act appropriately).
Inter-regional travel/Short-Haul	A 1 hr flight time or a driving distance of 500 mi (800 km) or less.
Transportation network company (TNC)	Ride-hailing or ride-sharing companies.
Urban air mobility (UAM)	Manned or unmanned systems for air passenger and cargo transportation within an urban area (Parker, 2017). UAM is often associated with small vertical-takeoff-and-landing (VTOL) aircraft, drones, and flying cars (Cook et al., 2019).

List of Acronyms

ACRP	Airport Cooperative Research Program
aMoD	Autonomous Mobility-on-Demand
AV	Autonomous Vehicle
DOT	Department of Transportation
EV	Electric Vehicle
FAA	Federal Aviation Administration
GFT	Goal Framing Theory
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
MaaS	Mobility-as-a-Service
NASA	National Aeronautics and Space Administration
RPK	Revenue Passenger Kilometer
SF	Commercial Short-Haul Flight
TaaS	Transportation-as-a-Service
TNC	Transport Network Company
TPB	Theory of Planned Behavior
UAM	Urban Air Mobility

Chapter II: Review of the Relevant Literature

This chapter reviews the extant literature on commercial short-haul flights (SF), autonomous mobility-on-demand (aMoD), and other transportation modes for inter-regional travel. It presents current knowledge about these topics and identifies the gaps in the literature. It reviews the relevant literature on the goal framing theory (GFT) and describes the use of the GFT as the theoretical foundation for this research. It also presents the literature foundation for this study's research models and main variables, providing justification and support for their selection. The conclusion of the chapter includes a discussion of this study's theoretical framework and research models based on the expanded GFT model, contextual trip attributes, COVID-19 variables, and passenger demographics.

Commercial Short-Haul Flight

Air transportation research does not always distinguish air travel distance (Mills & Kalaf-Hughes, 2017). IATA defines trip length based on the value of travel time savings and the availability of substitutes (IATA, 2010, p. 26). Typically, airlines define short-haul trips differently depending on their market focus. A review of extant literature found short-haul flight times between 1 to 3 hr. Southwest defines it as 500 mi (800 km) or less, while United Airlines delineates a flight within 650–800 mi (1,050–1,290 km) as short (Elking & Windle, 2014; Silk, 2018). For this research, short haul refers to a flight time of 1 hr or less or a driving distance of 500 mi (800 km) or less.

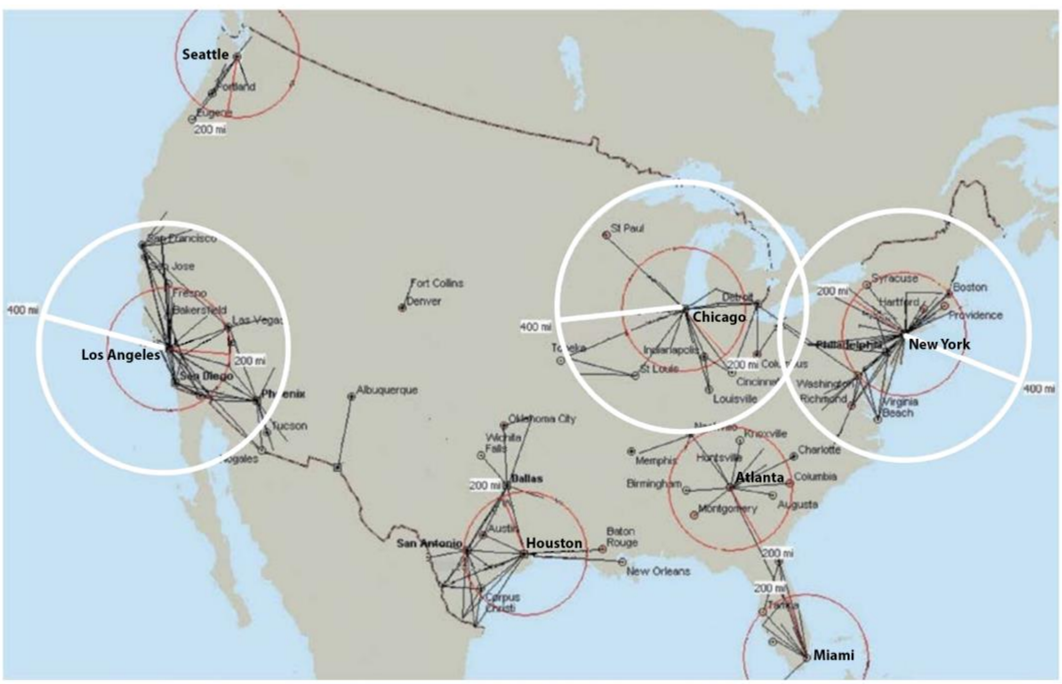
Murphy and Meilus (2012) and Elking and Windle (2014) maintain that short-haul travel is different from longer-haul air trips fundamentally and statistically, so should be treated as two different markets. In the 15 years from 1995 to 2010, Murphy and Meilus noted that while long-haul air traffic grew approximately 50%, short-haul traffic decreased by 26%. They studied the correlation between GDP and air passenger demand for these two markets. They found 0.97 and 0.41 correlation coefficients for long-haul and short-haul traffic, respectively, meaning that domestic long-haul air travel increased almost proportionately to the GDP growth when the U.S. economy was good. Whereas for short-haul, the increase is less than half the GDP growth. Lending support to the findings by Murphy and Meilus (2012), Elking and Windle (2014) found (a) short-haul air markets are more affected by changes in airline market concentration, (b) increased time needed for security screening post 9/11, and (c) changes in cost savings gained by lower LCC airfare. Several of their control variables showed statistically significant different effects between short- and long-haul markets. These findings show that short- and long-haul markets have markedly different characteristics and mode choice factors; thus, they are worthy of separate investigations.

Literature Review on SF

Focusing on inter-regional markets, the U.S. has approximately 81,000 city-pairs within 500 mi (800 km) of each other (U.S. BTS, 2021). Together, short-haul trips make up three-quarters of all trips (Ryerson & Kim, 2018). Little research, however, has been done in the SF travel segment in the past two decades (NAS, 2016). A 2019 inter-regional study by the NAS sought to understand the behavior and patterns of the most traveled SF segments in the United States. There were three research aims. The first was to learn where most transportation mode substitutions occur among planes, trains, autos, and buses. The second was to study where most out-of-town trips happen because this is the least researched segment. The third was to explore how America’s complex air, rail, and highway systems serve different geographical regions for different purposes with regional variabilities. As Figure 5 illustrates, the majority of the 200 most heavily-traveled city-pair markets in the U.S. are between 100 to 500 mi (160 to 800 km), concentrating on several super-regions (NAS, 2016). Some city-pairs cluster around the oldest U.S. cities where a densely connected rail system already exists, while others bundle on a close network of roads and air routes. While the car is the dominant transportation for short inter-regional distances, more people use SF as trip lengths increase, with a crossover at around 700 mi (1,130 km) (see Figure 6).

Figure 5

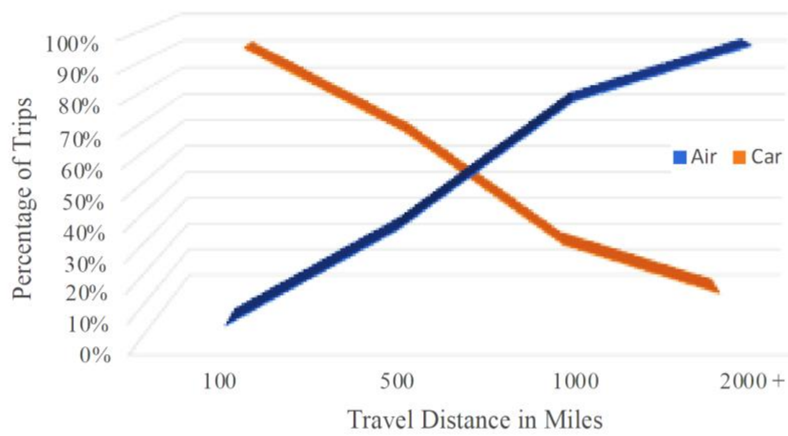
Most Heavily-Traveled Inter-Regional City-Pair Markets in the United States



Note. Adapted from “Interregional Travel: A New Perspective for Policy Making” by NAS, 2016, p. 83. Copyright 2016 by The National Academies Press.

Figure 6

Percentage of Air and Car Trips by Travel Distance

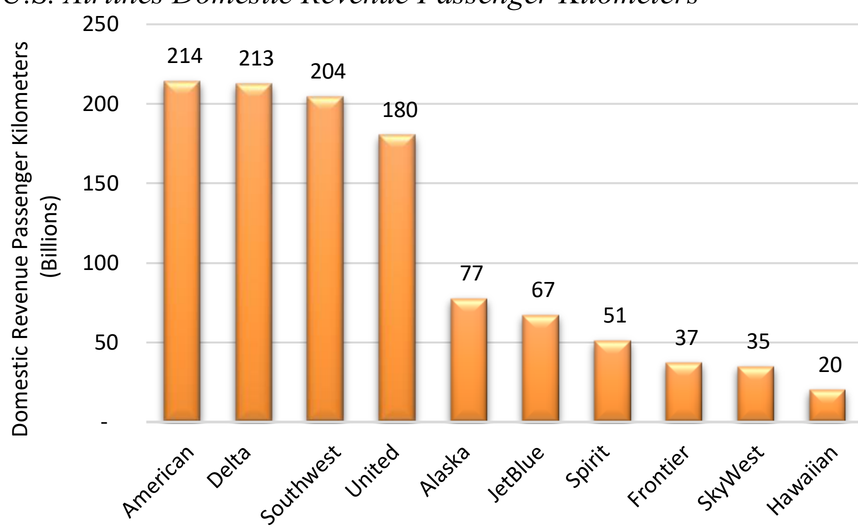


Note. Adapted from "Passenger Travel Facts and Figures," by the U.S. Department of Transportation Bureau of Transportation Statistics, 2016. In the public domain.

Arguably, the U.S. airline industry has an oligopoly structure with the four largest airlines (American, Delta, Southwest, and United) controlling three-quarters of the air transport market in 2019, as shown in Figure 7 (U.S. DoT, 2020). Business travelers who tend to be more price inelastic and, therefore, more stable and profitable, are at the center of every full-service airline's target, leaving the LCCs to focus on price-sensitive passengers (Soyk et al., 2018). According to Wolla and Backus (2018), LCCs such as Southwest (Southwest is also one of the four largest airlines), Spirit, and Frontier began expanding their SF routes in 2016. This route expansion has caused airfares to decline drastically. For example, the average one-way fare between Detroit and Philadelphia dropped from $300 before route expansion to $183 after expansion. Apart from business travelers who tend to be less flexible, price elasticities on short-haul routes tend to be higher than on long-haul routes (Cho & Min, 2018; Zhang & Wang, 2015). There is a greater chance for intermodal substitution on these shorter distance trips because these travelers have multiple transport options in response to airline ticket price increases.

Figure 7

U.S. Airlines Domestic Revenue Passenger Kilometers



Note. Adapted from "The Economics of Flying: How Competitive are the Friendly Skies?" by Woola & Backus, 2018, p. 4.

Short-haul or regional flights have advantages such as proximity to customers and brand loyalty (Marien et al., 2019). However, challenges could include network fragmentation, small catchment areas, frequent flight delays, copious crew bases, and high operational exposure (NAS, 2016; Vasigh et al., 2008). In addition, network planners for short-haul airlines must balance the number of service destinations to maintain adequate flight frequency (Corbo, 2017). Naturally, the lower the flight frequency, the less appealing it is to the business traveler; and the more destinations served, the greater the network appeal (Official Aviation Guide [OAG], 2020).

Another way to understand short-haul air travel in the United States is to study the evolution of Southwest Airlines (SWA), the leading airline in the short-haul regional market (Dobruszkes et al., 2017). Since SWA began service in 1967, it has consistently refined its business acumen and operational model to excel in four key areas: the point-to-point route network system (99 U.S. city-pairs and 10 international destinations), fleet commonality (Boeing 737 and its variants), fast aircraft turnaround times, and utilization of primary medium to small airports (Corbo, 2017). Even though LCCs have replicated these strategies worldwide, after five decades of operation, SWA is still the leading airline in the low-cost, no-frills air transportation category (Bachwich & Wittman, 2017).

As of February 2019, the U.S. had the highest number of LCC seats sold globally, followed by the United Kingdom and Spain. SWA continues to dominate the short-haul regional and LCC markets (Lieberman et al., 2018; Southwest Airlines, 2018). In 1990, SWA's annual passenger load for SF flights comprised nearly 59% of its annual load (U.S. BTS, 2021). As the airline matured and demand shifted, SWA's reliance on SF changed. In 2009, SF dropped to 35% of SWA's annual load (U.S. BTS, 2021). On average, SWA passengers are flying longer distances, increasing the average trip from 502 mi (807.9 km) each way in 1990 to 863 mi (1,389 km) in 2009, a 72% increase (U.S. BTS, 2021). Table 1 shows a decline in passengers flown on several SWA's SF routes between 1990 and 2009. The decline amounted to a reduction of 33% to 48% depending on the market. These SF reductions have created a strategic and operational challenge for SWA. Since 1987, SWA has flown the Boeing 737 almost exclusively as part of its fleet strategy. To minimize operating costs on a per-seat-mile basis while the number of profitable markets is shrinking, SWA has little choice but to reduce flight frequency to synergize the fixed costs.

Table 1

Decrease in SWA Short-Haul Passengers by City-Pair: 1990–2009

City-Pair	Flight Distance mi (km)	Number of Passengers		
		1990	2009	% Decrease Passengers
Dallas–Houston	225 (362) [a]	1,500,000	1,000,000	33
LA–Phoenix	370 (595)	2,200,000	1,300,000	41
Boston–NY	185 (298)	1,800,000	1,000,000	44
St. Louis–Kansas City	237 (381) [a]	430,600	223,835	48

Note. SWA = Southwest Airlines. From U.S. Department of Transportation Bureau of Transportation Statistics (2021). [a] Values rounded.

SF is vital to airport and airline revenues. On average, one-third of the flights in major hub cities are less than 500 mi (800 km) (Evans, 2014; NAS, 2016). For example, 40% of flights arriving at Chicago's O'Hare Airport are from cities less than 500 mi (800 km) away (U.S. BTS, 2021). A reduction in direct flights and flight frequency has accelerated the present trend of declining SF and air mode leakage in smaller and non-hub airports (NAS, 2019). Conversely, since 2000, major car manufacturers (Mercedes-Benz, BMW, Tesla, Toyota, and Ford) and technology companies (Google, Apple, Aptiv, Baidu, Bosch, Cisco, Microsoft, and Nvidia) have made significant advances in the development and testing of aMoD technologies in real-life scenarios under various traffic and weather conditions (Becker & Axhausen, 2017; Taeihagh et al., 2019). Furthermore, aMoD's potential improvement in passenger comfort and the convenience of point-to-point on-demand travel may further reduce SF in the future.

Autonomous Mobility-on-Demand

In potential use-case scenarios, aMoD service using on-demand driverless cars can be employed to transport people to and from work, school, and other activities. The vehicle could also park itself and charge its batteries while idle. A privately-owned AV that generates income is considered an aMoD. In August 2018, Singapore launched a pilot of self-driving taxis, thus becoming the world's first country to test the commercial application of aMoD technology. As of January 2019, Austin, Ann Arbor, Boston, Pittsburg, Phoenix, San Jose, and 16 other U.S. cities have piloted aMoD transportation (Belakaria et al., 2018). Globally, over a hundred cities such as Dubai, London, Sydney, and Amsterdam have launched large-scale aMoD pilots (Dia & Javanshour, 2017).

Ecosystem

This section on aMoD research defines aMoD and its ecosystem. It includes brief descriptions of autonomous or automated vehicles (AV), electric vehicles (EV), transport network companies (TNCs), transport-as-a-service (TaaS), mobility-as-a-service (MaaS), and urban air mobility (UAM) in the context of this research. This section also describes levels of automation, reviews scholarly research on aMoD (consumer perception and use intention), and presents the potential future impact of aMoD on SF.

In the last decade, the topics of aMoD and AV have garnered increasing attention from scholars, practitioners, and policymakers in the United States and globally. The idea that cars will one day drive themselves on demand, moving passengers and cargo while improving road safety, productivity, accessibility, and reducing CO_2 emissions is of interest to researchers (Ashkrof et al., 2019; Legacy et al., 2019; Taeihagh et al., 2019). While the terms driverless car, self-driving car, robocar, automated vehicle, and autonomous vehicle are used interchangeably in everyday parlance, researchers use these terms with nuanced meanings and precise context. For this study, *autonomous vehicle* (AV) refers to a fully autonomous driverless ground vehicle that operates without human input (Wadud, 2017; Zmud & Sener, 2017) and is similar to a computer-on-wheels, a ground-based version of the aerial drones (de Bruin, 2016). It uses various technologies such as radar, laser, GPS, odometry, LiDAR (light detection and ranging), and computer vision to detect its surroundings (Mehdy, 2017; Thomopoulos & Givoni, 2015). Using sensors located in different parts of the vehicle, AVs constantly maintain an accurate map of their surroundings. Video cameras and sonar software detect traffic lights, recognize and obey road signs, track other vehicles, and sense pedestrians (Krueger et al., 2019). Radar, ultrasonic, and LiDAR sensors monitor distances and detect curbs and lane markings. As computers-on-wheels, AVs rely on hard-coded rules, complex software algorithms (e.g., obstacle avoidance algorithms), machine learning, predictive modeling, smart-object discrimination, and powerful microprocessors to control steering, acceleration, and braking (Van Brummelen et al., 2018). Krueger et al. (2017) postulated a strong potential for merging traditional taxis, TNCs, car manufacturers, and technology companies to provide on-demand mobility using AVs. It is necessary to emphasize the distinction between AV and aMoD for this research. AV is a driverless vehicle (a product), while aMoD is an on-demand service using AV.

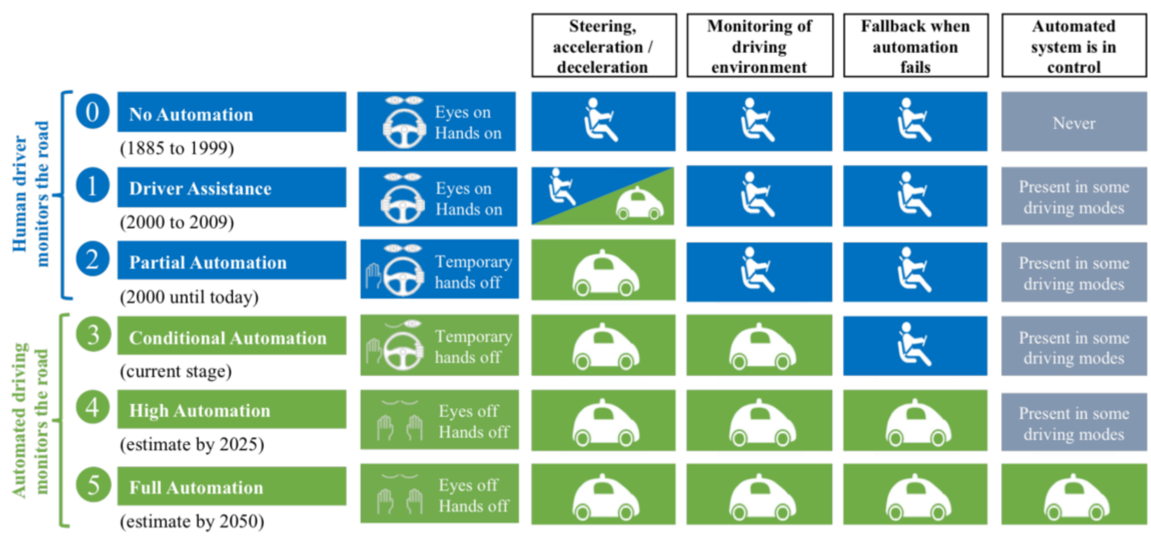
aMoD has the potential to deliver on-demand autonomous mobile services that were too expensive to offer before, such as driverless mobile food trucks, coffee shops, virtual reality theatres, medical clinics, and even professional services (Krueger et al., 2016; Pakusch et al., 2018). Without needing a dashboard and steering wheel, configurations of the interior of aMoD vehicles can accommodate multiple needs. This flexibility can enable businesses to provide potentially cheaper and more timely services to their customers (Becker & Axhausen, 2017; Fagnant & Kockelman, 2015).

Levels of Automation

Typically, the differentiation of AVs is by progressive levels of automation. Figure 8 shows the six levels of driving automation (Level 0 to Level 5) as defined in the SAE J3016 standard (Society of Automotive Engineers [SAE] International, 2021) that the U.S. DoT has adopted. Using the SAE definition, self-driving is Level 3 or Level 4, while driverless is Level 5 (full automation).

Figure 8

Overview of Automation Levels



Note. From “Management and Business of Autonomous Vehicles: A Systematic Integrative Bibliographic Review” by B. H. Cavazza et al. (2019), p. 4. Copyright 2019 by the International Journal of Automotive Technology and Management.

A thorough literature review found that there is no consistent differentiation between “automated” and “autonomous” vehicles, and the terms are often used interchangeably (Hancock et al., 2019; Riehl, 2018). Functionally, AV will not require steering wheels, brakes, and other driving controls inside the vehicle. This change could enable the vehicles to shapeshift to fulfill the passengers’ trip requirements such as sleeping, working, eating, exercising, and using virtual reality communication with friends and colleagues (Krueger et al., 2019). AV production was supposed to begin in the early 2020s (Bagloee et al., 2016; Bansal & Kockelman, 2017), but regulation and consumer adoption have continued to pose considerable uncertainties for large-scale production and implementation (Bansal & Kockelman, 2017; Campbell, 2017; Krueger et al., 2016). Implementation dates vary between researchers, practitioners, governments, and car manufacturers. Not surprisingly, every fatal accident involving aMoD technology delayed the forecast date. On average, car manufacturers are the most optimistic group, citing the early 2020s for aMoD availability. Market analysts view the late 2020s to mid-2030s as the potential adoption timeframe. Academics seem to gravitate toward 2030 to 2050 for aMoD to become a reality (Litman, 2019).

Literature Review on aMoD

Like autonomous flight, public perceptions remain the biggest hurdle for widespread aMoD acceptance (Ashkrof et al., 2019; Hardman et al., 2019; Soteropoulos et al., 2019). In the last decade, the public has vacillated between excitement over aMoD pilot implementation in various cities to serious concern about its safety, privacy, and hackability (Liljamo et al., 2018; Pakusch et al., 2018). In early 2018, the death of a pedestrian by an Uber self-driving test vehicle in Arizona added to consumer perception problems, prompting vehicle, equipment, and software companies to recalibrate their positions on autonomy and further delay launch projections. Nonetheless, ardent supporters contend that aMoD and AVs are the future of ground transportation because they are statistically safer than human-driven vehicles (Hand, 2017; Yuen et al., 2020). Detractors who love to drive will be reluctant to relinquish driving as a sport, a reaction not unlike that over the replacement of the horse for transportation over a hundred years ago (NAS, 2019).

aMoD has the potential to create a fundamental revolution in mobility (Meyer et al., 2017) by making traveling in a car potentially safer (Eriksson, 2014), less expensive (Chin, 2017; Meyer et al., 2017; Wen et al., 2019), more comfortable (Yuen et al., 2020), and more sustainable (Liyanage et al., 2019; Pakusch et al., 2018). It may substantially reduce private car ownership (Hand, 2017; Levin et al., 2017) and allow for better capital utilization (Litman, 2015), increase accessibility, and provide better use of in-vehicle travel time for work or relaxation (Fagnant & Kockelman, 2018). aMoD may be more accessible than flying for children, the physically challenged, and the elderly (Liu et al., 2019; Pakusch et al., 2018). The potential reduction in transportation costs is crucial for travelers (Fagnant & Kockelman, 2014, 2018). Fagnant and Kockelman (2014) estimated that aMoD would produce a substantial cost reduction compared to the human-driven car by assuming a vehicle investment of $70,000 and 50¢ per mile operating costs. Bösch et al. (2018) conducted a thorough cost-based analysis of aMoD, accounting for direct costs (capital costs, maintenance, and operations), external costs (congestion cost and crashes), and environmental costs. They compared the cost-per-mile of the private human-driven car, taxis, public transport, and aMoD and concluded vehicle automation substantially reduces costs. While the actual cost reduction depends on many variables (e.g., fleet size, vehicle management and overhead costs, locations, and demand), the median value is $18.63 per vehicle per day (Bösch et al., 2018, p. 87).

aMoD has been an increasingly studied topic in academia, especially in the past 7 years, and many studies focus on the much-debated aspects such as ethics (Fleetwood, 2017; Ro & Ha, 2019; Sparrow & Howard, 2017; Thomopoulos & Givoni, 2015) and legislation and liability (Simpson et al., 2019; Taeihagh et al., 2019). Essentially, laws embody a society's ethical values (Taeihagh et al., 2019). The two top arguments concerning ethical and moral dilemmas, such as potential job losses for truck and taxi drivers versus the loss of life in fatal accidents, are not easy to resolve (Taeihagh et al., 2019). Other key issues are the risk of cyber attacks and the difficulty of assigning insurance claims. Because aMoD has no driver, should the passenger have an override such as a panic button or control for braking in case of an accident? Who is liable when the aMoD vehicle is at fault? Is it the vehicle manufacturer, software provider, 5G service provider, passenger, or a combination of factors?

There are numerous potential benefits of aMoD, including improved convenience, accessibility, point-to-point flexibility, potentially enhanced safety with significantly reduced casualties, less air pollution due to lower CO_2 emissions, and quality-of-life enhancements for young and mobility-challenged travelers. However, the difficulties facing aMoD are substantial and range from technological and environmental to legislative and perceptual. Weather conditions could limit the functions of cameras and sensors. Density could interfere with LiDAR and radar signals. Tunnels, mountains, and tall buildings could constrain signals and reception, and mixing drivers and AV in traffic could create unintentional problems.

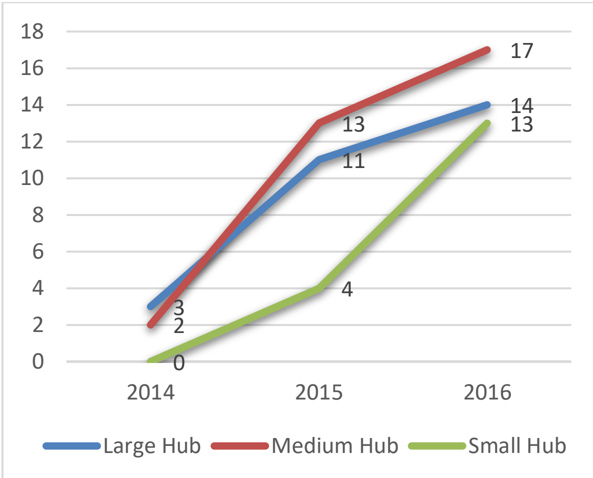
As of the writing of this research in 2022, there is no federal legislation on AV. Instead, the U.S. regulatory process has shifted from federal guidance for AVs to state mandates. There is wide digression at the state level: 41 states and the District of Columbia have passed AV legislation or issued executive orders (National Conference of State Legislatures, 2022). Some states have discussed a per-mile tax on AVs to minimize the rise of “zombie cars,” adding congestion and pollution (Schuelke-Leech et al., 2019). In the same argument, some lawmakers have proposed that all AVs must be electric to reduce emissions (Rietmann & Lieven, 2019). Would an AV be permitted to cross state lines if states decide on their AV laws? Although aMoD development, as measured by business deal volume, continues to increase with new partnerships and road tests, ethics, moral dilemmas, and regulation continue to be big challenges. Nonetheless, ethics, morals, and legislative issues are not a focus of this research.

Transportation models are changing, spurred by the rapid growth of TNCs and the decline of vehicle ownership by millennials and others (Henao & Marshall, 2019b). While Zipcar has been in service for two decades, the rapid adoption of TNCs such as Uber, Lyft, and Wingz since 2012 has transformed how people travel within cities and to/from airports (Shaheen & Cohen, 2019). TNCs provide a ride-hailing on-demand service that offers consumers door-to-door mobility (Davol, 2017, p. 147). The fare changes depending on time of use, demand, and distance traveled (Henao & Marshall, 2019a). The ride may be nonstop or shared with another party, depending on the type of service selected (Hahn & Metcalfe, 2017). As more people become concerned about the environmental impacts of transportation (road congestion and time lost in the daily commute), they become more receptive to ridesharing.

The rapid adoption of TNCs by travelers has created a new paradigm in transportation, leaving traditional taxi companies struggling to remain competitive (Clewlow et al., 2017). Mandle and Box's (2016) online survey of the 100 largest U.S. airports was one of the first studies demonstrating how TNCs affect airport operations and non-aeronautical businesses regardless of size. Their findings revealed a rapid increase in TNC permits from five airports in 2014 to 43 airports in 2016, as shown in Figure 9. The impact of TNCs on airport operations was already significant after only 18 months, including increased curbside and roadway congestion, a 30% decrease in taxicab trips, a 20% decline in the use of private vehicles, and a 13% reduction in rental car transactions (Mandle & Box, 2017, p. 5). This unprecedented increase in TNC adoption by air passengers provided a hint of aMoD's potential rapid adoption by air passengers once it becomes available (Shaheen & Cohen, 2019).

Figure 9

Number of TNC Permits Granted at Airports by Hub Size



Note. TNC = transport network companies. Individual airports in December 2016 reported data. Adapted from "Transportation Network Companies: Challenges and Opportunities for Airport Operators" by Mandle and Box, 2017. Copyright 2017 by The National Academies Press.

Sperling's 2017 research report "Three Revolutions in Urban Transportation" confirms that aMoD could reduce transportation costs by more than 40% and decrease CO_2 emissions by more than 80% (Institute for Transport & Development Policy [ITDP], 2017). This cost and CO_2 reduction are consistent with Bischoff and Maciejewski's (2016) findings. The researchers simulated a city-wide AV fleet in Berlin. They found that one AV could replace ten private vehicles (p. 243) in peak times with more fluent traffic flow and postulated that aMoD would improve this ratio further. Martinez and Viegas (2017) studied the effects of aMoD in Lisbon, a mid-size European city. Using an agent-based model, they found that full city-wide implementation of aMoD would significantly reduce traveled mileage by 30% and CO_2 emissions by 40% (p. 25). By reducing parking demand and traffic congestion, cities could reallocate these prime spaces to parklets, wider sidewalks, housing, and urban farms (Zakharenko, 2016).

Although aMoD is a nascent technology, there is a rapidly increasing number of studies on consumer attitudes and perception for aMoD, particularly in the last few years (Berliner et al., 2019; Haboucha et al., 2017; Hudson et al., 2019; Liljamo et al., 2018). Nevertheless, predicting the impact and ultimate adoption of aMoD is a shifting challenge. Menon (2017) conducted a multi-culture survey to gain insight into consumers' perceptions and intentions for aMoD adoption. His findings revealed that while four-fifths of the respondents expressed familiarity with the terminology, trust was an issue. Menon concluded that AV would likely have to overcome technological challenges and social barriers. In 2015, Zmud and Sener (2017) conducted an online survey with 556 people living in Austin, Texas, to determine the intention to use aMoD. Using a car technology acceptance model (cTAM), they found a split sample with half of the respondents indicating the intention to use while the other half did not. As expected, their findings revealed that people whose physical mobility prohibits them from driving showed a higher intention to use aMoD. Also, as expected, people who regularly use intelligent technologies (e.g., smartphones), TNCs, and other on-demand services show a higher intention to use aMoD. Intended users are not concerned with data privacy and thought that aMoD would be fun to use while reducing car accidents (p. 2516). Zmud and Sener (2017) hypothesized that once operational, aMoD might bring the most significant changes in consumer transport mode behavior by using aMoD for inter-regional point-to-point travel and with increased frequency (p. 2517). A year later, Sener, Zmud, and Williams (2019) expanded their geographic content by including three more Texas cities:

Dallas, Houston, and Waco. Using the same cTAM as the 2015 36-item Austin survey, the authors found that intent-to-use had increased 5% in just one year, from 50% to 55%. They also found that attitudes toward aMoD, namely, *perceived safety, performance expectation,* and *social influence,* are strongly associated with intention-to-use. In addition, *psychosocial variables* and *travel behavior attributes* are more critical in predicting intent to use than demographic variables. For example, as expected, respondents owning a Level-3 car such as a Tesla showed a higher intention to use aMoD. However, attitudes are a dynamic human attribute that can change rapidly based on contemporary events and social trends, underlining the importance of continued monitoring of aMoD research (Cai et al., 2019).

Few studies identify and contrast traveler's attitudes, perceptions, and intentions-to-use between car and air trips (LaMondia et al., 2016; NAS, 2019; Rice & Winter, 2018). The NAS (2019) research used five scenarios to identify the demographic and attitudinal differences between flyers and drivers. Using structural equation modeling (SEM) and the theory of planned behavior (TPB), the research report confirmed the hypotheses that four latent constructs influence transportation behavior: Long-term values, location of the traveler, shorter-term attitudes, and choice of short-haul mode. The nesting of other latent factors and observed variables make up these four latent constructs. For example, long-term values comprises three latent factors: value urbanism (walkable to a commercial district, being outside with people, and having a mix of people from different backgrounds); auto orientation (hedonic considerations such as love for the auto, an observed variable representing the desire to control one's own space in the car, and the ability and freedom to go whenever and wherever one wants to go); and values information technology (the importance of being productive, staying connected all day, and level of device ownership).

Gaps in the Literature

Even before it is an available service, aMoD is already disrupting the roadmaps of governments, urban planners, technology companies, car manufacturers, and transportation companies. It is likely that once operational, in addition to reducing airport parking revenues, aMoD may challenge airline revenue on SF (Rice & Winter, 2018). While there has been an increasing amount of research in the past 7 years on aMoD in engineering, design, legislation, ethics, city planning, and consumer perception and adoption, there is little research in the United States on aMoD's potential competition with SF. After an extensive literature search, there are only five studies investigating consumers' (not air passengers) modal choice between autonomous driving and commercial flying.

First, LaMondia et al. (2016) researched the potential changes in transport mode choices with different trip distances and found that for travel distances of under 500 mi (800 km), 25% of airline trips would shift to aMoD. Over this distance, 43.6% of the participants preferred flying. For distances greater than 1,000 miles, 70.9% preferred flying. However, there is a significant limitation with the research of LaMondia et al. They used a 10-year-old Michigan State 2009 Long-Distance Travel Survey to analyze the impact of aMoD on long-distance travel mode choice. Consequently, they had to create a synthetic population with copious assumptions on aMoD characteristics. Considering the survey was conducted for other purposes, they did not analyze attitudinal and behavioral attributes regarding SF and aMoD travel.

Second, the NAS (2019) conducted an online survey of 4,223 respondents in four U.S. metropolitan areas to examine travelers' choice to drive or fly for long-distance travel. The sample population was travelers who had flown or driven a trip of 300 mi (480 km) or more within the past year. The survey asked respondents to choose driving or flying by selecting from eight stated preferences (SP) with varying characteristics such as trip distance, purpose (business or leisure), and mode choice (car or plane). The research found that many of the choices between flying and driving depend on attitudes and values (p.106). From the point of view of airport operators, testing included five scenarios of various travel distances. The results demonstrated adverse current and future states for SF. As discussed in Chapter I, there is currently a shift in air passengers using automobiles for long-distance trips, with more significant increases in short trips of 500 mi (800 km) or less (BTS, 2016; Miller, 2017; NAS, 2019). Even though the report compared commercial flying with driving, the research differed from this present study. It focused on the issue of airport passenger leakage, long-range trips, and the use of the regular human-driven car; thus, it only tangentially explored aMoD.

The third study to investigate consumers' (not air passengers) modal choice between autonomous driving and commercial flying, Rice and Winter (2018) conducted an online consumer survey to determine if AV would significantly disrupt commercial air travel. Over 2,000 respondents were presented with scenarios of five city-pairs with varying travel times (5–45 hr of driving) and asked to rate their mode preferences. As the driving distance increased, the percentage of respondents choosing commercial flights increased regardless of whether they would prefer a driverless car or a typical human-driven car. Within a 5-hr drive, the same proportion of respondents (one-third) chose commercial flights. As the drive time increased to 7 hr, 62% with a manual car chose flight and only 45% with aMoD chose flight. Although their study confirms prior research that aMoD is a stronger competition to airlines in short-haul routes, it failed to provide information on the similarities and differences within the groups making these mode decisions. Nor did it predict mode choice or employ any foundation theories for the hypotheses.

Fourth, Perrine, Kockelman, and Huang (2020) used a 2010 rJourney database with 1.17 billion U.S. long-distance trips to study AV's potential inter-regional impacts. Like LaMondia et al. (2016), Perrine et al. had to add an artificial AV/aMoD mode to the 2010 database with numerous assumptions to model AV/aMoD's impact on the airline market. They estimated that AV/aMoD would reduce airline revenues by 47%.

The last study was another stated preference survey for traveler mode choice among public transportation, AVs, and typical human-driven cars. Ashkrof et al. (2019) collected data from 663 Dutch travelers on their trip attributes (travel time and cost), attitudinal factors, and demographics. Specifically, the authors investigated how travel distance and trip purpose influenced mode choice.

Three of these five studies used scenarios to identify non-air travelers' transport mode choices (Ashkrof et al., 2019; NAS, 2019; Rice & Winter, 2018). Two studies used 10-year-old research conducted for other purposes to construct artificial populations to project aMoD's impact (LaMondia et al., 2016; Perrine et al., 2020). More importantly, most studied the conventional human-driven car and long-distance trips, not aMoD and SF. No identifiable published research has explored air passengers' transportation choice between SF and aMoD in the United States. None was found to investigate passengers' modal choice between SF, aMoD, cars, trains, and buses, a more realistic inter-regional scenario. This study fills these gaps in the research literature by investigating factors that most influence air passengers' modal choice for inter-regional travel of 500 mi (800 km) or less. It seeks to identify air passenger clusters for SF and aMoD by exploring participant demographics and specific trip attributes. The objective is to understand inter-regional transportation mode choices based on GFT variables, contextual trip attributes, demographics, and COVID-19 variables.

aMoD may potentially become a formidable competition to SF in three crucial areas. First, one-third of all large/medium hub traffic serves short-haul routes, but the convenience and cost of aMoD may lure some passengers away from this critical air passenger market. Second, cities with small or non-hub airports have seen a drastic decline in service frequency (Marien et al., 2019; NAS, 2019). Instead of driving to an airport in another city to take a short-haul flight (airport passenger leakage) or endure the post 9/11 airport hassle, some passengers may use aMoD for their point-to-point journey (NAS, 2019). Third, people with mobility issues and groups of family, friends, or colleagues may choose to take aMoD together to increase fun and productivity and reduce cost. aMoD provides door-to-door convenience and flexibility and is not as sensitive to weather conditions as air travel (Webb, 2019). There can be various levels of interior amenities and luxury appropriate for different market sectors and price points, including more legroom, tables, food and drinks, virtual-reality television, movie programming, Wi-Fi, conference amenities, and entertainment console. (Cho & Jung, 2018; Menon, 2015). In addition, aMoD offers a higher level of convenience than traveling by plane. The time and hassle of getting to the airport, traveling through traffic, waiting in line to go through security, waiting to board the plane, and frequent flight delays are some of the inconveniences of air travel (Zhang & Wang, 2016). The space available to the passengers in aMoD may be larger and more luxurious than a commercial plane. Car companies are designing *shape-shifting* interiors for aMoD to fit the type of journey, bespoke to the passengers' needs (Gkartzonikas et al., 2019; Lustgarten & Le Vine, 2018). Traveling by aMoD could be like traveling in a mobile living room with an entertainment center. In this scenario, aMoD could substitute both airline seats and hotel rooms. In terms of price, a non-stop, round-trip flight between LAX and SFO may cost $250 or more. Ordering aMoD may be less expensive if the ride is shared.

The magnitude and timing of aMoD's impact on SF are likely to hinge on several factors (Rice & Winter, 2018): vehicle ownership (Woldeamanuel & Nguyen, 2018), consumer acceptance (Becker & Axhausen, 2017; Xu et al., 2018), cost (NAS, 2019) and most of all, public policy (Riehl, 2018). For example, a city could dictate that only aMoD are permitted to operate in the city core to improve air quality (Levin et al., 2017), enhance pedestrian safety (Deb et al., 2017; Hulse et al., 2018), and facilitate traffic flow (Shi & Prevedouros, 2016). This kind of policy would likely accelerate aMoD adoption (Yap et al., 2016). High-profile aMoD trials have taken place in the U.K., Sweden, U.S., Japan, Australia, and Singapore (Hardman et al., 2018; Zhang et al., 2016). The auto industry sees new competition from tech companies such as Google (Alphabet) and Alibaba. With a drastically weakened commercial aviation industry caused by COVID-19, IATA research estimates that 50% of the airlines may not survive the impacts (IATA, 2020). Consequently, a decline in commercial air travel may accelerate the development and adoption of aMoD.

Similar to severe acute respiratory syndrome COVID-2 (SARS-CoV), COVID-19 (SARS-CoV-2) is a coronavirus that can rapidly spread from human to human via airborne transmission and or by fomite transmission (touching infected surfaces) (Johns Hopkins University & Medicine, 2020). First detected in China in December 2019, by April 2020, COVID-19 had paralyzed most global economies, with demand for international air travel dropping 98.4% compared to April 2019 (IATA, 2020a). From March to April 2020, U.S. domestic traffic fell 95.7%, causing U.S. airlines to incur unprecedented losses and layoffs (IATA, 2020a). Within a year, U.S. domestic passenger load factor dropped from 89.2% in July 2019 to 49.6% in July 2020 (IATA, 2020c). Instead of the 4.3% annual growth forecasted by IATA (2020c), in June 2020, IATA announced 2020 would be the worst year ever for the airline industry (IATA, 2020b).

Unknowingly, commercial aviation contributed to the global spread of this pandemic in the first few months before general lockdowns and border closures (Gössling, 2020; Sun et al., 2020). Commercial aviation has become one of COVID's primary economic casualties (Sun et al., 2020; Tanrıverdi et al., 2020). In the United States, Cutler and Summers (2020) called COVID-19 the "$16 trillion virus. … the greatest threat to prosperity and well-being the U.S. has encountered since the Great Depression (p. 1495)." The aggregated direct economic losses, mental health conditions, and mortality could reach 90% of the U.S. annual GDP (Cutler & Summers, 2020).

An evaluation of the extant literature on transportation research reveals that while there is an increasing number of articles on COVID-19, many of these focus on lessons learned pre-COVID (Iacus et al., 2020; Tanrıverdi et al., 2020) or potential impacts on airports and the aviation network post-COVID (Serrano & Kazda, 2020; Sun et al., 2020). Some focus on aeropolitics (Macilree & Duval, 2020), while others explore the potential economic impact post-COVID (Linden, 2020; Suau-Sanchez et al., 2020). COVID's potential impact on leisure and business travelers is critical to understanding the potential COVID impact on SF and aMoD. Suau-Sanchez et al. (2020) conducted qualitative industry interviews to understand the demand side of commercial aviation and consumer behavior amid COVID. Their findings show a reduction in air transport demand in the immediate, medium, and long term. Initially, this drop in travel may be due to fear of contracting COVID while flying or a reduced level of disposable income. According to Suau-Sanchez et al. and supported by Linden (2020), these initial factors will be compounded by behavioral changes in the long term. Consistent with CAPA Centre for Aviation (2020c), Suau-Sanchez et al. concluded that leisure passengers would resume flying sooner than business travelers. Suau-Sanchez et al. and Linden found three factors influencing both leisure and business passengers' decisions to fly: health concerns, disposable income, and ticket prices. Using neural network models and Monte Carlo simulations, Truong (2021) found the weekly economic index as the most important predictor for COVID-19-influenced air travel. None of the reviewed transportation research on COVID-19 has investigated the influence of COVID on the transportation mode choice between aMoD and SF travel; therefore, this study addresses this gap by exploring the impact of COVID-19 related to health concerns, disposable income, ticket prices, and the health of the U.S. economy.

Cluster Analysis

Cluster analysis (CA), also called market segmentation, represents one of the primary techniques in transportation research used by academic researchers for knowledge creation (Dolnicar et al., 2014). CA is used in taxonomy classification and description (identifying natural groups within the data set), data simplification (analyzing groups of similar observations versus individual observations), and relationship identification (revealing relationships not otherwise discovered) (Hair et al., 2017, p. 428). CA classifies objects or respondents on a set of researcher-selected characteristics, making it critical that the researcher selects each variable objectively based on prior research, extant literature, and reasoned judgment (Hair et al., 2017). In the transportation industry, many strategic and financial decisions are made based on results from CA, including airport classification (Adikariwattage et al., 2012; Cui et al., 2017; Magalhães et al., 2015), airline categorization (Truong et al., 2020; Urban et al., 2018), and passenger mode choice segmentation (Bösehans & Walker, 2020; Kuljanin & Kali, 2015; Westin et al., 2020); however, there is only one scholarly research study found on aMoD using CA. Using latent profile analysis in CA with a sample of 1,345 Australians (97% drivers and 3% non-drivers), Pettigrew, Dana, and Norman (2019) found that Australians are not familiar with the concept of aMoD. Five clusters were identified based on respondents' self-reported knowledge of aMoD, perceptions of various aspects of aMoD, and aMoD use intentions. Pettigrew et al. titled the five segments with distinct profiles: Non-Adopters (29%), Ridesharing (20%), aMoD Ambivalent (19%), Likely Adopters (17%), and First Movers (14%). First Movers showed strong interest in AVs and aMoD and are likely to be strong influencers toward broader aMoD adoption.

Multinomial Logistic Regression

Multinomial logistic regression (MNL, also called multinomial logit) is one of the primary methods for categorical data analysis and a generalization of the binary regression model. Instead of two categories for the nominal/ordinal response variable, MNL has three or more categories. There is one empirical transportation study identified that is grounded in the goal framing theory (GFT) using CA and MNL. In a large University Travel Survey in England, Bösehans and Walker (2020) used GFT (see the Theoretical Framework section) to compare to the results of their prior research obtained by using the theory of planned behavior (TPB). They found that GFT supported their earlier TPB findings with evidence that the GFT traveler clusters seem to be more stable and can be segmented based on the goal frames—hedonic, gain, and normative. Their findings are significant because they validated GFT as "a parsimonious way to replace the various attitudinal variables" commonly used in prior CA research (Bösehans & Walker, 2020, p. 247). As such, GFT may add a new theoretical element to transportation segmentation research with CA and MNL as valuable analytical techniques. Bösehans and Walker found three clusters of mode-independent supramodal clusters that could be distinguished across traveler types, regardless of their mode choices. While Krueger et al. (2016) argued that a mode choice decision results from a behavioral disposition toward that mode, Bösehans and Walker's three supramodal clusters provided evidence that it may not need to be. This finding means that mode choices might be due to interactions between the traveler's goals (hedonic, gain, and normative) and the trip context.

Theoretical Framework

Frames are lenses, subconscious mental models through which people view the world. There is a line of decision research that uses various framing theories. The premise is that people's decisions change based on their situation frame. In turn, their attitudes, emotions, and behavior change (Castiglioni et al., 2019). Therefore, frames are essential in decision and choice theories because they affect how people act. This research used GFT as its grounded theory. However, it is vital to understand why the theory of reasoned action (TRA), the theory of planned behavior (TPB), the technology acceptance model (TAM), and the unified theory of acceptance and use of technology (UTAUT) were inappropriate for this study, although their use is routine in transportation research. These theories are briefly discussed and collectively evaluated.

Evaluating Behavioral Theories

The TPB is an attitude-behavioral framework for understanding and predicting human behavior (Ajzen, 1991). Evolved from the theory of reasoned action (TRA) (Ajzen & Fishbein, 1980), Ajzen added *perceived behavioral control* to TRA in 1985 to recognize the fact that it is a chief factor influencing both behavioral intention and behavior (Ajzen, 1985). The behavior of a future service such as aMoD could not be directly measured because it was not operational at the time of this research. However, it is possible to evaluate behavioral intentions as a function of an individual's *attitude toward the behavior*, the *subjective norms around the behavior*, and *the degree of perceived control* the individual believes they have over the behavior (Ajzen, 1991). Testing of TPB shows it has good model predictability for explaining behavioral intention (41% to 68%) and behavior (28% to 34%) (Chen & Yan, 2019; Pan & Truong, 2018). A search of the literature revealed that TPB was broadly used in studies of passenger intention and behavior, including low-cost carrier selection (Buaphiban & Truong, 2017; Truong et al., 2020), the modal choice between HSR and LCCs (Pan & Truong, 2018), intention to use fully autonomous driving systems (Chen & Yan, 2019), and attitude toward drone usage as a service-delivery mode (Ramadan et al., 2016).

Developed by Davis in 1989, TAM began as an information system theory to model user acceptance of technology. TAM focuses on *perceived ease of use* and *perceived usefulness*. It has been used in transportation research studies on consumers' intentions to use AVs (Müller, 2019; Panagiotopoulos & Dimitrakopoulos, 2018). However, inconsistent use of TPB and TAM is frequent in scholarly research (Cheng, 2019; Moták et al., 2017). TAM is appropriate when technology is available for evaluation by individuals regarding its adoption, whereas TPB is appropriate when evaluating an individual's intention to use a current or future service (Cheng, 2019; Schepers & Wetzels, 2007). TAM use is most prevalent in technology acceptance research (Lai, 2017). Incidentally, Cheng (2019) found that the TPB model provides a more robust prediction of behavioral intentions (adjusted R^2 = .678) compared to the TAM model (R^2 = .469) and that the combined model (TPB + TAM) only increased the explanatory power by a small amount. The third technology acceptance model frequently used is UTAUT. It is a unified technology acceptance model developed by Venkatesh et al. It consolidates constructs from TRA, TPB, TAM, and a few other theories to include *performance expectancy*, *effort expectancy*, *social influence*, and *facilitating conditions* (Venkatesh & Davis, 2000). UTAUT use is frequent in future technology acceptance research, such as Nordhoff et al.'s (2020) multi-country study on the public acceptance of

Level 3 AVs and Yuen et al.'s (2020) study to understand factors that influence the adoption of shared autonomous vehicles. In a longitudinal study conducted in 2003, Venkatesh and Davis validated UTAUT to explain 70% of the variance for *behavioral intention to use* and approximately 50% in *actual use*.

The TPB, TAM, UTAUT, and their extensions use behavioral theories to predict behavioral intention. They differ in influential factors used to predict acceptance. Lai (2017) and Rahman, Lesch, Horrey, and Strawderman (2017) independently assessed TPB, TAM, and UTAUT for their predictive power and concluded that their utilities depend on specific research problems, variables, and measurements. The advantages of the behavioral theories (TPB, TAM, UTAUT, et al.) include their usefulness for understanding factors that lead to behavioral intention and prediction for mode choice (Bianchi et al., 2017; Wang et al., 2016). Furthermore, they are flexible frameworks that are "open to the inclusion of additional predictors" (Ajzen, 1991, p. 199), such as *past behavior* (Bamberg et al., 2003). However, these theories have some limitations. First, these theories do not include other behavioral factors such as *emotions* and *hedonic values,* which could drive behavioral intentions (Westin et al., 2020). Second, they assume that humans are rational beings who make decisions based on available information. One of the general criticisms of these behavioral theories is that they pay too much attention to reasoned action and not enough to unconscious motives and control (Bösehans & Walker, 2020). Third, they do not consider *habit*, *contextual factors*, and *demographics* (Bösehans & Walker, 2020; Westin et al., 2020). Consequently, GFT is more appropriate for this research to use as a foundational theory.

Goal Framing Theory

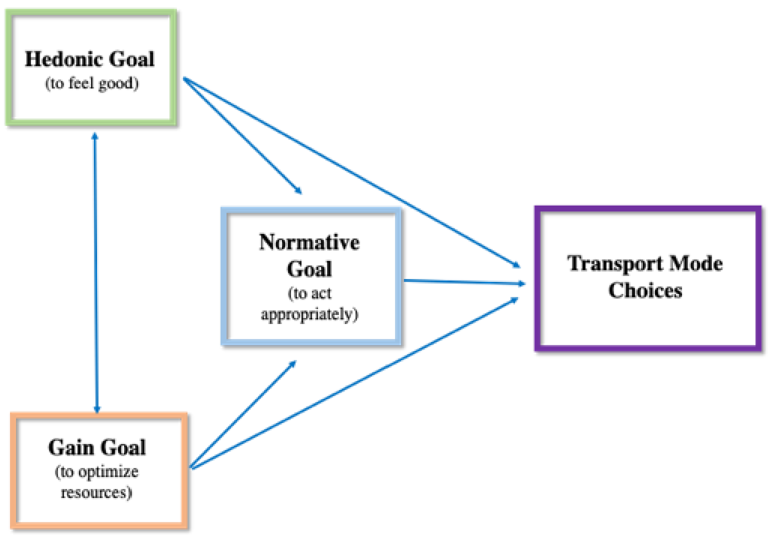
The GFT has recently been used successfully in transportation and segmentation research (Bösehans & Walker, 2020; Marley & Swait, 2017; Westin et al., 2020). This theory posits that multiple goals (which may or may not be compatible) are always active in people's life. These goals change in their relative importance in different situations and frame people's decisions, which influences what people do and how they do it (Lindenberg, 2016; Steg et al., 2016). The activated goal frame determines what information receives attention and what action will be taken (Bösehans & Walker, 2020).

In essence, GFT is about the power of goals to drive cognitive processes and motivation (Steg et al., 2016). Three overarching GFT goals influence information processing and behavior. These goals have been studied and validated (see Figure 10): *hedonic* (to feel good and self-enhancement), *gain* (to optimize personal resources), and *normative* (to act appropriately regarding socially and culturally accepted norms and behaviors) (Bösehans & Walker, 2020; Légal et al., 2016; Lindenberg & Steg, 2013; Steg et al., 2016; Westin et al., 2020).

A *hedonic goal frame* relates to how an individual wants to feel good about himself or herself by choosing behaviors that bring happiness and wellbeing. In the context of travel, this includes *comfort*, *ease of effort*, *independence/perceived control*, *habit,* and *satisfaction* with the primary transport mode. A *gain goal frame* causes the traveler to optimize his/her resources such as *money*, *time*, and *convenience*. A *normative goal frame* triggers the traveler to do what is considered proper, such as *environmental concerns* with various transport modes. Social norms refer to informally-enforced rules (Lindenberg & Steg, 2013). For example, the GFT applies to transportation behaviors (choices) based on the goal of achieving cleaner air. Air transport contributes to 2% of all carbon emissions (Larsson et al., 2019). Presently, there is no electric commercial air transport, but aMoD will operate on an electric platform with cleaner emissions, which should appeal to passengers with a strong normative goal frame (Greenblatt & Shaheen, 2015; Pakusch et al., 2018).

Figure 10

Goal Framing Theory and Transportation Choices



These goal frames have different degrees of importance for the traveler at different times and will “frame” his/her modal decisions (Bösehans & Walker, 2020). Lindenberg and Steg (2013) theorized that the dominant goal has the most substantial influence on one’s thoughts and behaviors. The other two goals act in the background by strengthening the dominant goal if they are compatible or weakening it if they conflict (Lindenberg & Steg, 2007; Steg et al., 2016). Lindenberg and Steg (2007) posited that part of these goal frames can only be measured by values that transcend situations, making them more stable. They asserted that values affect beliefs, attitudes, norms, intentions, and behaviors, essential factors in GFT.

Expanded Goal Framing Theory

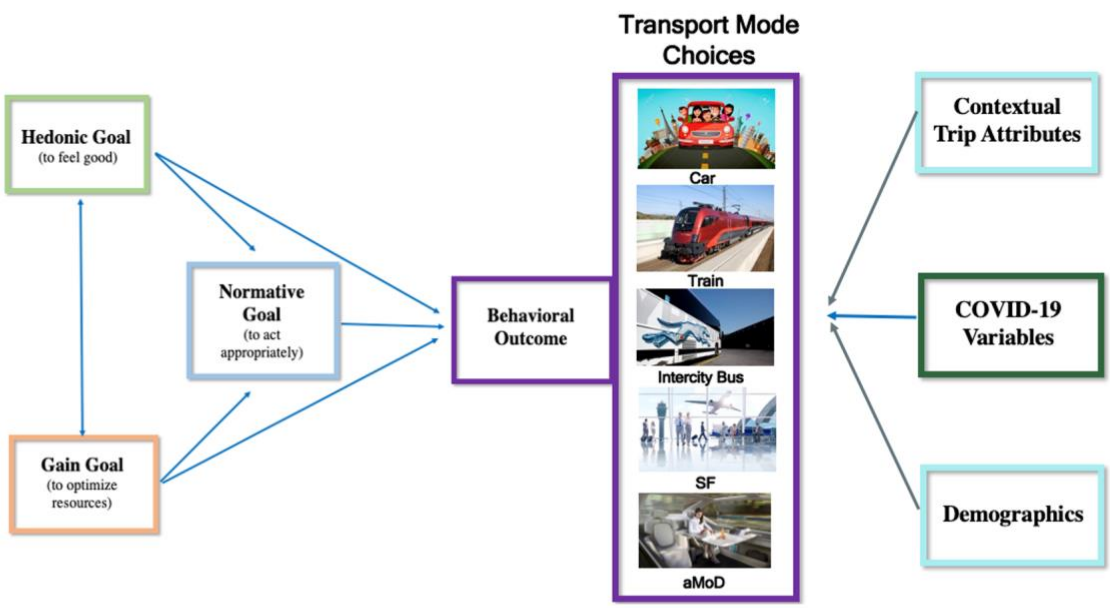
Some literature provided substantial evidence that transportation mode decisions are not rational (Innocenti et al., 2013; Lois & López-Sáez, 2009; Steg, 2005; Thomas & Walker, 2015). Steg (2005) used different methods (inductive and deductive), different motives (instrumental, symbolic, and affective), and different types of car use to provide empirical evidence that travel behavior is dependent on *contextual factors* (which the author called *situational characteristics*, p. 160). Moreover, symbolic and affective motives are essential in predicting mode choice (Steg, 2005). Lois and López-Sáez (2009) used SEM to further validate Steg's (2005) findings. Although their variables did not measure precisely the same way, Lois and López-Sáez confirmed that *affective motivations* are the dominant factor in predicting mode choice. They also found that *demographics* are chief predictors.

Other researchers have validated these findings using different research methods. Innocenti et al. (2013) conducted a laboratory experiment to investigate determinants of mode choice and concluded that travelers show stickiness, cognitive heuristics, and biases toward transport mode choice leading to "robust deviations from rational behavior" (p. 165). Their experiment clearly showed "available information is not properly processed; cognitive efforts are generally low, and rational calculations play a limited role" (p. 167) for repeated travel mode choices. They established that travel mode choice is influenced by psychological and subjective factors such as *habit* and *emotions* (p.167); so, must be considered for mode choice prediction. Even though some extended

TPB models have included habit and environmental concerns, some researchers argue that these TPB extensions have "obscured the theory beyond recognition" (Bösehans & Walker, 2020, p. 245). Figure 11 shows the expanded GFT including the *Contextual Trip Attributes*, *COVID factors*, and *Demographics* utilized in this present study.

Figure 11

Expanded Goal Framing Theory Utilized in This Study



Note. Adapted from "Normative, Gain and Hedonic Goal Frames Guiding Environmental Behavior" by S. Lindenberg & L. Steg, 2007, *Journal of Social Issues*, *63*(1) (https://doi.org/10.1111/j.1540-4560.2007.00499.x). Copyright 2007 the Journal of the Society for the Psychological Study of Social Issues and "Goal-Framing Theory and Norm-Guided Environmental Behavior" by S. Lindenberg & L. Steg, 2013, in H. C. M. van Trijp (Ed.), *Encouraging Sustainable Behavior: Psychology and the Environment* (1st ed.) (https://doi.org/10.1111/j.1540-4560.2007.00499.x). Copyright 2013 by Psychology Press.

Literature Support for the Variable Selection

Strong conceptual and empirical support for variable choice is critical for CA and MNL for different reasons (Hair et al., 2017). The importance of strong conceptual support is apparent in three common criticisms of CA (Hair et al., 2017, p.419). First, there is no statistical basis for drawing inferences from a sample to a population with CA. There is no unique solution because varying researcher inputs result in different solutions. Second, the identification of clusters does not validate their existence. Strong conceptual support and validation are critical in making the CA findings relevant and meaningful. Third, the cluster variate is entirely specified by the researcher, making the selection, addition, and deletion of relevant variables a significant impact on results. For these reasons, careful selection of variables is of the utmost importance. As for the MNL model using the maximum likelihood (ML) method, it is essential to minimize the number of predictor variables because too many predictors create high-dimensional settings, weakening maximum likelihood estimates (Hair et al., 2017). Therefore, careful selection of variables is critical to obtain interpretable and reliable MNL and CA models.

There is research on the effects of trip characteristics (cost, delay, travel time, and demographics) on aMoD as a mode choice, but the findings are city- or country-specific; thus, not transferable (Bansal et al., 2016; Haboucha et al., 2017; Krueger et al., 2016; Zhang et al., 2018). The reason is that different regions may have different availability of transport modes. Travelers may also have unique perceptions of mode choice at different times and in different conditions. Cai et al. (2019) conducted a study in Singapore to obtain insights on consumers' perceptions of aMoD through a Stated Preference survey. They sought to determine if familiarity using on-demand apps such as Uber and Grab would influence acceptance of aMoD service. Using a logit kernel model, the authors found that 31% of public transport users would consider using aMoD. Surprisingly, 57% of drivers said they would give up driving and use aMoD. They also found that gender, education, income, cost, travel time, expected delay, and the traveler's value for convenience are predictors of aMoD as a mode choice. Contrary to Rice et al. (2019) and Zmud and Sener's (2017) findings, Cai et al. found *familiarity* is not a factor for mode choice in Singapore.

This study is grounded using GFT as its theoretical framework. Table 2 summarizes the GFT variables evaluated in this study using a 5-point Likert scale. Chapter III discusses the specific variables for the CA and MNL models and presents the operational definitions for all variables.

Table 2

Expanded GFT Variables

Variable	Conceptual Definition	Sources
	Hedonic Goal (to Feel Good)	
Effort/Access	Travelers' perceptions of the efficiency and ease of access in using their main transport mode	Bösehans & Walker (2020); Lindenberg & Steg (2007; 2013); NAS (2019); Wadud (2017); Zmud & Sener (2017)
Comfort	Travelers' perceptions of personal space, seat comfort, and general comfort	Anable (2005); Bösehans & Walker (2020); Lindenberg & Steg (2007; 2013); Zmud & Sener (2017)
Self-Efficacy/ Independence [a]	Travelers' perceived independence and control of the transport mode choice and trip	Bandura (1997); Bösehans & Walker (2020); Chen & Yan (2019); NAS (2019); Thomas et al. (2014); Zmud & Sener (2017)
Habit [a]	Travelers' automaticity of using their main transport mode	Bösehans & Walker (2020); Lindenberg & Steg (2007; 2013); Thomas & Walker (2015); Verplanken & Orbell (2003)
Satisfaction [a]	Travelers' general level of satisfaction with their main transport mode for ground distances 100-500 mi (160-800 km)	Bösehans & Walker (2020); Lindenberg & Steg (2007. 2013); Millan et al. (2016); Thomas & Walker (2015)
Trust [a]	Trust is important in modal choice decisions. Trust in transport mode is highly correlated to fear of using and trusting the operator	Adnan et al. (2018); Becker & Axhausen (2017); Menon (2017); Rice et al. (2019); Schellekens (2015); Zhang et al. (2019); Zmud & Sener (2017)
Hedonic Values	Travelers' perceived hedonic values from the main mode, gained from experience and pleasurable emotions elicited by the mode	Bösehans & Walker (2020); Lindenberg & Steg (2007; 2013); NAS (2019); Westin et al. (2020)
	Gain Goal (to Optimize Resources)	
Cost	Travelers' perceptions of how the total trip (one-way, point-to-point) cost meets expectations	Anable (2005); Bösehans & Walker (2020); Lindenberg & Steg (2007; 2013); NAS (2019)
Convenience	Travelers' perceived convenience in using their main transport mode	Bösehans & Walker (2020); Cai et al. (2019); De Looff et al. (2018); Wadud (2017); NAS (2019); Zmud & Sener (2017)
Travel Time	Total travel time in hours to travel point-to-point from origination to destination.	Bösehans & Walker (2020); Cai et al. (2019); NAS (2019); Wadud (2017); Zmud & Sener (2017)
Value of Time [a]	Amount of money a passenger is willing to pay to save time or travel time's opportunity cost	De Looff et al. (2018); NAS (2019); Wadud (2017); Zmud & Sener (2017)
	Normative Goal (to Act Appropriately)	
Biospheric Values and Subjective Norms	Pro-environmental value. Environmental concern is important to some people in their transport mode choice	Anable (2005); Lindenberg & Steg (2007; 2013); Thomopoulos et al. (2015); Haboucha et al. (2017); Westin et al. (2020); Bösehans & Walker (2020)

Note. [a] Variables added to the original GFT based on the literature review.

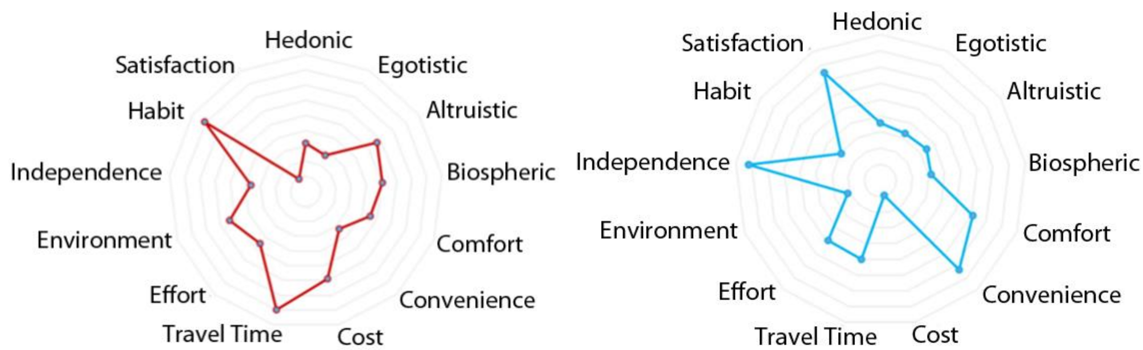
Literature Support by Variable

Self-efficacy/Independence. Independence is an original element in the GFT; however, the expanded GFT model includes self-efficacy regarding a traveler's perceived control due to the importance of perceived autonomy (as in independence) and control over the traveler's transport mode resources and opportunities. Because of its direct impact on human behavior, self-efficacy is an essential component of TPB and is relevant in this context. It affects our choices regarding human motivation and our confidence to do something successfully (Bösehans & Walker, 2016). Factors affecting self-efficacy include modeling or vicarious experience, social persuasion, and psychological factors (Bandura, 1977, 2006).

Habit. This variable refers to a traveler's typical behavior pattern automatically triggered by specific cues (Bösehans, 2018). Generally, the literature supports that travel behavior encompasses a strong component of habit (Thomas & Walker, 2015). Travel habit has been added to prior behavioral models such as the Radman et al. (2017) research on advanced driver assistance systems using TAM, TPB, and UTAUT and the Moták et al. (2017) study on precursor variables of intent-to-use autonomous shuttles. Although segmentation research rarely measures travel habits (Bösehans & Walker, 2020), Bösehans and Walker (2020) and Thomas and Walker (2015) added *habit* to their models. They found it was one of the chief variables in cluster differentiation. Figure 12 presents examples of two distinct clusters in Bösehans and Walker's model, illustrating how one cluster has a strong habit *z*-score while the other does not.

Figure 12

Sample Clusters by Mean Z-Scores



Note. The left image shows clustering on *Travel Habit*, and the right image shows clustering on *Independence* as found in Bösehans and Walker's (2020) model.

Satisfaction. This variable conveys the traveler's general level of fulfillment relating to their primary transport mode. Satisfaction is in the original GFT framework as a component of the hedonic goal (to feel good). As found in Bösehans and Walker's (2020) transportation research, satisfaction, comfort, convenience, cost, travel time, effort, independence, and environment vary significantly between mode users, as illustrated in Figure 12. Therefore, satisfaction is suitable for discriminating between air passenger clusters in the research.

Value of Time. This variable is the opportunity cost for travel time. In a way, the value of time is a crucial aspect of travel time (Cai et al., 2019; NAS, 2019). While travel time is in the original GFT, time value is not. The expanded GFT model includes the *value of time* as a component of the *gain* goal (to optimize resources). Both SF and aMoD are associated with the research on the value of time (De Looff et al., 2018; Homem et al., 2019; van den Berg & Verhoef, 2016; Zmud & Sener, 2017). Wadud (2017) explored where aMoD might offer the most significant benefits and found that higher-income households had a higher perceived value of time and perceived aMoD as a means of increasing productivity (p.174). The NAS (2019) found that travelers would equate an hour of driving to save half an hour of flying, signifying the difference in the value of time via different mode choices, even by the same traveler. In the future, customization of aMoD for different needs such as sleeping, eating, entertaining, exercising, working, or just relaxing, can provide options for different trip requirements. Increased productivity while using aMoD may reduce stress, improve health, and enhance the economy (NAS, 2019).

Trust and Perceived Safety/Risks. This variable is a critical factor in transportation mode choice. Trust is important in modal choice decisions (Rahman et al., 2017; Zhang et al., 2019; Zmud & Sener, 2017), especially if it involves an innovative and new mode choice that passengers are less familiar with (Ashkrof et al., 2019; Vance & Malik, 2015). In researching factors on trust in novel service/technology, Li, Hess, and Valacich (2008) found four statistically significant factors: (a) reputation of the organization; (b) cost/benefit; (c) trust in the organization's integrity; and (d) subjective norm, a form of peer pressure, similar to the normative goal in GFT. Ashkrof et al. (2019) found that trust in aMoD is the most significant latent variable measured by *t*-values and magnitude compared to the other factors (p. 10). Consistent with Ashkrof et al., Molnar et al. (2018) found that trust in aMoD is the most critical factor in explaining future aMoD acceptance. As expected in a nascent service like aMoD, people and the government perceive trust as the most critical concern (Molnar et al., 2018). Trust-related concerns include aMoD's capability to adhere to traffic laws (Schellekens, 2015), consumer trust in aMoD’s reliability under all weather conditions (Zhang et al., 2019), trust in data privacy and protection from software hacking (Kyriakidis et al., 2015), and aMoD’s certainty in avoiding irrational and unpredictable pedestrian and driver behavior (Noy et al., 2018). Improving trust increases acceptance. Empirical research by Yang and Xu (2019) concluded that trust has direct and indirect effects on acceptance; the direct effect is more important in explaining behavioral intention and willingness to use, while the indirect effect is essential in influencing general acceptance.

Trust, distrust, perceived safety, perceived risks, and perceived benefits are closely related, and trust can be a predecessor of perceived risk (Molnar et al., 2018). Generally, aviation safety has improved since the 1970s, even though passenger count has doubled every 15 years (Barros et al., 2010). In the past 10 years, there were only two commercial flight fatalities in the U.S., one in 2018 and one in 2019, as recorded by the National Transportation Safety Board (Airlines for America, 2021). In 2021 alone, there were over 36,000 driving-related fatalities (U.S. DoT, 2022). Nevertheless, a proven safety record and consumer perception of safety and trust are not necessarily the same.

Consistent with Li et al.’s findings, trust in flying is highly correlated to fear of flying and trust in the operator (Vance & Malik, 2015). The fatal Boeing 737 Max accidents in 2018 (Lion Air Flight 610) and 2019 (Ethiopian Airlines Flight 302) have increased the public’s concern about fully turning over critical safety systems to automation. The resultant grounding of all Boeing 737 Max planes worldwide shook passenger confidence in automation (Slotnick, 2020). Compilation of public opinion polls by the Advocates for Highway & Auto Safety (2020) shows that the public holds deep skepticism about aMoD. Half of U.S. adults surveyed believe aMoD is more dangerous than human-driven vehicles, and two-thirds believe it should adhere to higher safety standards than human-driven cars (Advocates for Highway & Auto Safety, 2020). These consumer perceptions highlight the challenges facing aMoD adoption. Nevertheless, compared with human-driven cars, aMoD has a better driving record so far (Hulse et al., 2018; Teoh & Kidd, 2017). In 2017, one fatality occurred per 94 million mi (151.3 million km) driven by people (Radfar, 2017) versus one fatality per 222 million mi (357.3 million km) driven with Tesla's Level 3 autonomous cars (Hai, 2017). Even the cause of the one Tesla fatality was attributed to human error by drivers in the other vehicles (Hai, 2017).

As the autonomous level increases, so should safety (Noy et al., 2018; Rödel et al., 2014). If aMoD becomes the norm, reluctant passengers may use the on-demand mobility service because their friends and family do so, just as some of today's passengers with aviophobia fly because of the social and professional expectations to do so (Vance & Malik, 2015). Sener et al. (2019) found that *perceived safety, performance expectation,* and *social influence* indicated the strongest associations with intention-to-use aMoD. Using SEM, Zhang et al. (2019) found that trust could improve perceived benefits and reduce perceived safety risks. More importantly, *perceived benefits* are more important than *perceived risks* in determining aMoD acceptance. Their findings offer insights into increasing aMoD acceptance by increasing trust and decreasing society's perceived risks and benefits of aMoD (Zhang et al., 2019, p. 339).

While technology companies, car manufacturers, and ride-share operators invest heavily in aMoD development, the general public's safety perception lags. Understandably, most people in the United States hear about AV or aMoD from the media, and some may have seen accidents caused by Level 3 and 4 vehicles. Very few people in the United States have been in a driverless car or a driverless shuttle. Therefore, the media, friends, and family influence public perception instead of objective safety data. With MNL, it is essential to minimize the number of predictor variables because too many predictors create high-dimensional settings, weakening the maximum likelihood estimates (Hair et al., 2017). Furthermore, with both CA and MNL, it is critical to avoid confounding variables. In this case, while perceived safety, perceived risks, perceived benefits, and distrust are essential factors based on extant literature, they are not explicitly investigated in this research. For this present study, the *trust* variable encompasses perceived risks and safety.

Cost. While cost is part of the original GFT framework, it deserves a special mention due to its importance in transportation research (Bösehans & Walker, 2020; De Looff et al., 2018; NAS, 2019; Zmud & Sener, 2017). Cost in this research refers to a passenger's perception of how the total trip cost meets his or her expectations. Cost and time are archetypal tradeoffs in transportation, with a common perception that flying saves time and driving saves money (Chen et al., 2019). The value of time is also a factor in the cost equation (Wadud, 2017; see also NAS, 2019). Driving a car requires the driver to focus on driving, while flying and aMoD allow the passengers to use travel time for other pursuits. Compared to the car and aMoD costs, flying costs are relatively stable once the air ticket is purchased. For SF, the total trip costs include the airfare and the costs to travel to and from the airport. Unlike SF, the costs of car and aMoD travel depend on many variables, including traffic density, the number of stops, the number of travelers sharing the ride, the type and size of car used, gasoline (car), and electricity (aMoD) costs, supply and demand at the time of service (aMoD), vehicle utilization, toll road pricing, and other route and behavior variables (Bansal & Kockelman, 2017; Krueger et al., 2019). This present research focuses on short-haul travel under 500 mi (800 km), so it does not consider hotel costs .

Demographics, COVID-19, and Contextual Variables. The remaining research variables relate to demographics, COVID-19, and contextual items. (See Tables 3 and 4 for a list of the conceptual definitions and support in the extant literature. Operational definitions are presented in Chapter III.) In addition to the typical passenger and household demographics (age, gender, income, and education), it is necessary to include the following because of their importance and relevance in transport mode choice research, particularly with inter-regional trips and aMoD: (a) physical mobility, (b) children in the household, (c) vehicle ownership, (d) previous crash history, (e) driver's license, and (f) length of time with driver's license (Rice et al., 2019; Whittle et al., 2019). aMoD may offer enhanced mobility to the young, elderly, infirm, and people without driver's licenses. However, the findings may not be generalizable to this broader population if their demographics do not match the study's selected demographics. Therefore, this study compares the demographics of participants (sample) with the demographics of the air passenger population.

Table 3

Demographic and COVID-19 Variables

	Conceptual Definition	Source
	Demographic Variables	
Age	There are systematic differences between age groups in travel perceptions, perceived risky behavior, and new technologies. Age may also reflect mobility limitations (i.e., older and younger people tend to travel less).	Meyer et al. (2017); Rice et al. (2015); Venkatesh et al. (2003)
Children in Household	Generally, the higher this number, the fewer long-distance trips depending on trip purpose and duration.	Sener et al. (2019); Ullman & Aultman-Hall (2020)
Education	Highest level of education attended.	Venkatesh et al. (2000; 2003); Rice et al. (2015)
Gender	There are systematic differences between gender in decision-making and perceived risky behavior. Men typically travel more overall, but some studies show that women travel more for leisure.	Hardman et al. (2018); Ullman & Aultman-Hall (2020); Zmud & Sener (2017)
Household Income	Total income earned by everyone living in the same house. Income confounds with age in some studies.	NAS (2019); Rice et al. (2015); Venkatesh et al. (2003)
Physical Mobility	Level of physical mobility of self/friends/family traveling together. Flying may be challenging for people with mobility issues. aMoD and driving may increase mobility opportunities for the physically challenged.	Becker & Axhausen (2017); Schellekens (2015); Zhang et al. (2019)
Previous Crash History	Vehicle crash (personal/family/friends) history influences modal choice.	NAS (2019)
Vehicle Ownership	The number of vehicles per household can influence transport mode decisions. Vehicle ownership may vary by generation and city/suburban residency.	Cai et al. (2019); Sener et al. (2019); Zmud & Sener (2017)
	COVID-19 Variables	
COVID-19 Fear	The extent of the fear of contracting COVID while traveling	Linden (2020); Suau-Sanchez et al. (2020); Sun et al. (2020)
Disposable Income Change	The positive or negative impact of a change in disposable income	Linden (2020); Suau-Sanchez et al. (2020)
Ticket Price	An increase or decrease in ticket price	Serrano & Kazda (2020); Suau-Sanchez et al. (2020)

Note. aMoD = autonomous mobility-on-demand.

Table 4

Contextual Trip Variables

Variable	Conceptual Definition	Source
Direct Flight	Percentage of direct versus indirect flights at the nearest airport	NAS (2019); Wadud (2017)
Time to Nearest Airport	Drive time between home and the nearest airport	NAS (2018)
Current Main Mode	Typical mode to travel distances 100–500 mi (160–800 km) using fly, drive (conventional car), aMoD, intercity bus, or intercity train	Berliner et al. (2019); Bösehans & Walker (2020); NAS (2018)
Neighborhood Type	Urban, suburban, rural	Berliner et al. (2019); Bösehans & Walker (2020); NAS (2018)
Future Transport Mode	Fly, drive (conventional car), aMoD, bus, or train in the future when aMoD is available	Bösehans & Walker (2020); Hess et al. (2018)
Trip Party Size	Total number of passengers traveling together	NAS (2019); Perrine et al. (2020); Wadud (2017); Zmud & Sener (2017)

Note. aMoD = autonomous mobility-on-demand; NAS = National Academy of Sciences, Engineering, and Medicine.

Research Models

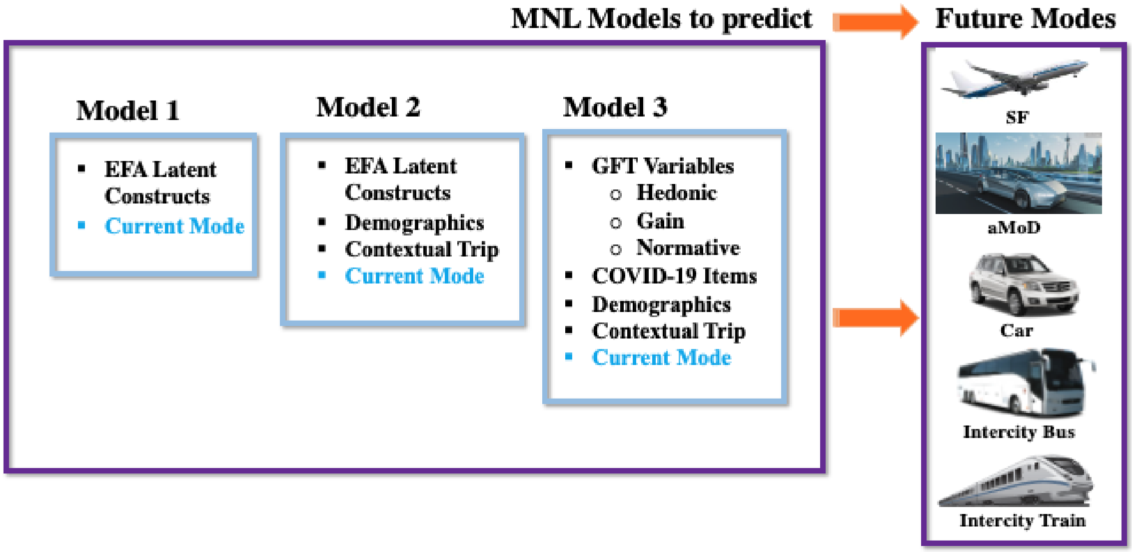
There are three MNL models and two CA models in this study.

Future Multimodal Transportation Choice Models

In the MNL models, the dependent variable (DV) is the future mode choice with five categories (SF, aMoD, car, intercity bus, and intercity train). The independent variables (IVs) are the exploratory factor analysis (EFA) latent constructs, the GFT goals (hedonic, gain, and normative), contextual trip attributes, COVID-19 variables, and demographics. Figure 13 shows the three MNL models using various combinations of variables and the EFA latent constructs (details are discussed in Chapter III).

Figure 13

Multimodal Transportation Choice Models



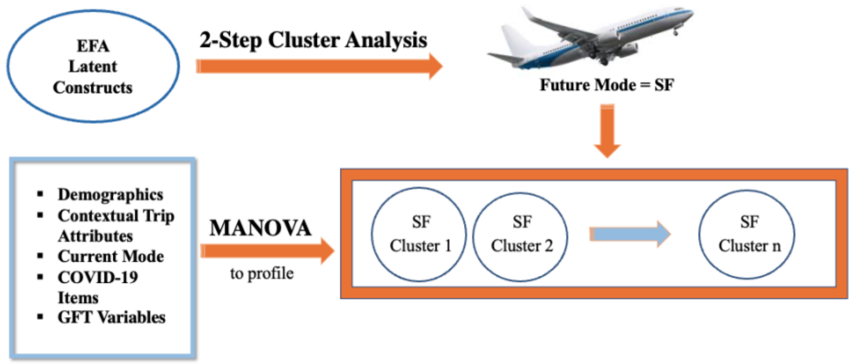
Note. SF = commercial short-haul flight; aMoD = autonomous mobility-on-demand; GFT = goal framing theory; EFA = exploratory factor analysis; MNL = multivariate logit.

Short-Haul Flight Clusters Model

The SF clusters model uses the two-step CA to segment SF passengers based on the EFA latent constructs. Passenger demographics, contextual trip attributes, COVID-19 items, and the GFT variables are used to profile the distinct SF clusters based on their similarities as shown in Figure 14. MANOVA is used to test for subgroup differences.

Figure 14

SF Clusters Model



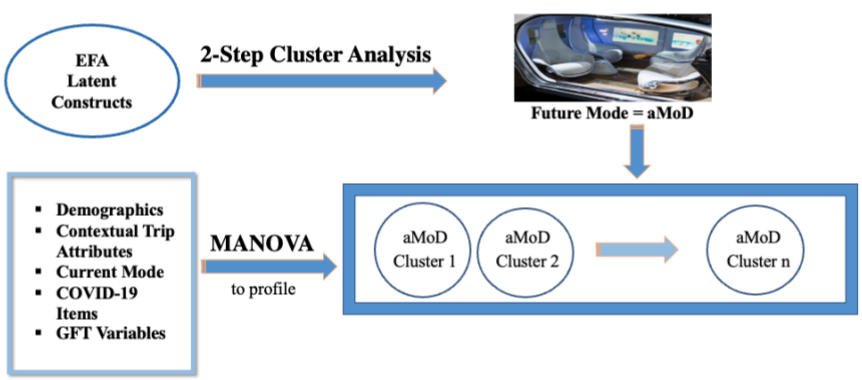
Note. EFA = exploratory factor analysis; GFT = goal framing theory; MANOVA = multivariate analysis of variance; SF = commercial short-haul flight.

Autonomous Mobility-on-Demand Clusters Model

Similar to the SF Clusters model, the aMoD clusters model uses two-step CA to segment aMoD passengers as shown in Figure 15.

Figure 15

aMoD Clusters Model



Note. aMoD = autonomous mobility-on-demand; EFA = exploratory factor analysis; GFT = goal framing theory; MANOVA = multivariate analysis of variance.

Summary

Since 2000, while the total U.S. air passenger market grew by 25% (IATA, 2020d), air traffic under 500 mi (800 km) shrank by 30% (Miller, 2017; Silk, 2018). With more short-haul travel choices, passengers routinely evaluate the price, convenience, comfort, time, and difficulty required for post 9/11 airport security screening between air and other transport modes, particularly the car. With America's robust car culture, aMoD is a particularly compelling potential competition to flight. This chapter has presented a comprehensive review of the extant literature on SF and aMoD. This literature synthesis has revealed the research gaps, established the scope of this study, supported the GFT as the theoretical foundation for this research, and justified the selection of the research variables. It has also discussed the research framework and the five research models for predicting modal choice and segmenting SF and aMoD passengers using EFA, MNL, two-step CA, and MANOVA.

Chapter III describes the research method, population, sample selection (including sampling frame, sample size, and sample strategy), data collection process, ethical considerations, the measurement instrument, and data analysis approach.

Chapter III: Methodology

This quantitative research aims to gain a deeper understanding of air passengers' modal choice in inter-regional travel in the United States. Specifically, this research seeks to develop a future multimodal choice model to identify factors that most influence air passengers' transportation decisions based on the GFT variables, contextual trip attributes, demographics, and COVID-19 items. This study evaluates the similarities and differences of the distinct short-haul flight (SF) and autonomous mobility-on-demand (aMoD) passenger segments. The academic foundation for the grounded theory, research method, and selection of variables is supported in the relevant extant literature review. This chapter describes the research approach, including the research design, procedure, population, sample size, sampling frame, sampling strategy, measurement instrument, data collection process, treatment of the data, and data analysis methods. It also explains the handling of the ethical considerations and the reliability and validity assessments.

Research Method Selection

This study uses quantitative method and survey design to investigate what most influences U.S. air travelers' mode of transportation choice for inter-regional travel of 500 mi (800 km) or less. Quantitative methods emphasize objective measurements to explain a particular phenomenon (Creswell, 2014). Due to their ability to efficiently provide researchers with useful data for analysis, surveys are one of the most used research designs in social sciences (Vogt et al., 2012). A web-based survey design was selected instead of an in-person survey because of the following advantages (Vogt et al., 2012):

- During the COVID-19 pandemic, an online survey platform was one of the few practical and physically safe methods for data collection.
- Screening questions with qualifying logic could be effectively used.
- An online survey can be administered with total respondent anonymity, ensuring respondent privacy and confidentiality, thus more reliable data input.
- Sensitive demographic questions such as age, income, physical mobility, and crash history can be answered privately.
- Skip logic can be set up to ensure respondents answer only the applicable questions.
- An online survey platform can direct respondents to fill in missing responses and eliminate data interpretation and input errors.
- A survey with a large sample size administered via an online platform can save money and time compared to in-person administration.

Population/Sample

Population and Sampling Frame

The population of interest is air passengers who are 18 years or older, who have traveled on a commercial flight domestically at least once in the prior 2 years, and who live in the United States. The accessible population was screened to fulfill these requirements for the following reasons: Respondents needed to (a) be 18 years or older to represent air passengers with more defined personal attitudes, intentions, and goals, which is consistent with online knowledge workers' minimum age and requirements stipulated by the Institutional Review Board's (IRB's) minimum age policy; (b) be air passengers since this research focuses on the perspectives of air passengers; and (c) live in the U.S. at the time of the research, so that each had an equal opportunity to make the inter-regional transport mode decision (commercial short-haul flight, aMoD, inter-regional train, inter-regional bus, or drive/ride in a car).

The sampling frame for this research consisted of the population of workers who were members of Amazon Mechanical Turk (MTurk), an online crowdsourcing platform for human intelligence tasks (HITs) such as surveys and other brief on-demand tasks. MTurk provided a time- and cost-effective way to generate ideas, perceptions, and opinions (Barends & de Vries, 2019; Buhrmester et al., 2018) and has become a practical alternative to traditional in-person surveys (Mortensen & Hughes, 2018). For the results to be generalizable, the sample must be representative of the general population. Random sampling, the gold standard in social science research, means each qualified member of the population has an equal probability of completing the survey (Creswell & Creswell, 2018). Due to MTurk's sampling mechanism, using MTurk as a sampling frame is considered a convenience sample, not a random sample. A convenience sample may undermine the representativeness and generalization of the results by introducing sampling bias: Selecting a sample where members do not have an equal probability of being selected. Despite MTurk's convenience sampling, samples are representative of the U.S. population in many areas of social sciences research (Hunt & Scheetz, 2019; Rouse, 2020; Walter et al., 2019). In addition, a considered and carefully-planned sampling strategy was deployed to minimize sampling biases to achieve valid and reliable results (see the Sampling Strategy section).

Sample Size

Generally, population size, confidence level, margin of error, and effect size influence the required sample size. However, the sample size also depends on the statistical tests and research methods used (Field, 2013). The sample size estimations for MNL and CA are different. The larger of the two minimum sample sizes was used for this research since it satisfied the requirements of both analysis methods.

The MNL uses a maximum likelihood estimation (MLE) method which requires a large sample size and does not have assumptions regarding normality, linearity, or homoscedasticity (Hair et al., 2017). Similar to CA, there is no formula to estimate sample size for MNL. Schwab (2002) provided a sample size guideline of a minimum of 10 cases per IV. This present research has 37 IVs, equating to a sample size of 370.

Given that CA is an exploratory technique, the sample size is not about statistical inference and cannot be calculated using a formula (Hair et al., 2017). In this case, CA has "strong mathematical properties but not statistical foundations" (Hair et al., 2017, p. 436). Accordingly, it requires a sample size large enough to form functionally (managerially) useful, meaningful, and substantial segments. The crucial requirements of other statistical methods, such as normality, linearity, and homoscedasticity, are not essential for CA. Consequently, valid CA analyses focus on two other critical issues: sample representativeness and multicollinearity (Dolnicar et al., 2014). As the CA findings are only as good as the sample representativeness, all efforts were made in this research to improve sample representativeness. Up until 2014, there were no guidelines for CA sample size calculation. Because CA relies on extant literature and reasoned judgment, Hair et al. (2017) advise scaling the sample size based on the number of input variables. In addition, multiple input variables may benefit from an unsupervised multivariate data reduction method such as principal component analysis (PCA) to reduce the risk of overfitting. Since CA is exploratory, any CA algorithm will form clusters of individuals, regardless of whether they are meaningful. In 2014, Dolnicar et al. demonstrated that a sample size of 70 times the number of input variables is adequate to provide reliable and valid results. Since the EFA latent constructs were used as input variables for the 2-step CA, an estimation was made for a minimum sample size of 1,400.

Sampling Strategy

The primary objective of sampling is to obtain a representative sample so the results can be generalized to the population. Due to the popularity of MTurk as a survey platform for scholarly research in recent years, there has been an increase in studies examining its representativeness. Mortensen and Hughes (2018), Thomas and Clifford (2017), and Buhrmester, Kwang, and Gosling (2011) found that MTurk met and sometimes exceeded psychometric standards associated with published research. Hunt and Scheetz (2019) highlighted two critical steps for MTurk (and other survey methods) to achieve valid and reliable results: engage qualified participants and validate collected data. The methods to recruit and engage qualified participants are discussed in this section, and validating collected data is discussed in the Validity Assessment Method section in this chapter.

Careful planning and proper screening are critical when conducting scholarly research on MTurk. This study devised a well-planned sampling strategy to minimize sampling bias. Buhrmester et al. (2018) observed that MTurk data could be compromised if the workers are inattentive or dishonest. The following are some of the strategies used by MacInnis, Boss, and Bourdage (2020), Hunt and Scheetz (2019), and Loepp and Kelly (2020) to minimize bias, improve data quality, reduce MTurk worker misrepresentation, and engage qualified participants which this study has employed:

- Screen for participants with higher approval ratings. 98% or higher was used in this research.
- Use attention checks.
- Do not advertise the eligibility criteria.
- Compensate every participant to reduce motivation to misrepresent.
- Block duplicates from proxies or VPNs that allow repeat participants to complete the survey multiple times using different IP addresses and block non-U.S. MTurk workers by screening IP addresses.
- Hire master workers as they are less likely to provide dishonest answers.
- Exclude workers who have accepted many HITs in the past 3 months.

Paolacci and Chandler (2014), Woods et al. (2015), Kuang et al. (2015), and Hunt and Scheetz (2019) are some of the researchers who have validated that MTurk workers are as diverse as traditional random samples and are representative of the U.S. population in some aspects. Therefore, with proper screening, a sample from MTurk is considered representative of the population (Gandullia et al., 2020; Hunt & Scheetz, 2019).

Demographics of the research respondents were compared to the published research on air passengers. Specifically, the potential similarities and differences between MTurk and air passenger samples were considered when interpreting the generalizability of the findings. To obtain high-quality data, it is essential to select participants with MTurk approval ratings of 98% or higher and a history of completing more than 100 prior surveys (Rice et al., 2019). While providing an incentive to MTurk knowledge workers can increase response rates, offering compensation that is too high may evoke a negative response from the knowledge workers (Buhrmester et al., 2018). For this research, $2 was considered an appropriate compensation amount for a survey that averaged an 8-min completion time based on the completion times of 25 pretest and 161 pilot study participants. Pretesting the survey instrument and conducting pilot studies helped avoid or minimize sampling bias and improve generalizability. The snowball sampling method was not considered to minimize the risk of sampling bias in the pilot study and the full-scale survey (Vogt et al., 2012). In summary, this research utilized a well-designed sampling strategy to increase the external validity and generalizability of the findings.

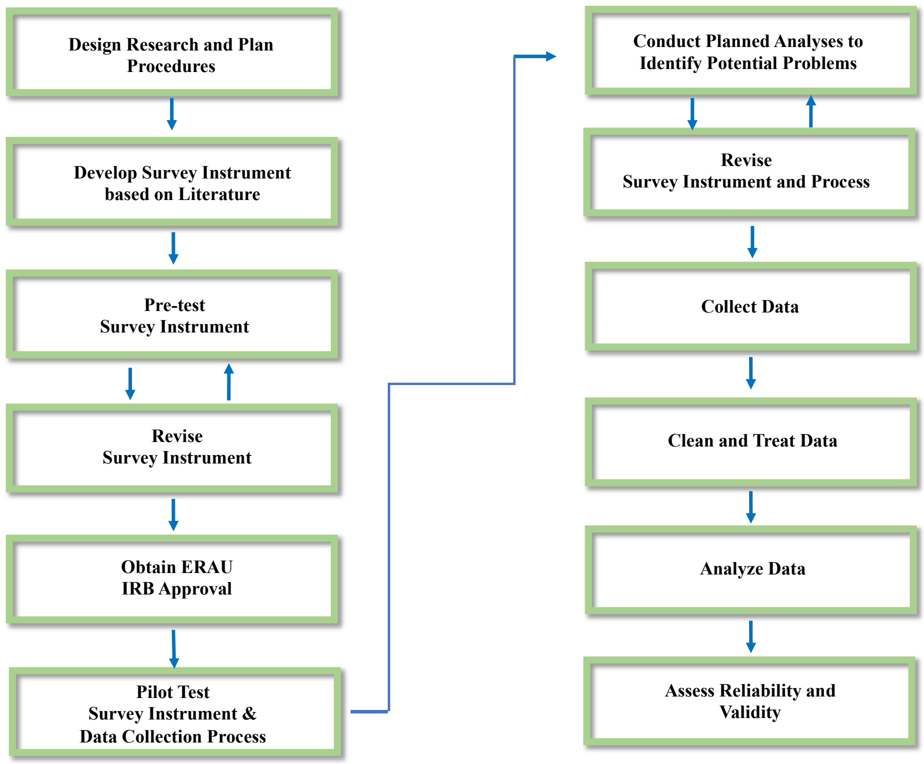
Data Collection Process

Design and Procedures

This study employed a quantitative research design with a survey instrument to investigate associations between variables in cluster analysis and to determine the relationship between the IVs and DV in multinomial logit. The population, sampling frame, and sample size were determined as part of the research plan. Figure 16 illustrates the research design and procedure, and the sections that follow describe each step of the procedure with sufficient detail so that other scholars can replicate this research to increase validity.

Figure 16

Research Design Procedure



Note. ERAU = Embry-Riddle Aeronautical University; IRB = Institutional Review Board.

Apparatus and Materials

Research variables and questionnaire items were gleaned from extant literature to further strengthen the validity of the survey (Vogt et al., 2012). Regardless of origin, it was essential that the questionnaire was relevant, short, clear, precise, non-biased, properly worded, and ordered (Babbie, 2016). Therefore, some items needed to be modified for context. To make it easier for the respondents, items were grouped by themes. There were three main sections in the questionnaire based on the literature: (1)

Demographics; (2) GFT variables, contextual trip attributes, and COVID factors; and (3) Future-oriented items of on-demand driverless cars.

Survey Pretest

Pretesting the instrument was done by soliciting feedback from three groups of people: (a) Those who were experienced in airport, commercial airline, and transportation mode research; (b) Those who had a good knowledge of SF or aMoD; (c) Those who qualified for the screening questions as a U.S. air passenger (defined as someone 18 years or older and who had flown on a commercial airline within the United States in the prior 24 months). Survey pretesting was an important step to ensure the questions accurately reflected the purpose of the research and that the respondents were able and willing to answer the questions. In addition to feedback on content, comments were sought on wording, ambiguity, biased or leading questions, double-barreled questions, question ordering, skip patterns, measurement scales, and time to complete the questionnaire (Babbie, 2016).

This questionnaire was pretested over a six-week period with 26 subject matter experts and air passengers. The pretest helped to refine the questionnaire content, wording, and flow, in addition to discovering ways to engage the respondents and increase their interest when completing the questionnaire. The average completion time for the pretest survey was 15 min. A phone or face-to-face interview was conducted following the pretest survey to gauge respondents' perceptions of the instrument, accuracy of understanding, and ease of completion. The average interview time per pretest was 90 minutes. Pretest details are presented in Chapter IV.

Survey Pilot Study

After the pretest and appropriate modifications were made to the survey instrument on Survey Monkey and MTurk (the online survey platform), the researcher applied for ERAU's IRB approval. Once the IRB approved the research (see Appendices A and B), a pilot study was conducted on 161 participants of the target population using MTurk. This was a crucial refinement step before launching the survey to identify problem areas, reduce measurement errors, and improve instrument validity and reliability.

The pilot study assessed the sampling plan, survey process, response rate, further refinement of the questionnaire, and response options. The instrument was user-tested for flow, proper skips, and display on different computer devices including smartphones, tablets, and laptops. The pilot study provided an average survey completion time of 8 min 27 sec. In addition to testing the average survey completion time and the survey process, the pilot respondents' survey data were critical in identifying potential issues in the planned analyses to ensure problems could be resolved at this stage.

To test for instrument reliability, Cronbach's alpha measured the internal consistency (reliability) between items on the scale. All GFT and COVID-19 items were positively worded and rated using a 5-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*). The Cronbach's alpha for the pilot study was 0.801, which is considered good internal consistency. Cronbach alpha for the sub-scales was also calculated and provided similar good internal consistency. Details of the pilot study results are presented in Chapter IV.

Sources of the Data

Using the MTurk platform, survey data were collected from respondents 18 years or older who had flown in the prior 24 months and resided in the U.S. Other data required for data analysis were generated from SPSS and Microsoft Excel. Demographics from the respondents of this research were compared with those obtained from Airlines for America (A4A) to ensure the data were representative of the flying population.

Ethical Considerations

Embry-Riddle Aeronautical University (ERAU) is fully committed to safeguarding the rights and welfare of human subjects in research conducted by ERAU faculty and students (ERAU, n.d.). Therefore, all research involving human subjects must comply with both Federal law and ERAU policies to ensure that the guiding principles embodied in the Belmont Report are followed and that no participant is subject to unreasonable physical or emotional harm (ERAU, n.d.). During the first year of ERAU's Ph.D. program, every student is required by its IRB policy to complete mandatory IRB training. For this research, a web-based IRB Human Subject Protocol application was submitted to the IRB Committee and to this researcher's Dissertation Committee Chair for review and approval. The application included a written plan with details on how the research procedures would protect the rights and welfare of the human subjects, the survey instrument, an informed consent document, and other relevant information. (See the Permission to Conduct Research Form in Appendix A and the Human Subjects Protocol Application in Appendix B.) As principal investigator, this researcher was responsible for all aspects of this research, including ensuring the research was conducted according to the approved protocol.

There were a few important ethical considerations. The first was to protect human subjects from any potential harm. Even though the survey method is one of the least intrusive research designs (Vogt et al., 2012), respondents were asked some personal questions, including demographic data that were not publicly available. They were asked questions about their trip attributes, opinions, and attitudes. Thoughtful questionnaire design and sensitive and appropriate question wording were important. Strict ethical measures such as blocked IP addresses and password coded files were essential. This research was designed to avoid causing stress to the respondents. For example, the survey design did not demand an answer when the respondent was unable or unwilling to provide one. Therefore, the respondents were free to skip any questions. In addition, the questionnaire had an average completion time of less than 9 min so that respondents were not exhausted by the survey.

The second ethical consideration relates to the respondents' informed and voluntary consent. A written explanation of the study objectives, the nature of the research, and voluntary consent were provided at the questionnaire's introduction. Respondents were reminded that their participation was absolutely voluntary and that they could terminate the survey at any time.

The third ethical consideration concerned the respondents' privacy and the confidentiality of their identity and data. Respondents' identities were kept anonymous. Any identifying information was coded. For example, because identification through IP addresses was possible, this information was blocked and not recorded. The data were stored anonymously, and the database was password protected. Respondents checked a box to acknowledge they had read the informed consent and agreed to proceed with the survey. (See the Data Collection Device in Appendix D.)

Measurement Instrument

A research instrument is a measurement tool. For most survey research conducted in the social sciences, the measurement instrument for consistent data collection from respondents is a questionnaire that provides a standard set of items and response options. The questionnaire should accurately measure the research variables with appropriate scales or an open-ended question that must be coded before analysis. Based on the extant literature, this survey instrument comprises items from the 16 GFT variables, 8 contextual trip attributes, 5 COVID items, and 13 demographic variables. The survey instrument contained 69 items gleaned from the literature review and refined and modified through the pretest and pilot study.

The survey contained an introduction with the purpose, survey procedures, and a consent form explaining voluntary participation in this research (see the Participant Informed Consent Form in Appendix C). Following the introduction, items were grouped by themes to help respondents organize their thoughts. Using the appropriate rating scale for each variable was essential for a valid instrument. The scale needed to accurately represent the respondent's range of attitudes and opinions. A 5-point Likert scale was used for the GFT variables. A 5-point Likert scale, as opposed to a 7-point or 10-point scale, can capture the respondents' true opinions with enough distinction between values (Babbie, 2016) and allows the responses to be compared to the extant literature. There was one open-ended question at the end of the questionnaire to offer respondents an opportunity to provide additional comments. If the respondent completed the questionnaire too fast, the answers would not be incorporated into the dataset. Based on the pilot study results, answers from respondents who completed the survey in less than 6 min were eliminated.

Constructs

A construct is a latent variable, a concept that cannot be directly observed and must be measured using observable indicators. The constructs of interest in this study are the latent constructs, which are the results of the data reduction method with exploratory factor analysis. Using the 16 GFT variables (hedonic goal, gain goal, and normative goal) and the 5 COVID-19 items, the EFA analysis formed four constructs (with a clean pattern matrix) that represented the three GFT Goals and the COVID-19 items (see Chapter IV for details).

Variables and Scales

Of the 21 GFT and COVID variables, 16 are the expanded GFT variables that are derived from the grounded theory from which this research is based. Five are COVID-related variables. There are contextual trip variables and demographics gleaned from extant transportation literature. The operational definitions of the study variables and scales are shown in Table 5.

Table 5

Operational Definitions (Questionnaire Items) for Variables with Scales

Variable	Operational Definition	Scale
	GFT Hedonic Goal (to Feel Good) [a]	
H1_Eff	24. Generally, my main transport mode for inter-regional is efficient.	Likert/Metric
H2_Comfort	24. I will not sacrifice comfort even if I have to pay slightly more.	Likert/Metric
H3_SelfEff	24. I believe issues that may pop up during my travels can be resolved.	Likert/Metric
H4_Habit	24. I am quite predictable in terms of how I travel.	Likert/Metric
H5_Satisfaction	24. Most of the time, I am happy with the transportation I use when I travel to other cities.	Likert/Metric
H6_Trust	24. In general, I trust my main inter-regional mode is safe.	Likert/Metric
H7_Hedonic	24. Traveling is fun for me.	Likert/Metric
Variable	GFT Gain Goal (to Optimize Resources) [a]	
G1_Cost	24. Cost is very important to me when I travel for leisure.	Likert/Metric
G2_Convenient	24. Convenience is very important to me when I travel.	Likert/Metric
G3_Travel_Time	24. I usually try to minimize my total travel time.	Likert/Metric
G4_Value_Time	24. When I travel, I value my time doing something nice or useful, such as watching a movie, working, or sleeping.	Likert/Metric
	GFT Normative / Biospheric Goal (to Act Appropriately) [a]	
B1_Env	25. Preserving the environment is very important when I decide how I travel.	Likert/Metric
B2_Moral	25. I feel moral obligation to protect the environment.	Likert/Metric
B3_EV	25. I think electric vehicles are good for the environment.	Likert/Metric
B4_SN1	25. People who are important to me tend to care about the environment.	Likert/Metric
B5_SN2	25. It is important for me to be a role model for my family in environmental protection.	Likert/Metric
	Contextual Trip Attributes [a]	
Airport_Dist	34. Approximately, how long does it take to drive from your home to the nearest airport? 15 minutes, 15-30 minutes, 31-45 minutes, 46-60 minutes, > 1 hour	Ordinal
Dir_Fl_pc	35. Pre-COVID, on average, what percentage of the time does your home airport offer direct flights to where you need to go? 0%-20%, 21%-40%, 41%-60%, 61%-80%, 81%-100%?	Ordinal
L_Car_#P	36. On average, roughly how many people, including yourself, travel together when you travel for leisure? by car (driving) 1, 2, 3, 4 or more	Ordinal
L_SF_#P	36. On average, roughly how many people, including yourself, travel together when you travel for leisure? by plane (flying) 1, 2, 3, 4 or more	Ordinal
SF_if over	20. I usually fly if the driving distance is over: 3, 4, 5, 6, 7, 8 hours	Ordinal
Car_SF_2hrs	21. What is the likelihood of driving a car instead of flying if the trip is a 2-hour drive?	Likert/Metric
Car_SF_5hrs	21. What is the likelihood of driving a car instead of flying if the trip is a 5-hour drive?	Likert/Metric
Car_SF_8hrs	21. What is the likelihood of driving a car instead of flying if the trip is an 8-hour drive?	Likert/Metric

Variable	Operational Definition	Scale
aMoD_Timing	28. I think driverless cars will be transporting people in the United States: within 3, in 3-5, in 6-10, in 11-20, over 20 years, Never	Ordinal
aMod_50pc	29. I believe 50% of the cars on the road will be driverless cars in the United States: by 2030, by 2040, by 2050, beyond 2050, Never	Nominal
EV_50pc	30. Most people think that 50% of the cars will be electric in the United States: by 2030, by 2040, by 2050, beyond 2050, Never	Nominal
aMoD_SF2hrs	32. What is the likelihood of you using driverless cars instead of driving if the trip is 2 hours drive?	Likert/Metric
aMoD_SF5hrs	32. What is the likelihood of you using driverless cars instead of driving if the trip is 5 hours drive?	Likert/Metric
aMoD_SF8hrs	32. What is the likelihood of you using driverless cars instead of driving if the trip is 8 hours drive?	Likert/Metric
aMoD_SF	33. I would use a driverless car instead of flying on inter-regional trips.	Likert/Metric
	Current and Future Mode Choice	
MODE_Future	31. In the future, assuming driverless cars are readily available, safety, legal regulation issues are solved, what do you think you would use most for inter-regional travel? driverless car, drive a car myself/driven by others, fly, take an inter-regional bus, take an inter-regional train	Nominal
MODE_Current	22. Pre-COVID, when I traveled to inter-regional cities, I usually: drove, flew on an airplane, took an inter-regional bus, took an inter-regional train	
	COVID-19 [a]	
C1_Fear	27. I am concerned with getting COVID-19 when I travel.	Likert/Metric
C2_Variants	27. I think COVID-19 and variants will get worse.	Likert/Metric
C3_Income	27. My disposable income has increased since COVID started.	Likert/Metric
C4_Tprice	27. Even during COVID, I could be tempted to travel by air if the ticket price was low enough.	Likert/Metric
C5_Economic	27. I think the economy is gradually recovering.	Likert/Metric
	Demographics [a]	
Gender	2. Identify myself as: Female, Male, Other.	Nominal
Age	3. Self-report measure: 18-24, 25-34, 35-44, 45-54, 55-64, 65-74, > 74 years old	Nominal
Education	4. Highest level of education attained: Attended high school, high school diploma, Bachelor's degree, Master's degree, Ph.D./Post-doctorate	Nominal
HH_Income	5. Annual household income (total from work, investments, and retirement funds): <$30,000, $30,001-$50,000, $50,001-$100,000, $100,001-$150,000, $150,001-$200,000, >$200,000	Ordinal
Children_#	6. Number of children under 18 years old living in your household: 0, 1, 2, 3, or more	Ordinal
Cars_#	7. Total number of cars owned by household: 0 [No license], 1, 2, 3 or more	Ordinal
HH_DL_#	8. How many people in the household have a driver's license? 0, 1, 2, 3 or more	Ordinal
Years_DL	9. How long have you had a driver's license? I do not have a driver's license, < 3 years, 3-8 years, 9-15 years, > 15 years	Ordinal
Drive_Freq	10. How often do you drive? I do not drive, <1 time per week, 1-2 times per week, 3-5 times per week, >5 times per week	Nominal
Urban_Rural	12. I live in: city (large urban area), suburb (large residential area near big city), small city, rural America, countryside/small town village.	Nominal
Mobility_Issue	14. Do you or someone in your family use a wheelchair or walker? yes/no	Nominal

Variable	Operational Definition	Scale
Biz_Travel_Freq	16. Pre-COVID, on average, I traveled for business: once a year, 2-6 times a year, 7 or more times a year, not travel for business.	Nominal
Car_Injury	13. In the past, have you been in a car accident when someone got injured? yes/no	Nominal
COVID_W_Home	15. During COVID, the estimated percentage of time I work from home: 100%, 75%, 50%, 25%, 0%, I do not work	Nominal
COVID_Vac	17. I am vaccinated against COVID-19: yes/no	Nominal
COVID	18. I have/had COVID-19: yes/no	Nominal
COVID_Air	19. I have traveled by air during COVID: yes/no	Nominal
Fly_Miles	11. On average, roughly how many miles a year did you fly within the U.S. pre-COVID? <5,000, 5,000-10,000, 10,001-25,000, >25,000 miles.	Ordinal
Ibus_Used	23. I have used the following transport mode at least once in the United States: inter-regional bus: yes/no	Nominal
Itrain_Used	23. I have used the following transport mode at least once in the United States: inter-regional train: yes/no	Nominal

Note. aMoD = autonomous mobility-on-demand; GFT = goal framing theory. [a] Self-report measures.

Data Analysis Approach

Reliable and valid survey research means that the research results consistently represent the population of interest. To achieve reliable and valid research, this study focused on thoughtful planning and meticulous execution in every step, including the research design, the sampling strategy, the data collection method, the survey instrument, question wording and order, data cleaning, data treatment, appropriate data analyses, and reporting. Because of how vital and omnipresent these issues are, reliability and validity trade-offs have been discussed throughout Chapter III. The data analysis methods and approach serve to increase the results' reliability and validity.

Means and standard deviations were conducted for metric and Likert scale variables. Frequency and percentages were calculated for nominal and ordinal variables. IBM SPSS Version 28 was used for data preparation and univariate and multivariate analyses, including assumptions testing and the identification of normality, missing values, and outliers. The data analyses relevant to answering the research questions included descriptive statistics, EFA, MNL, two-step cluster analysis, and MANOVA.

Participant Demographics

After the first section, which was the introduction and screening, the second section of the survey instrument was participant demographics. Table 5 shows a list of demographic variables derived from the literature review. Cultural factors were not included since the study is delimited to the U.S. Information regarding participant's state and city of residency (Cai et al., 2019; Zmud & Sener, 2017) and ethnicity/generational culture (Gkartzonikas & Gkritza, 2019; Trinh et al., 2018) could have provided more dimensions for understanding the distinct clusters. However, CA and MNL both would have better performance if the number of variables was restricted. Therefore, these demographic variables were not included. Of the 20 relevant demographic variables, four are COVID-related.

Reliability Assessment Method

Research reliability focuses on the consistency of results, specifically whether the data collection techniques and the analytic procedures would produce consistent findings if the research were repeated at a different time or by another researcher (Field, 2012). While there are many threats to research reliability, participant and researcher errors and biases are some of the most common threats. *Participant error* is defined as anything that could alter the way a participant performs. *Participant bias* is defined as any factor that causes a respondent to provide a false response. As described earlier, the questionnaire was pretested with 26 industry and research experts and pilot-tested with 161 respondents to minimize issues that could potentially cause participant errors and biases. *Researcher error* is defined as anything that alters a researcher's interpretation. *Researcher bias* is defined as any intentional or unintentional bias a researcher may have towards the research process, analyses, or findings. This researcher was mindful of the potential for researcher errors and biases. Again, meticulous procedures were put in place to reduce researcher errors and biases, such as the pretest, pilot study, and use of an online survey. Reliability and validity testing of the survey instrument was also an important step to ensure the questions were valid and the measurement scales were reliable.

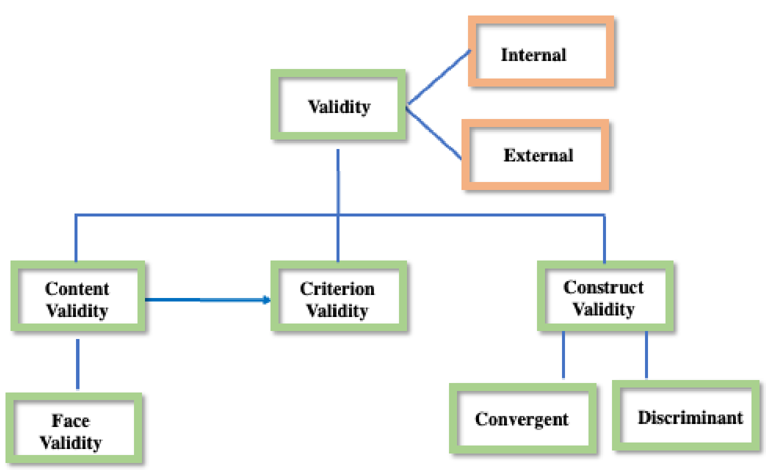
Instrument reliability is concerned with the consistency of the measurement tool. An instrument is reliable when scores on the items are consistent across constructs and stable over time to create reproducible results (Babbie, 2016). Cronbach's alpha is a popular method for testing the internal consistency of scale items (Hair et al., 2017). A Cronbach's alpha of 0.7 or higher is considered reliable (Hair et al., 2017). To improve instrument reliability, survey questions were pilot tested and pretested. The researcher tested for construct reliability using the pilot-test results to further improve the instrument. The items were worded in a simple, concise, and precise manner, and sequenced appropriately to avoid order bias. Since this quantitative research used an online platform for data collection, inter-rater reliability (reliability across different researchers) was unnecessary. Once the full set of final survey data was available, Cronbach's alpha was conducted again to ensure internal reliability.

Validity Assessment Method

Instrument validity is the extent to which an instrument measures what it is designed to measure (Babbie, 2016). Figure 17 shows the main types of validity that were considered in this study.

Figure 17

Validity in Quantitative Research



Content Validity. This assessment method relates to comprehensiveness and is not tested statistically. Each aspect of the study objective should have adequate representation in the survey instrument. Content validity uses the combination of logical reasoning, a thoughtful review of the extant literature, and expert opinions (Babbie, 2016). It can be seen as a prerequisite to criterion validity because it serves as an indicator of whether the intended factors are measured. For example, if some items were irrelevant to the study objectives or they measured something immaterial, this would create potential biases.

The survey instrument was developed based on factors validated in prior research on GFT, SF, and aMoD (Bösehans & Walker, 2020; Lindenberg & Steg, 2013; National Academies of Sciences, 2019; Vance & Malik, 2015; Westin et al., 2020; Zmud & Sener, 2017). While realizing the fact that validated factors from different studies would be combined, this was still the best approach due to the lack of research on the choice of aMoD over SF. The pilot study and pretest addressed content validity by ensuring the survey items were representative of the research purpose. Content validity of both the survey items and the overall measurement scale was evaluated in the pretest by having subject experts rate each item and the scale for its relevance to the study objective. An average congruency of 93% at the pretest indicated strong content validity.

Face Validity. This assessment method is a surface-level evaluation of the survey content to ensure each question relates to the research objective. For this research, expert opinions such as the researcher’s committee chair, colleagues, and industry experts were solicited during the pretest to address face validity.

Criterion Validity. This assessment method determines the extent the survey accurately predicts specific behavior. The criterion is an external measurement, usually by an established test that has been validated. Intention and behavior are difficult to measure, particularly toward a service that is yet to happen. Since GFT is relatively new in transport research, its predictive power is still unknown, particularly in air transportation research. However, the predictive power should improve by thoughtful variable selection. For this research, certain items were compared to relevant items in the extant literature to determine any correlation between them. A high correlation indicated good criterion validity.

Construct Validity. This assessment method determines the degree to which the measured items accurately reflect the theoretical construct they are designed to measure (Hair et al., 2017). Because a construct cannot be directly observed, it must be measured using observable indicators. For example, the hedonic goal from the GFT is not directly observable. However, an individual's hedonic goal can be estimated using previously validated factors such as a traveler's perception of the efficiency and ease of access, comfort, and other variables. Construct validity improves when the construct has been validated by prior research. To achieve construct validity, this researcher ensured that there was strong literature support for the variable choice (see the details in Chapter II). This research measures a mix of observed variables and constructs. Construct validity can be evaluated through two construct-validation processes (Campbell & Fiske, 1951): convergent validity and discriminant validity.

Convergent Validity. This assessment method determines the extent to which items of the same construct are correlated. In other words, convergent validity provides empirical evidence that items that make up a specific construct should share a high proportion of variance in common. Factor loadings were used to evaluate convergent validity. High factor loadings on a construct indicate that the items converge on a common point: the latent construct. Factor loadings of .5 or higher are acceptable, and .7 or higher indicate good convergent validity (Hair et al., 2018).

Discriminant Validity. This assessment method provides empirical evidence that the constructs are uniquely different (Hair et al., 2018). While there are various ways to test the discriminant validity of constructs, a validated novel approach is the Heterotrait-Monotrait Ratio (HTMT). According to Kline (2016), HTMT values close to 1 indicate a lack of discriminant validity. HTMT values < .85 demonstrate evidence of discriminant validity. Being slightly more conservative, Hair et al. (2018) suggest HTMT < .9 as evidence of discriminant validity. Again, before data analyses and model testing are conducted, it is essential to ensure that the data are reliable and valid, because unreliable and invalid data will result in high variation, poor model fit, and incorrect model estimation. As for construct validity, both convergent and discriminant validity must be proven before testing the model.

Internal Validity. This assessment method refers to whether the questions accurately explain the research outcome. Internal validity can be improved through survey design, procedure, and bias reduction. Tests for correlations were used for internal reliability in this study. This step is important to highlight inconsistencies or unexpected issues (Vogt et al., 2012).

External Validity. This assessment method refers to how generalizable the findings from a sample are to other persons in the population, settings, and times.

Thoughtful and careful sampling strategies improve the external validity of a convenience sample. The well-planned sampling strategy for this study is discussed in the Sampling Strategy section in this chapter.

Measurement Errors and Biases. Measurement error occurs when there is a difference between the true value and the measured value. Errors can be random or systematic. Measurement errors arise with poor question wording and poor question sequencing. Measurement error can be minimized by (a) avoiding bias in questions; (b) avoiding double-barreled questions; (c) making the response categories clear and logical; (d) using complete and straightforward sentences; (e) avoiding questions that are too complex and time-consuming; (f) using mutually exclusive categories, and (g) planning ahead for analysis. There are four main types of research biases: sampling, response, non-response, and question order.

***Sampling Bias*.** This problem occurs when members of a sample do not have an equal probability of being selected. This bias was avoided or minimized in this study by following the selection process outlined in the Sampling Strategy section and by using pretesting and pilot testing.

***Response Bias*.** This problem includes recall bias and confirmation bias and is a serious threat to the validity and reliability of the research results. Recall bias is introduced by respondents having to rely on their memory of a past event. Confirmation bias occurs when respondents provide answers to present themselves in a better light. Potential response biases were minimized in this study by using clear and concise wording of survey items, as verified by the pretest and pilot study.

***Non-response Bias*.** This type of bias is one of the most overlooked research problems that can pose a great threat to the validity of survey results. It happens when the required information is not obtained because some potential respondents were inaccessible, and some respondents in the sample did not answer many of the questions (because they were either unwilling or unable). These survey data issues become non-response bias when non-responders differ from the responders in a meaningful way, making the results unrepresentative of the population. In this case, the error comes from an absence of selected respondents or their responses instead of the collection of wrong data. To reduce non-response bias, the questionnaire must have a logical flow, a personable and professional introduction, interesting content, short length, concise wording, clear online presentation, and appropriate incentives.

There are two main types of non-response biases: item and unit. Item non-response bias occurs when some questions are not answered (missing data). Unit non-response bias is typically caused by the researcher's inability to reach some respondents or respondents who refuse to participate. Two methods were used to identify potential unit non-response bias. The first involved comparing the data from initial and late respondents. The second involved comparing the demographic survey data to known air passenger population demographics. A chi-square test was conducted to compare available demographics between respondents and non-respondents (those who answered less than 50% of the survey questions). Details of the results are presented in Chapter IV.

The most important method in reducing non-response bias is a properly designed survey as described in the Research Design Procedure section. However, once non-response bias is identified, there are four post-survey methods to adjust the results: case deletion, imputation, weighting, or expand the survey sample. Case deletion is a solution if there are not too many missing values. Imputation relies on available respondent data on other variables. Missing values can be replaced by the mean values of the variables to impute or by values estimated in a regression by other explanatory variables. Weighting involves post-stratification in a two-step process of first identifying a set of control variables for the population that the sample should match and then calculating weights to adjust the sample variables to the control variables to bring the sample distribution in line with the population. If the results are very different between respondents and non-respondents, more data would need to be collected to reduce this bias.

Question Order Bias. This problem occurs when a respondent answers differently to questions based on the order of the survey items. This bias is minimized by keeping the survey items short and clear, avoiding loaded questions, avoiding difficult concepts, and ensuring the survey is relevant and does not take too long to complete. The pretest and pilot study served to minimize question order bias.

Data Treatment. It is important to ensure missing data, coding errors, and aberrant values are examined prior to running analyses. The objective of this stage is to identify and fix data errors. Since responses are automatically captured in the database without human input, coding errors are minimized by using an online survey. Data cleaning is an important step in data treatment. Regardless of how data are collected, there are usually many sources of error that need to be identified and corrected. For example, 16 questionnaires with incomplete answers or straight-lined answers were discarded from this study.

Missing Data. Missing values can cause a loss of information or skewness of the data. To improve the validity of the results, it is essential to understand why some data are missing. If the data are missing at random, then it is safe to remove the data with missing values. If the missing data form a non-random pattern, or if more than 10% of the data are missing, then the missing data must be treated through listwise deletion, pairwise deletion, imputation, or a model-based approach (Hair et al., 2017). However, if the values missing are not at random, removing the cases with missing values can insert bias into the results. The problem with missing data is common in survey research and can impact the research results profoundly.

Typically, it is better to keep data than to remove them. The researcher must exercise critical judgment before removing observations. There are times when the variable should not be removed even with more than 50% missing values if that variable is significant in the research (Hair et al., 2017). There are four common ways to handle missing values. First, delete the observation when there are too many missing values. This is indicative of the respondent not paying attention, or the respondent genuinely was not able to answer the questions. Second, delete the variable. If many respondents did not answer a particular question, for example, over 20%, it is an indication that there are issues with the survey item. It could be too private, too intrusive, too vague, or too difficult. Third, impute with mean, median, or mode. Fourth, use logic to predict what the missing value most likely would be if the item had been answered. Of the 1,425 data sets collected in this study, missing values were computed using mean, mode, and logical deductions.

Outliers. Next, the univariate and multivariate outliers from all the metric (Likert) variables were examined. Outliers can be problematic if they are not representative of the population, distorting results from statistical tests. A univariate outlier is an extreme value. Boxplots, a useful detection tool for univariate outliers, were conducted. A multivariate outlier is a combination of extreme scores on two or more variables. In multivariate analysis, Mahalanobis D-square was used to identify outliers across all variables (Hair et al., 2017). High D-square values (> 100) represent observations farther from the general distribution of observations. Since SPSS does not directly determine Mahalanobis D-square, this analysis can be performed using regression analysis. Both univariate and multivariate outliers affect the outcome of statistical analyses. Nevertheless, there are many approaches to handle outliers. Since there were few outliers in this study, they were dropped from the dataset. Outliers can also be transformed, capped, or assigned a new value (Hair et al., 2017), which was not required in this study. The scatterplot of standardized predicted value and residual was performed to confirm that there were no remaining outliers after removing the outlier cases.

Assessment of Normality. Neither CA nor MNL has a normality requirement. MANOVA, however, has a normality assumption that must be satisfied and is discussed in detail in the MANOVA section and in Chapter IV.

Data Analysis Process

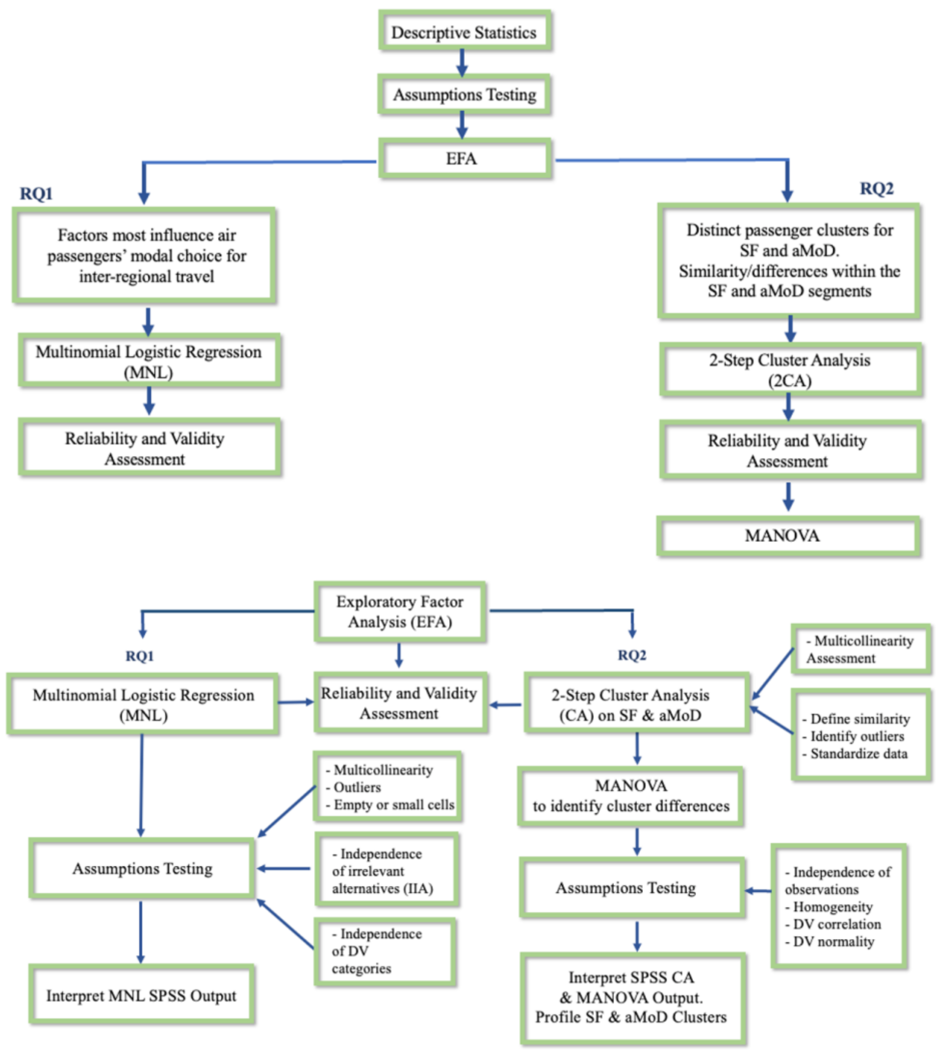
Four data analysis methods were used to answer two research questions:

RQ_1. Based on goal framing theory variables, contextual trip attributes, COVID-19 variables, and demographics, what factors most influence air passengers’ modal choice for inter-regional travel distances of under 500 mi (800 km)?

RQ2. What distinct passenger clusters exist for SF and aMoD? How are these clusters similar/different within the SF and aMoD segments? Figure 18 shows a summary of the research analyses.

Figure 18

Summary of Statistical Analyses



Note. The top flowchart shows the broad steps for the analyses and the lower one presents more details including assumptions testing. aMoD = autonomous mobility-on-demand; SF = commercial short-haul flight; RQ = research question.

Descriptive Statistics. Descriptive statistics were conducted using IBM SPSS Version 28. At this stage, one-way analysis of variance (ANOVA) and chi-square tests were used to compare some of the responses from MTurk with industry findings.

Exploratory Factor Analysis

EFA was performed to minimize the number of constructs for CA and MNL. It validated the GFT constructs with the pattern matrix. Details of the results are discussed in Chapter IV.

Extraction and Rotation Methods. The EFA using the principal component analysis (PCA) extraction method considers all the available variances (unique and error variances). PCA was most appropriate for this study as data reduction was a primary objective, focusing on the minimum number of factors needed to account for the maximum portion of the total variance. Typically, the unrotated method does not show clear factors, as rotation causes factor loadings to be more clearly differentiated. There are two methods of factor rotations: oblique and orthogonal. The oblique method provides information about the extent to which the factors are correlated with each other. The oblique Promax rotation was appropriate for this study because it handles a large dataset well and assumes correlations among the variables (which tested true as explained earlier).

Factor Loadings. Small factor loadings (coefficients) with absolute values less than .3 were suppressed to avoid showing low factor loadings in the matrix. Factor loadings greater than .5 are acceptable (Hair et al., 2018). If there is a good rationale to keep an observed variable, or there are too few observed variables in a factor, then there is a case to keep the variables (Hair et al., 2018).

Scree Plot. The scree plot was used to determine the number of factors by finding the "elbow" of the plot based on the cut-off point of an eigenvalue of 1.

Sample Adequacy and Inter-Correlation Among Variables. The KMO generally indicates whether the variables can group into a smaller set of underlying factors. A KMO value of 0.6 or higher is an indication to proceed (Hair et al., 2018). The results of KMO, Bartlett's test, the individual MSAs, and extracted communalities all provided empirical evidence that the overall inter-correlation requirement was met, and the observed variables are adequate and appropriate for use in an EFA.

Total Variance Explained. Four factors extracted explained 52.6% of the variance in the model. Details are in Chapter IV.

Pattern Matrix. The loadings in the pattern matrix are regression coefficients making each row effectively a regression equation for each construct. The final 4-construct EFA model presented itself neatly in the pattern matrix as shown in Appendix L. These four constructs validated the three GFT goals (Hedonic, Gain, and Normative) and the COVID-19 items.

Multinomial Logistic Regression

Also called multinomial logit, multinominal logistic regression (MNL) is a classification method that predicts the probability of an outcome (a dependent variable) with three or more discrete categorical values. It is a simple extension of binary logistic regression. Like binary logistic regression, MNL uses maximum likelihood estimation

(MLE) to evaluate the probability of categorical membership (nominal and ordinal). The log odds of the outcomes (modal choices) are modeled as a linear combination of the IVs (predictor variables). The IVs are metric in scale. In this research, MNL was used to model the nominal outcome variable *MODE_Future* with five distinct transport choices: *aMoD, SF, car, inter-regional bus,* and *inter-regional train*. Figure 13 in Chapter II summarized the three MNL models using varying combinations of variables and the GFT and COVID-19 latent constructs (IVs). The future mode choice with five categories (SF, aMoD, car, inter-regional bus, inter-regional train) is the dependent variable (DV). The following are critical areas to consider in using MNL.

Assumption of Independence of Irrelevant Alternatives. Assumption of independence of irrelevant alternatives (IIA) means that adding or removing alternative outcome categories does not affect the odds among the remaining outcomes. The IIA is a core hypothesis in rational choice theory. In some situations, when MNL is used to model choices, it may impose too much constraint on the relative preferences between the different alternatives. If the IIA is violated, nested logit or the multinomial logit may be used instead.

Assumption of Independence of DV Categories**.** The MNL assumes independence among the DV choices (but not the typical assumptions of normality, linearity, or homoscedasticity) and non-perfect separation. In this research, the assumption is that the choice of flying is not dependent on the choice of taking a train or a bus. This assumption is met because these mode choice categories are all independent of each other. The Hausman-McFadden test was run to test the assumption of independence (Field, 2014). Details are presented in Chapter IV.

***Outliers*.** Like linear regression, MNL is sensitive to outliers and other unusual observations. The Data Treatment section in this chapter describes the treatment for outliers in detail.

***Multicollinearity*.** Typical of generalized linear models, multicollinearity must be evaluated when conducting MNL. Multicollinearity happens when there are high correlations among the IVs, leading to unreliable or unstable estimates of the DV. Pairwise correlation coefficients between the IVs (predictors) and the Variance Inflation Factor (VIF) are common methods to detect multicollinearity. A correlation coefficient greater than 0.5 is a concern, and over 0.8 indicates multicollinearity. The formula VIF = 1/(1- R^2), where R^2 is the coefficient of determination, indicates how much variation of a DV is explained by the IV. While there is no definitive VIF value for determining the presence of multicollinearity, a general guideline is that a VIF of 1 means that there is no multicollinearity for that variable. Any VIF value less than 3 is good, and a VIF value greater than 10 indicates multicollinearity (Field, 2014).

***Empty or Small Cells*.** Cross tabulations between categorical IVs (predictors) and the DV would yield the number of cases in each cell. If a cell has few cases, the model may be unstable.

***MNL Procedure and Output*.** For a nominal DV (*Future Modal Choice*) with five categories, the MNL model estimates four (5-1) logit equations. SPSS was used to compare all combinations of the five groups using SF as a reference category. Details of the MNL procedures and output are in Chapter IV.

Cluster Analysis

As a form of multivariate analysis, CA is commonly used for taxonomy classification and description (identifying natural groups within the data set), data simplification (analyzing groups of similar observations versus individual observations), and relationship identification (revealing relationships not otherwise discovered) (Hair et al., 2017, p. 428). In this research, CA was used as an exploratory technique to reveal passenger subgroups with similar GFT, travel, demographic, and COVID-19 characteristics. The CA process reveals the "natural structure among the observations based on a multivariate profile" (Hair et al., 2017, p. 415).

CA has been employed in transportation literature published in the last several decades (Dolnicar et al., 2014; Urban et al., 2018). Even though CA and factor analysis both concern grouping of some sort, CA groups objects and respondents, whereas factor analysis groups variables (Hair et al., 2017). CA classifies objects or respondents on a set of researcher-selected characteristics, making it critical that the researcher selects each variable objectively based on prior research, extant literature, and reasoned judgment (Hair et al., 2017). The objective of CA is not to build a predictive or correlation model. Its goal is to assess similarity, thereby gaining a deeper understanding of the homogeneity within the cluster and dissimilarities between the clusters. There are four critical areas that must be addressed in the research design phase when performing CA.

The first is to identify univariate and multivariate outliers before partitioning begins. The handling of outliers is presented in the Outliers and the Data Treatment sections. The second critical area is to define similarity, which involves the researcher consciously selecting a similarity measure and specifying the approach to be used for input to the hierarchical clustering algorithm. When segments are identified in CA, both the magnitude and the pattern of the responses are considered. Correlational measures consider only the responses' patterns and not the absolute values; therefore, they were not used to define similarity in CA in this study. Typical similarity measures in SPSS include Euclidean distance, squared Euclidean distance, and Mahalanobis distance (D^2). Given the sensitivity of some procedures to the similarity measures, several distance measures were used in this study. The results were compared to each other and to other theoretical and known patterns.

The third issue relates to data standardization. Most CA using distance measures are sensitive to differing variable scales and magnitudes. Variables with larger dispersion/standard deviation generally have more impact on the final similarity results (Hair et al., 2017, p. 434). Since all clustering variables in this study used the same scale, no standardization was required. The fourth critical design issue relates to the sample size and is addressed in the Sample Size section.

A critical differentiator between CA and other multivariate analyses is that CA is the only multivariate technique that does not estimate the variate empirically. This makes the researcher's selection of the variables from extant research and the definition of the cluster variate critically important. Therefore, it is imperative that the researcher "employ whatever objective support is available and be guided by reasoned judgment in the design and interpretation stages" (Hair et al., 2017, p. 425). It is also critical for the researcher to avoid the use of highly redundant variables as input to CA (p. 434). Over 20 variables were considered but not included in the final set of variables for this study due to this critical point, including familiarity, privacy, flexibility, and risk perception.

Consequently, because CA is more art than science, and statistical results are produced regardless of the actual existence of any data structure, the researcher must have a strong conceptual basis (Hair et al., 2017, p. 419), which is demonstrated in the results presented in Chapter IV.

The importance of strong conceptual support is further demonstrated by the three most common criticisms of CA (Hair et al., 2017, p. 419). First, CA has no statistical basis for drawing inferences from a sample to a population and that there is no unique solution as different solutions can be obtained by varying researcher inputs. Second, the identification of clusters does not validate their existence. Third, the cluster variate is solely specified by the researcher making the selection, addition, and deletion of relevant variables greatly impactful to the results. Due to these potential issues with CA, the selected research methodology and design rely on strong conceptual support based on primary literature discussed in Chapter II.

CA Procedure and Output. Before CA was performed, multicollinearity was assessed to verify that no clustering variables exhibited correlations above 0.9 as recommended by Hair et al. (2017). Multicollinearity exists when there are high intercorrelations among the IVs; thus, acting as a type of disturbance in the data, making it hard to assess the IVs' relative importance in explaining the variation caused by the DV. Multicollinearity has a unique impact on CA compared to other multivariate techniques because there is no DV. In CA, multicollinearity acts as a form of implicit weighting. Although it may not be apparent to the researcher, the implicit weighting affects the analysis and the results. Highly correlated variables effectively represent the same concept, so if redundant variables are included, that construct will get disproportionate weighting compared to other variables; thus, likely skewing the results toward that construct. Therefore, it is essential to examine the variables used in CA for substantial collinearity. Hair et al. (2017) suggested four potential solutions (p. 437):

- Select variables to avoid redundancy based on extant literature.
- Reduce variables to equal numbers in each set of correlated measures.
- Use a distance measure that compensates for the correlation (i.e., Mahalanobis distance, D^2).
- Factor the variables before clustering and either select one cluster variable from each factor or use the resulting factor scores as cluster variables.

Two-step CA can handle both metric and categorical (ordinal and nominal) data in the same model. The three GFT goals and the COVID-19 constructs were used in the hierarchical CA to identify the number of clusters. Using SPSS Version 28, a stepwise clustering procedure was used. Ward's method with squared Euclidean distance was used to generate clusters that were homogeneous and relatively similar in size. It is useful to keep the ratio of cluster sizes under 2.5 to ensure that the largest cluster size would not be more than 2.5 times the smallest cluster size. Using both the dendrogram and the agglomerations schedule helped with the cluster decision. Squared Euclidean distance was used to measure the similarities between clusters. The dendrogram helped in visually identifying clusters with the squared Euclidean distance on the horizontal axis. Once the clusters were defined, they were profiled using the demographic variables, contextual trip attributes, and the GFT constructs. The clusters were compared using these profiling variables. One-way ANOVA, chi-square, and Welch tests assessed cluster differences. When there was statistical significance, one-way ANOVA (Gabriel's tests), chi-square (standardized residuals), and Welsh tests (Games-Howell) were used to identify cluster differences. The agglomeration coefficients were used to guide the optimal number of clusters. Since there was no clear indication for cluster cut-off point, cluster centroids were saved (three to seven cluster solutions) and imported into a k-means analysis for further examination. Subsequently, this researcher selected the number of cluster solutions based on the variance ratio criterion, hit ratios from discriminant analyses, and an examination of the non-transformed variable means for various cluster solutions. Multiple discriminant analysis was used to help confirm the validity of the cluster solution. The two-step CA model summary displays the cluster quality. Variable importance was also examined to adjust cluster comparison.

Multivariate Analysis of Variance

Multivariate Analysis of Variance (MANOVA) is a multivariate technique that examines the relationships between several categorical IVs and two or more continuous DVs. While ANOVA evaluates the differences between groups using *t*-tests (for two means) and *F*-tests (between three or more means), MANOVA was used in this research to identify differences in attributes between the clusters.

Assumptions Testing for MANOVA. To ensure key assumptions were met before conducting any multivariate analysis helped boost effect sizes and improve the validity of the results (Field, 2010; Hair et al., 2017). Any serious violations of the assumptions must be detected and corrected, if possible, as MANOVA requires independence of observations, homoscedasticity, correlation of DVs, and normality of the DVs. The following assumptions testing, a critical step, was conducted before additional analyses were conducted.

Independence of Observations. More of a research design than a test, this requirement is met if there is no relationship between the observations in each group or between the groups themselves. For this research design, each respondent can only choose one transport mode with no respondent being in more than one mode choice.

Homoscedasticity/Homogeneity. There are two common methods to test for homoscedasticity. First is the multivariate test of homogeneity (i.e., Box's M test of equality of covariance matrices). Box's M test determines if two or more covariance matrices are equal and its results are sensitive to any departures from normality. If the samples are from non-normal distributions, then Box's M test may be testing for non-normality. The null hypothesis of Box's M states that the observed covariance matrices for the DVs are equal across groups. A large *p*-value indicates a non-significant test result (suggesting the covariance matrices are equal). The second method is the univariate test of homogeneity (or Levene's test of equality of error variances). Levene's tests were applied across all levels of IVs. If the Levene's test was non-significant, then the homoscedasticity assumption was met. However, if the test of homogeneity requirement was not met, Hair et al. (2013) argues that if the sample sizes in the IV groups are large enough, no remedies would be needed. This was confirmed by observing the boxplots with the variances (sizes of the boxes) between the groups in the IVs.

Correlation of DVs. Bartlett's test for sphericity is the most widely used test for determining correlations among all DVs and assessing whether collectively, intercorrelation exists (Hair et al., 2017, p.706). The null hypothesis of a Bartlett's test postulates the variables are not correlated (orthogonal). A significant degree of intercorrelation exists when $p < .001$.

Normality of DVs. This is a critical assumption for MANOVA (Byrne, 2010: Hair et al., 2017). Considering there is no direct test for multivariate normality, univariate normality is usually tested for all DVs as a surrogate. Normality can be checked using two methods. The first was the use IBM AMOS to detect both kurtosis and skewness values. Kurtosis severely affects tests of covariances and variances (Byrne, 2010). A kurtosis value of zero in AMOS indicates perfect normality; however, values of < 5 are considered acceptable (Byrne, 2010). If the values are too high, the researcher can transform the variables using SPSS or run two models with and without transformation then compare the results. The second method to test normality was use of descriptive analysis in SPSS. The Q-Q *plot* was used since the histogram for a Likert scale data rarely shows the normal distribution. If normality for DVs is violated, Hair et al. (2013, p.686) posit that a larger sample size, as used in this research, will minimize the impact to the validity of the results.

MANOVA Procedure and Output. This step involves running all four multivariate tests: Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root. Significance levels of $p < .01$ indicate the significant impact of the IVs on the DVs; therefore, a researcher can assume the covariance matrices are not equal across groups. Next, this researcher examined the interaction effect of the IVs and looked for Partial Eta Square values. This was followed by Levene's Test of Equality of Error Variances. The researcher looked for non-significant *p* values. Between-Subjects Effects testing examined the significance and level of impact of the IVs on each of the DVs. In identifying effect sizes, the model fit was determined by examining mean vector equivalents across groups (Hair et al., 2017). If there is a statistically significant difference in the means (when an ANOVA *F*-test is significant), specific differences between the group means would be determined by post-hoc analysis (i.e., Tukey HSD [honestly significant difference], Scheffé's LSD [least significant difference]).

The model fit for the two-step CA was evaluated using the *F*-value. If the MANOVA test has a p-value < .05, there is a significant difference among the clusters. The cluster distances indicated the heterogeneity across the clusters. The larger the distance meant the more dissimilar the clusters.

Summary

This chapter described the research method, population, and sample selection, including sampling frame, sampling strategy, and sample size. It explained the research design, data collection process, survey pretest, survey pilot study, and data sources. Development of the measurement instrument was outlined, and the variables and scales were presented. The critical area of ethical considerations and IRB approval were discussed. The Data Analysis Approach sections explained the details of data treatment plan and reliability and validity assessments, including how multinomial logit was selected to model the nominal outcome variable of *future mode*; cluster analysis was applied to segment each of the two distinct groups of SF and aMoD passengers; and MANOVA was used to test cluster differences within the SF clusters and aMoD clusters. This chapter concluded with the research procedures for each assessment and their respective assumptions testing and outputs.

Chapter IV: Results

The primary objective of this chapter is to answer the two research questions to identify factors that most influence air passengers' modal choice for inter-regional travel (distances of under 500 mi or 800 km) and ascertain passenger clusters, similarities, and differences existing within the SF and aMoD clusters. The first section in this chapter presents the survey pretest and pilot study findings that informed the full-scale study. The second section reports the demographics, descriptive statistics, and statistical results based on multiple univariate and multivariate analyses. The EFA results established and validated four latent constructs with a good model fit, which were used as input for the two-step cluster analysis (instead of 22 observed GFT and COVID-19 variables). The MANOVA results feature the similarities and differences within the distinctive segments of aMoD and SF passengers. The results of MNL highlight the key predictors of future transport mode choice once aMoD is available on U.S. roads. Findings from these analyses provide insights into air passengers' inter-regional travel decision-making.

Survey Pretest and Pilot Test Results

Survey Pretest

The questionnaire was pretested over six weeks, from April 8 to May 20, 2021, with 26 participants (4 researchers, 10 air passengers, and 12 aviation and other transportation practitioners). The instrument was user-tested for proper organizational flow, skips, and display on different computer devices, including smartphones, computer tablets, and laptops. The average completion time for the pretest survey was 15 min. A follow-up phone or face-to-face interview was conducted to gauge the respondents' perceptions of the instrument, accuracy of understanding, and ease of completion. The average interview time was 90 min. The results from the pretest helped refine the questionnaire content, wording, and flow and to discover better ways to engage the respondents and increase their interest when completing the questionnaire. There were three valuable outcomes.

The first finding concerned testing the definition and presentation of the concept of driverless cars. One of the most considered and discussed areas in this research was whether respondents would understand the meaning of aMoD. Four different diagrams of driverless cars and five levels of automation were presented to the pretest participants to discern the most effective and clear communication. This pretest was instrumental in the decision to present only the five levels of automation in graphics in the pilot and the full-scale survey. The pretest participants made it clear that no pictures or diagrams were necessary because the concept of on-demand driverless cars was easy to understand by a short written definition.

The second finding dealt with combined leisure and business travel in the GFT items. Some pretest participants suggested the survey should separate leisure travel and business travel because the two types of travel might involve different attitudes and decision criteria. Therefore, at the beginning of the pretest, some GFT items were presented in the leisure and business travel sections (cost, convenience, comfort, the hedonic idea of fun, etc.). However, as the pretest continued, it was found that some respondents would provide straight-line answers to many of these questions the second time they were asked. For example, missing values or straight-line answers occurred in the business section after the respondents had completed the leisure questions either because they were bored after seeing very similar questions or tired from answering a long series of similar questions. Therefore, the decision was made to have only one set of GFT items in the questionnaire for the study. This decision shortened the survey to under 10 min while increasing participants' engagement.

The third finding concerned the time to complete the questionnaire. Even though the pretest participants were interested in the ideas of driverless cars and short-haul flights, an average response time of 15 min was too long to hold their full attention. Reducing the GFT items served to minimize completion time.

Survey Pilot Study

Pretesting the survey instrument and conducting pilot studies helped avoid or minimize sampling bias and improve generalizability. The pilot study using MTurk was conducted from June 10–25, 2021. After eliminating respondents with over 30% missing values (n = 3) and straight-lining responses (n = 4), results from 154 participants were used to perform the pilot reliability and validity assessment. The pilot study provided an average completion time of 8 min 27 s.

Instrument Reliability and Validity. One of the main objectives of the pilot study was to test the reliability of the survey instrument, so Cronbach's alpha (α) was used to measure the reliability/internal consistency between items on each of the scales (see Table 6 and Appendix E). It was important not to mix positively and negatively worded items because the variables in the negatively worded items would need to be reverse coded to measure the reliability of the items on a scale. All 22 items were rated using a 5-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*). The α for the pilot study was 0.801 for all 22 items, representing good internal consistency. Cronbach's alpha for the GFT sub-scales of Hedonic (0.749) and Normative Goals (0.759) provided good internal consistency. The scale reliability for the GFT Gain Goal (α = 0.630) needed improvement. With an α of 0.430, the COVID-19 scale did not provide evidence of good internal consistency. Deleting C1 would increase the Cronbach's alpha for the COVID-19 construct to 0.49 (see Table 6 and Appendix E), which was still too low to provide evidence for reliability. Therefore, Gain Goal and COVID-19 items were modified for the full-scale survey.

Table 6

Cronbach's Alphas for Pilot Study Constructs

Construct	Item	α
GFT hedonic goal	H1: Generally, my main transport mode for inter-regional travel is efficient. H2: I will not sacrifice comfort even if I have to pay slightly more. H3: I know I can resolve issues that may pop up during my travels. H4: I believe I can control events that affect me. H5: I am quite predictable in terms of how I travel. H6: In general, I am happy with the transportation I use when I travel to other cities. H7: If my family and friends use Uber/Lyft, I trust that it is safe for me to use too. H9: Traveling is fun for me.	0.749
GFT gain goal	G1: Cost is very important to me when I travel for leisure. G2: Convenience is very important to me when I travel. G3: When I travel, I value my time doing something nice or useful, such as watching a movie, working, or sleeping. G4: I usually try to minimize my total travel time. G5: I think driverless cars will be cheaper to use compared to flying. G6: I think driverless cars are more convenient than flying in general.	0.630
GFT normative goal	B1: Preserving the environment is very important when I decide how I travel. B2: When I travel by CAR for inter-regional trips, I am satisfied with my environmental impact. B3: When I travel by AIR for inter-regional trips, I am satisfied with my environmental impact.	0.759
COVID-19 influence	C1: I am concerned with getting COVID when I travel. C2: My disposable income has reduced because of COVID. C3: Even during COVID, I could be tempted to travel by air if the ticket price was low enough.	0.430

Note. GFT = goal framing theory.

Due to the small sample size, only the statistical results from EFA were relevant. The EFA was used to assess the actual rather than theoretical correlations among the items. The two measures used to determine sample adequacy were the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. The KMO evaluates the overall inter-correlation among variables and varies from 0 to 1. Generally, KMO indicates whether the variables can group into a smaller set of underlying constructs. A KMO value of 0.6 or higher is an indication to proceed. If KMO < 0.5, the factor analysis results will not be useful (Kaiser & Rise, 1974). The KMO = .699 and was considered good. Bartlett's test was significant ($\chi^2 = 611.360$; 136, $p < .001$). These two measures showed that the overall inter-correlation requirement was met, and the observed variables were adequate and appropriate for conducting the EFA. The pattern matrix of the pilot data showed a 4-factor solution (see Appendix F). The principal component extraction method was used because it makes no distributional assumptions. Promax rotation algorithm was appropriate because it assumes correlations amongst the variables. This 4-factor solution converged in five iterations. The extracted communalities of all 22 items had communalities > .5, which is deemed good. Regarding the total variance explained, four factors were extracted, explaining 50.3% of the variance in the model, which is considered acceptable.

Final Instrument and Procedures

The findings from the pilot study informed changes to both the instrument and the procedures. The key changes encompassed the following:

- Minor revisions in the wording. For example, "below high school" may sound judgmental, so the wording was replaced with "attended high school."

Another example was the addition of a category in gender called "other" to be more inclusive. Three out of 1,441 responses chose the "other" category.

- Under Annual Household Income, deleted "over $300,000".
- To ensure more participants would answer the aMoD section carefully, the aMoD items were moved forward to the third part of the instrument.
- The COVID-19 item on disposable income (C2) was changed from negative to positive so that all items were aligned positively for the analyses.
- The 21 GFT and COVID-19 items were separated into smaller sections to minimize respondent fatigue.
- The following items were deleted:
    - The two Likert scale items on the cost and convenience of driverless cars in the GFT Gain Goal (G5 and G6) to avoid biasing respondents in their future transport choice.
    - The safety item, "I think flying is safer than driving," to avoid biasing respondents for subsequent questions.
    - The item on the total cost for business travel because it was similar to another item on travel cost.
    - The item on the use of TNC to/from the airport during the EFA analysis.
    - The item on trust for TNC, "If my family and friends use Uber/Lyft, I trust that it is safe for me to use too," based on results from EFA.
    - The item on control, "I believe I can control events that affect me," because it was similar to the other control/self-efficacy question. The

correlation coefficient was > 0.9.

    - The two sets of questions on “the degrees of satisfaction with driving and flying (regarding personal space, environmental impact, safety, and general feeling).” While the results would be interesting, the answers were tangential to the research objectives.

- Several items were added:
    - Based on the weak Cronbach’s alpha value of the COVID-19 scale, added two COVID-19 items to assess how the economic conditions and changes in the COVID-19 variants during the pandemic affected respondents’ current and future transportation decisions. The additions were: “I think the economy is gradually recovering” and “I think COVID and its variants will get worse.”
    - Even though Cronbach’s alpha for the GFT Normative Goal was considered reliable ($\alpha = .759$), this construct could be improved with more theoretical support. After reviewing the relevant literature, the following four items were added:

        (a) “I feel a moral obligation to protect the environment.”

        (b) “I think electric vehicles are good for the environment.”

        (c) “People who are important to me tend to care about the environment.”

        (d) “It is important for me to be a role model for my family in environmental protection.”

More than 20 items in the pilot instrument were deleted or modified, and six items were added. Therefore, it is important to note that the variable/item names in the full-scale study might not be the same as in the pilot. The pilot and pretest results were used to refine the questionnaire, making it more concise and precise. In addition to improving the reliability and validity of the instrument, these refinements also reduced the completion time, potentially minimizing respondent fatigue.

Full-Scale Survey Results

Data Preparation

Of the 69 items in the final instrument, all except one were closed-ended. With MTurk collecting and recording responses automatically without human input, there were no coding errors or aberrant values in the dataset. Nevertheless, data cleaning was an essential step in data treatment.

Missing Values. The problem with missing data is common in survey research and can impact the research results profoundly. From 1,441 total observations, 16 were removed: six had over 15% of missing values, four had over 20% of straight-line answers, and six respondents completed only the demographics section. These eliminations left 1,425 completed observations for analysis. From the 69 variables, most had two or three missing values. None of the five COVID-19 items had any missing values. The GFT Normative Goal items had only one or two values missing. Even the two variables with the most missing values, Item 21: “aMoD rollout timing” and Item 22: “timing with 50% aMoD on the road,” had less than 1.5% missing values.

Four ways to handle missing values were considered. The first is to delete the observation when there are too many missing values. This step led to the removal of 16 observations. Second, delete the variable if too many respondents skipped an item. No variables had to be deleted from the study results. Third, impute with mean, median, or mode. Missing values of the Likert-scale and categorical questions were imputed with the mode. Fourth, use logic to predict the missing value. Logical deduction was applied to missing values for the transport mode choice items (MODE_Pre-COVID and MODE_Future) based on the participants' responses to the items on the construct.

Outliers and Normality. Univariate outliers from all the metric variables were found to be minimal and were within the highest and lowest scores. Figure 19 presents select examples of boxplots for univariate outliers. The Q-Q plot, boxplot, and histogram are graphical techniques to check univariate normality. In a Q-Q plot, for data that are normally distributed, the points fall on a straight diagonal line, as shown in Figure 20.

Figure 19

Example Boxplots Plots Showing Univariate Outliers

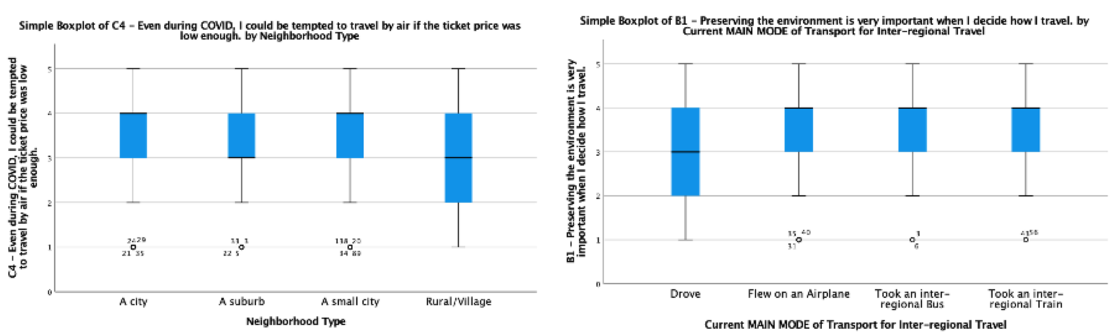
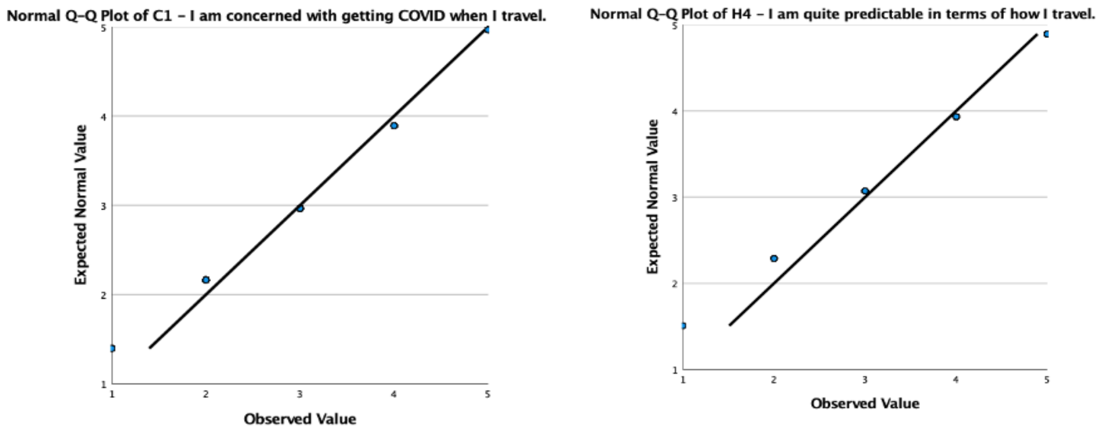


Figure 20

Example Q-Q Plots Showing Univariate Normality



A multivariate outlier is the combination of extreme scores on two or more variables. High Mahalanobis D^2 values (> 100) represent observations farther from the general distribution of observations. Mahalanobis D^2 was performed using regression analysis (See Appendix G for the multivariate outlier assessment using Mahalanobis D^2; where: Prob_Mah_D^2 = 1 – Cumulative χ^2 [Mah_D^2, 69]). Thirty-seven observations where $p < .001$ (indicating multivariate outliers) were removed from the database. Therefore, the usable sample for analyses $N = 1{,}388$ (1441-16-37), which is 96.3% of the collected observations. The scatterplots of standardized predicted values and residuals were used to confirm no remaining outliers after removing the outlier cases to ensure all values were within +/– 3 on both the x-axis and the y-axis. While normality is not a requirement for MNL and 2-step CA, it is a prerequisite for EFA and MANOVA and will be discussed in the Assumptions Testing section.

Non-Response Bias Testing

Non-respondents were quantified as participants who (a) answered only the demographics section, (b) gave straight-line responses, or (c) did not answer more than 15% of the items. There were 12 observations in the non-response category. Select demographic variables were used to compare respondents to non-respondents to assess non-response bias. The examined variables included Age, Education, Total Household Income, Number of Children Living at Home, Years with Driver's License, and Drive Frequency. The chi-square (χ^2) test of independence measured whether there is a relationship between two categorical variables and if the difference is due to chance. The χ^2 test results indicated no significant differences between respondents and non-respondents (see Table 7).

Table 7

Results from the Non-Response Bias Analysis

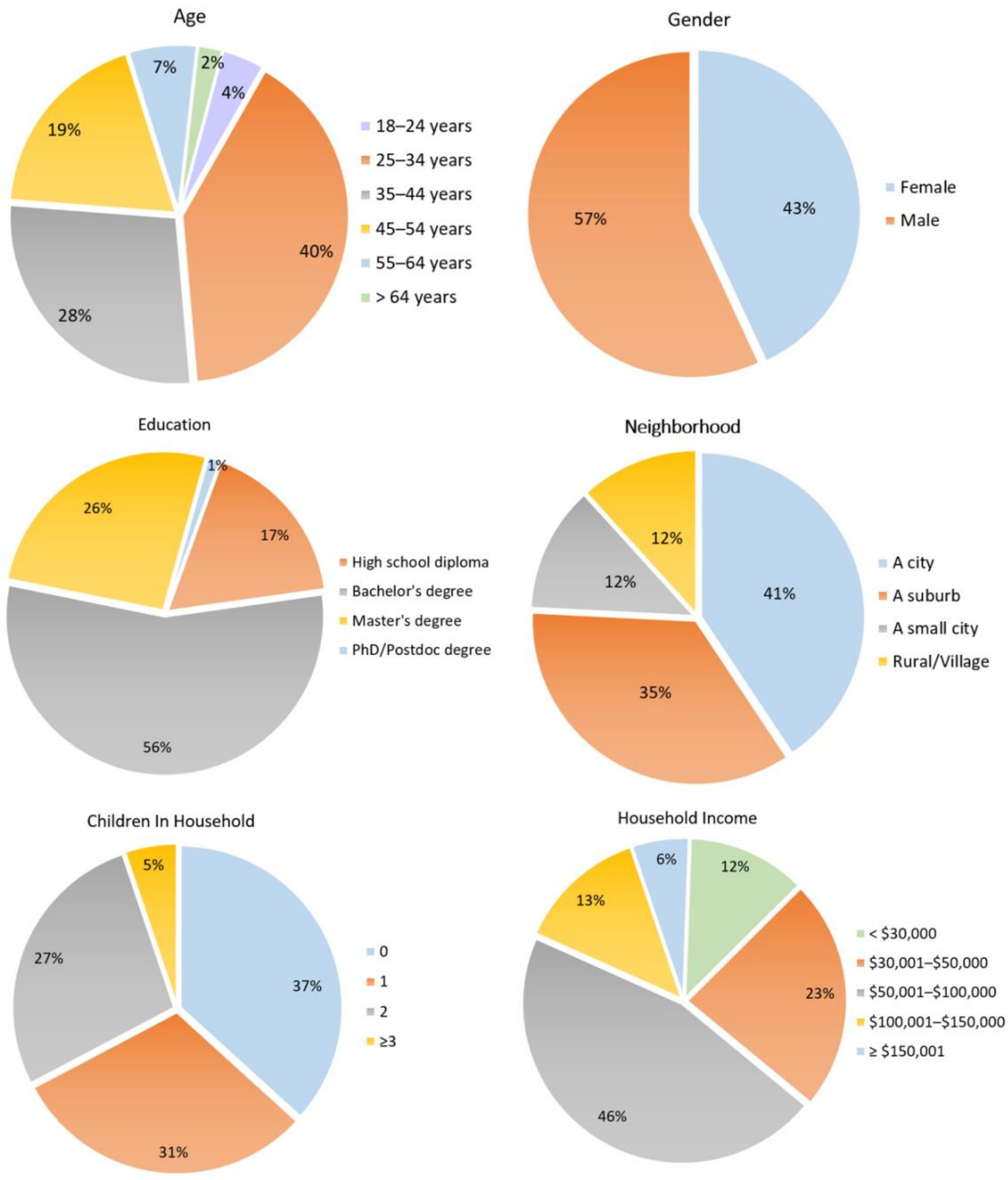
Demographics	χ^2	*df*	*p*
Age	7.218	6	0.301
Education	0.865	4	0.930
Total Household Income	4.125	5	0.532
Number of Children Living at Home	2.089	3	0.554
Years with Driver's License	1.126	4	0.890
Drive Frequency	2.669	4	0.615

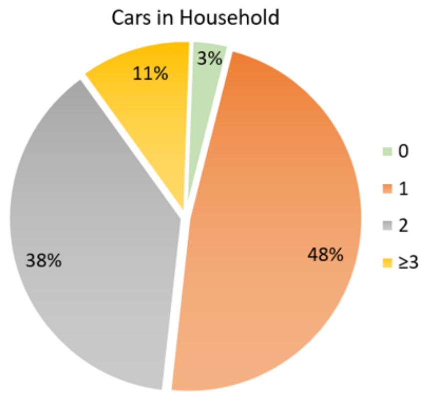
Passenger Demographics and Contextual Trip Characteristics

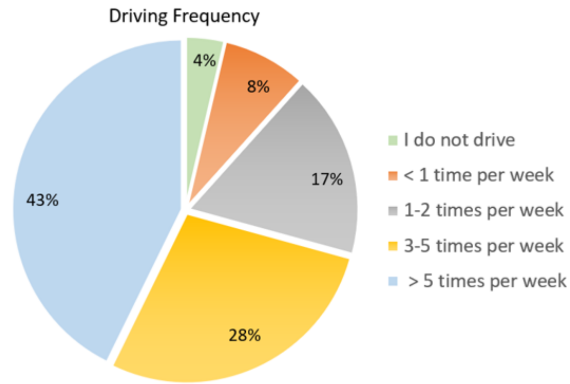
As presented in Figure 21, the study participants' demographics show there were more men (57%) than women (43%). The majority were between 25 and 34 (40%) and 35 and 44 (28%) years old. More than half (56%) had a bachelor's degree, and a quarter (26%) had a master's degree. The majority (76%) reported living in a city or a suburb, and only 12% reported living in rural America. Slightly over one-third (37%) of the participants had no children living in the household. Most participants (46%) reported a household income of $50,001 to $100,000 and 1 in 5 (19%) reported a household income over $100,000. Not surprisingly, for a country with a vibrant car culture, almost every respondent (99%) had at least one driver's license in the household. Only 3% of the respondents were not licensed to drive. Eighty-seven percent had been licensed for over three years. Almost half (48%) of the study participants reported having one car in their household, with 38% owning two vehicles. Only 3% did not have a car in the household. In terms of driving frequency, 43% percent drove more than 5 times per week.

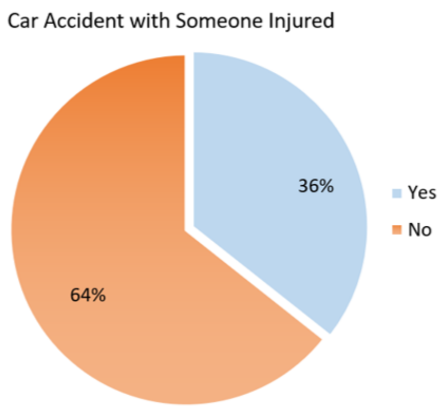
Figure 21

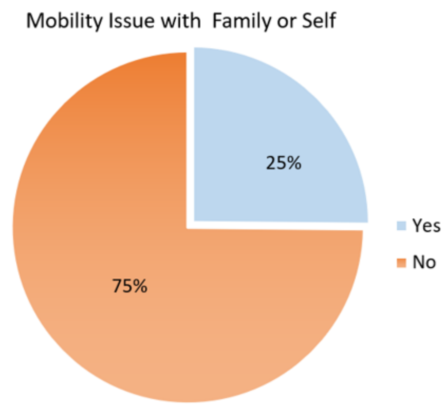
Demographics

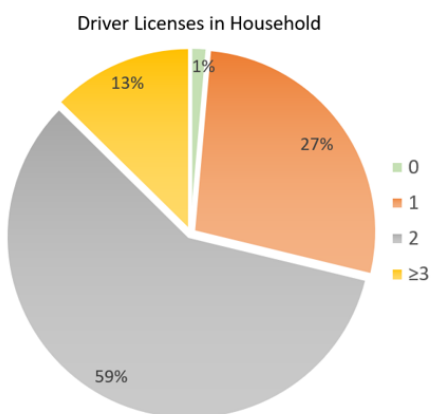


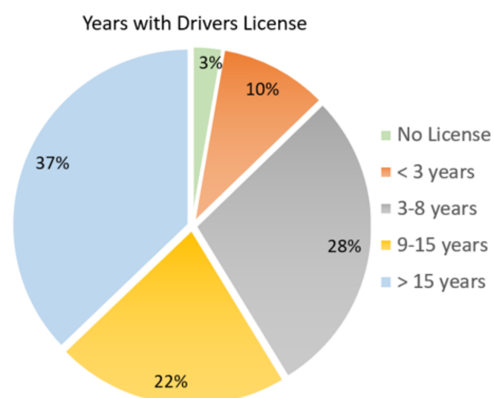

Cars in Household
3%
11%
38%
48%
0
1
2
≥3

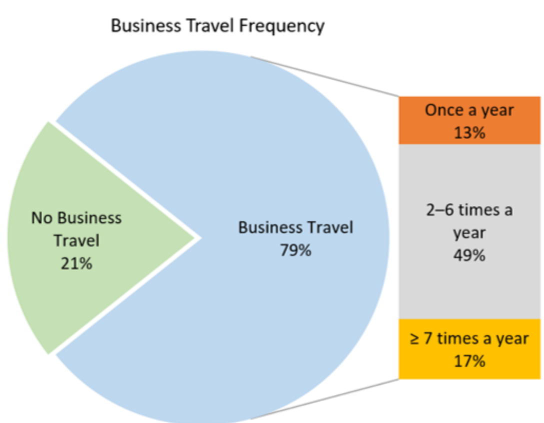

Driving Frequency
4%
8%
17%
43%
28%
I do not drive
< 1 time per week
1-2 times per week
3-5 times per week
> 5 times per week


Car Accident with Someone Injured
36%
64%
Yes
No


Mobility Issue with Family or Self
25%
75%
Yes
No


Driver Licenses in Household
1%
13%
27%
59%
0
1
2
≥3


Years with Drivers License
3%
10%
37%
28%
22%
No License
< 3 years
3-8 years
9-15 years
> 15 years


Business Travel Frequency
No Business Travel 21%
Business Travel 79%
Once a year 13%
2–6 times a year 49%
≥ 7 times a year 17%

The χ^2 test results presented in Table 8 show the respondents' choices of current transport modes are significantly different based on prior car accident experiences involving an injury (χ^2 (3) = 50.363, p < .001) or someone in the household having mobility issues (χ^2 (3) = 100.5, p < .001). There is a significantly higher percentage of respondents who had prior car accidents with injuries chose inter-regional bus (58%) than drive (29%) or SF (37%). Similarly, a much lower percentage of the sample chose to drive (12%) than take an inter-regional bus (48%) if someone in the household has mobility issues. Likewise, the χ^2 test results for future transport mode choices are significant with the same two variables. In this case, a much lower percentage of the sample chose aMoD (20%) and SF (21%) than inter-regional bus (46%) as their future mode choice if someone in the household has mobility issues.

Table 8

Chi-Square Test Results for Current and Future Main Modes

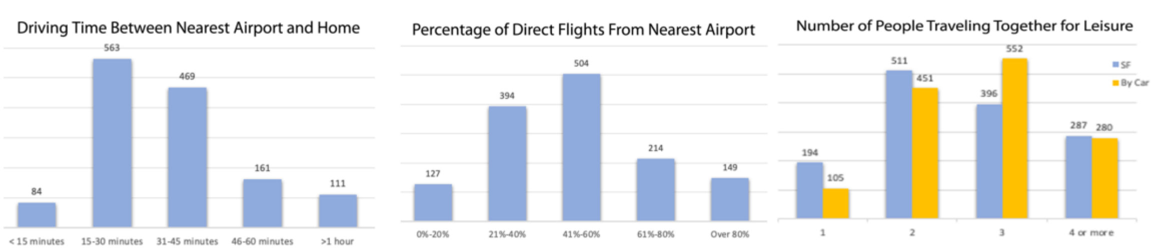
Main Mode	Prior Car Accident with Injuries	Chi-Square Results			Mobility Issue: Self or Family	Chi-Square Results		
	%	χ^2	*df*	*p*	%	χ^2	*df*	*p*
Current Mode		50.363	3	< .001		100.500	3	< .001
SF	37				30			
Drive a Car	29				12			
I-Bus	58				48			
I-Train	26				25			
Future Mode		19.635	4	< .001		41.614	4	< .001
aMoD	31				20			
SF	34				21			
Drive a Car	38				26			
I-Bus	54				46			
I-Train	37				36			

Note. aMoD = autonomous mobility-on-demand; I-Bus = inter-regional bus; I-Train = inter-regional train; SF = commercial short-haul flight.

Regarding business travel, 79% traveled for business before COVID. Almost half of the respondents (49%) traveled for business 2 to 6 times per year, and 17% traveled 7 or more times per year. Contextual trip variables provided a deeper understanding of the study respondents' trip characteristics. As illustrated in Figure 22, most participants (74%) reported residing 15–45 min from their nearest airport. Only 8% resided more than 1 hr drive from the nearest airport. Thirty-six percent reported 41%–60% of their flights were direct flights from their home airport, and 11% reported that over 80% of their flights were direct flights. Most of the time, respondents traveled alone (14%) or with one other person (37%) when flying commercially to another inter-regional city for leisure. However, only 17.6% of the respondents reported driving alone when traveling for leisure. Most of the time, they traveled with one (32%) or two or more people (60%). As expected, for inter-regional trips for leisure, the likelihood of driving increases when the traveling party is larger than two people.

Figure 22

Contextual Trip Characteristics



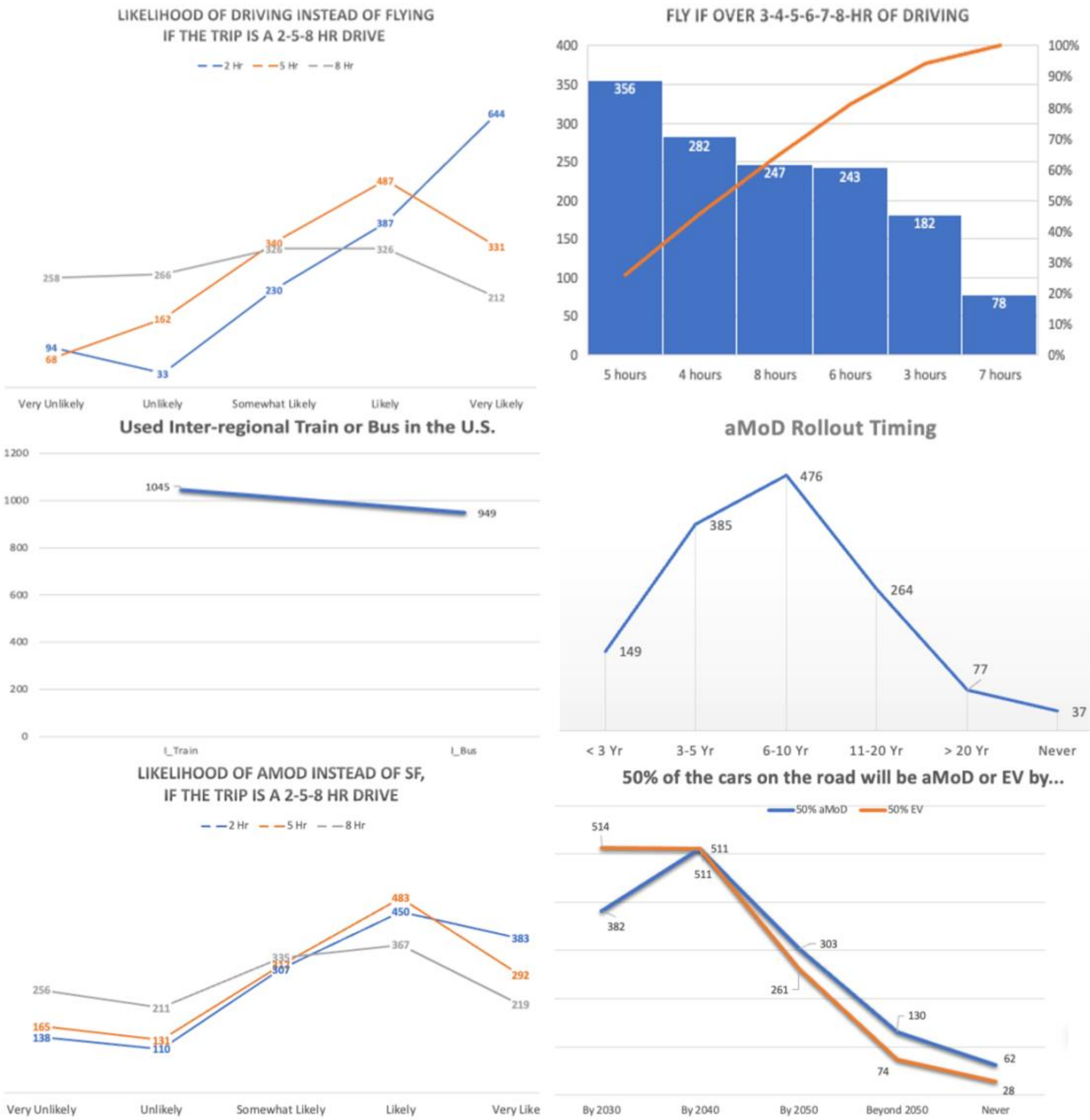
Note. SF = commercial short-haul flight.

Travel Mode Choice Behavior, Attitudes, and Perceptions

Figure 23 presents the likelihood of driving instead of flying when the trip is a 2-, 5-, or 8-hr drive. Almost half (46%) of the respondents said they were very likely to drive instead of fly if the trip is a 2-hr drive. This percentage dropped to 24% for a 5-hr drive and 15% for an 8-hr drive. For a distance requiring an 8-hr drive, 19% of the respondents reported they would be very unlikely to drive instead of fly. For a drive time of 4 or 5 hr, 20% and 26%, respectively, would choose flying instead of driving. The results showed that 75.3% of the respondents had traveled by inter-regional train and 68.4% had used an inter-regional bus in the United States. Thirty-four percent of the respondents believed aMoD would be commercially available in the United States in 6 to 10 years; 28% predicted 3 to 5 years; less than 3% thought it would never happen. Thirty-seven percent believed that by 2030, half of the cars traveling on U.S. roads would be EVs, while 27% speculated half of the cars would be aMoD. Interestingly, 36% of the respondents believed half of the cars on the road would be either aMoD or EV by 2040. The likelihood of using aMoD instead of SF when the trip was 2-5 hr drive time was higher than a trip with an 8-hr drive time.

Figure 23

Travel and Mode Choice Perceptions

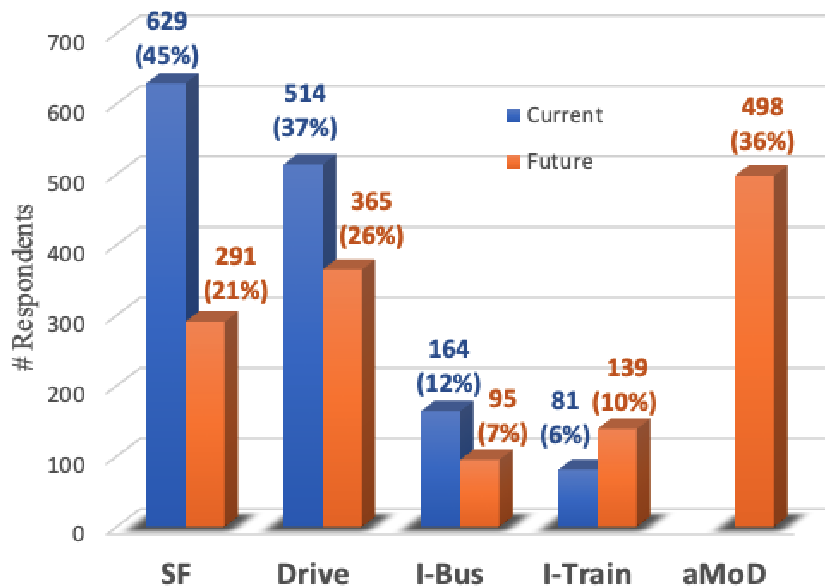


Note. aMoD = autonomous mobility-on-demand; EV = electric vehicle; SF = commercial short haul flight.

The terms current and pre-COVID are used interchangeably in this study because when the survey was conducted, COVID-related restrictions were still dynamic, particularly in travel and transportation. Therefore, the term pre-COVID was used in the data collection instrument so the respondents would answer the questions with a "normal" frame of mind. Figure 24 compares the current and future main transport choices when aMoD is available. Thirty-six percent (*n* = 498) of the current air passengers chose aMoD as their future primary transport mode. Table 9 shows the shifts in mode choices from the current to the future. Forty-five percent (*n* = 629) chose SF as their current main mode, but it fell to 21% (*n* = 291) for future travel. Thirty-seven percent (*n* = 514) chose driving as their current main mode, but when aMoD is available in the future, only 26% (*n* = 365) would still choose driving. Fourteen percent (*n* =192) who had chosen SF shifted to aMoD for travel in the future. There were 17% (*n* = 236) who would drive before showed intention to use aMoD as their main mode in the future. Thus, 36% (498 out of 1,388) of the participants who currently rely on short-haul flights or driving for inter-regional travel would take aMoD as their main mode of transportation when it becomes available to them in the future. It is important to point out that in the future, more participants (*n* = 139) anticipate traveling by inter-regional train as their main transportation mode compared to 81 currently.

Figure 24

Pre-COVID and Future Main Transport Mode Choices



Note. aMoD = autonomous mobility-on-demand; I-Bus = inter-regional bus; I-Train = inter-regional train; SF = commercial short-haul flight.

Table 9

Current and Future Transport Choices for Inter-Regional Travel

Current Mode	Future Mode					
	aMoD	SF	Drive	I-Bus	I-Train	Total
	n	*n*	*n*	*n*	*n*	*n*
SF	192	213	124	49	51	629
Drive	236	50	188	13	27	514
I-Bus	46	20	36	31	31	164
I-Train	24	8	17	2	30	81
Total	498	291	365	95	139	1,388

Note. aMoD = autonomous mobility-on-demand; I-Bus = inter-regional bus; I-Train = inter-regional train; SF = commercial short-haul flight.

Figure 25 shows that 87% of respondents flew less than 10,000 mi per year. Only 2% flew more than 25,000 mi annually. Table 10 provides more information regarding current and future main transport mode choices by annual miles flown. As expected, of the most-traveled flyers (i.e., 13% who fly more than 10,000 mi per year), 48% [(72+11)/(147+27)] chose SF as their primary current mode. However, in the future, when aMoD is available, that percentage drops to 22% [(33+5)/(147+27)], less than half of the current passengers. In contrast, aMoD would gain 34% [(50+9)/(147+27)] in the most-traveled segment of air passengers. More than half of the current most-traveled air passengers would choose to use aMoD as their main transport choice in the future, thus taking business away from the airlines.

Figure 25

Annual Domestic Miles Flown

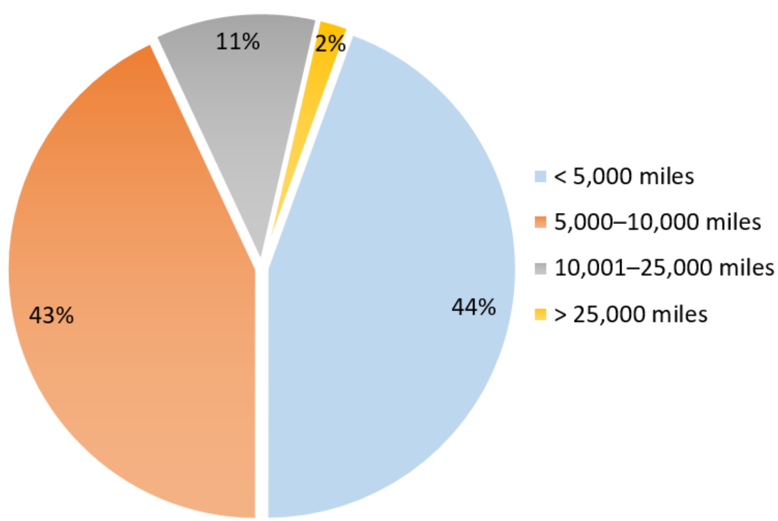


Table 10

Main Transport Mode Choices Based on Annual Miles Flown

	Current Main Transportation Mode					
		SF	Drive	I-Bus	I-Train	Total
Annual Air Miles		*n*	*n*	*n*	*n*	*n*
< 5,000 mi		207	333	42	35	617
5,000–10,000 mi		339	143	89	26	597
10,001–25,000 mi		72	33	28	14	147
> 25,000 mi		11	5	5	6	27
Total		629	514	164	81	1,388
	Future Main Transportation Mode					
	aMoD	SF	Drive	I-Bus	I-Train	Total
Annual Air Miles	*n*	*n*	*n*	*n*	*n*	*n*
< 5,000 mi	241	104	193	27	52	617
5,000–10,000 mi	198	149	132	59	59	597
10,001–25,000 mi	50	33	32	8	24	147
> 25,000 mi	9	5	8	1	4	27
Total	498	291	365	95	139	1,388

Note. aMoD = autonomous mobility-on-demand; I-Bus = inter-regional bus; I-Train = inter-regional train; SF = commercial short-haul flight.

COVID-19 Characteristics

The following three yes/no items focused on COVID-19 related experiences.

1. I am vaccinated against COVID-19.

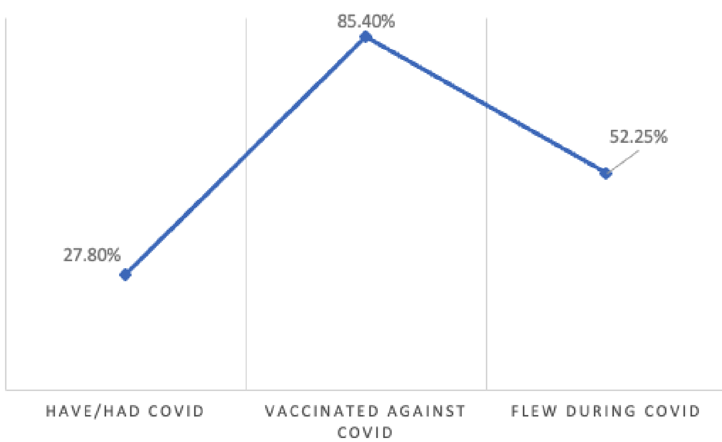
2. I have/had COVID-19.

3. I have traveled by air during COVID.

Responses to these three questions and information from their cross-tabulations provided a better understanding of travel behavior during COVID-19. Throughout the data collection period (October 2021), 61% of the U.S. population had been fully vaccinated, and 73% had received at least one dose (Mayo Clinic, n.d.). The sample population had a higher vaccination percentage of 85%, and 27.8% stated they had/have contracted COVID (see Figure 26). Slightly over half (52%) of the respondents had traveled by air during the pandemic. Cross tabulations of these COVID-related results (with significant chi-square tests) yielded a deeper understanding of air travelers' perceptions and behaviors (see Table 11). As expected, a higher percentage of the air travelers who fly over 5,000 mi (8,047 km) annually flew during the pandemic. Air passengers who selected SF or inter-regional bus as their current and future mode choices had a higher chance of flying during COVID.

Figure 26

COVID-19 Status



Regarding COVID-19 immunization, air passengers who fly less than 5,000 mi per year had a lower percentage of vaccination (79%) than air passengers who fly over 25,000 mi per year (96%). The air passengers who fly over 25,000 mi per year had the highest percentage of COVID-19 cases (52%), but those who chose inter-regional buses were nearly as high (51%). Travelers who selected "drive" as their main current mode had the lowest percentage of COVID-19 cases (18%). Air passengers who chose aMoD or SF also had a low percentage of COVID cases (23% and 24%, respectively).

Table 11

COVID-19 cf Annual Air Miles and Main Transport Mode Choices

	Flew During the COVID Pandemic n = 724		Vaccinated Against COVID-19 n = 1,186		Experienced COVID-19 n = 386	
	n	%	*n*	%	*n*	%
Annual Air Miles						
< 5,000	234	38	485	79	112	18
5,000–10,000	379	64	546	92	216	36
10,001–25,000	95	65	129	88	44	30
> 25,000	16	59	26	96	14	52
Current Mode						
SF	364	58	555	88	183	29
Drive	231	45	414	81	91	18
I-Bus	96	59	143	87	83	51
I-Train	33	41	74	91	29	36
Future Mode						
aMoD	253	51	427	86	115	23
SF	171	59	242	83	71	24
Drive	162	44	307	84	109	30
I-Bus	61	64	82	86	42	44
I-Train	77	55	128	92	49	35

Note. aMoD = autonomous mobility-on-demand; I-Bus = inter-regional bus; I-Train = inter-regional train; SF = commercial short-haul flight. N = 1,388. Chi-square test results show significant differences at the $p < .001$ level.

Sample Representativeness. The sample demographics were compared with those obtained from Airlines for America (A4A) to ensure the data were representative of the flying population (the sample population of this study). A4A conducts an annual survey to track their understanding of air travelers in America. The most recent survey was conducted in January 2021. A sample of 10,000 air travelers (defined as someone over 18 years of age who has flown commercially within the past 2 years) was randomly drawn from Ipsos's online panel. The gender and age characteristics of the sample were compared to that of the flying population, as shown in Table 12. While the number of males and females between the sample and population was virtually identical, the participants in the sample were younger than the U.S. air passenger profile.

Table 12

Demographic Characteristics of the Participants and the Flying Population

Characteristic	Study Participants	Flying Population
	%	%
Gender		
Female	43	42
Male	57	58
Age (years)		
18–24	4	5
25–34	40	16
35–44	28	19
45–54	19	24
55–64	7	22
≥ 65	2	14

Descriptive Statistics

Descriptive statistics were conducted using SPSS for the 21 GFT and COVID-19 Likert scale variables in two ways: as a full sample (N = 1,388) and by the MODE_Future choices of aMoD (n = 498) and SF (n = 291) (see Table 13). Respondents who chose aMoD as a future mode choice for inter-regional travel had higher mean scores than SF respondents for the following variables: H1, H3, B1, B2, B3, B4, B5, C1, and C5. All five GFT normative goals were higher for the aMoD respondents. Air passengers who had chosen aMoD as their intended future mode were more environmentally conscious. They felt that preserving the environment was a moral obligation and electric vehicles were good for the environment. People who were important to these respondents also cared about the environment (normative), and they saw themselves as environmental role models for their friends and family. These aMoD respondents were more worried about COVID-19 when they traveled. They had higher self-efficacy scores and reported their current main inter-regional transport was efficient.

Air passengers who chose SF as their future inter-regional transport mode tended to have higher scores on the GFT gain goals: G2, G3, and G4. Convenience is important to them. They try to minimize their travel time. When traveling, they value their time doing something nice or useful, such as watching a movie, working, or sleeping. As loyal air passengers, they would not sacrifice comfort and found traveling fun.

Table 13

GFT and COVID-19 Variables by aMoD and SF

	Total *n* = 1,388		aMoD *n* = 498		SF *n* = 291	
Items	*M*	*SD*	*M*	*SD*	*M*	*SD*
H1: Main transport is efficient	3.77	0.729	3.84	0.660	3.77	0.803
H2: I will not sacrifice comfort	3.34	1.039	3.23	1.034	3.36	1.059
H3: I can resolve travel issues	3.87	0.716	3.97	0.700	3.84	0.751
H4: Predictable how I travel	3.79	0.841	3.79	0.789	3.76	0.900
H5: Happy with main transportation	3.92	0.744	3.92	0.717	3.95	0.799
H6: Main transport mode is safe	3.94	0.767	3.98	0.745	3.96	0.825
H7: Traveling is fun for me	3.84	0.956	3.85	0.965	3.92	0.963
G1: Cost is very important	3.90	0.869	3.95	0.881	3.92	0.845
G2: Convenience is important	3.95	0.796	3.97	0.788	4.04	0.800
G3: Minimize total travel time	3.74	0.880	3.74	0.890	3.87	0.861
G4: When traveling, I value my time	3.81	0.845	3.81	0.817	3.97	0.798
B1: Preserving environment	3.39	0.978	3.47	0.971	3.35	1.020
B2: Environmental moral obligation	3.65	0.976	3.77	0.927	3.54	1.034
B3: EV is good for environment	3.89	0.910	4.08	0.821	3.77	1.017
B4: Care about environment	3.72	0.911	3.80	0.889	3.68	0.935
B5: Environmental role model	3.60	1.014	3.67	0.955	3.59	1.001
C1: COVID travel concern	3.40	1.050	3.45	1.045	3.35	1.117
C2: Worry COVID variants get worse	3.31	1.052	3.20	1.041	3.26	1.074
C3: Income increased since COVID	3.02	1.200	2.96	1.192	3.03	1.190
C4: Travel by air if price is low	3.38	1.139	3.35	1.093	3.42	1.193
C5: The economy is recovering	3.42	0.958	3.48	0.926	3.36	0.984

Note. aMoD = autonomous mobility-on-demand; EV = electric vehicles; GFT = goal framing theory; SF = commercial short-haul flight.

Analysis Process

After completing the data preparation including treating missing values and assessing univariate and multivariate outliers, the data were ready for assumptions testing.

Assumptions Testing

Assumptions for the four principal analyses are presented in Table 14, followed by the tests of basic assumptions for these analyses.

Table 14

Summary Table of Assumptions Testing

	EFA	MNL	2CA	MANOVA
No outliers	✓	✓	✓	✓
No missing values	✓	✓	✓	✓
Adequate sample size	✓ (>200)	✓	✓	✓
Normality	✓			Multivariate
Linearity of variables	✓			
Interval/metric data [a]	✓			✓
Inter-correlation among variables [b]	✓			
Homoscedasticity/Homogeneity				✓
No multicollinearity (< .9)	✓	✓	✓	
Groups of similar size			✓	
IIA		✓		
Independence of DV categories		✓		

Note. 2CA = 2-step CA; DV = dependent variable; IIA = Independence of irrelevant alternatives. Blank cells indicate the test was not applicable. [a] Likert scale data are treated as interval data (metric) for analyses. [b] Used KMO and Bartlett's test of sphericity.

Sample Adequacy and Inter-Correlation Among Variables. As performed in the pilot EFA, the two measures used to determine sample adequacy were the KMO and Bartlett's test. The KMO and Bartlett's test results provided empirical evidence that the overall inter-correlation requirement was met. The observed variables were adequate and appropriate for use in an EFA (see the results from the KMO and Bartlett's test in the EFA section).

Univariate and Multivariate Normality. The Q-Q plots established a good degree of univariate normality for the GFT and COVID variables (see Figure 20). For the MANOVA analysis, multivariate normality (i.e., normality of multiple dependent variables together) must be fulfilled. Appendix H presents two different methods for multivariate assessment. The first was Mahalanobis distance: The Mahalanobis maximum distance of 15.946 < $\chi 2$ distribution critical value of 26.296 (p = .05, df = 16) indicates multivariate normality exists. The second method employed IBM AMOS to calculate kurtosis. A kurtosis of 0 means perfect normality and K < 5 is acceptable (Byrne, 2010). As seen in Appendix H, all Kurtosis values were < 1. Both methods provided evidence that multivariate normality exists, and no variable transformation was necessary to ensure the model fit.

Linearity. As an important test assumption for many multivariate analyses, linearity assumes that the correlation between variables is linear. To test this assumption, the bivariate correlation for each pair of variables was examined to detect any non-linear correlation. The SPSS output in Appendix I shows the Pearson correlation coefficients between all pairs of variables along with significance levels. As reported in its table note, one asterisk indicates the correlation is significant at the .05 significance level, two asterisks denote the correlation is significant at the .01 level, and 91% of all bivariate correlations were significant, indicating linearity.

There were only four negative correlations, and all were non-significant between:

- C3 (negative COVID Income), as expected, and H1 (Efficiency), H5 (Satisfaction), and H6 (Trust).
- C4 (COVID Ticket Price) and C1 (COVID fear).

The other non-significant bivariate correlations were between:

- C1 (COVID Fear) and H3 (Self-efficacy) and H6 (Trust).
- G2 (Convenience) and C2 (COVID Variants), C3 (negative COVID Income), and C4 (COVID Ticket Price).

Homoscedasticity / Homogeneity of Variance. The assumption of homoscedasticity implies that the variance of the residuals is equal across the whole continuum of the independent variable. In other words, the assumption of homoscedasticity indicates that the prediction equation is equally good for the entire spectrum of the data. There are two ways to test for the assumption of homoscedasticity. The first is based on an examination of a scatterplot. From the visual inspection, the condition of homoscedasticity is not satisfied. The second method is to use correlation. The SPSS output in Appendix J shows that the Pearson correlation of –.254 and the Spearman correlation of –.206 are statistically significant at the .01 level. Therefore, the assumption of homoscedasticity was not satisfied.

Multicollinearity. The presence of multicollinearity in regression analysis implies that redundant information exists in the model, which can lead to unstable regression coefficient estimates (Hair et al., 2017). Multicollinearity occurs when two or more of the IVs (predictor variables) are highly correlated (> .9). While there are many tests for multicollinearity, three common methods are correlation analysis, tolerance, and the variance inflation factor (VIF). The SPSS outputs in Appendix I and Appendix K show that these tests were within the guidelines indicating no multicollinearity.

Independence of DV Categories. As a part of the MNL assumptions, the independence of DV categories was fulfilled. The DV is MODE_Future (Future main inter-regional transport mode) which has five discreet and independent categories: aMoD, Drive, SF, Inter-regional Bus, and Inter-regional Train. Respondents were allowed to choose only one of the five as their main transport mode for inter-regional travel in the future once aMoD is available.

Exploratory Factor Analysis Results

Assumptions for EFA were tested and the observed variables were found adequate and appropriate for use in an EFA. The next steps were:

1. Determine the extraction and rotation methods.

2. Assess the number of factors to be retained.

3. Describe the factors and the items loaded on the factor.

4. examine the reliability and validity.

Interpretation of the results is presented in Chapter V.

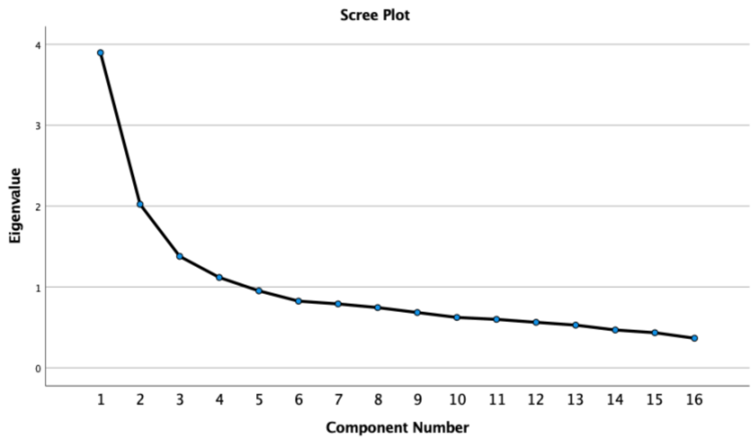
Extraction and Rotation Methods. The EFA used the principal component analysis (PCA) extraction method as data reduction was a primary objective. PCA focused on the minimum number of factors needed to account for the maximum portion of the total variance. Typically, rotation causes factor loadings to be more clearly differentiated. The oblique Promax rotation was appropriate for this study because it handles a large dataset well and assumes correlations among the variables.

Factor Loadings. Small factor loadings (coefficients) with absolute values less than .3 were suppressed to avoid showing low factor loadings in the matrix. Factor loadings greater than .5 were acceptable. There were cross-factor loadings where an item could be attributed to more than one factor in the initial models. However, the final EFA model presents factor loadings greater than .5 with no cross-factor loadings.

Scree Plot. Figure 27 shows the four-construct model based on the cut-off point of eigenvalue of 1. This was confirmed by the pattern matrix shown in Table 15.

Figure 27

Scree Plot Showing a Four-Construct Structure



Sample Adequacy and Inter-Correlation Among Variables. The KMO generally indicates whether the variables can group into a smaller set of underlying factors. A KMO value of > .6 is an indication to proceed. The KMO measure of sampling adequacy (MSA) = .813. Bartlett's test of sphericity was significant: χ^2 (120) = 4750.484, *p* < .001. The anti-image matrix shows the individual MSA test for each item > .5. The extracted communalities were good, with values > .25. All 16 items > .40, and 10 items had communalities extraction > .5. The results of KMO, Bartlett's test, the individual MSAs, and extracted communalities all provided empirical evidence that the overall inter-correlation requirement was met; thus, the observed variables were adequate and appropriate for use in an EFA.

Total Variance Explained. In total, the four constructs extracted explained 52.6% of the variance in the model. The first factor (F1) for the GFT Normative Goal was the most important and explained almost half of the variance (24.4%). The second factor (F2) for GFT Hedonic Goal explained 12.6% of the variance. The third factor (F3) for the COVID-19 Influence explained 8.6% of the variance. The fourth factor (F4) for the GFT Gain Goal explained 7% of the variance.

Pattern Matrix. The final 4-factor EFA model presented itself neatly in the pattern matrix, as shown in Table 15. F1 had five items that formed the GFT Normative Goal. Even though two of the items (C1 and C2) would be expected to group with the COVID-19 related items rather than the normative items, it is understandable that C1 and C2 are in F1 because the media and personal subjective norms potentially influence COVID concerns. F2 also had five items that formed the GFT Hedonic Goal naturally. The F3 had three items grouped together to form COVID-19 Financial Influence, and F4 had three items that formed the GFT Gain Goal. Four items were removed during the EFA process: GFT Hedonic H2: I will not sacrifice comfort even if I have to pay slightly more, GFT Hedonic H4: I am quite predictable in terms of how I travel, GFT Gain G1: Cost is very important to me when I travel for leisure, and GFT Normative B1: Preserving the environment is very important when I decide how I travel.

Table 15

Pattern Matrix of the Final EFA Model

	Items in Pattern Matrix [a]	Constructs			
		1	2	3	4
B2	I feel a moral obligation to protect the environment.	0.802			
B4	People who are important to me tend to care about the environment.	0.728			
B5	It is important for me to be a role model for my family in environmental protection.	0.766			
C1	I am concerned with getting COVID when I travel.	0.686			
C2	I think COVID and its variants will get worse.	0.581			
H1	Generally, my main transport mode for inter-regional travel is efficient.		0.645		
H3	I believe issues that may pop up during my travels can be resolved.		0.618		
H5	Most of the time, I am happy with the transportation I use when I travel to other cities.		0.662		
H6	In general, I trust my main inter-regional transport mode is safe.		0.643		
H7	Traveling is fun for me.		0.625		
C3	My disposable income has increased since COVID started.			0.727	
C4	Even during COVID, I could be tempted to travel by air if the ticket price was low enough.			0.792	
C5	I think the economy is gradually recovering.			0.490	
G2	Convenience is very important to me when I travel.				0.589
G3	I usually try to minimize my total travel time.				0.783
G4	When I travel, I value my time doing something nice or useful, such as watching a movie, working, or sleeping.				0.540

Note. PCA extraction method. Promax with Kaiser Normalization rotation method.

[a] Rotation converged in five iterations.

Validity and Reliability Assessment

This section describes procedures that provided evidence of the validity and reliability of the instrument.

Discriminant validity. The Heterotrait-Monotrait Ratio (HTMT) values in Table 16 show that all values are below .85. According to Kline (2016), this demonstrates evidence of discriminant validity. Appendix I shows that the item correlation coefficients that were not between factors (i.e., non-shaded areas) were mostly < .2, providing further evidence of discriminant validity.

Table 16

HTMT Values Showing Discriminant Validity

	F1	F2	F3	F4
F1				
F2	0.36			
F3	0.48	0.28		
F4	0.41	0.67	0.38	

Note. HTMT = Heterotrait-Monotrait Ratio.

Convergent Validity. All factor loadings for the items within each construct were statistically significant and mostly ranged between .3 and .7 (i.e., colored areas in Appendix I), indicating good convergent validity.

Reliability Assessment. Table 17 presents the final constructs with the items and α. F1 (GFT Normative Goal) and F2 (GFT Hedonic Goal) have good α. F3 (COVID-19 Financial) and F4 (GFT Gain Goal) have marginally acceptable α (Kline, 2016). These results show that internal consistency for these constructs is reasonable.

Table 17

Final Constructs, Items, and Internal Consistency

Construct		Item	α
F1: GFT normative goal	B2	I feel a moral obligation to protect the environment.	0.761
	B4	People who are important to me tend to care about the environment.	
	B5	It is important for me to be a role model for my family in environmental protection.	
	C1	I am concerned with getting COVID when I travel.	
	C2	I think COVID and its variants will get worse.	
F2: GFT hedonic goal	H1	Generally, my main transport mode for inter-regional travel is efficient.	0.691
	H3	I believe issues that may pop up during my travels can be resolved.	
	H5	Most of the time, I am happy with the transportation I use when I travel to other cities.	
	H6	In general, I trust my main inter-regional transport mode is safe.	
	H7	Traveling is fun for me.	
F3: COVID-19 financial	C3	My disposable income has increased since COVID started.	0.534
	C4	Even during COVID, I could be tempted to travel by air if the ticket price was low enough.	
	C5	I think the economy is gradually recovering.	
F4: GFT gain goal	G2	Convenience is very important to me when I travel.	0.584
	G3	I usually try to minimize my total travel time.	
	G4	When I travel, I value my time doing something nice or useful, such as watching a movie, working, or sleeping.	

Note. GFT = goal framing theory.

Five COVID-19 items were added to this research to test any pandemic effects in the MNL and CA models. As mentioned earlier, C1 and C2 were expected to group under COVID-19, but instead, they grouped under the Normative construct. As a data-driven method, EFA was useful to validate the observed variables and the latent constructs. It is logical for C1 and C2 to be in F1 (the Normative goal) because the media and an individual's subjective norms potentially influence COVID concerns. Further discussion of the EFA model with and without the COVID items is provided in Chapter V.

Multinomial Logistic Regression Analysis Results

The previous sections focused on data preparation, assumptions testing, reliability and validity assessments, data reduction, and construct confirmation. With the validated

EFA model, the four latent constructs were used in the MNL models. To answer RQ_1, respondents were asked to select their future transportation mode, which was used as the dependent variable in the MNL models: “In the future, assuming safety, legal, and regulation issues are solved, and driverless cars are readily available in everyday life, what do you think you would use most for inter-regional travel?” Five categories were offered to the respondents to simulate real-life options once aMoD is available. Sample sizes by future mode choice were: aMoD (*n* = 498; 35.9%), SF (*n* = 291; 21%), Drive (*n* = 365; 26.3%), Inter-regional bus (*n* = 95; 6.8%), and Inter-regional train (*n* = 139; 10%). While the DV for the three MNL models stayed the same, each of the three MNL models had a different mix of independent variables to determine the best MNL model. Table 18 shows three MNL models with a summary of the key results.

Model Fit

The model fit information was used to evaluate the overall fit of the MNL models. Table 18 shows the test results for all three MNL models.

The likelihood ratio chi-square (χ^2) test (stepwise method) indicated statistical significance, meaning there was a significant improvement in the fit of each of the models relative to the baseline null model with no predictors. It also provided evidence of a significant relationship between the DV and IVs in all three MNL models. All three MNL models showed non-significant Pearson and deviance chi-square results, indicating that these models all had a good model fit.

Table 18

Three MNL Models with Key Results

	Model 1	Model 2	Model 3
IVs (Predictors)	F1: GFT Normative Goal F2: GFT Hedonic Goal F3: COVID Economic F4: GFT Gain Goal MODE_Current	F1 F2 F3 F4 MODE_Current 13 demographics 7 contextual trip	5 GFT Hedonic 3 GFT Gain 3 GFT Normative 5 COVID-19 MODE_Current 13 demographics 7 contextual trip
# IVs	*n* = 5	*n* = 25	*n* = 37
Model Fit Results			
Likelihood-Ratio $\chi2$	$\chi^2(28) = 337.945$ $p < .001$	$\chi^2(100) = 379.734$ $p < .001$	$\chi^2(348) = 799.415$ $p < .001$
Pearson $\chi2$	$\chi^2(5400) = 5113.376$ $p > .05$	$\chi^2(5432) = 5124.377$ $p > .05$	$\chi^2(5184) = 4993.616$ $p > .05$
Deviance $\chi2$	$\chi^2(5400) = 3646.232$ $p > .05$	$\chi^2(5432) = 3667.496$ $p > .05$	$\chi^2(5184) = 3247.816$ $p > .05$
Pseudo R^2 Results			
Cox & Snell	0.216	0.239	0.438
Nagelkerke	0.228	0.253	0.463
McFadden	0.083	0.094	0.197
Significant Predictors			
	F1	F1	C1 (Travel COVID fear) C2 (COVID variants fear)
	F2	F2	H1 (Travel efficiency)
	F3	F4	H3 (Self-efficacy) H5 (Transport satisfaction) G3 (Min. total travel time) G4 (Value of time) B4 (Environment subjective norm) [b]
	MODE_Current	MODE_Current Household income Years with driver's license Air travel during COVID F3 [b] Business travel freq. [b]	MODE_Current Household income Years with driver's license Annual miles flown [b] Age No. of cars owned by HH Neighborhood type Family/self-mobility issues

Note. Stepwise method. aMoD = autonomous mobility-on-demand; Freq. = frequency; GFT = goal framing theory; HH = household; SF = commercial short-haul flight; MNL = multinomial logistic regression; Min. = minimum; No. = number.

[a] Inter-regional travel $\leq$ 500 mi (800 km). [b] $p \cong .05$.

The *pseudo* R^2 values improved from M1 to M2 to M3. There is no strong guidance in the literature on how these should be interpreted, but Smith and McKenna (2013) suggest the rule of thumb for an indicator of a good fit should be in the range of .2 to .4 (p. 18). Using this guideline, the Pseudo R^2 measures for M3 exhibited the best model fit—Cox and Snell (.438), Nagelkerke (.463), and McFadden (.197)—indicating M3 accounted for 19.7% to 46.3% of the variance that was observed in the outcome, which can be explained by the IVs in M3. These Pseudo R^2 values were synonymous with the effect size; therefore, M3 represented good-sized effects (Smith & McKenna, 2013).

Effects of the IVs

The Likelihood Ratio tests provided evaluations of the overall contribution of each IV to the models (using the conventional α=.05 threshold). Significant predictors (p < .05) of all three MNL models are presented in Table 18. For M1, four of the five IVs were significant predictors of the future transport mode choice: F1: $\chi^2(4) = 32.449$, p < .001; F2: $\chi^2(4) = 26.325$, p < .001; F4: $\chi^2(4) = 4.908$, p < .001; and MODE_Pre-COVID: $\chi^2(12) = 206.711$, p < .001. M2 and M3 had 9 and 16 significant predictors, respectively. Mode_Current was a common predictor for all three models, whereas Household Income and Years with a Driver's License were common predictors for M2 and M3. Since M3 used all observed variables (instead of the four latent constructs), the GFT and COVID variables revealed added "characters" within the latent constructs:

- GFT Hedonic Goal: H1 (Efficiency), H3 (Self-efficacy), and H5 (Satisfaction)
- GFT Gain Goal: G3 (Min total travel time) and G4 (Value of time)
- GFT Normative Goal: B4 (Environment subjective norm)
- COVID Influence: C1 (Travel COVID fear) and C2 (COVID variants fear)

Parameter Estimates: Odds Ratio

All three MNL models exhibited good model fit. However, M3 had the highest overall pseudo R^2 (Nagelkerke $R^2 = .463$) and predictive percentages (48.4%) and was selected to be the best MNL model for the odds ratio analysis. The result from the statistically significant parameter estimates of M3 is presented in Table 19.

Table 19

Statistically Significant Parameter Estimates for MNL Model 3

	Future Main Mode	B	Std. Error	Wald	*df*	*p* [a]	Exp(B)
aMoD	B2: Environmental moral obligation	0.320	0.11	9.03	1	0.003	1.377
	H3: Travel issues can be resolved	0.351	0.12	8.19	1	0.004	1.420
	H5: Happy with main transportation	0.626	0.30	4.29	1	0.038	1.871
	G4: When I travel, I value my time	-0.242	0.11	4.98	1	0.026	0.785
	C5: Economy is recovering	0.211	0.10	4.97	1	0.026	1.235
	[MODE_Current = SF]	-0.384	0.11	13.25	1	< .001	0.681
Drive	Have/Had COVID	-0.503	0.22	5.31	1	0.021	0.605
	Family or Self with Mobility Issue	-0.487	0.24	4.08	1	0.043	0.614
	Traveled by Air during COVID	0.703	0.19	14.01	1	< .001	2.019
	Vaccinated against COVID	-0.623	0.28	4.94	1	0.026	0.537
	G4: When I travel, I value my time	-0.381	0.12	10.93	1	< .001	0.683
	No. of Cars owned by Household	-0.330	0.16	4.55	1	0.033	0.719
	[MODE_Current = SF]	-1.538	0.49	9.96	1	0.002	0.215
I -Bus	C4: SF if the price was low enough	0.365	0.15	5.72	1	0.017	1.440
	G3: Minimize total travel time	-0.559	0.17	10.31	1	0.001	0.572
I - Train	Highest Level of Education	0.452	0.19	5.70	1	0.017	1.571
	No. of Cars owned by Household	-0.402	0.19	4.30	1	0.038	0.669
	Total Household Income	0.364	0.13	8.01	1	0.005	1.439
	[MODE_Current = Drive]	-2.172	0.56	15.02	1	< .001	0.114
	[MODE_Current = SF]	-3.496	0.51	47.67	1	< .001	0.030

Note. MNL = multinomial logistic regression; No. = number. SF = commercial short-haul flight. The reference category is SF. [a] Significance is at the 5% level of confidence.

For respondents who had chosen aMoD as their future transport mode, six predictor variables were statistically significant (B2, H3, H5, G4, C5, and MODE_Current = SF). The parameter estimates B coefficients and odds ratio Exp(B) provided information comparing each transport mode choice against SF, the reference category. The B coefficients demonstrated the signs of the effects. For example, among the respondents who chose aMoD instead of SF as their future mode, the more they valued their time (G4), the less likely they chose aMoD over SF. In other words, respondents who valued their time were more likely to select SF as their future transport mode. Respondents who were more loyal to SF (MODE_Current = SF) would be less likely to choose aMoD. Naturally, loyal SF respondents were more likely to choose SF as their future transport mode. Respondents who scored higher on self-efficacy (H3) were more likely to choose aMoD than SF. Similarly, respondents who scored higher on environmental moral obligation (B2) and felt that the economy was recovering (C5) were more likely to choose aMoD than SF.

The odds ratio Exp(B) reflected the change in the odds concerning group membership for every one-unit increase on the predictor variable (see Appendix L). The odds ratio value > 1 indicated that the odds of the outcome falling in the aMoD (the comparison group) relative to the odds of the outcome falling in SF (the reference group) increases as the variable increases. Thus, aMoD (the comparison outcome) is more likely. Using the aMoD respondents as an example again, respondents who scored one point higher on environmental moral obligation were 1.377 times more likely to use aMoD than SF. For respondents who chose aMoD as their future transport mode, those who rated self-efficacy one point higher (from 4 to 5 on the Likert scale) were 1.42 times more likely to use aMoD than SF. Regarding the value of time, the B coefficient was negative (– 0.242) and the Exp(B) = 0.785. This means that aMoD respondents who scored one point higher on the value of time were more likely to choose SF than aMoD by a factor of 0.785, meaning the odds were decreasing with the increasing score on the value of time. As the score for the value of time increases by one point (from 4 to 5 on the Likert scale), the odds ratio for a respondent choosing aMoD compared to SF decreases by 21.5% (1 – 0.785).

Similarly, MODE_Current = SF had a significant negative impact on the future MODE choice of the respondents (B = – 0.384, Wald = 13.25, $p < .001$). As Current MAIN MODE=SF increased by 1 unit, the odds ratio for a respondent choosing aMoD compared to SF decreased by 31.9% (1 – 0.681), assuming the other predictors were constant. Age, gender, education, household income, number of children, neighborhood, prior car accidents, mobility issues, drive frequency, annual fly miles, COVID vaccination, the distance between home and the nearest airport, as well as the percentage of direct flights to destinations were not statistically significant in influencing future mode choice for aMoD compared to SF.

There were seven predictors for the future transport choice "to drive or ride" instead of SF. Three of the seven were COVID related: whether the respondent had contracted COVID, traveled by air during COVID, and were vaccinated against COVID. If the respondent had contracted COVID-19, the odds of choosing SF instead of driving were reduced by 39.5%. Yet, if the respondent had traveled by air during the pandemic, they were 2.02 times more likely to choose to drive instead of flying. This shows that COVID-19 had a significant impact on the respondents' choice of future transport mode if they had chosen the "drive" option as their future mode choice.

There were only two predictors of inter-regional bus transportation choice: C4 (SF if the price was low enough) and G3 (minimize total travel time). When C4 increased by one point, the odds of the respondents choosing inter-regional bus travel over SF increased by 1.44 times. This seems logical. Someone who responded to C4 with a 5 (*strongly agree*) on the Likert scale would be 1.44 times more likely to choose inter-regional bus than SF compared to a respondent who responded to the item with a 4 (agree), as fare cost might be one of the motivators for choosing inter-regional bus as a transport mode. G3 (minimize total travel time) has a significant negative impact on the choice of inter-regional bus compared to SF. As the score of minimizing total travel time increased by one point, the odds ratio for a respondent choosing aMoD compared to SF decreased by 42.8% (1 – 0.572). Inter-regional train had five predictors: education, number of cars owned by the household, total household income, and the current mode choices for Drive and SF.

In summary, three multinomial logistic regression models were tested to determine if any of the combinations of the four latent constructs, the GFT variables, the COVID-19 variables, the 13 demographics, and the seven contextual trip variables best predicted the likelihood of the future transport mode choice for inter-regional trips when aMoD is available. The results of MNL Model 3 were statistically significant: $\chi 2(348) = 799.415$, $p < .001$, and with a good effect size, Nagelkerke $R^2 = .463$. Twelve IVs were statistically significant in predicting the future mode choice 48.4% of the time. Model 3 correctly predicted aMoD as a future mode choice 65.5% of the time. SF was correctly predicted 45% of the time.

2-Step Cluster Analysis Results for aMoD and SF

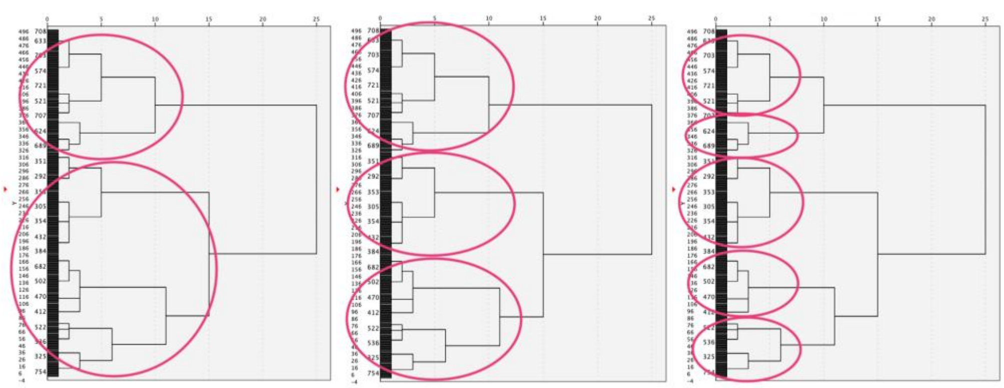
The 2-step CA results were used to answer RQ_2 to determine distinct passenger clusters for SF and aMoD and identify the similarities and differences within the SF and aMoD segments. CA works effectively with a concise model with fewer variables: only the four latent constructs—GFT Hendonic Goal, GFT Gain Goal, GFT Normative Goal, and COVID Financial—were used to cluster the distinct aMoD and SF groups.

aMoD Clusters

Ward's method was chosen to create more evenly sized clusters. The squared Euclidean distance was selected as the interval measure. The visual evaluation based on the dendrogram generated from the aMoD hierarchical clustering (as shown in Figure 28) shows that the 2-, 3-, and 5-cluster solutions seemed to offer a good solution. Using the K-means clustering algorithm, the 2-cluster aMoD solution stabilized after the 7th iteration, the fastest to stabilize compared to the 3-cluster solution (18th iteration) and 5-cluster solution (8th iteration). All clustering criteria were statistically significant; the high *F* values indicated that they were all critical in determining the clustering of passengers.

Figure 28

Dendrograms of aMoD Clusters Showing 2-, 3-, and 5-Cluster Solutions

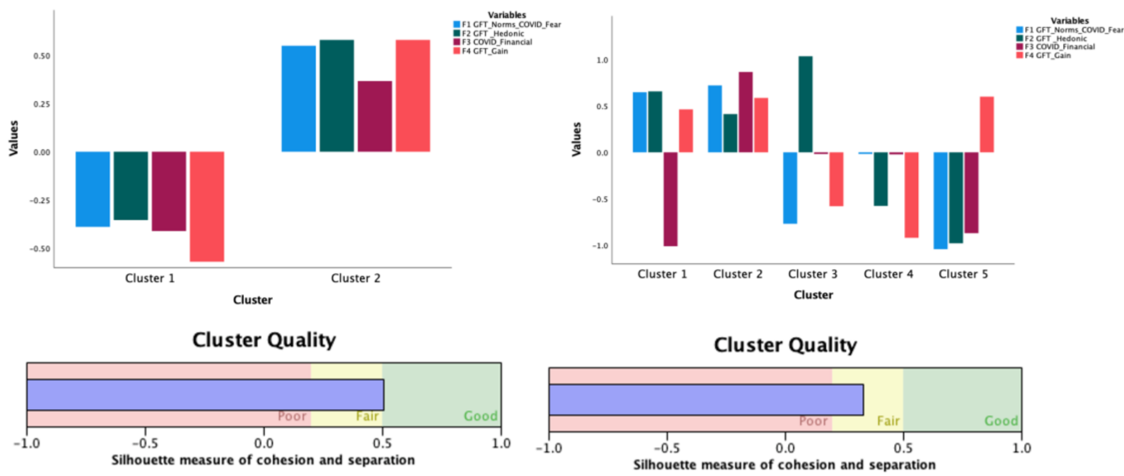


Note. Dendrograms are using Ward linkage with rescaled distance. The pink ovals identify cluster solutions.

Figure 29 shows the final cluster centers of the four latent constructs and the cluster quality of the 2- and 5-cluster solutions based on the silhouette measure of cohesion and separation, which simultaneously measured how the data points were within each cluster and how the clusters were different from one another. CA would only be appropriate for the data if the cluster quality was good. The aMoD 2-cluster solution showed a better cluster quality than the 5-cluster solution.

Figure 29

Final Cluster Centers of the 2-Cluster and 5-Cluster aMoD Models



Note. Left image: Final aMoD cluster centers for the four latent constructs and cluster quality for the 2-cluster solution. Right image: Final aMoD cluster centers for the four latent constructs and cluster quality for the 5-cluster solution.

Validating the Optimal aMoD Cluster Solution. Four methods were used to validate the 2-cluster solution as a stable and meaningful aMoD cluster model:

1. ***Iteration History Using the K-Means Algorithm*.** The aMoD 2-cluster solution stabilized after the 7th iteration, the fastest to stabilize compared to other solutions.
2. ***Final Cluster Centers*.** All cluster solutions had different initial and final cluster centers. The 2-cluster aMoD solution demonstrated highly discriminatory final cluster centers, as shown in Figure 29.
3. ***Agglomeration Coefficients*.** Table 20 shows that the largest percentage increase in the agglomeration coefficient (24.05%) occurred when transitioning from a 2-cluster solution to a single cluster solution, indicating that the 2-cluster aMoD solution would be the most stable.
4. ***Significantly Different Means with High F Values*.** While all cluster solutions yielded significant F tests, the 2-cluster ANOVA identified that the means of F1, F2, F3, and F4 were statistically significant with high F values, providing further evidence that the clusters were valid:

   F1: $F(496) = 172.400$, $p < .001$, F2: $F(496) = 148.434$, $p < .001$,

   F3: $F(496) = 98.281$, $p < .001$, and F4: $F(496) = 234.694$, $p < .001$.

Evaluation of the dendrogram, iteration history, final cluster centers, cluster quality, agglomeration schedule, and high F-values provided evidence that a 2-cluster solution had more discriminant clusters for the aMoD model. Therefore, the 2-cluster aMoD solution was adopted.

Table 20

Agglomeration Schedule for aMoD Clusters

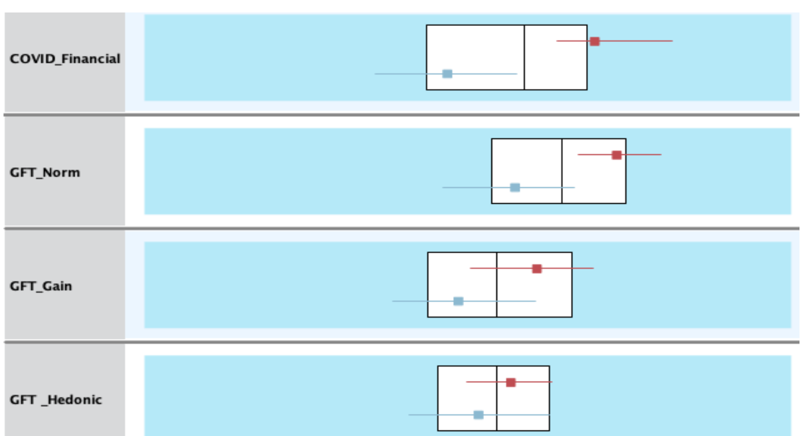
Stage	Cluster Combined		Coefficients	% Increase in Coefficient	Number of Clusters
	Cluster 1	Cluster 2			
1	418	419	0	0	498
2	417	418	0	0	497
…					
492	1	2	914.637	8.06	6
493	6	7	986.799	7.89	5
494	16	181	1129.032	14.41	4
495	6	29	1286.465	13.94	3
496	1	6	1497.620	16.41	2
497	1	16	1857.780	24.05	1

Note. aMoD = mobility-on-demand.

Figure 30 shows the cluster comparison with the box and whiskers which provided another good visual presentation of the differences between the two aMoD clusters. The whiskers were the horizontal line with a square cluster median. The box represents one standard deviation on each side, with the middle line being the mean of that latent construct.

Figure 30

Cluster Comparisons of the aMoD Model: Four Constructs



Note. Cluster 1: Blue boxes and whiskers. Cluster 2: Red boxes and whiskers.

The cluster model fit was evaluated using the *F*-value. Results of the MANOVA indicated that there was a statistically significant difference between the two aMoD clusters (Clusters 1 and 2) on the combined DVs: Wilks lambda = .303, $F(31, 466) = 34.620$, $p < .001$, partial $\text{Eta}^2 = .697$, observed power > .99. (Four multivariate tests: Pillai's trace, Wilks' lambda, Hotelling's trace, and Roy's largest root were conducted, and all yielded similar results). The effect size (practical significance) was large, accounting for 69.7% of the variance of the DV. The observed power of .99 indicated a 99% chance that the results could have been significant. Therefore, follow-up ANOVA tests were conducted.

Profiling the Two aMoD Clusters. Examining the demographic and contextual trip variables not included in the cluster variates provided a richer description of the two aMoD clusters. Of the 29 variables, 18 showed statistically significant differences between the clusters and were used to identify the differences across the two aMoD clusters (See Table 21). Because they are nominal variables, cross-classification with chi-square tests was used to identify the group similarities (statistically non-significant chi-square values) and differences (statistically significant chi-square values). Post-hoc tests were unnecessary because the IV (aMoD_2C) had only two categories (Cluster 1 and Cluster 2).

Appendix M presents the cluster details of the remaining 11 demographic and contextual trip variables with non-significant chi-square values. These 11 variables are similar between the two aMoD clusters: age, number of driver's licenses in the household, number of cars owned by the household, years with driver's license, weekly drive frequency, car accident when the respondent or someone was injured, whether the respondent indicated “yes” to have/had COVID, whether the respondent had traveled by air during COVID, the distance between home and the nearest airport, and perception of aMoD timing in the United States. It is important to note that the segment characteristics are probabilistic (and not deterministic), meaning the cluster descriptions may not necessarily apply to all members of a cluster.

Table 21

Profiles of the Two aMoD Clusters

Demographic and Trip Characteristics	Cluster 1[a] Suburban Rural Drivers	Cluster 2[b] Urban Educated Flyers	Chi-Square Results		
	%		χ^2	*df*	*p*
Education			29.401	4	< .001
Attended high school	0%	0%			
High school diploma	26%	10%			
Bachelor’s degree	55%	58%			
Master’s degree	18%	32%			
Ph.D./Postdoc	2%	0%			
Household Income			11.909	5	.036
< $30,000	13%	14%			
$30,001 to $50,000	27%	21%			
$50,001 to $100,000	41%	47%			
$100,001 to $150,000	13%	11%			
$150,001 to $200,000	3%	7%			
> $200,000	3%	1%			
No. of Children in Household			14.941	3	.002
0	46%	31%			
1	30%	32%			
2	20%	31%			
3 or more	4%	6%			
Mobility Issue			6.356	1	.012
Yes	15%	24%			
No	85%	76%			
Neighborhood			19.173	3	< .001
City	35%	54%			
Suburb	41%	29%			
Small city	13%	10%			
Rural/Village	12%	7%			
Business Travel			35.609	3	< .001
Once a year	13%	13%			
2-6 times a year	42%	51%			
7 or more times a year	11%	22%			
Did not travel for business	34%	13%			
% Direct Flights from Home Airport			19.096	4	< .001

Demographic and Trip Characteristics	Cluster 1[a] Suburban Rural Drivers	Cluster 2[b] Urban Educated Flyers	Chi-Square Results		
	%		χ^2	*df*	*p*
0-20	14%	5%			
21-40	26%	33%			
41-60	28%	38%			
61-80	18%	14%			
Over 80	15%	10%			
MODE_Current			29.946	3	< .001
Drive	59%	35%			
SF	32%	46%			
Inter-regional Bus	7%	12%			
Inter-regional Train	2%	7%			
Inter-Regional Bus Used			12.655	1	< .001
Yes	60%	75%			
No	40%	25%			
Inter-Regional Train Used			28.53	1	< .001
Yes	64%	85%			
No	36%	15%			
Annual Miles Flown			8.436	3	0.038
< 5,000 mi	53%	44%			
5,000–10,000 mi	39%	41%			
10,001–25,000 mi	7%	14%			
> 25,000 mi	2%	2%			
No. of People Traveling for Leisure by Car			19.535	3	< .001
1	10%	5%			
2	40%	27%			
3	33%	44%			
4 or more	17%	24%			
No. of People Traveling for Leisure by Air			24.921	3	< .001
1	20%	11%			
2	42%	36%			
3	26%	25%			
4 or more	12%	28%			
Fly If Over a Certain Drive Time			13.305	5	.021
3 hr	10%	19%			
4 hr	20%	21%			
5 hr	19%	24%			
6 hr	19%	14%			
7 hr	8%	7%			
8 hr	24%	17%			
Timing When 50% Cars are aMoD			21.073	4	< .001
By 2030	22%	36%			
By 2040	40%	42%			
By 2050	30%	18%			
Beyond 2050	8%	4%			
Never	0%	1%			
Timing When 50% Cars are EV			19.154	4	< .001
By 2030	34%	52%			
By 2040	42%	28%			
By 2050	18%	17%			
Beyond 2050	5%	3%			
Never	1%	1%			

Demographic and Trip Characteristics	Cluster 1[a] Suburban Rural Drivers	Cluster 2[b] Urban Educated Flyers	Chi-Square Results		
	%		χ^2	*df*	*p*
% Work from Home During COVID			25.528	5	< .001
100%	34%	35%			
75%	24%	31%			
50%	13%	19%			
25%	7%	8%			
0%	17%	6%			
I do not work	6%	1%			
Vaccinated Against COVID			3.842	1	.047
Yes	83%	89%			
No	17%	11%			

Note. aMoD = Autonomous mobility-on-demand; EV = electric vehicles; SF = commercial short-haul flight. [a] Cluster 1: *n* = 255 (51.2%). [b] Cluster 2: *n* = 243 (48.8%).

To explore deeper, Hair et al. (2018, p. 227) suggest that the original variables may provide additional information to the clusters if the cluster analysis is performed using EFA scores. A one-way multivariate analysis of variance (MANOVA) was conducted to investigate if the 16 GFT observed items and the five COVID-19 variables differed significantly between the two aMoD clusters. Earlier in this chapter, Shapiro-Wilks indicated that the assumption of normality was fulfilled ($p < .05$). Mahalanobis distance was used to assess multivariate outliers; the critical value was not exceeded, making this assumption tenable. The association between the DVs was significant. The correlation coefficient was less than .9; thus, multicollinearity was not a concern. However, the assumption of the homogeneity of variance-covariance was violated based on the results of the Box's test: $M = 793.848$, $F(496, 740319.266) = 1.498$, $p < .001$.

The tests of between-subjects effects showed the significance and the level of impact of the aMoD cluster membership on each of the DVs. Table 22 shows significant differences in the variable means between the two clusters. Results from the MANOVA tests demonstrated sufficient evidence to support the statistically significant differences between aMoD Clusters 1 and 2 for each of the 4 EFA constructs, the 16 GFT variables, and the 5 COVID-19 variables. Figures 30 and 31 graphically illustrate the differences between the aMoD clusters at the latent factor level and the observed variable level, respectively. To explain the significant relationships at the variable level, G3, G4, and H4 were used as examples. G3, G4, and H4 had large effect sizes indicating there was a large practical significance: G3 (minimize travel time): $F(1, 496) = 145.417$, $p < .001$, partial $\text{Eta}^2 = .227$, observed power > .99; G4 (value of time): $F(1, 496) = 197.373$, $p < .001$, partial $\text{Eta}^2 = .285$, observed power > .99; H3 (self-efficacy): $F(1, 496) = 74.249$, $p < .001$, partial $\text{Eta}^2 = .130$, observed power > .99. The strength of the relationship between G3 and the cluster membership was strong, accounting for 22.7% of the variance of the DV, and G4 accounted for 28.5% of the variance of the DV. The observed power of over .99 indicated an over 99% chance that the results could have become significant. As shown in Table 22, Cluster 1 had all negative mean scores on the 4-factor clustering criteria, whereas Cluster 2 had all positive scores. The passengers in aMoD Cluster 2 had significantly higher mean scores than Cluster 1 for all latent factors and the GFT and COVID-19 attributes.

Table 22

Comparisons Between aMoD Clusters

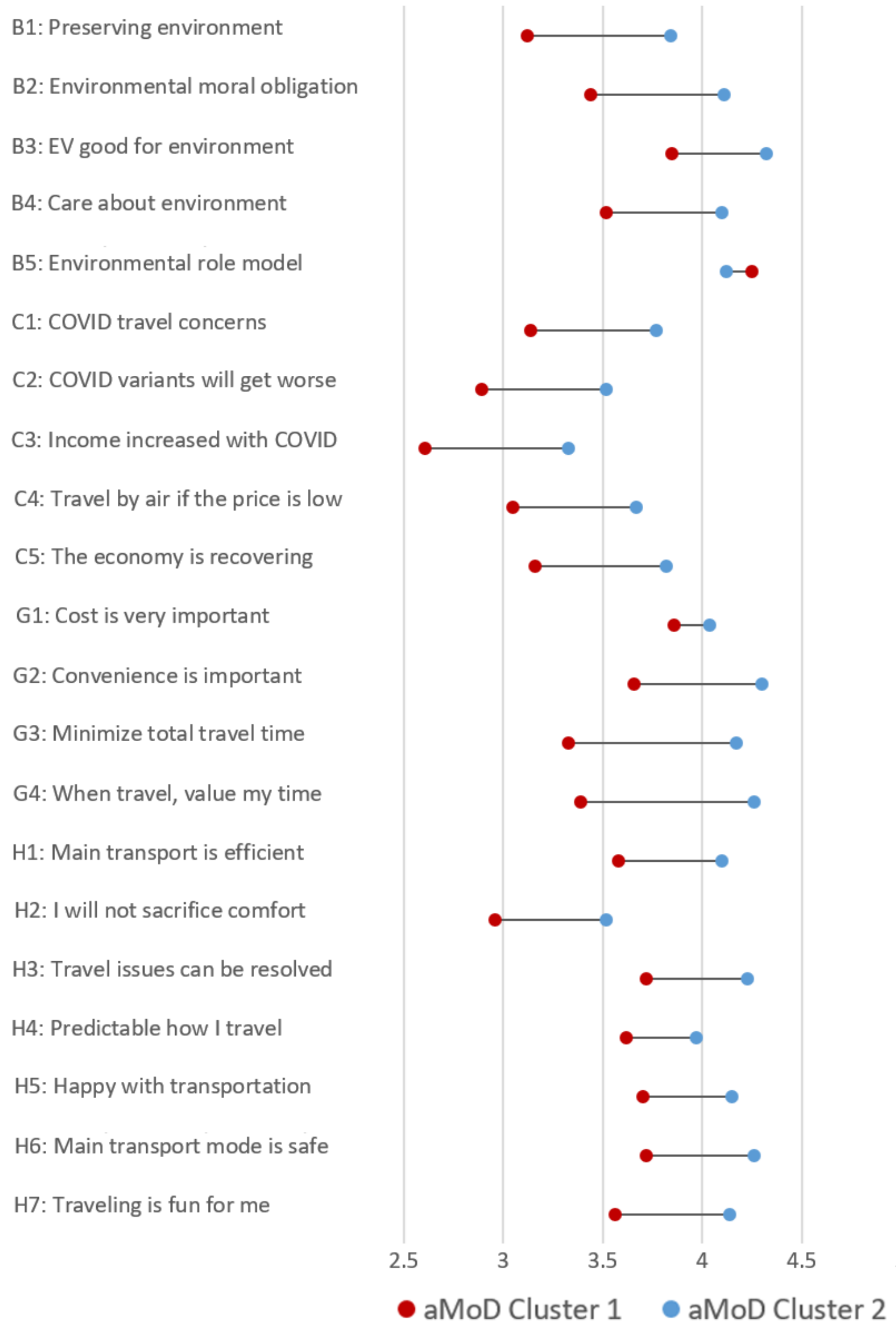
EFA Factors	Cluster 1[a] *M*	Cluster 2[b] *M*	MANOVA Results *F*-ratio	Sig.	Partial Eta^2
F1: GFT_Norm	-0.39	0.55	172.400	< .001	0.258
F2: GFT_Hedonic	-0.35	0.58	148.434	< .001	0.230
F3: COVID_Financial	-0.41	0.37	98.281	< .001	0.165
F4: GFT_Gain	-0.57	0.58	234.694	< .001	0.321
GFT and COVID-19 Variables					
B1: Preserving environment	3.12	3.84	79.785	< .001	0.139
B2: Environmental moral obligation	3.44	4.11	73.087	< .001	0.128
B3: EV good for environment	3.85	4.32	44.365	< .001	0.082
B4: Care about environment	3.52	4.10	58.535	< .001	0.106
B5: Environmental role model	4.25	4.12	132.509	< .001	0.211
C1: COVID travel concerns	3.14	3.77	50.728	< .001	0.093
C2: COVID variants will get worse	2.89	3.52	51.179	< .001	0.094
C3: Income increased with COVID	2.61	3.33	49.448	< .001	0.091
C4: Travel by air if the price is low	3.05	3.67	43.440	< .001	0.081
C5: The economy is recovering	3.16	3.82	73.803	< .001	0.130
G1: Cost is very important	3.86	4.04	5.145	.024	0.010
G2: Convenience is important	3.66	4.30	100.207	< .001	0.168
G3: Minimize total travel time	3.33	4.17	145.417	< .001	0.227
G4: When travel, value my time	3.39	4.26	197.373	< .001	0.285
H1: Main transport is efficient	3.58	4.10	92.303	< .001	0.157
H2: I will not sacrifice comfort	2.96	3.52	39.579	< .001	0.074
H3: Travel issues can be resolved	3.72	4.23	74.249	<.001	0.130
H4: Predictable how I travel	3.62	3.97	25.316	<.001	0.049
H5: Happy with transportation	3.70	4.15	54.265	< .001	0.099
H6: Main transport mode is safe	3.72	4.26	76.964	< .001	0.134
H7: Traveling is fun for me	3.56	4.14	49.896	< .001	0.091

Note. aMoD = Autonomous mobility-on-demand; EV = electric vehicles; GFT = goal framing theory; SF = commercial short-haul flight.

[a] Cluster 1: *n* = 255 (51.2%). [b] Cluster 2: *n* = 243 (48.8%).

Figure 31

Comparisons of the Significant aMoD Cluster Means: by Variable



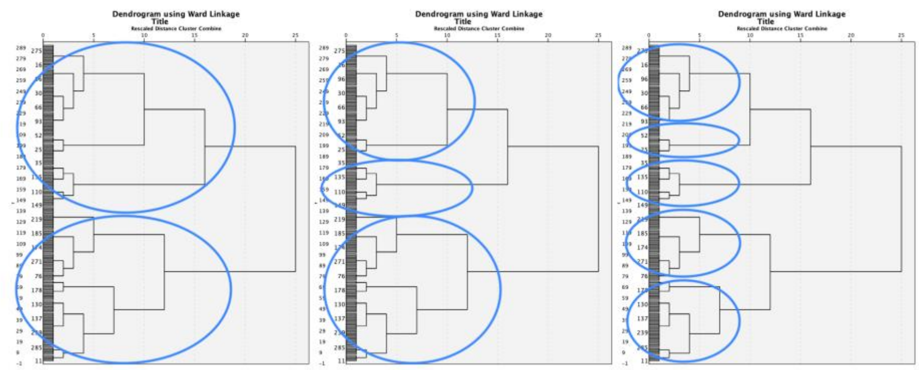
Note. aMoD = autonomous mobility-on-demand.

SF Clusters

Figure 32 shows the dendrogram generated from the SF hierarchical clustering, indicating the 2-, 3-, and 5-cluster solutions.

Figure 32

Dendrograms of SF Clusters Identifying the 2-, 3-, and 5-Cluster Solutions



Note. Dendrogram using Ward linkage with rescaled distance. Blue ovals identify the SF cluster solutions.

In comparing the three SF cluster solutions, all clustering criteria were statistically significant for the 2- and 5-clusters, as shown in Table 23. The high *F* values of F1, F2, and F4 indicated they were important in determining the clustering of respondents who chose SF as their future main mode. F3 in the 3-cluster solution was not significant $F(288) = 1.472$, $p = .231$, indicating F3 (COVID_Financial) was relatively unimportant. Considering the statistically insignificant F3 value in the 3-cluster, further analysis was conducted on the 2- and 5-cluster solutions.

Table 23

Comparison of SF Cluster Solutions

	2-Cluster *df* = 289		3-Cluster *df* = 288		5-Cluster *df* = 286	
Latent Constructs	*F*	Sig.	*F*	Sig.	*F*	Sig.
F1: GFT normative	91.314	< .001	232.865	< .001	128.027	< .001
F2: GFT hedonic	189.632	< .001	98.498	< .001	76.250	< .001
F3: COVID financial	4.920	< .027	1.472	.231	100.978	< .001
F4: GFT gain	149.232	< .001	92.003	< .001	51.224	< .001

Note. GFT = goal framing theory; SF = commercial short-haul flight.

Validating the Optimal SF Cluster Solution. Four methods were used to validate the 2-cluster solution as a stable and meaningful SF cluster model:

1. ***Iteration History Using the K-Means Algorithm*.** The SF 2-cluster solution stabilized after the 5th iteration, the fastest to stabilize.
2. ***Final Cluster Centers*.** The 2-cluster SF solution demonstrated highly discriminatory final cluster centers, as shown in Figure 33.
3. ***Agglomeration Coefficients*.** Table 24 shows that the largest percentage increase in the agglomeration coefficient (24.32%) occurred when transitioning from a 2-cluster solution to a single cluster solution, indicating that the 2-cluster SF solution would be the most stable.
4. ***Significantly Different Means with High F Values*.** While both the 2- and 5-cluster solutions yielded significant *F*-tests, the 2-cluster solution had the highest *F* values: F1: $F(289) = 91.314$, $p < .001$), F2: $F(289) = 189.632$, $p < .001$), F3: $F(289) = 4.900$, $p < .001$), and F4: $F(289) = 149.232$, $p < .001$).

Evaluation of the iteration history, final cluster centers, agglomeration schedule, and high F-values provided evidence that a 2-cluster solution had more discriminant clusters for the SF model. Therefore, the 2-cluster solution was adopted.

Figure 33

Final Cluster Centers of the 2-Cluster SF Model

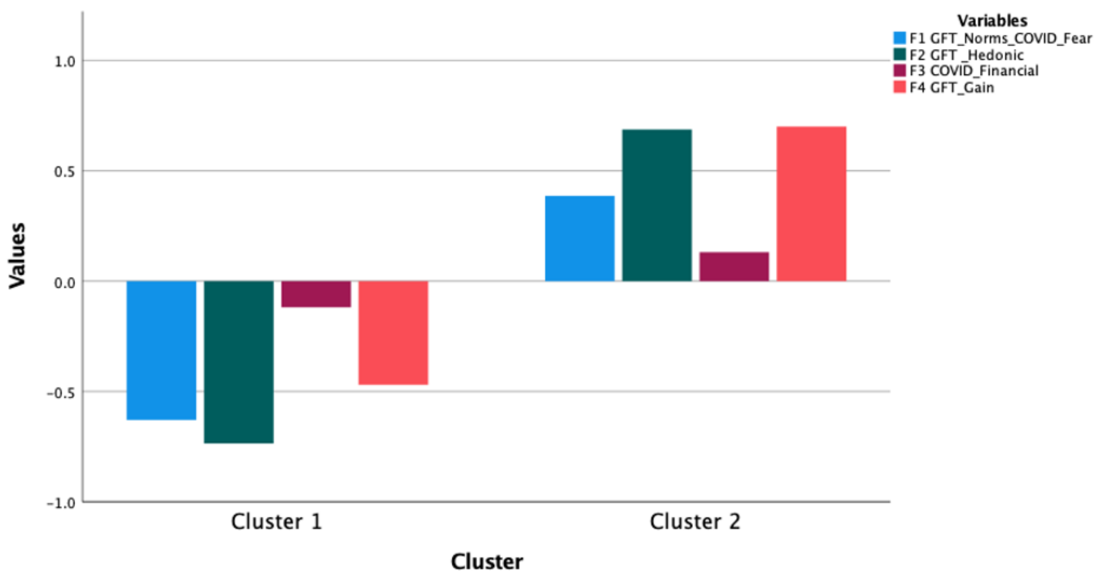


Table 24

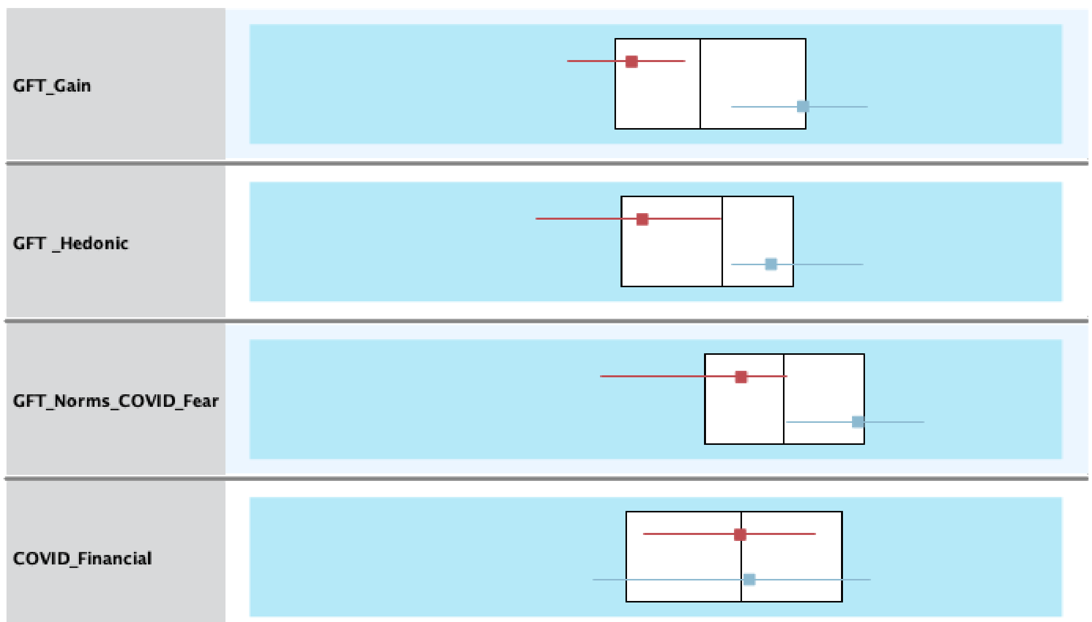
Agglomeration Schedule for SF Clusters

Stage	Cluster Combined		Coefficients	% Increase in Coefficient	Number of Clusters
	Cluster 1	Cluster 2			
1	1139	1140	0	0	291
2	956	957	0	0	290
…					
286	868	972	631.496	10.79	5
287	864	865	727.888	15.26	4
288	868	924	844.236	15.98	3
289	864	887	996.923	18.09	2
290	864	868	1239.392	24.32	1

Figure 34 shows how the two SF clusters differed by construct. Cluster 1 SF passengers consist of travelers who did not highly rank GFT gain, hedonic, or normative goals. Each of these mean values was below the sample mean. Conversely, Cluster 2 SF passengers valued their GFT gain goals and GFT normative goals so highly that the Cluster 2 means of these goals were at 1 *SD* above the sample means.

Figure 34

Cluster Comparisons of the SF Model: Four Constructs



Note. SF = commercial short-haul flight. Cluster 1: Red boxes and whiskers. Cluster 2: Blue boxes and whiskers.

Profiling the Two SF Clusters. Examining the demographic and contextual trip variables not included in the cluster variates provided a richer description of the two SF clusters. Of the 29 variables, 4 showed statistically significant differences between the clusters and were used to profile air passengers across the two SF clusters to identify the differences (See Table 25). Appendix N presents the cluster details of the remaining 25 demographic and contextual trip variables with non-significant chi-square values. In other words, SF clusters show more similarities than differences.

Table 25

Profiles of the Two SF Clusters

Significant Demographic and Trip Characteristics	Cluster 1[a] Apathetic Travelers	Cluster 2[b] Loyal Habitual Flyers	Chi-Square Results		
	%		χ^2	*df*	*p*
Gender			11.274	2	0.004
Female	33%	52%			
Male	66%	48%			
Timing when 50% Cars are EV			13.479	4	0.009
By 2030	26%	41%			
By 2040	41%	32%			
By 2050	19%	17%			
Beyond 2050	9%	11%			
Never	5%	0%			
Number of People Traveling for Leisure by Car			17.505	3	<.001
1	5%	11%			
2	38%	23%			
3	44%	38%			
4 or more	14%	28%			
Number of People Traveling for Leisure by Air			34.764	3	<.001
1	8%	18%			
2	51%	32%			
3	30%	17%			
4 or more	11%	34%			

Note. EV = electric vehicles; SF = commercial short-haul flight.

[a] Cluster 1: n = 133 (45.7%). [b] Cluster 2: n = 158 (54.3%).

To explore deeper, MANOVA was conducted to investigate if the 16 GFT observed items and the five COVID-19 variables differed significantly between the two SF clusters. Earlier in this chapter, Shapiro-Wilks indicated that the assumption of normality was fulfilled ($p < .05$). The multivariate outliers' assumption was tenable as the critical value of the Mahalanobis distance was not exceeded. The association between the DVs was significant. The correlation coefficient was less than .9; thus, multicollinearity was not a concern. Nevertheless, the assumption of the homogeneity of variance-covariance was violated based on the results of the Box test: M = 785.045, F(496, 238065.530) = 1.405, $p < .001$.

The MANOVA indicated a statistically significant difference between the two SF clusters on the combined DVs. Wilks Lambda = .309, F(31, 259) = 18.650, $p < .001$, partial Eta^2 = .691, observed power > .99. Four multivariate tests: Pillai's trace, Wilks' lambda, Hotelling's trace, and Roy's largest root were conducted, and all yielded similar results. The effect size was large, accounting for 69.1% of the variance of the DV, showing practical significance. The observed power of over .99 indicated an over 99% chance that the results could have come out significant. Thus, follow-up ANOVA tests were conducted.

The tests of between-subjects effects showed the significance and the level of impact of the SF cluster membership on each of the DVs. Table 26 shows significant differences in the variable means between the two clusters. Post-hoc tests were unnecessary because the IV (SF_2C) had only two categories (Cluster 1 and Cluster 2). Results from the MANOVA tests demonstrated sufficient evidence to support that SF Clusters 1 and 2 were statistically significantly different from each other for each of the 4 EFA constructs, the 16 GFT variables, and 3 of the 5 COVID-19 variables. The differences between the cluster means of C3 (income increased during COVID) and C4 (would travel by air if the ticket price was low enough) were not statistically significant, indicating that these variables were not important in differentiating the clusters.

Table 26

Comparisons Between SF Clusters

EFA Factors	Cluster 1[a] *M*	Cluster 2[b] *M*	*F*-ratio	Sig.	Partial Eta²
F1: GFT_Norm	-0.63	0.39	91.314	< .001	0.240
F2: GFT_Hedonic	-0.74	0.69	189.632	< .001	0.396
F3: COVID_Financial	-0.12	0.13	4.920	.027	0.017
F4: GFT_Gain	-0.47	0.70	149.232	< .001	0.341
GFT and COVID-19 Variables					
B1: Preserving environment	2.95	3.68	43.036	< .001	0.130
B2: Environment moral obligation	3.12	3.89	46.554	< .001	0.139
B3: EV good for environment	3.36	4.11	44.779	< .001	0.134
B4: Care about environment	3.29	4.01	50.141	< .001	0.148
B5: Environmental role model	3.12	3.98	65.230	< .001	0.184
C1: COVID travel concerns	2.94	3.69	36.536	< .001	0.112
C2: COVID variants will get worse	2.98	3.51	18.566	< .001	0.060
C5: The economy is recovering	3.00	3.66	36.234	< .001	0.111
G1: Cost is very important	3.72	4.09	14.220	< .001	0.047
G2: Convenience is important	3.62	4.39	86.233	< .001	0.230
G3: Minimize total travel time	3.44	4.23	78.636	< .001	0.214
G4: When travel, value my time	3.52	4.35	106.273	< .001	0.269
H1: Main transport is efficient	3.32	4.15	104.242	< .001	0.265
H2: I will not sacrifice comfort	3.08	3.60	18.341	< .001	0.060
H3: Travel issues can be resolved	3.48	4.14	68.388	< .001	0.191
H4: Predictable how I travel	3.41	4.06	44.317	< .001	0.133
H5: Happy with transportation	3.50	4.32	105.000	< .001	0.266
H6: Main transport mode is safe	3.53	4.32	87.273	< .001	0.232
H7: Traveling is fun for me	3.51	4.27	52.098	< .001	0.153

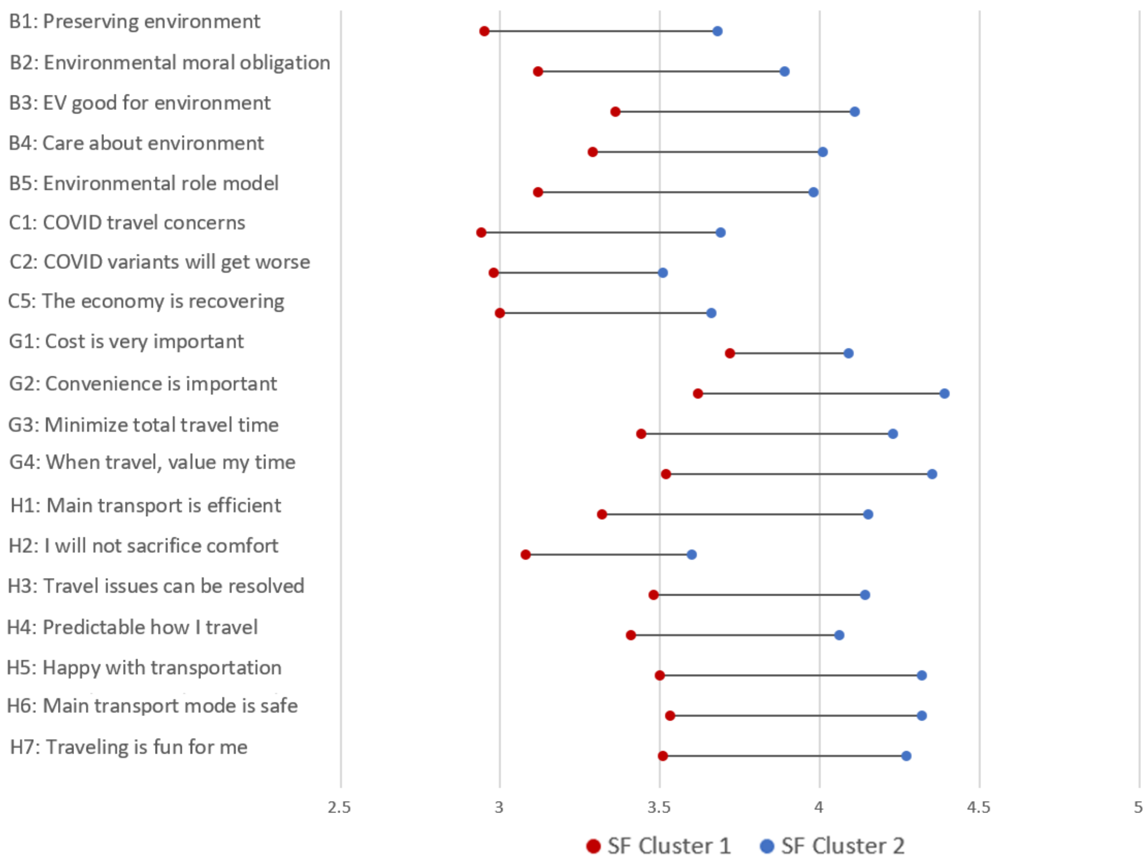
Note. EV = electric vehicles; GFT = goal framing theory; SF = short-haul flight.

[a] Cluster 1: *n* = 133 (45.7%). [b] Cluster 2: *n* = 158 (54.3%).

Figures 33 and 34 graphically illustrate the differences between the SF clusters at the latent construct level. All four clustering latent constructs were statistically significant indicating each was important in clustering respondents who chose SF as their future main mode for inter-regional transportation. To add more details, Figure 35 shows the significant SF cluster differences by variable. SF Cluster 1 scored lower on every item compared to Cluster 2. Of the 13 demographic variables, only gender was significant. Three contextual trip variables were significant in profiling the SF clusters.

Figure 35

Comparisons of the Significant SF Cluster Means: by Variable



Note. SF = Commercial short-haul flight.

Summary

This chapter presented multiple univariate and multivariate statistical analyses to answer the two research questions. Findings from the univariate analyses provided insights into each measured characteristic of the sample population. Assumptions testing was conducted to ensure the results were reliable and valid. Multinomial logistic regression was used to identify factors that most influence air passengers' modal choice for inter-regional travel distances of under 500 mi (800 km). A 2-step CA was performed to identify distinct passenger clusters for SF and aMoD. Multivariate analysis of variance was used to validate statistically significant similarities and differences existing within the distinctive segments of SF and aMoD clusters. These results demonstrated that passenger segmentation based on multiple GFT variables, demographics, and trip characteristics could provide deeper insights into aMoD and SF passengers.

Chapter V presents a detailed discussion of the findings of the MNL, 2-step CA, and MANOVA. The discussion includes the use of GFT hedonic, gain, and normative goals in the context of air transportation research literature. It also provides the conclusions of this study and recommendations for future research.

Chapter V: Discussion, Conclusions, and Recommendations

The Discussion section of this chapter summarizes the chief research findings concerning the study's objectives, two research questions, and theoretical framework. It synthesizes the findings into the extant literature and evaluates the appropriateness of the GFT in the context of the study findings and air transportation research in general. The Conclusions section presents the deductions drawn from the findings, including theoretical and practical contributions of this study and the generalizability and limitations of its findings. The Recommendations section offers several opportunities to extend this original research in the future.

Discussion

Relevant univariate and multivariate analyses were conducted on the sample of 1,388 usable data observations. This discussion section describes and interprets the findings from the descriptive statistics, EFA, MNL, 2-step CA, and MANOVA to answer the two research questions. It describes the multimodal transportation model for future passenger mode choice and the distinct SF and aMoD clusters. Finally, the discussion section situates the chief findings in the relevant extant research.

Passenger Characteristics

Respondent characteristics (demographics, contextual trip variables, and COVID-related items) are comparable to those of the air passenger population. The survey population is considered representative of U.S. air passengers based on the following reasons. Firstly, even though some of the sample's demographic characteristics were slightly different from the U.S. air passengers (a younger and slightly more educated sample), other sample's characteristics were very similar to those of the air passengers (i.e., gender and neighborhood). Secondly, a rigorous sampling strategy minimized sampling errors, thereby enabling greater generalization of the findings. Third, a non-response bias test indicated no significant differences between non-participants and the respondents. Lastly, prior air transportation research supports many of the findings regarding demographic characteristics.

Becker and Axhausen (2017) and the NAS (2018) suggested that previous car crashes where someone was injured influenced a passenger's transportation mode choice. Similarly, Zhang et al. (2019) and the NAS (2018) found that the physical mobility of people traveling together also affects their mode choice. Results from this research support these literature findings. Even though 36% of the respondents had experienced a car accident in which someone was injured, only 29% of those who chose "drive a car" as their current main transport mode had experienced a car accident with injuries. This means "current drivers" had less prior experience of an accident with injuries than those using other main transport modes. In contrast, inter-regional bus travelers had a much higher percentage who had experienced car accidents with injuries before (current users = 58%; future users = 54%). Regarding mobility issues, 25% of the respondents or a family member has issues. Like the results for prior car accidents, a much lower percentage (12%) who have experienced mobility issues chose "driving a car" as their current mode choice. The inter-regional bus was the category with the highest percentage of respondents with someone in the household having mobility issues (current users = 48%; future users = 46%).

Contextual trip variables offered a deeper understanding of the study respondents' contextual trip characteristics and added further dimensions to the multimodal transportation choice model and the SF and aMoD cluster models. The distance between the respondents' homes and the nearest airport affected their current mode choice but not their future mode choice. Most respondents (74%) live between 15 to 45 min from the nearest airport. Only 8% live more than 1 hr drive from the nearest airport. Those who live between 15 to 45 min from the airport are more likely to rely on commercial short-haul flights or use an inter-regional bus than respondents who lived farther away. Like the results for home distance from the nearest airport, the percentage of short-haul flights from the home airport influenced the respondents' decisions with their current but not future mode choices. As expected, participants who drive as their primary mode for inter-regional leisure travel tend to drive with more people than participants who prefer SF. Business travel and its frequency influences current and future travel mode decisions. Before the pandemic, four of five respondents traveled for business, with 49% traveling for business 2 to 6 times per year and 17% traveling 7 or more times per year. Non-business travelers were more likely to select "driving a car" as their main mode (42%) versus flying (10%), inter-regional bus (3%), and inter-regional train (12%).

Current and Future Mode Choice

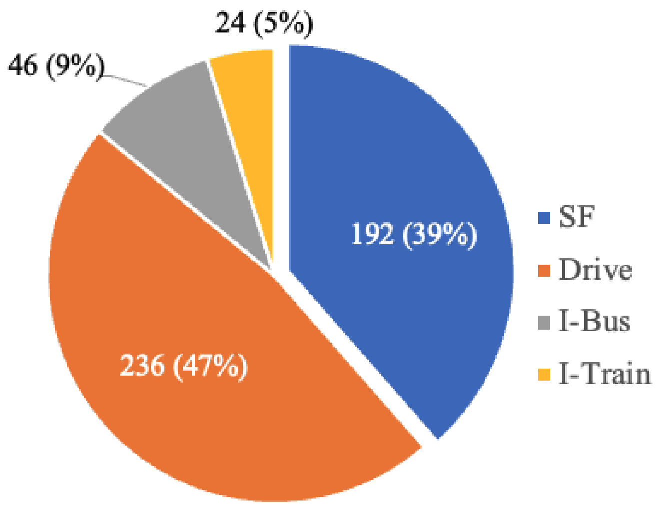
When the questionnaire was administered in October 2021, COVID-19 was still ongoing with significant impacts on the travel and transportation industries. As stated in Chapter IV, the terms current and pre-COVID mode choices are used interchangeably in this study and the term pre-COVID was used in the instrument so that the respondents would answer the questions with a "normal" frame of mind.

This study investigated passengers' travel behavior, perceptions, and attitudes toward inter-regional travel as part of passenger characteristics. The drive-time decision between SF air travel, driving, and aMoD transportation has not been studied before; therefore, this study adds to the knowledge of inter-regional ground and air transportation. The results show a 4 to 5 hr drive is the deciding factor beyond which most respondents would choose to fly instead of drive. Almost half (46%) of the respondents are very likely to drive instead of fly if the trip is a 2-hr drive. This percentage falls to 24% for a 5-hr drive and 15% for an 8-hr drive. The likelihood of using aMoD instead of SF if the trip is a 2 to 5 hr drive is higher than an 8 hr drive.

Regarding respondents' perception of aMoD and EV's rollout timing and usage, 1 in 3 passengers believe that aMoD will be commercially available in the U.S. in 6 to 10 years and 3 in 10 believe 3 to 5 years to be the aMoD rollout timeframe. Less than 3% believe aMoD will never become available. By 2030, 1 in 3 predict that half of the cars on the U.S. roads will be EVs, while 1 in 4 believe that half of the cars will be aMoD. Interestingly, by 2040, an equal percentage of the respondents (36%) predict that half of the cars on the roads will be both aMoD and EV. When comparing the current and future main transport choices (when aMoD is available), 36% (498) of the current air passengers will choose aMoD as their future primary transport mode. Figure 36 shows where the future aMoD passengers will come from: 39% (192/498) of future aMoD passengers will shift from the short-haul aviation transportation segment and almost half (236/498, 47%) will come from the traditional car (ground transportation) market. 46 out of 498 (9%) will be from the inter-regional bus and 5% will come from the inter-regional train.

Figure 36

Transportation Sources of Future aMoD Passengers

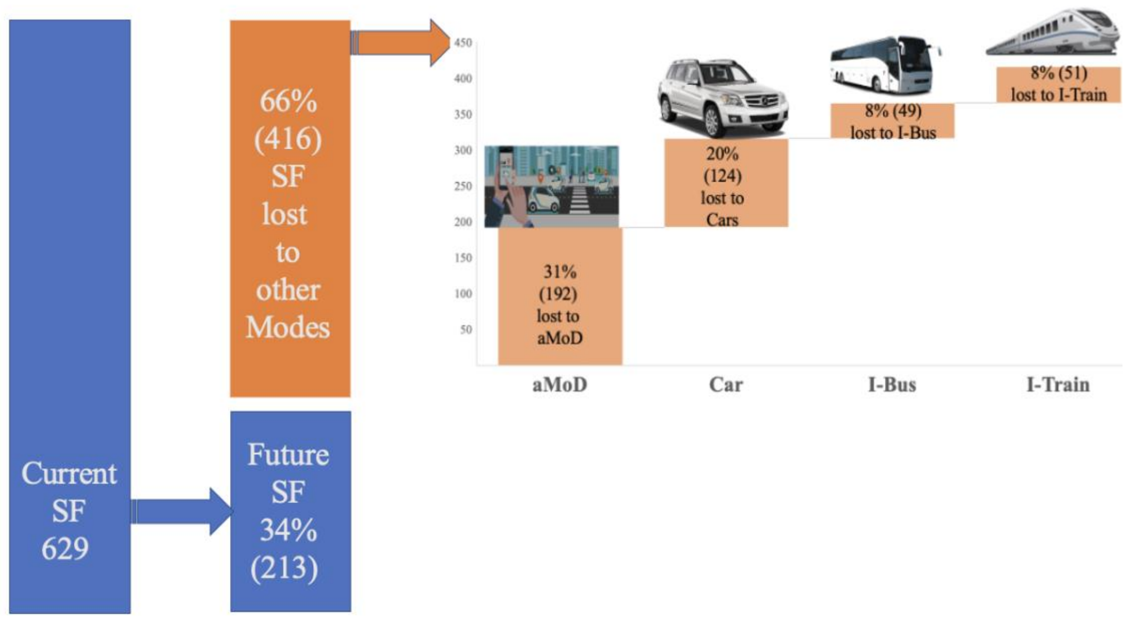


Note. aMoD = autonomous mobility-on-demand; SF = commercial short-haul flight; I-Bus = inter-regional bus; I-Train = inter-regional train.

Figure 37 shows the potential passenger shifts in mode choice from the current SF to future modes once aMoD is available. Of the 45% (*n* = 629) of the sample population who use SF as their current primary transportation mode for inter-regional travel, only 34% (*n* = 213) would continue relying on SF as their future transport mode. This means that 66% (*n* = 416) of the current SF passengers plan to shift to other transport modes in the future. Based on these research findings, the most significant SF market share loss (31%) may be to aMoD, and its second-largest loss (20%) may be to the conventional car. Furthermore, an additional 8% may be lost to the inter-regional bus segment and another 8% to the inter-regional train segment. In a 2016 study, LaMondia et al. estimated over 25% of the SF market will shift to the aMoD market. It can be assumed that air passengers' familiarity with aMoD has improved in the time since their study was published; therefore, these findings compare favorably with the 34% who plan to choose aMoD for the future.

Figure 37

Predicted Shift of SF Air Passengers to Other Transportation Modes



Note. aMoD = autonomous mobility-on-demand; SF = commercial short-haul flight; I-Bus = inter-regional bus; I-Train = inter-regional train.

Even the dominant car industry may lose market share to aMoD; 37% (514/1388) of the sample population who currently rely on driving for inter-regional travel may be reduced to 26% (n = 365) once aMoD becomes available. Of this driving population, 236/514 (46%) showed intention to use aMoD as their main inter-regional transportation mode in the future. It is interesting to note that while every transport mode loses passengers to the aMoD segment, the inter-regional train segment is expected to increase market share from 6% (n = 81) to 10% (n = 139 passengers). Such remarkable growth of 72% in the inter-regional train market could be explained by the increased popularity of high-speed trains where the trains are becoming a fierce competition to the airlines in some geographical areas, as discussed in Chapter III.

As expected, of the most traveled flyers (the 13% who fly more than 10,000 mi [16,094 km] per year), 48% of them currently choose SF as their primary transportation mode. However, in the future when aMoD is available, that number is expected to fall to 22%, a drop of 54% from the current number of air passengers. In contrast, aMoD will gain 34% in the most traveled segment of air passengers. Thus, more than half of the current most-traveled air passengers may be lost to aMoD in the future. The most-traveled passengers may be the most-profitable passengers. This dramatic shift from SF to aMoD may have a negative financial impact on airlines and airports. This finding is in line with Perrine et al.'s (2020) research. Perrine et al.'s model results showed that aMoD use may cause a decline in airline revenues by almost half (47%) and a 6.7% reduction in U.S. air passenger miles. Such shifts in transport mode choice would significantly affect many aviation- and transportation-related organizations, such as airlines, airports, infrastructure, land use planning, airway and highway congestion, ground vehicle and airplane design and manufacturing, and the travel and hospitality industries.

Pandemic Influences

Considering this air passenger study was conducted during the COVID-19 pandemic, the potential effects of the pandemic had to be evaluated. External shocks such as COVID-19 in 2020 reduced U.S. air demand by an unprecedented 66% (CAPA, 2021). Yet, by October 2021, 19 months after the initial pandemic "lock-down," half of the respondents (52%) had traveled by commercial air carrier during the pandemic. As expected, a high percentage were frequent air travelers who fly at least 5,000 mi (8,047 km) domestically per year. Respondents who selected SF or inter-regional bus for their current or future mode choices demonstrated a greater likelihood of flying during the pandemic. Regarding vaccination against COVID-19, frequent air travelers who fly over 25,000 mi (40,236 km) per year have the highest percentage of COVID-19 vaccination (96%), and surprisingly, the highest percentage of them have had COVID-19 (52%). This finding may be due to the contagious nature of the pandemic, particularly during the initial few months when there were no clear health safety guidelines.

Thomas and Darling (2021) found a university degree increases the likelihood to be vaccinated by 43%. Their finding is consistent with this study's findings that the percentage of vaccination increases with increases in the level of education. Respondents with a Bachelor's (88%), Master's (91%), or Ph.D. or post-doc degree (94%) have substantially higher vaccination rates than those who graduated from high school (68%) or attended high school (25%).

COVID-related influences are modeled along with the GFT variables, contextual trip attributes, and participant demographics to evaluate the impacts on air passengers' future transport mode decisions. Respondents who selected "drive a car" as their primary transport choice had the lowest vaccination percentage (81%) and, surprisingly, the lowest percentage of having had COVID-19 (18%). It is possible that this group is more mindful of self-isolation which explains their much lower percentage of COVID-19 infection. In comparison, those who chose the inter-regional train had the highest vaccination percentage (91%), and those who chose the inter-regional bus had the highest percentage of COVID-19 infection (51%). Regarding future mode choice, passengers who selected aMoD and SF had the lowest percentages of COVID-19 infection (23% and 24%, respectively). These results indicate the future mode choices of aMoD and SF might not be related to the pandemic fear which needs to be further explored.

Descriptive Statistics and Open-Ended Responses

Compared to those who selected SF, air passengers choosing aMoD as their future transport mode tend to be more environmentally conscious. Future aMoD travelers feel that those important to them care about the environment (normative), and they see themselves as an environmental role model for their friends and family. They believe that preserving the environment is a moral obligation and that electric vehicles are good for the environment. These findings on environmental and normative sentiments are consistent with those found in the research of Bösehans and Walker (2020), the NAS (2019), Vance and Malik (2015), and Westin et al. (2020). Future aMoD passengers have a higher sense of self-efficacy. Importantly, although these future aMoD passengers consider their current main inter-regional transport to be efficient, they plan to switch to aMoD when it becomes available to them.

While responses to the open-ended question added more dimensions and texture to the collected scale data, the respondents' comments only reinforced the current knowledge obtained in this research. Convenience is essential to air passengers who choose SF as their future inter-regional transport mode. Future SF passengers want to minimize their travel time. When traveling, they value their time doing something nice or useful. Many of these loyal air passengers do not want to sacrifice comfort, and they consider traveling to be fun. One air passenger stated, "*plane travel will remain supreme* *when time and convenience are involved*." Convenience is seen as one of the benefits of aMoD, particularly for the young, elderly, and travelers with pets. One respondent says, "*I'd travel more if driverless cars were available because I wouldn't feel stressed about getting lost or feeling tired from driving long hours ... especially traveling with children*."

As a counterpoint to convenience, some respondents mention the increased airport hassles after 9/11 as something to avoid at all costs. *"I live an hour from the airport and navigating the airport itself is time-consuming, a 2-hour flight can cost me 5 to 6 hours. I find it very annoying to spend that much time not accomplishing anything."*

As discussed in the literature review, safety and trust are intertwined and are necessary conditions for aMoD to be adopted. Control and self-efficacy are essential to some passengers, as is the value of their time. One passenger felt strongly about his/her fear of safety by saying, "*Autonomous cars will never be safe because corporations will always cut corners in their development and manufacture to increase profits. If driverless cars become widespread during my lifetime, I will fly more to avoid them*."

The dichotomy of the love and hate of the car shows up powerfully in the comments. Some respondents love driving for fun and value their freedom, "*traveling is my hobby, and I enjoy long drives*," while others are utterly "*anti-cars*." This latter group wants "*walkable cities with clean air*," preferring public transport and a "*carless*" society. Respondents harbor extreme feelings regarding driverless cars, ranging from "*I can't wait to use it*" to "*Just because we have the technology doesn't mean we should use it*."

One of the surprises in this research concerns the shift to inter-regional train travel. Of the four current transport mode choices, every mode is projected to lose passengers to aMoD except the train, which is expected to increase from 6% to 10% of the total future transport market. Unsolicited, more than ten respondents cite the train as their current and future mode choice. Two respondents even mention the Hyperloop in the future as economical time-saving transportation.

Responses to RQ_1: Future Transport Model

RQ_1. *Based on goal framing theory variables, demographics, contextual trip attributes, and COVID-19 items, what factors most influence air passengers' modal choice for inter-regional travel distances of under 500 mi (800 km)?*

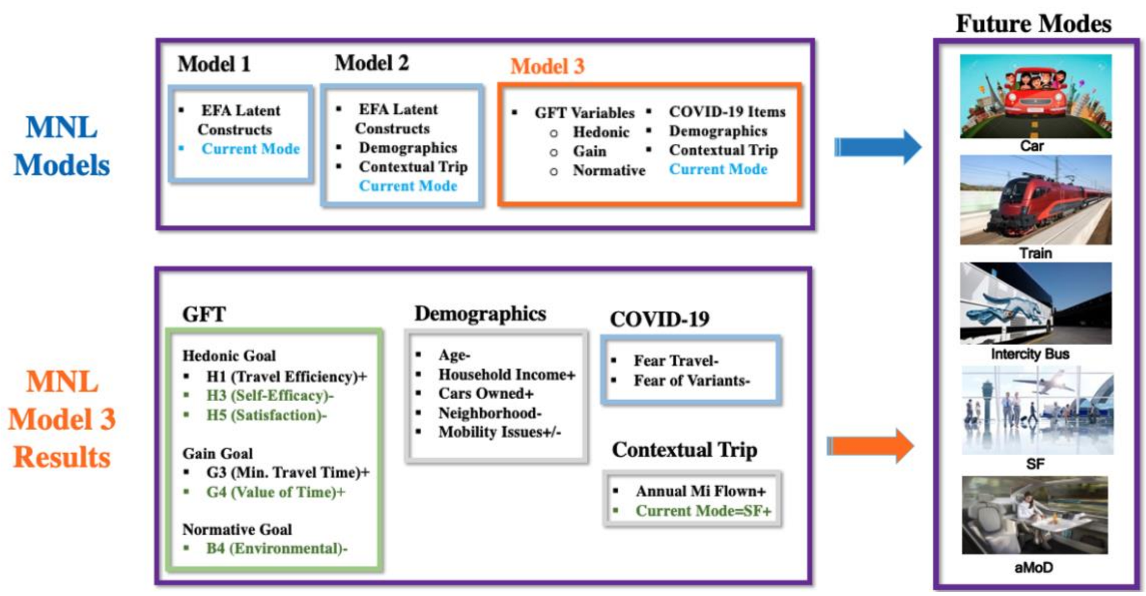
This section answers RQ_1. It discusses the 16 future mode choice predictors identified and explains the odds ratio of predictors on each future transport option. To address the current inter-regional transportation environment in the United States, four modes are considered main transportation: SF, driving a car, inter-regional bus, and inter-regional train. To address the future of this transportation environment, there will be five primary modes once aMoD is available for everyday travel: aMoD and the current four inter-regional options.

Three MNL models were tested to determine the optimal combination of the four latent constructs, GFT variables, COVID-19 variables, 13 demographics, and seven contextual trip variables in predicting the future transport mode choice. Figure 38 shows the 16 significant predictors for the best MNL model. The *current transport mode* is the most stable and consistent predictor, as it is the only variable that is a predictor in all three MNL models. Note, latent constructs F1 (GFT_Norms) and F2 (GFT_Hedonic) are common in two of the three models.

GFT Variables. The GFT is a theory with hedonic, gain, and normative goals as latent constructs. This theory has been applied to and validated by various social sciences studies including ground transportation. Almost half of the observed variables from the three GFT constructs were significant predictors in the final MNL model. Based on extant literature, *self-efficacy*, *value of time*, *habit*, and *trust* were added to the GFT framework for this study as shown in Figure 38. While *self-efficacy* and *value of time* were found useful in predicting future mode choice, *habit* and *trust* were not. (See the detailed discussion of GFT variables in Chapter II.)

Figure 38

Predictors for Future Transport Modes



Note. aMoD = autonomous mobility-on-demand; GFT = goal framing theory; min. = minimum; SF = commercial short-haul flight.

Habit. A traveler's habit denotes a typical behavior pattern triggered automatically by specific cues. *Habit* was not a predictor for future mode choice in this study. This finding is contrary to the land-based transport research results found by

Bösehans and Walker (2016), Thomas and Walker (2015), and Bösehans (2018). It is possible that Bösehans, Thomas, and Walker were studying everyday commutes (bus, walk, bike, etc.) whereas this research explores future transport modes which may not be as habit dependent.

Trust. *Trust* was not a predictor for future transport choices in this study. Trust is typically a critical factor in transportation research (Rahman et al., 2017; Zhang et al., 2019; Zmud & Sener, 2017), especially if it involves a new and innovative technology that passengers are less familiar with (Ashkrof et al., 2019; Vance & Malik, 2015). Ashkrof et al. (2019) and Molnar et al. (2018) found that trust in aMoD is the most critical factor in explaining future aMoD acceptance. Trust-related concerns include aMoD's capability to adhere to traffic laws (Schellekens, 2015), reliability under all weather conditions (Zhang et al., 2019), data privacy and protection from software hacking (Kyriakidis et al., 2015), and assurance in avoiding irrational and unpredictable pedestrian and driver behavior (Noy et al., 2018). Consequently, for governments and companies to overcome trust issues, they need to deal with passengers perceived social barriers and technological challenges. For this research, the four current transport mode choices were all familiar to the respondents. The future choice, aMoD, might be a transportation option that only becomes viable far into the future; therefore, it could have seemed more of a concept than a "real" transport mode to some respondents, which could explain why trust was not a predictor for future mode choice.

Another possibility is the fact that trust has many facets. As discussed in Chapter II, this study does not directly and deeply explore the different dimensions of trust. Empirical research by Yang and Xu (2019) concluded that trust has direct and indirect effects on acceptance. The direct effect is more important in explaining behavioral intention and willingness to use, while the indirect effect is essential in influencing general acceptance. Subjective norms may also play a role in trust and perceived safety. Based on extant literature, perceived safety, risks, benefits, and distrust are variables closely related to trust.

Self-Efficacy. *Self-efficacy* was added to the expanded GFT model because it affects personal choices regarding self-confidence in doing something successfully, especially in travel decisions (Bösehans & Walker, 2016). Bösehans' (2018) finding that *self-efficacy* is a key cluster variable in transport mode choice is consistent with findings from this present study.

Value of Time. This study found *value of time* to be a predictor of future mode choice; air passengers who value their time were 21.5% more likely to choose SF than aMoD. These findings lend support to Wadud's results (see Table 30) which state that higher-income households had a higher perceived value of time and that these higher-income households might equate higher automation as a means of increasing productivity (p.170). The value of time is associated with research on SF and aMoD (De Looff et al., 2018; Homem et al., 2019; van den Berg & Verhoef, 2016; Zmud & Sener, 2017). The NAS (2019) found that travelers would equate differences in the value of time via different mode choices. For example, travelers mentally equate 30 min of flying to 1 hr of driving.

Environmental Subjective Norm. Consistent with extant research, this study's subjective norm with environmental values was a predictor of future mode choice (Bösehans & Walker, 2020; Westin et al., 2020). As shown in Table 5, extant research supports age, household income, number of cars owned by the household, years with a driver's license, and mobility issues as predictors for future mode choice. The finding that neighborhood (city, suburban, and rural) is a predictor lends support to the National Academies of Science's (2019) findings that urban passengers most likely live near a major airport and rural passengers may need to drive a longer distance to a bigger airport with more direct flights. This present research finds more air passengers who live in rural America (39%) will choose driving as their future mode choice compared to passengers living in cities (22%). In contrast, for aMoD travel, more air passengers who live in cities (39%) will choose aMoD as their future transport mode compared to passengers living in rural communities (29%).

COVID-19. This study measured air passengers' perceptions and phenomena during the pandemic and found the fear of contracting COVID-19 when traveling is a predictor of future mode choice. This finding is consistent with Sun et al. (2020) and Linden (2020). The pandemic is currently a dynamic and global health concern; however, COVID-19 may cease to be a predictor for future travel decisions once the pandemic becomes endemic or a similar contagion as the flu.

Statistically Significant Parameters

This section discusses the meaning of the statistically significant parameter estimates (odds ratios) for each future transport mode choice. (See Chapter IV for the technical interpretation of the odds ratio.) Because odds ratios can be difficult to both convey and understand, Table 27 summarizes what it means for each predictor variable. It is important to note that SF is not presented as a separate mode choice in the table because it is the reference category to which every mode is compared.

Table 27

Future Main Transport Mode Predictions

Mode	Predictor Variable *	Odds Ratios per Unit Increase
aMoD	B2: Environment moral obligation	1.38 times more likely to choose aMoD than SF
	H3: Travel issues can be resolved	1.42 times more likely to choose aMoD than SF
	H5: Happy with transportation	1.87 times more likely to choose aMoD than SF
	G4: When I travel, I value my time	21% more likely to choose SF than aMoD
	C5: The economy is recovering	1.24 times more likely to choose aMoD than SF
	The current main mode is SF	32% more likely to choose SF than aMoD
Drive	Have/had COVID	39% more likely to choose SF than driving
	Family/self with a mobility issue	39% more likely to choose SF than driving
	Traveled by air during COVID	2.02 times more likely to choose driving than SF
	Vaccinated against COVID	46% more likely to choose SF than driving
	G4: When I travel, I value my time	32% more likely to choose SF than driving
	No. of cars owned by household	28% more likely to choose SF than driving
	The current main mode is SF	78% more likely to choose SF than driving
I-Bus	C4: SF if the price was low enough	1.44 times more likely to choose inter-regional bus than SF
	G3: Minimize total travel time	43% more likely to choose SF than inter-regional bus
I-Train	Highest education level	1.57 times more likely to choose inter-regional train than SF
	No. of cars owned by household	33% more likely to choose SF than inter-regional train
	Total household Income	1.44 times more likely to choose inter-regional train than SF
	The current main mode is driving	89% more likely to choose SF than inter-regional train
	The current main mode is SF	97% more likely to choose SF than inter-regional train

Note. aMoD = autonomous mobility-on-demand; No. = number; SF = commercial short-haul flight. The reference category is SF. * $p < .05$.

Predictors for aMoD in Relation to SF. Earlier findings reveal environmental protection is one of the predictors of future mode choice. The odds ratio analysis reveals that air passengers who feel strongly about environmental protection are more likely to choose aMoD as their future main transport mode than SF by 38%. Passengers who “strongly agree” with environmental protection are 38% more likely to choose aMoD than SF as their future primary mode compared to those who only “agree” with this construct. The analysis also indicates self-assured air passengers are 42% more likely to select aMoD as opposed to SF. Those who are happy with their current main transport choice are 87% more likely to choose aMoD over SF. Those optimistic about the economy recovering are 23.5% more likely to use aMoD in the future than SF.

Two predictors favor SF over aMoD. Household income is a predictor of future mode choice and air passengers who value their time are 21.5% more likely to choose SF rather than aMoD. These findings lend support to findings by De Looff et al. (2018). Also, loyal passengers who chose SF as their current primary transport mode for inter-regional travel are 31.9% more likely to select SF as their future mode instead of aMoD.

Non-Predictors for aMoD. Based on the odds ratio analysis, numerous variables do not appear to influence the future choice of aMoD over SF. Age, gender, education, household income, number of children, neighborhood, prior car accidents, mobility issues, drive frequency, annual fly miles, COVID vaccination, the distance between home and the nearest airport, and the percentage of direct flights to inter-regional destinations do not have a significant influence on future mode choice for aMoD.

Predictors for Driving Compared to SF. Of the seven predictors for driving as a future transport mode, only one favors driving over SF. Air passengers who had traveled by air during the pandemic are twice as likely to choose driving versus SF as their future mode. This is understandable because flying during the pandemic meant dealing with extra annoyances such as maintaining 6 ft distance from other air travelers waiting in queues, reductions in airport and airline services, and rigid mask mandates. Any additional hassles may worsen an already tense flying experience for some passengers. Furthermore, the FAA (2022) reports 2021 was the worst year on record for unruly air passenger behavior in the United States, and 72% of the 6,000 cases were mask related. The agency also reports the level of violence and aggression worsened with a spike in serious incidents. From 1995 to 2020, the FAA's average annual investigations rose from 182 to 1,081 cases, a 5-factor increase over the 25-year average (FAA, 2022). Naturally, such incidents can lead to long flight delays when an aircraft must divert or turnaround in response to unruly passengers.

Three of the seven predictors for driving are COVID related. They are whether the respondent (a) contracted COVID-19, (b) received a COVID-19 vaccination, and (c) traveled by air during the pandemic. Surprisingly, for air passengers who had COVID, the odds of choosing SF instead of driving is 39.5% higher. Yet, if the respondent had traveled by air during COVID, he or she is 2.02 times more likely to choose driving instead of flying. Passengers who are vaccinated against COVID-19 are 46.3% more likely to select SF in lieu of driving.

Although the pandemic had a significant impact on the respondents' choice of driving as their future transport mode, two predictors are more unexpected. The first is mobility issues for family or self. Air passengers who have mobility issues (self or family member) are 39% more likely to choose SF as their future mode choice than driving. Based on the literature, mobility issues would be a logical predictor of aMoD use because one of the benefits of driverless cars is greater accessibility for people with mobility limitations. The second surprising finding pertains to the number of cars owned by the household. Air passengers who own more cars are 28% more likely to choose SF as their future mode choice than driving.

Predictors for Inter-Regional Bus Compared to SF. There are two predictors for choosing the inter-regional bus in relation to SF. First, air passengers who would fly during the pandemic if the airfare was low enough are 1.44 times more likely to choose inter-regional bus as their future mode choice than SF. This could be because bus travelers are more money-conscious than SF passengers. Second, air passengers who aim to minimize their total travel time are 43% more likely to choose SF as their future mode choice than inter-regional bus.

Predictors for Inter-Regional Train Compared to SF. This category has five predictors. First, air travelers whose current mode choice is driving are 88.6% more likely to pick SF than inter-regional train travel. Second, this percentage increases to 97% if their current mode choice is SF, meaning loyal SF passengers will almost certainly select SF as their future mode instead of an inter-regional train. Third, air passengers with higher household incomes are 43.9% more likely to use the inter-regional train in the future instead of SF. The fourth predictor is the level of education. Similar to household income, the likelihood of choosing inter-regional train over SF increases 1.57 times with each education degree obtained. The fifth predictor is car ownership. Surprisingly, passengers with more cars owned by the household are 33% more likely to select SF than the inter-regional train as a future transport mode choice.

While it is essential to recognize the future transport mode choice predictors, it is as critical to identify the latent factors and variables that are non-predictors in the final MNL model. The four latent factors validated by the EFA were not in the final model. In contrast, six of the original 16 GFT variables were better predictors in the final model, as presented in Figure 4. The GFT variables that fail to predict future mode choice include *effort/access*, *comfort*, *hedonic values*, *convenience*, and *cost*. It is possible that these variables are specific to each individual mode choice, and therefore, are critical only when they are in direct comparison with specific measures by mode choice. In this case, evaluation of these variables by travel scenarios may yield results different from this study.

When asked about the future, the respondents may focus on higher-level concepts versus detailed-level variables. Cost and time are archetypal tradeoffs in transportation, with a common perception that flying saves time and driving saves money (Chen et al., 2019). As such, the value of time is also a factor in the cost equation (NAS, 2019; Wadud, 2017). While the value of time is a predictor, cost is not. The reason may be because of not defining or comparing the cost of aMoD to other transport modes for this study and not knowing the specific timing for the future aMoD rollout. Other non-predictors are:

- H7: Traveling is fun for me.
- G2: Convenience is very important to me when I travel.
- B5: It is important for me to be a role model for my family in environmental protection.
- C3: My disposable income has increased since COVID started.
- The number of children living at home.
- The number of driver's licenses in the household.
- Driving frequency.
- A car accident in which someone was injured.
- Business travel pre-COVID.
- Distance between home and the nearest airport.
- Percentage of direct flights from the home airport.

In summary, this section focused on RQ_1. Sixteen future mode choice predictors were identified and discussed, and the meaning of the odds ratios of the predictors for each future transport option were reviewed.

Responses* to *RQ₂*: *Distinct SF and aMoD Clusters

RQ_2. *What distinct passenger clusters exist for SF and aMoD? How are these clusters similar/different within the SF and aMoD segments?*

This section answers RQ_2. The focus is on understanding the air passengers who make up the distinct SF and aMoD segments.

Distinct SF Passenger Clusters. Four EFA latent constructs are used to cluster the future SF passengers to understand their distinct characteristics. Examination of the demographic and contextual trip attributes not included in the cluster variates provide the similarities and differences between the two SF clusters (see Table 28). There are slightly more members in SF Cluster 2 than in Cluster 1. SF Cluster 1 consists of apathetic travelers who are neutral about most issues, from various aspects of hedonic and gain goals to their environmental attitudes. There are twice as many males as females in this segment. The apathetic air passengers have no particular care about most travel attributes, even the pandemic. They have no travel habits and no opinions about the value of time, convenience, or comfort. They are not concerned about the environment and do not feel obliged to be an environmental role model for their friends and family. When traveling for leisure, they tend to travel in a smaller group than Cluster 2.

SF Cluster 2 is comprised of loyal habitual flyers. These happy SF flyers feel that flying is safe and very efficient. They have strong self-efficacy with travel issues and are more reluctant to sacrifice comfort compared to apathetic travelers. The loyal habitual flyers think traveling is fun and are happy with inter-regional transportation in general. They are keen to minimize travel time and have a strong value of time. In terms of environmental norms, loyal habitual flyers show moderate concerns about the environment and being environmental role models to their friends and family. They think EV is good for the environment and expect 50% of the cars in the United States to be EV in 2030, a decade faster than apathetic travelers. They perceive the economy to be recovering and show medium concern toward getting COVID or its variants while traveling. Indeed, they would travel by air if the ticket price were low enough during COVID. While traveling for leisure, loyal habitual flyers tend to fly with more people together than by car. Surprisingly, they consider cost more critical in their decision than apathetic travelers.

Table 28

Differences Between SF Clusters

	SF Cluster 1: Apathetic Travelers *n* = 133 (45.7%)	SF Cluster 2: Loyal Habitual Flyers *n* = 158 (54.3%)
GFT Hedonic Goal [a]	Main transport is reasonably efficient	Main transport was very efficient
	Less happy with current main transport	Happy with current main transport
	Will sacrifice comfort	Reluctant to sacrifice comfort
	Weaker self-efficacy with travel issues	Strong self-efficacy with travel issues
	No travel habit	Stronger travel habit
	Neutral about inter-regional transportation	Happy with inter-regional transportation
	No particular opinions about SF safety	Feels safe about SF
	Traveling is neither fun nor not fun	Traveling is fun
GFT Gain Goal [a]	Cost is less important than C2	Cost is more important than C1
	Total travel time not as important	Keen to minimize travel time
	Average value of time	Strong value of time
	Convenience is not as important	Convenience is very important
GFT Environmental Norms [a]	No concern about the environment	Moderate concern about the environment
	No environmental moral obligation	Moderate environmental moral obligation
	Not an environmental role model	Moderate environmental role model
	Neutral about EV	Positive about EV; good for the environment
COVID Fear & Financial Concerns [a]	No concern about COVID-19/variants	Medium concern about COVID-19/variants
	Perceive economy not recovering	Perceive economy was recovering
	Will not travel by air even if price is low during pandemic	Will travel by air if price is low enough during pandemic
Demographics	Twice the number of men	Almost equal number of men and women
Contextual Trip Attributes	Fewer people travel together for leisure by car (2 or 3)	More people travel together for leisure by car (3 or 4 or more)
	Slightly fewer people travel together for leisure by air (2 or 3)	Slightly more people travel together for leisure by air (2 or 4 or more)
	Expects 50% EV in the U.S. by 2040	Expects EV in the U.S. by 2030

Note. EV = electric vehicle; GFT = goal framing theory; SF = commercial short-haul flight. [a] Latent constructs.

While there are differences between the apathetic travelers and the loyal habitual flyers, there are more similarities between these two SF groups than differences. Table 29 lists the similarities.

Table 29

Similarities Between SF Clusters

Similarities Between Apathetic Travelers and Loyal Habitual Travelers
1. Current main transport mode (majority are SF)
2. Age (most between 25–54 years)
3. Education (most have a bachelor's or master's degree)
4. Household income (most earn between $50,001–$100,000)
5. Number of children living in the household (very few have 3 or more)
6. Number of driver's licenses in the household (most have 2)
7. Years with a driver's license (most > 15 years)
8. Number of cars owned by the household (most have 1 or 2)
9. Weekly drive frequency (most > 5 times per week)
10. Neighborhood (most in cities and suburbs)
11. Mobility issues (majority do not have any)
12. Distance from home to the nearest airport (most 15–30 min)
13. Direct flights (most home airports offer 41%–60%)
14. Annual miles flown (most are 5,001–10,000 mi)
15. Fly if over a certain drive-hours (average 5 hr, lower than aMoD clusters)
16. Frequency of business travel (most 2–6 times a year)
17. Vaccinated against COVID-19 (majority are vaccinated)
18. Have/had COVID-19 (majority have not had COVID)
19. Traveled by air during COVID (most have flown during COVID)
20. % work from home during COVID (75%–100%, higher than aMoD clusters)
21. Inter-regional bus and train (most have used them)
22. aMoD timing in the U.S. (most state 6–10 years)
23. Timing when 50% of cars in the U.S. are aMoD (by 2040)

Note. SF = commercial short-haul flight.

Taken together, these findings suggest that while there are distinct differences between the two SF clusters, SF passengers as a group reveal more similarities than differences.

Discussion of the Distinct aMoD Passenger Clusters. Four EFA latent constructs are used to cluster future aMoD passengers to understand their distinct characteristics. Examination of the demographic and contextual trip attributes not included in the cluster variates provides a rich description of the two aMoD clusters as shown in Table 30. These two almost equal-sized clusters differ in multiple dimensions. Considering aMoD is a future transport mode choice, all 498 passengers have shifted to aMoD from other transportation options. As shown in Figure 38, 47% shift from “drive a car” and 39% shift from SF to aMoD. The results in Table 30 clearly illustrate the genesis of the new aMoD passenger segments.

The aMoD Cluster 1 consists of the suburban rural drivers. Many live in the suburbs or rural America, and naturally, their current transport mode is predominantly driving a conventional car. While their current primary mode is moderately efficient, compared to Cluster 2, suburban rural drivers are less happy with their current main transport. When aMoD is available, suburban rural drivers will switch to aMoD as their primary transport mode choice. Suburban rural drivers tend to express negative sentiments towards the GFT goals (hedonic goals, gain goals, and environmental subjective norms). Specifically, the suburban rural drivers have weaker self-efficacy with travel issues and are more willing to sacrifice comfort for other travel attributes. Total travel time is not as important, and their value of time is not as strong as it is to Cluster 2 passengers. They are neutral about EVs and the environment. Incomes of suburban rural drivers fell during the COVID-19 pandemic, and they perceive a worsening economy. This group of travelers is not concerned about COVID-19 and its variants, and a lower percentage of them are vaccinated against COVID-19 compared to Cluster 2.

Table 30

Differences Between the aMoD Clusters

Differences	aMoD Cluster 1: Suburban Rural Drivers *n* = 255 (51.2%)	aMoD Cluster 2: Urban Educated Flyers *n* = 243 (48.8%)
GFT Hedonic Goal [a]	Main transport is fairly efficient	Main transport is very efficient
	Less happy with current main transport	Happy with current main transport
	Will sacrifice comfort	Reluctant to sacrifice comfort
	Weaker self-efficacy with travel issues	Strong self-efficacy with travel issues
GFT Gain Goal [a]	Total travel time not important	Keen to minimize travel time
	Average value of time	Strong value of time
	Convenience is not as important	Convenience is very important
GFT Normative Goal [a]	Neutral about the environment	Pro-environment subjective norm
	Neutral about EV	Positive about EV
	Income decreased during pandemic	Income increased during pandemic
	Perceives economy is not recovering	Perceives the economy is recovering
	Will not travel by air even if price is low during pandemic	Will travel by air if price is low enough during pandemic
Demographics	Lower education	Higher education
	Lower household income	Higher household income
	Fewer children living in the household	More children living in the household
	Fewer with mobility issues	More with mobility issues
	Reside in suburbs and rural America	Reside in cities
	Fewer work at home during pandemic	More work at home during pandemic
	Fewer vaccinated against COVID-19	More vaccinated against COVID-19
Contextual Trip Attributes	Majority drive as current transport mode	Majority choose SF as current transport mode
	Less frequent business travel	Frequent business travel
	Fewer direct flights from home airport	More direct flights from home airport
	Fewer annual miles flown	More annual miles flown
	Lower percentage use I-bus and I-train	Higher percentage use I-bus and I-train
	Fewer will travel for leisure by car	More will travel for leisure by car
	Fewer will travel for leisure by air	More will travel for leisure by air
	Fly if over 5.7 hr of driving	Fly if over 5.3 hr of driving
	Expects aMoD and EV rollout later	Expects aMoD and EV rollout sooner

Note. aMoD = autonomous mobility-on-demand; EV = electric vehicles; I-bus = inter-regional bus; I-train = inter-regional train; SF = commercial short-haul flight.

[a] Latent constructs.

Suburban rural drivers would not travel by air during COVID even if the price were low. Demographically, they tend to be less educated, have lower household incomes, and have fewer children living in the household. Compared to Cluster 2, a lower percentage of suburban rural drivers have mobility issues and fewer work remotely from home. They do not travel for business as much as the urban educated flyers. They have accrued fewer annual air miles and their home airports offer fewer direct flights than Cluster 2. Suburban rural drivers are less optimistic about EV and aMoD's rollout timing. On average, they would fly only when the drive time is over 5.7 hr.

The aMoD Cluster 2 consists of urban educated flyers. Many live in the cities and their current transport mode is predominantly SF. Miller (2017) found 90% of air passengers flying short-haul routes choose direct flights, with only 10% willing to connect, demonstrating SF markets are dependent on the availability of direct flights. This study supports Miller's findings that the availability of direct flights is a significant segmentation attribute. Urban educated flyers want direct flights because they aim to satisfy their GFT goals of minimizing total travel time and maximizing the value of time. They view their current main mode as very efficient and are happy with their current main transport. Nevertheless, when aMoD is available, they will choose aMoD as their main transport mode. The urban educated flyers tend to feel optimistic about the GFT goals (hedonic goals, gain goals, and environmental subjective norms). Specifically, they have strong self-efficacy with travel issues and are less willing to sacrifice comfort for other travel conveniences. Indeed, convenience is critical to them. Incomes of the urban educated flyers rose during the pandemic, and they perceive the economy as recovering well. They are pro-environment and are hopeful about EV and aMoD's rollout in a timely manner. They are frequent business travelers and have accrued more annual air miles compared to suburban rural drivers. This group of travelers is more concerned about COVID-19 and its variants and a higher percentage of them are vaccinated against

COVID-19 compared to suburban rural drivers. However, they would travel by air during the pandemic if the ticket price were low enough. Demographically, urban educated flyers tend to have higher levels of education and higher household incomes and have more children living in the household. Compared to suburban rural drivers, a higher percentage of them have mobility issues (themselves or a family member). A higher percentage of the urban educated flyers work remotely from home. Their home airports offer more direct flights. On average, urban educated flyers fly instead of driving when the drive time is over 5.3 hr.

While there are many differences between suburban rural drivers and urban educated flyers, these two aMoD groups are similar in:

- gender (more men than women),
- age (mostly between 25–44 years),
- number of driver's licenses in the household (most have 2),
- years with a driver's license (most are > 15 years)
- number of cars owned by the household (most have 1 or 2),
- weekly drive frequency (most > 5 times per week),
- distance from home to the nearest airport (most are 15–30 minutes),
- have/had COVID-19 (the majority had not contracted COVID),
- aMoD timing in the United States (most are 6–10 years)

In summary, these findings indicate there are distinct differences and similarities between the two aMoD clusters.

Conclusions

This study aimed to develop a model to identify factors that most influence U.S. air passengers' inter-regional modal choice in the future when aMoD is available. Furthermore, it sought to identify passenger clusters for SF and aMoD and evaluate the similarities and differences of these clusters. The findings support the GFT as a theoretical framework for the future mode choice model and as a foundation for clustering and profiling the SF and aMoD segments. Of the 16 significant predictors for the MNL Model, the current main transport mode was found to be the most critical predictor. All three GFT constructs were significant predictors in the final MNL model. *Self-efficacy*, *value of time*, *habit,* and *trust* were new variables added to the GFT framework based on extant literature. The first two were found useful in predicting future mode choice; *habit* and *trust* were not.

Using the four latent constructs—GFT hedonic goal, GFT gain goal, GFT normative goal, and COVID influence—this research clustered air passengers who selected SF and aMoD separately, resulting in distinct SF and aMoD clusters. There are two SF clusters: apathetic travelers and loyal habitual flyers. It is alarming that 66% of the current SF passengers intend to shift to other transport modes once aMoD is available; 31% of the current SF market share could be lost to aMoD and 20% to conventional driving. Furthermore, over half of the current most-traveled air passengers intend to use aMoD as their main transport choice in the future. The loyal habitual flyers are important passengers to the aviation industry as they form the core of SF flyers. Future aMoD passengers come mainly from the current SF (47%) and car/drive (39%) modes. This study found two clusters within the aMoD category: suburban rural drivers and urban educated flyers. As frequent business travelers, urban educated flyers have accrued more annual air miles than suburban rural drivers. Airlines and airports cannot afford to lose these SF customers to aMoD.

During this study, the pandemic was (and continues to be) a global health concern, so it is addressed. While this research considered the potential influence of the COVID pandemic, the primary focus is on travel choices in general. The results indicate that the fear of COVID-19 and its variants is a predictor of future mode choice, consistent with Sun et al. (2020) and Linden (2020). There are a few findings that are worth mentioning. Unlike the extant literature (Becker & Axhausen, 2017; NAS, 2019; Zhang et al., 2019), prior car accidents and mobility issues do not seem to influence SF passengers' current and future mode choices. Non-business travelers are more likely to select driving as their future main mode. The distance between one's home and the nearest airport affects the current but not future transportation choices. Those living within 45 min of an airport are more likely to fly SF than those who live farther away. The decision point where most would choose to fly instead of drive is between 4 and 5 hr. Nearly half of the air passengers are very likely to drive instead of fly if the trip is a 2-hr drive. The likelihood of using aMoD instead of SF increases if the trip is a 2 to 5 hr drive. Considering these findings, airports and airlines must improve their understanding of their current and future customers to protect and increase their market share.

Theoretical Contributions

This study makes six theoretical contributions to the body of aviation and inter-regional transportation literature. Each one is a first in its category.

1. GFT is a theory with hedonic, gain, and normative goals as latent constructs. This theory has been applied to and validated by various social sciences studies, including ground transportation. However, this study is the first application of GFT to air transportation research. The GFT constructs were used as core input on the multimodal model for inter-regional travel and SF and aMoD cluster models. Based on the extant literature reviewed in Chapter II, two new GFT variables, *self-efficacy* and *the value of time* were found useful in predicting future mode choice and in the SF and aMoD cluster models.
2. While there have been increasing studies on aMoD in the past few years, there is no identifiable aMoD research on SF and inter-regional travel. This multimodal study presents the first exploratory model examining SF and aMoD clusters in the context of inter-regional transportation in the United States.
3. This research presents the first multimodal model using SF, aMoD, and the full array of current transport modes to gain a more realistic set of transportation options for inter-regional travel. This is accomplished by using multivariate logistic regression with 4 current and 5 future modes instead of the typical binary logistic regression with 2 mode choices.
4. With the increasing popularity of aMoD, prolific research has focused on different geographical locations, levels of automation, customer attitudes and perceptions, legal and regulatory challenges, and technical improvements. Studies have addressed different perspectives, including local and national

governments, AV passengers, commercial drivers (who may lose their jobs), insurance companies, manufacturers, disabled, young, and elderly. This study is the first to examine the perspectives of air passengers in aMoD research, thus gaining more insight into the potential competing modes in the inter-regional transportation market.

5. Examination of the five COVID-19 items added to this research to test for any pandemic effects in the MNL and CA models is a new theoretical contribution. These items are significant in the future transport choice models and in the SF and aMoD cluster models.
6. The drive-time decision between SF, driving, and aMoD has not been studied previously. Therefore, findings from this study add to the scholarly knowledge of both inter-regional ground and air transportation.

Practical Contributions

Transportation planning, infrastructure design, and policy-making take time. Four practical contributions of this research provide actionable insights for aviation and other transport planners, operators, and designers:

1. A better understanding of factors influencing future transport mode choices and characteristics of the different SF and aMoD passenger segments can help aviation operators and planners develop and improve service and communications strategies to keep and grow their customer base. For example, the data suggest that loyalty matters: Loyal SF passengers are more likely to choose SF and less likely to choose aMoD as their future mode choice. Knowing the extent of potential competitive threats from aMoD and

the characteristics of the aMoD and SF clusters provides operators and planners the “what” and “to whom” to focus their efforts.

2. Emerging ground transportation technologies such as aMoD may substantially impact competitiveness and revenues in the U.S. airline industry. Significant shifts in ground and air mode shares revealed in this study may have crucial impacts on airlines, airports, infrastructure, future land use planning, airway and highway congestion, and the travel and hospitality industries. Until this study, little was known about the degree to which aMoD might impact SF, the characteristics of air passengers most inclined to select aMoD over SF, and the loyal air passengers who would stay with SF when aMoD is available. U.S. airlines and airports will need to consider changes in ground transport modes in their planning, including potential impacts on operations and business models, to remain viable and relevant.
3. Since planes travel faster than aMoD, city-pairs that are more than an 8-hr drive (500 mi or 800 km) should be largely immune to these ground alternatives. Nevertheless, inter-regional travel between city-pairs such as Los Angeles–San Francisco and Houston–Dallas may become dominated by aMoD. This research provides timely information to assist airlines and cities of all types and sizes in planning for the potential mid-to-long-term impact of aMoD.
4. Understanding the similarities and differences of early adopters of aMoD provides aviation operators with details needed to create critical business and communication strategies for passenger retention.

Limitations of the Findings

Although there are limitations in the scope and research design in this study, the importance of its findings is retained due to the thoughtful sampling strategy and execution. Inter-regional transport modes of the future may include advanced forms of urban air mobility where aerial vehicles may have the capacity to travel up to 500 mi (800 km). However, this study was limited to inter-regional transportation focusing on aMoD and did not investigate other potential forms of future ground and air vehicles.

Time and budget constraints contributed to limitations in the research design. Probability random sampling offers representativeness and is the gold standard of research. While this study did not use random sampling, every effort was employed in the research design and execution to minimize threats to external validity to enable the generalizability of the findings to air passengers and relevant future contexts. For example, steps included a thoughtful sampling strategy supported by a non-response bias test to strengthen external validity. In addition, the data were collected at a single point in time using an online data collection method. This study can be repeated at different geographical locations over time to demonstrate and enhance the reliability of the results.

Legal and regulatory implications, safety and security, and the economic impact of aMoD were not a part of this study. Given the rapid advancements in technology, safety and security environments, regulations, and economic conditions, it was not feasible to include these factors in the first exploratory study of SF and aMoD.

Survey research is an excellent methodology because it is designed to capture the attitudes, opinions, and perceptions of a large number of people at a point in time. However, close-ended items limit the freedom of expression respondents have on areas of interest. While there was one open-ended question in the instrument used in this study, the richness of the data collected on each scale item is limited.

Recommendations

The results of this study prompt several recommendations for the aviation industry, future research methodology, and future research.

Recommendations for the Aviation Industry

The U.S. commercial aviation industry is a low-margin business coupled with a declining long-term profit trend and intermittent volatility (Bachwich & Wittman, 2017; Saxon & Weber, 2017). However, SF is a large market critical to airlines, airports, travelers, and regional and local economies. With the approaching introduction of aMoD as a viable future mode choice in inter-regional travel, there will be substantial shifts in transport modes that could significantly disrupt the aviation industry. Shaheen and Cohen (2019) cited transportation network companies (TNC) as catalysts for aMoD. Indeed, the rapid adoption of TNC by travelers has created a new paradigm in transportation, leaving traditional taxi companies struggling to remain competitive (Clewlow et al., 2017). Prior to TNC, passenger behavior regarding ground transportation to and from airports had remained relatively stable in the United States. As such, airport access and facility planning directly and almost proportionately correlated to originating air passenger forecast. While TNC affected airport curbside traffic, it did not compete with airlines. This dynamic is expected to change with aMoD which will directly compete with SF. Consequently, aMoD will impact the revenues and operations of airports and airlines.

This study found that 45% of air passengers (629/1,388) currently use SF as their primary mode for inter-regional travel; however, only 34% of these SF passengers

(213/1,388) anticipate continuing with SF once aMoD is operational, which supports Rice and Winter's 2018 findings. This is a 66% reduction to SF's market share, with most of the loss (192/1,388) going to aMoD. Therefore, it behooves stakeholders, managers, and planners of airports, airlines, and cities to understand the characteristics of the SF and aMoD passenger segments and predictors for SF and aMoD as inter-regional mode choices.

Loyal SF passengers are likely to choose SF in the future, but airlines need to do everything possible to please these loyal customers to keep them from shifting to aMoD. Loyal passengers value their time while traveling and aim to minimize their total travel time. They do not want to sacrifice comfort even though they are confident they can fix any travel issues. To expand this vital group of customers, airlines may need to improve their end-to-end service to convert neutral customers to loyal customers and nurture loyal customers to become ambassadors. This customer retention strategy involves approaching client service from the passengers' perspectives and not from the airlines' traditional operational viewpoint. Diller (2022) reported that United and American airlines have initiated a limited version of transport-as-a-service (TaaS) in a few markets where customers buy a ticket that includes plane and bus fares and seamless luggage transfer. Customers also earn miles and loyalty points while they are being transported on inter-regional buses with leather seats and free Wi-Fi. While the motivation for this air/bus partnership may be due to pilot shortage and cost control, forcing airlines to focus on larger airports and more profitable routes (Diller, 2022), this air-to-bus connection is an excellent first step toward TaaS.

Environmental concerns add another dimension to the SF challenge. This research found that air passengers who are more pro-environment tend to choose aMoD or the train as their future primary transport mode; therefore, the aviation industry must improve customers' perception of commercial aviation's environmental impact. More than half of the current most-traveled air passengers intend to use aMoD as their primary future transport choice. These frequent flyers are the airlines' most valued customers, and they cannot afford to lose them. Again, knowing who they are from the cluster models developed in this study could help airlines improve their communications and service strategies.

Another beneficiary of the SF market shift is the train. As mentioned earlier, while every other current transport mode loses passengers to aMoD, the inter-regional train segment might increase its total future market share from 6% to 10%. Convenience and the pro-environmental movement may have contributed to this shift. There is increasing pressure for regulators and governments to ban, tax, or otherwise disincentivize SF in favor of greener modes such as rail and HSR. Traveling by HSR is eco-friendly, using only one-eighth of the electricity per passenger mile compared to commercial aviation and 14 times less carbon-intensive than car travel (B1M, 2019). In parts of Europe, SF is banned where there is a rail substitute that can serve the destination within a reasonable time.

In a few densely populated urban areas of the United States, the train is already fierce competition for the airlines. Having the most congested airspace nationally, the Northeast experienced half of all airspace delays in 2017 (Federal Aviation Administration [FAA], 2020). As a result, whether due to air traffic density or weather conditions, airports in this region rank near the bottom of a list of 284 airports in North America for on-time performance (Rowland, 2020). Collectively, American, Delta, JetBlue, and United sold 11.8 million seats in 2019, while Amtrak had 12.1 million passenger trips in the same period, slightly more than all airline seats combined (BTS, 2020). Notably, Amtrak carried three times more passengers than all U.S. airlines combined for the 207 mi (333.3 km) Washington–New York city pair (BTS, 2020). As environmental pressure increases and HSR's availability improves, this shift may pose an additional economic threat to SF.

Last and most importantly, if airlines are to thrive and remain relevant, they must expand the view of themselves as full-service providers in the mobility business and not purely as commercial flyers. Over a century ago, the train was the dominant choice of transportation for passengers in the United States. Nevertheless, owners and operators narrowly defined it as "the train business" versus "the transportation business." While the train industry focused on train services, train passengers migrated to driving cars, and the car's dominance has lasted for over a century. Fast forward to 2022, if airlines continue to see their industry as solely in the business of flying people and goods as opposed to being in the mobility business providing TaaS/MaaS, they may lose the market to new forms of mobility such as aMoD, urban air mobility (UAM), and Hyperloop. Adaptation requires a fundamental shift by taking "a first principle" approach to serving travelers. Doing so can transform the aviation industry and its ecosystem, and time is of the essence.

Recommendations for Future Research Methodology

There are two recommendations for future research methodology. The first recommendation relates to the data collection instrument. Although meticulous care was taken to develop the pretest and pilot study, because the GFT is new to air transportation research, more items can be added to the GFT constructs to be validated using CFA and SEM to strengthen the instrument. This may improve the Cronbach's alphas for the GFT gain goal.

The second recommendation is to use probability random sampling. If the top 10 airlines in the U.S. provide their passenger list for the past 2 years for research, probability random sampling can ensure greater generalizability to the air passenger population. This effort would be cost- and time-intensive and would require the airlines to cooperate, which may be an unsolvable challenge.

Recommendations for Future Research

There are seven recommendations for future research:

1. While this study has revealed an initial perspective on the multimodal transportation choice model and the SF and aMoD cluster models, the increasing availability of data as aMoD emerges is likely to require refinements to these inter-regional transportation models. Until aMoD is fully operational on U.S. roads, public perceptions of aMoD will continue to fluctuate with its media attention. Consequently, periodic research with greater nuances can make valuable contributions to the knowledge in this area of air transportation research. For example, remote work (telework) is likely to remain higher than pre-pandemic levels or even increase over time,

negatively impacting business travel frequency. Potential threats from remote work to inter-regional travel could be examined in future research. Similarly, as the U.S. population ages, the demographics of inter-regional travelers will change, impacting the aMoD and SF clusters and model results obtained in this study. Therefore, the implications of such changes should also be investigated in the future.

2. The future multimodal transportation choice model and the cluster models can be modified to include other emerging transportation modes. Potential candidates include urban air mobility and Hyperloop. Together, aMoD, UAM, and hyperloop could form a seamless air-ground door-to-door MaaS.
3. SEM can use a structural measurement to determine a theoretical causal model. Bearing in mind the GFT framework is new in aviation research, SEM may provide important insights into the use of GFT in air transportation study.
4. It could be beneficial to repeat this study at different geographical locations over time to enhance the reliability of the results. Transportation research is different based on history, culture, and geographical locations. Changes in times, locations, and cultures can provide richer insights in the transportation similarities and differences between countries and cultures.
5. Since aMoD has not been commercially implemented yet, it is an opportune time to begin longitudinal research to study changes in attitudes and perceptions on SF, aMoD, and other travel modes over time. An observational study of this magnitude could provide needed information to the air transportation industry.

6. The results from this study showed that 36% of the current air passengers are likely to choose aMoD as their future primary transport mode. Furthermore, 39% of future aMoD passengers are likely to come from the short-haul aviation transportation segment and almost half are likely to come from the traditional ground transportation market. To gain a deeper understanding of airport leakage from small- and medium-sized airports to the bigger hubs, extend the research by Ryerson and Kim (2018) to examine the impact of aMoD transport mode on the magnitude of airport leakage based on airfare and availability of direct flights.
7. A proven safety record and consumer perceptions of safety and trust are not necessarily the same, yet all are important enablers and inhibitors of transportation use. This study examined safety and trust as variables, not as constructs, and assumed perception of trust and safety would not inhibit aMoD adoption once aMoD becomes available in everyday life. Yet, these constructs are intertwined and necessary conditions for aMoD to be widely adopted. Therefore, future research could extend this research by focusing on safety and trust constructs to identify their similarities and differences between and within aMoD and SF clusters.

Summary

This chapter discussed the implications of critical findings in answering the RQs. The future introduction of aMoD as a viable mode choice, combined with the knowledge that 39% of the future aMoD passengers may come from the SF market, makes it prudent for today's aviation and transportation planners, managers, and operators to understand key predictors in the future transport modes and the characteristics of the SF and aMoD passenger segments. Practically, the findings in this study provide actionable insights for these decision-makers to incorporate into their strategy, planning, and communications. Theoretically, this study focused on short-haul U.S. air routes for travel distances of 500 mi (800 km) or less and explored future mode choice predictors and SF and aMoD passenger clusters, thereby addressing significant knowledge gaps in aviation and transportation literature. Researchers can build on this study to help develop the body of research on inter-regional travel, the goal framing theory, the future transport mode choice model, and the SF and aMoD cluster models.

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Appendix A

Permission to Conduct Research

Embry-Riddle Aeronautical University
Application for IRB Approval
EXEMPT Determination Form

Principal Investigator: Agatha Kessler Fentress

Other Investigators: Dr. Dothang Truong

Role: Student **Campus:** Worldwide **College:** Aviation/Aeronautics

Project Title: Survey of Commercial Short-Haul Flight or Autonomous Mobility-on-Demand: Modeling Air Passengers' Modal Choice

Review Board Use Only

Initial Reviewer: Teri Gabriel **Date:** 06/03/2021 **Approval #:** 21-127

Determination: Exempt

Dr. Beth Blickensderfer
IRB Chair Signature: Elizabeth L. Blickensderfer Digitally signed by Elizabeth L. Blickensderfer Date: 2021.06.08 12:42:54 -04'00' 06/08/2021

Brief Description:

The purpose of this research project is to determine the factors that affect a passenger's transportation mode choice for inter-regional travel, specifically between commercial short-haul flight and driverless cars in the future. Participants will be asked to complete an online survey about their beliefs, attitudes, and opinions. Participants will be recruited through MTurk and the survey will collect data through Survey Monkey.

This research falls under the **EXEMPT** category as per 45 CFR 46.104:

☑ (2) Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording) if at least one of the following criteria is met: (Applies to Subpart B [Pregnant Women, Human Fetuses and Neonates] and does not apply for Subpart C [Prisoners] except for research aimed at involving a broader subject population that only incidentally includes prisoners.)

Appendix B

Human Subjects Protocol Application

EMBRY-RIDDLE
Aeronautical University
FLORIDA | ARIZONA | WORLDWIDE

3 June 2021

Human Subject Protocol Application

Campus:	**Worldwide**	College:	**COA**
Applicant:	**Agatha Kessler Fentress**	Degree Level:	**Doctorate**
ERAU ID:		ERAU Affiliation:	**Student**

Project Title:	**Survey of Commercial Short-Haul Flight or Autonomous Mobility-on-Demand: Modeling Air Passengers' Modal Choice**
Principal Investigator:	**Agatha Kessler Fentress**
Other Investigators:	**Dr. Dothang Truong**

Submission Date:	**05/27/2021**
Beginning Date:	**06/15/2021**
Type of Project:	**Survey**

Type of Funding Support (if any):

Questions:

1. Background and Purpose: Briefly describe the background and purpose of the research.

Background: While overall commercial air passenger traffic has increased steadily in the past decades in the United States, domestic air travel under 500 miles has declined even before the deleterious drop in air travel caused by COVID-19. Commercial short-haul flight (SF) is essential to airlines because it accounts for one-third of hub traffic with higher profit margins. The introduction of autonomous mobility-on-demand (aMoD) may pose a potential revenue and operational threat to SF in the coming decades.

Short-haul air transport is a challenging business because airlines that fly short-haul routes compete with other airlines in addition to substitute transportation modes (cars, trains, and inter-city buses). Environmental concerns have added another dimension to the challenge. There is increasing pressure for regulators and governments to ban, tax, or otherwise disincentivize short-haul flights in favor of greener modes such as rail and high-speed rail (HSR). For instance, in parts of Europe, short-haul flights are banned where there is a rail substitute that can serve the destination within a reasonable time. As environmental pressure increases and HSR's availability improves, this may happen in the United States one day. Incidentally, aMoD may also be one of the green substitutes for short-haul flights. While there has been various scholarly research on SF and aMoD, there is no identifiable research investigating the modal choice between SF and aMoD and the similarities and differences amongst SF and aMoD passengers.

Purpose: This research aims to gain a deeper understanding of air passengers' modal choice in short-haul (inter-regional) travel in the United States. First, it will develop a predictive model to identify factors that most influence U.S. air passengers' modal choice, principally SF and aMoD. Second, it will identify passenger clusters for each mode. Within SF and aMoD clusters, this research will evaluate the similarities and differences of these passenger segments. While this research will consider COVID factors, it is about travel choices in general, not just during the pandemic.

2. Time: Approximately how much time will be required of each participant?

Based on the results from twenty-four pre-test participants ranging from subject matter experts, air passengers, and researchers, this survey will take approximately 20 minutes to complete.

3. Design, Procedures and Methods: Describe the details of the procedure(s) to be used and the type of data that will be collected.

This will be a quantitative research using a survey design for data collection. The sampling frame consists of the population of workers who are members of Amazon® Mechanical Turk® (MTurk), an online crowdsourcing platform for Human Intelligence Tasks (HITs). MTurk participants will be provided a link to the electronic survey integral to the MTurk Human Intelligence Task (HIT) posting. This survey will collect data through Survey Monkey on general demographics, Goal Framing Theory (GFT) variables, contextual trip attributes, and COVID variables. Pre-testing the survey instrument and conducting pilot studies can help avoid/minimize sampling bias and improve generalizability. Pre-testing has been completed. Pilot studies will begin as soon as IRB approval is obtained.

The Goal Framing Theory will be the theoretical foundation. Two-step cluster analysis (CA), multivariate analysis of variance (MANOVA), and multinomial logit (MNL) will be used for data analyses. No personal information other than general demographic data will be collected or recorded to protect the participant's anonymity.

4. Measures and Observations: What measures or observations will be taken in the study?

Gender, age, education, household income, number of cars owned, experience with car accident, physical mobility, and driving and flying experiences will be collected as demographic information. Participant's opinions and attitudes on the GFT (gain, hedonic, and environmental goals) and COVID variables will be measured using a 5-point Likert scale. Contextual travel characteristics (such as names of the nearest home airport, driving time to the airport, availability of direct flight, trip lengths, travel frequency, and travel preferences) will be measured using nominal, ordinal, interval, and ratio scales. The collected data from the online survey will be transferred to an Excel spreadsheet for data cleaning and treatment. IBM SPSS will be used to perform data analyses.

The survey introduction contains pertinent information for respondents to review before beginning the survey. This section consists of the purpose of the research, eligibility, risks and discomforts, benefits, the confidentiality of records, compensation, contact information, voluntary participation, and consent. If consent is given, the participant will answer 15 demographic questions, 30 Goal Framing Theory and COVID items, 13 contextual travel questions, and 14 future-oriented travel questions.

5. Participant Population and Recruitment Procedures: Who will be recruited to be participants and how will they be recruited. Any recruitment email, flyer or document(s) must be reviewed by the IRB. Note that except for anonymous surveys, participants must be at least 18 years of age to participate.

The target population consists of air passengers 18 years or older who have traveled on a commercial flight domestically at least once in the past two years and live in the United States. MTurk participants will be screened based on these criteria. Approximately 1,600 participants will be recruited for this study. For MTurk workers, qualifications for survey participants will be detailed in the Human Intelligence Task (HIT) as a screening mechanism. There is no specific recruitment document. All information is contained in the Informed Consent Form.

6. Risks or Discomforts: Describe any potential risks to the dignity, rights, health or welfare of the human subjects. All other possible options should be examined to minimize any risks to the participants.

There is little risk associated with participation in this study. In the rare case that participants feel uncomfortable with any question, they may skip them. Due to the voluntary nature of this survey, if participants would like to end the survey at any time (whether due to discomfort or not), they are free to do so.

7. Benefits: Assess the potential benefits to be gained by the subjects as well as to society in general as a result of this project.

While there are no direct benefits to the participants in this survey, results may help airports, airlines, governments, and the transportation industry to understand the degree of the potential competitive threats from autonomous vehicles. Results may also provide aviation operators with the details needed to create critical business and communication strategies for a better passenger experience.

8. Informed Consent: Describe the procedure you will use to obtain informed consent of the subjects. How and where will you obtain consent? See Informed Consent Guidelines for more information on Informed Consent requirements.

The informed consent form will be presented to participants at the beginning of the online survey. Participants will indicate they have read the consent form and agree to participate by selecting 'Agree' on the consent form page. Those who do not consent to the study will not continue to participate.

9. Confidentiality of Records: Will participant information be anonymous (not even the researcher can match data with names), confidential (Names or any other identifying demographics can be matched, but only members of the research team will have access to that information. Publication of the data will not include any identifying information.), or public (Names and data will be matched and individuals outside of the research team will have either direct or indirect access. Publication of the data will allow either directly or indirectly, identification of the participants.)?

Anonymous

9b. Justify the classification and describe how privacy will be ensured/protected.

No name, address, phone number, email, or other identifying information will be collected/recorded. Only basic demographic information will be collected. The online survey system (MTurk and Survey Monkey) will not save IP addresses or other identifying information. All data will remain anonymous. In addition, data in digital files will be password-protected and only the researcher will have access to them.

10. Privacy: Describe the safeguards (including confidentiality safeguards) you will use to minimize risks. **Indicate what will happen to data collected from participants that choose to "opt out" during the research process.** If video/audio recordings are part of the research, describe how long that data will be stored and when it will be destroyed.

Respondents' participation is anonymous. The questions are designed so that no personal identification will be included. Their survey answers will be sent to a link at MTurk, where data will be stored in a password-protected electronic format. MTurk does not collect identifying information such as their names, email addresses, or IP addresses. Therefore, their responses will remain anonymous. No one will be able to identify who they are or what they answered. Findings will be shared only in an anonymous format. While the data may be used in the future as part of a longitudinal study, they will be kept completely anonymous.

Participants that choose to "opt-out" during the research process will be considered non-respondents. The data collected from these non-respondents (incomplete surveys) will be used to compare available demographic data between respondents and non-respondents to evaluate non-response bias. Again, all data will be anonymous and analyzed in aggregate. No video or audio recordings are planned.

11. Economic Considerations: Are participants going to be paid for their participation?

Yes

11b. What will the compensation be?
Describe your policy for dealing with participants who 1) Show up for research, but refuse informed consent; 2) Start but fail to complete research.

Participants will be paid $2 for their participation. Those who refuse informed consent will not be compensated. However, those who have started but fail to complete the survey will still be paid.

By submitting this application, you are signing that the Principal Investigator and any other investigators certify the following:
1. The information in this application is accurate and complete
2. All procedures performed during this project will be conducted by individuals legally and responsibly entitled to do so
3. I/we will comply with all federal, state, and institutional policies and procedures to protect human subjects in research
4. I/we will assure that the consent process and research procedures as described herein are followed with every participant in the research
5. That any significant systematic deviation from the submitted protocol (for example, a change in the principal investigator, sponsorship, research purposes, participant recruitment procedures, research methodology, risks and benefits, or consent procedures) will be submitted to the IRB for approval prior to its implementation
6. I/we will promptly report any adverse events to the IRB

Electronic Signature:

Agatha Kessler Fentress

Appendix C

Participant Informed Consent Form

INFORMED CONSENT FORM

Survey of Commercial Short-Haul Flight or Autonomous Mobility-on-Demand: Modeling Air Passengers' Modal Choice

Purpose of this Research: You are invited to participate in a research project to determine the factors that affect a passenger's transportation mode choice for inter-regional travel, specifically between commercial short-haul flight and driverless cars in the future. You will be asked to complete an online survey about your beliefs, attitudes, and opinions. The completion of the survey will take approximately twenty minutes.

Eligibility: To participate in this survey, you must be 18 years or older, live in the United States, and have traveled by air in the past two years.

Risks or discomforts: The risks of participating in this survey are no greater than what is experienced in everyday life.

Benefits: While there are no direct benefits to you as a participant, this research may help the transportation industry provide a better passenger experience for all.

Confidentiality of records: The questions are designed so that no personal identification will be included. The online survey system will not collect or save identifying information such as your name, email address, or IP address. No personal information will be collected other than basic demographic descriptors. No one will be able to identify you or your answers. Therefore, your responses to this survey will be anonymous. In addition, your survey answers will be stored in a password-protected file on a password-protected computer. No one other than the researcher will have access to the computer or the file. While the data may be used in the future as part of a longitudinal study by this researcher, there will be complete anonymity.

Compensation: You will be offered $2 for taking part in this survey.

Contact: This survey is part of a research project led by Agatha Kessler, a Ph.D. student at Embry-Riddle Aeronautical University. If you have any questions or would like additional information about this study, please contact Agatha Kessler, kesslea3@my.erau.edu, or the faculty member overseeing this project, Dr. D. Truong, truongd@erau.edu. For any concerns or questions as a participant in this research, contact the Institutional Review Board (IRB) at 386-226-7179 or via email teri.gabriel@erau.edu.

Voluntary Participation: Your participation in this study is completely voluntary. You may discontinue your participation at any time without penalty or loss of benefits to which you are otherwise entitled.

CONSENT. By checking AGREE below, I certify that I am 18 years or older, live in the United States, and have traveled by air in the past two years. I understand the information on this form, and voluntarily agree to participate in the study.

If you do **not** wish to participate in the study, please check DISAGREE. Please print a copy of this form for your records. A copy of this form can also be requested from Agatha Kessler, kesslea3@my.erau.edu.

☐ Agree ☐ Disagree

Appendix D

Data Collection Device

U.S. Inter-regional Travel Survey

I. Demographics

2. Gender (I identify myself as…)

- Female
- Male
- Other

3. Age

- 18-24
- 25-34
- 35-44
- 45-54
- 55-64
- 65-74
- > 74

4. Highest level of education attained

- Attended high school
- High school diploma
- Bachelor's degree
- Master's degree
- Ph.D./Post-doctorate

5. Annual household income (total from work, investments, and retirement funds)

- < $30,000
- $30,001 to $50,000
- $50,001 to $100,000
- $100,001 to $150,000
- $150,001 to $200,000
- > $200,000

6. The number of children under 18 years old living in your household

- 0
- 1
- 2
- 3 or more

7. Total number of cars owned by the household

- 0
- 1
- 2
- 3 or more

8. How many people in the household have a driver's license?

- 0 [No license]
- 1
- 2

- 3 or more

9. How long have you had a driver's license?

- I do not have a driver's license
- < 3 years
- 3-8 years
- 9-15 years
- > 15 years

10. How often do you drive?

- I do not drive
- < 1 time per week
- 1-2 times per week
- 3-5 times per week
- > 5 times per week

11. On average, roughly how many miles a year did you fly within the U.S. pre-COVID? For example: One- way flight distance between…
* San Francisco - Los Angeles = 350 miles
* Denver – New York = 1600 miles
* Chicago – Seattle = 1700 miles

- < 5,000 miles
- 5,000–10,000 miles
- 10,001–25,000 miles
- > 25,000 miles

12. I live in

- A city (large urban area)
- A suburb (a large residential area near to a big city)
- A small city
- Rural America/countryside/small town/village

13. In the past, have you or your family been in a car accident when someone got injured?

Yes No

14. Do you or someone in your family use a wheelchair or a walker?

Yes No

15. During COVID, the estimated percentage of time I work from home

100%
75%
50%
25%
0%
I do not work

16. Pre-COVID, on average, I traveled for business

- Once a year
- 2-6 times a year
- 7 or more times a year
- I did not travel for business

17. I am vaccinated against COVID-19

- Yes
- No

18. I have/had COVID-19

- Yes
- No

19. I have traveled by air during COVID

- Yes
- No

II. Questions on Inter-regional Travel

In this survey, the term “travel” refers to inter-regional travel of 100 to 500 miles within the U.S. Typically, it is within one hour of flying or 3-8 hours of driving. For example, traveling between the following cities:

* San Francisco - Los Angeles/San Diego
* Denver - Santa Fe/Albuquerque
* Boston - New York/Washington D.C.
* Houston - Dallas/San Antonio/Austin
* Miami -Tampa/Orlando

20. Usually, I would **fly** if the driving distance is **over**

- 3 hours
- 4 hours
- 5 hours
- 6 hours
- 7 hours
- 8 hours

21. What is the likelihood of you **driving a car instead of flying**, if the trip is a...

	Very Unlikely	Unlikely	Somewhat Likely	Likely	Very Likely
2 hours' drive					
5 hours' drive					
8 hours' drive					

22. Pre-COVID, when I **traveled** to **inter-regional cities**, I usually

- Drove
- Flew on an airplane
- Took an inter-regional bus
- Took an inter-regional train

23. I have used the following transport mode **at least once in the United States.**

	Yes	No
Inter-regional Train	☐	☐
Inter-regional Bus	☐	☐

Please indicate how strongly you agree or disagree with each statement below.

24. This section focuses on your **general feelings, beliefs, and perceptions**

	Strongly Disagree	Disagree	Somewhat Agree	Agree	Strongly Agree
Generally, my main transport mode for inter- regional travel is efficient.	☐	☐	☐	☐	☐
I will not sacrifice comfort even if I have to pay slightly more	☐	☐	☐	☐	☐
I believe issues that may pop up during my travels can be resolved.	☐	☐	☐	☐	☐
I am quite predictable in terms of how I travel.	☐	☐	☐	☐	☐
Most of the time, I am happy with the transportation I use when I travel to other cities.	☐	☐	☐	☐	☐
In general, I trust my main inter-regional transport mode is safe.	☐	☐	☐	☐	☐
Traveling is fun for me.	☐	☐	☐	☐	☐
Cost is very important to me when I travel for leisure.	☐	☐	☐	☐	☐
Convenience is very important to me when I travel.	☐	☐	☐	☐	☐
I usually try to minimize my total travel time.	☐	☐	☐	☐	☐
When I travel, I value my time doing something nice or useful, such as watching a movie, working, or sleeping.	☐	☐	☐	☐	☐

25. On the **Environment**

	Strongly Disagree	Disagree	Somewhat Agree	Agree	Strongly Agree
Preserving the environment is very important when I decide how I travel.	☐	☐	☐	☐	☐
I feel moral obligation to protect the environment.	☐	☐	☐	☐	☐
I think electric vehicles are good for the environment.	☐	☐	☐	☐	☐
People who are important to me tend to care about the environment.	☐	☐	☐	☐	☐

It is important for me to be a role model for my family in environmental protection.

26. On **Technology**

	Strongly Disagree	Disagree	Somewhat Agree	Agree	Strongly Agree
Technology is my friend.					
I am dependent on technology.					
I use the Internet for information regularly.					
I think it is important to keep up with the latest trends in technology.					
I was one of the first people to use Uber or Lyft to/from the airport.					
I am familiar with the concept of driverless cars.					

27. On **COVID-19**

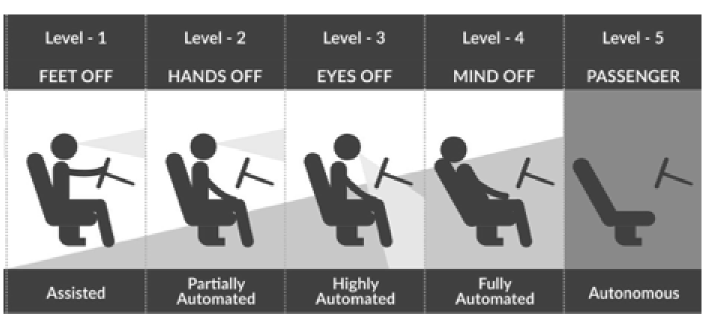
	Strongly Disagree	Disagree	Somewhat Agree	Agree	Strongly Agree
I am concerned with getting COVID when I travel.					
I think COVID and its variants will get worse.					
My disposable income has increased since COVID started.					
Even during COVID, I could be tempted to travel by air if the ticket price was low enough.					
I think the economy is gradually recovering.					

III. Future-Oriented Questions

We are still focusing on **inter-regional travels**. This section is interested in **your opinions of how you may travel if driverless cars are available**.

The figure below shows the **levels of driving automation**. In the future, cars may be Level-5 (fully autonomous). A **driverless car**, sometimes called a **self-driving car**, is a car that can go from place to place **without a driver**. The main features are **self-driving**, **electric**, and **on-demand**.

In 2021, most cars are Levels 1-3. Tesla cars are currently between Levels 3-4.



28. The questions below focus **on Level-5 (fully autonomous),** where the cars perform all driving tasks and **no driver is required**. Functionally, the cars will not have steering wheels, brakes, and other driving controls. This will free the cars to be versatile in size and functions to fulfill the passengers' trip requirements such as working, eating, watching a movie, or sleeping.

I think **driverless cars** will be transporting people in the United States…

☐ Within 3 years ☐ In 3-5 years ☐ In 6-10 years ☐ In 11-20 years ☐ Over 20 years ☐ Never

29. I believe **50%** of the cars on the road will be **driverless cars** in the United States…

☐ By 2030
☐ By 2040
☐ By 2050
☐ Beyond 2050
☐ Never

30. Most people think that **50%** of the cars will be **electric** in the United States …

☐ By 2030
☐ By 2040
☐ By 2050
☐ Beyond 2050
☐ Never

31. In the future, assuming safety, legal, and regulation issues are solved, and driverless cars are readily available in everyday life, what do you think you would **use the most for inter-regional travel**?

☐ Use a driverless car
☐ Drive a car myself/driven by others
☐ Fly
☐ Take an inter-regional bus
☐ Take an inter-regional train

32. What is the likelihood of you **using a driverless car** instead of **flying**, if the trip is a…

	Very Unlikely	Unlikely	Somewhat Likely	Likely	Very Likely
2 hours' drive	☐	☐	☐	☐	☐
5 hours' drive	☐	☐	☐	☐	☐
8 hours' drive	☐	☐	☐	☐	☐

33. Please indicate how strongly you agree or disagree with each statement below if driverless cars are readily available on-demand in the U.S.

	Strongly Disagree	Disagree	Somewhat Agree	Agree	Strongly Agree
I would use a **driverless car** instead of **flying** on inter-regional trips.	☐	☐	☐	☐	☐
I trust that driverless cars will be **safe** if they are allowed on the road.	☐	☐	☐	☐	☐
Generally, I think driverless cars will be **cheaper** to use than flying.	☐	☐	☐	☐	☐
I think driverless cars are more **convenient** than flying in general.	☐	☐	☐	☐	☐

I would use a **driverless car** instead of **driving** on inter-regional trips.

If I were to ride in a driverless car, I may be **relaxed** enough to fall asleep.

34. Approximately, how long does it take to drive **from your home to the nearest airport**?

- < 15 minutes
- 15 – 30 minutes
- 31 – 45 minutes
- 46 – 60 minutes
- > 1 hour

35. Pre-COVID, on average, what percentage of the time your home airport offers **direct flights** to where you need to go?

0% - 20% 21% - 40% 41% - 60% 61% - 80% Over 80%

36. On average, roughly how many people, **including yourself,** travel together when you **travel for leisure**?

	1	2	3	4 or more
By Car (driving)				
By Plane (flying)				

37. If there is anything that is not included in this survey that you think is important to your decision for inter-regional travel in the future, please share here.

38. You are almost done. Please:
Select the **FIRST CODE** below and **ENTER** it in the **"Survey Code" box in MTurk**
Select "**CLICK TO SAVE RESPONSES**" below to complete this survey.

AV101

EV201

AV301

EV401

AV501

EV601

AV701

EV801

AV901

Appendix E

Pilot Study: Cronbach's Alpha for the COVID-19 Items

The Cronbach's alpha for the COVID-19 scale (α=.430) did not provide evidence of good internal consistency. As seen in the column "Cronbach's Alpha if Item Deleted," removing C1 would increase the Cronbach's alpha value to .49 which was still too low to provide evidence for reliability. In addition, C1 was critical for the COVID-19 construct. A practical solution was to add two items to this construct representing respondents' perception of their economic conditions and the degree they worry about the variants of the COVID-19 pandemic.

Reliability Statistics

Cronbach's Alpha	N of Items
.430	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
C1 I am concerned with getting COVID when I travel.	6.66	3.454	.167	.490
C2 My disposable income has reduced because of COVID.	6.95	2.632	.362	.129
C3 Even during COVID, I could be tempted to travel by air if the ticket price was low	6.69	3.011	.258	.336

Appendix F

Pilot Study: EFA Pattern Matrix

The pattern matrix of the pilot data stabilized as a 4-factor solution. The principal component extraction method was used as it makes no distributional assumptions. Promax rotation algorithm is appropriate because it assumes correlations amongst the variables.

Pattern Matrix[a]

	Component			
	1	2	3	4
H6 In general, I am happy with the transportation I use when I travel to other cities.	.772			
H9 Traveling is fun for me.	.736			
H3 I know I can resolve issues that may pop up during my travels.	.693			
H1 Generally, my main transport mode for inter-regional travel is efficient.	.675			
B2 In general, when you travel by CAR for inter-regional trips, how satisfied are you with ENVIRONMENTAL IMPACT?		.830		
B3 In general, when you travel by AIR for inter-regional trips, how satisfied are you with ENVIRONMENTAL IMPACT?		.802		
C2 My disposable income has reduced because of COVID.		.642		
C3 Even during COVID, I could be tempted to travel by air if the ticket price was low		.579		
G4 I usually try to minimize my total travel time.			.704	
G2 Convenience is very important to me when I travel.			.690	
G1 Cost is very important to me when I travel for leisure.			.674	
H5 I am quite predictable in terms of how I travel.			.509	
B1 Preserving the environment is very important when I decide how I travel.				.830
C1 I am concerned with getting COVID when I travel.	.309			.529
G3 When I travel, I value my time doing something nice or useful, such as watching a movie, working, or sleeping.			.383	-.400

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Appendix G

Multivariate Outliers Assessment using Mahalanobis D-Square

Results before removing the 36 observations with multivariate outliers.

	aMoD_Drive	aMoD_Trust_R	Airport_Dist	Dir_Fl_pc	L_Car_#P	L_SF_#P	filter_$	MAH_1	Probability_Mah_D	MAH_2	Prob_Mah_D2	MAH_3	Prob_Mah_D3
1	Strongly Agree	Somewhat Agree	> 1 hour	41%-60%	2	1	Selected	118.34042	.00020	77.95808	.0000	106.45698	.0012
2	Agree	Strongly Agree	15-30 minutes	Over 80%	3	2	Selected	111.82295	.00085	65.13020	.0007	106.06572	.0013
3	Strongly Agree	Strongly Agree	31-45 minutes	21%-40%	1	3	Selected	112.66123	.00071	79.72983	.0000	106.04643	.0013
4	Agree	Strongly Agree	31-45 minutes	61%-80%	3	4 or more	Not Selected	116.92340	.00028	83.31751	.0000	105.83658	.0014
5	Strongly Agree	Strongly Agree	31-45 minutes	41%-60%	2	2	Selected	128.88761	.00002	77.31569	.0000	105.79093	.0014
6	Strongly Agree	Strongly Agree	31-45 minutes	21%-40%	2	1	Selected	128.45802	.00002	63.17886	.0012	105.51056	.0014
7	Agree	Strongly Disagr...	< 15 minutes	41%-60%	4 or more	4 or more	Not Selected	125.12632	.00004	71.58950	.0001	105.01165	.0016
8	Strongly Agree	Strongly Agree	15-30 minutes	Over 80%	2	2	Not Selected	112.03036	.00081	56.59872	.0065	104.81647	.0017
9	Strongly Agree	Strongly Agree	15-30 minutes	Over 80%	4 or more	4 or more	Selected	122.17695	.00008	60.31284	.0026	104.57057	.0018
10	Strongly Agree	Agree	31-45 minutes	21%-40%	4 or more	1	Selected	115.90300	.00035	82.27647	.0000	104.48781	.0018
11	Strongly Disagr...	Strongly Disagr...	> 1 hour	21%-40%	1	2	Not Selected	115.78831	.00036	66.28579	.0005	104.33968	.0018
12	Strongly Disagr...	Strongly Disagr...	15-30 minutes	61%-80%	4 or more	4 or more	Not Selected	126.94700	.00003	80.05180	.0000	103.99015	.0020
13	Strongly Agree	Strongly Disagr...	< 15 minutes	0%-20%	3	2	Selected	120.85039	.00011	65.35981	.0007	103.64475	.0021
14	Agree	Disagree	31-45 minutes	21%-40%	2	2	Selected	111.08193	.00099	58.90214	.0037	103.34435	.0023
15	Disagree	Strongly Disagr...	31-45 minutes	21%-40%	4 or more	3	Not Selected	113.53667	.00059	82.76463	.0000	103.28410	.0023
16	Strongly Agree	Agree	15-30 minutes	41%-60%	3	2	Not Selected	116.50728	.00031	90.61431	.0000	103.17962	.0023
17	Strongly Disagr...	Strongly Disagr...	15-30 minutes	21%-40%	2	2	Not Selected	115.41234	.00039	81.12479	.0000	103.11762	.0024
18	Somewhat Agree	Somewhat Agree	31-45 minutes	41%-60%	3	2	Not Selected	106.99018	.00230	85.56587	.0000	103.07892	.0024
19	Strongly Disagr...	Strongly Disagr...	46-60 minutes	Over 80%	2	2	Not Selected	110.50632	.00112	60.91357	.0022	102.45541	.0027
20	Somewhat Agree	Somewhat Agree	46-60 minutes	21%-40%	2	2	Not Selected	108.07451	.00185	89.01671	.0000	102.28381	.0028
21	Disagree	Strongly Disagr...	31-45 minutes	Over 80%	4 or more	2	Not Selected	123.64580	.00006	68.35703	.0003	101.14157	.0035
22	Strongly Disagr...	Strongly Agree	46-60 minutes	61%-80%	4 or more	4 or more	Not Selected	104.95893	.00343	71.48630	.0001	100.90866	.0037
23	Strongly Disagr...	Strongly Disagr...	> 1 hour	61%-80%	4 or more	4 or more	Not Selected	112.77345	.00069	39.07573	.2155	100.78913	.0038
24	Agree	Strongly Disagr...	< 15 minutes	Over 80%	4 or more	4 or more	Not Selected	109.59296	.00136	50.00511	.0292	100.41304	.0041
25	Disagree	Disagree	> 1 hour	0%-20%	4 or more	1	Selected	119.27397	.00016	34.73242	.3854	100.08594	.0043
26	Agree	Strongly Disagr...	31-45 minutes	0%-20%	2	1	Not Selected	114.00924	.00053	60.96647	.0022	99.93722	.0044
27	Strongly Agree	Somewhat Agree	31-45 minutes	Over 80%	1	1	Not Selected	106.84302	.00237	55.06887	.0093	99.74842	.0046
28	Somewhat Agree	Somewhat Agree	> 1 hour	0%-20%	4 or more	1	Not Selected	112.78811	.00069	67.72544	.0003	99.54023	.0048

Results after removing the 36 observations with multivariate outliers:

Observations farthest from the centroid (Mahalanobis distance)

Observation number	Mahalanobis d-squared	p1	p2
866	53.526	.000	.009
500	50.774	.000	.000
499	50.764	.000	.000
1	50.115	.000	.000
865	46.789	.000	.000
3	46.651	.000	.000
864	46.411	.000	.000
867	43.455	.000	.000
870	42.628	.000	.000
10	42.615	.000	.000
869	42.374	.000	.000
503	42.274	.000	.000
1250	42.199	.000	.000
868	41.641	.000	.000
11	41.620	.000	.000
877	41.368	.000	.000
872	41.268	.001	.000
1155	41.138	.001	.000
17	40.992	.001	.000
513	40.844	.001	.000
7	40.485	.001	.000
6	40.282	.001	.000
502	40.269	.001	.000
501	40.241	.001	.000
876	39.898	.001	.000
8	39.665	.001	.000
504	39.652	.001	.000
1252	39.511	.001	.000
21	38.851	.001	.000

Appendix H

Multivariate Normality Assessments

Method 1. The Mahalanobis distance (maximum) of 15.946 < the chi-square distribution critical value of 26.296 (p = .05, df = 16). These results provided evidence that multivariate normality exists.

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	451.23	958.90	724.31	100.578	1387
Std. Predicted Value	-2.715	2.332	.000	1.000	1387
Standard Error of Predicted Value	11.382	44.545	20.862	5.731	1387
Adjusted Predicted Value	446.29	959.63	724.32	100.626	1387
Residual	-819.152	835.029	.000	402.419	1387
Std. Residual	-2.033	2.073	.000	.999	1387
Stud. Residual	-2.038	2.076	.000	1.000	1387
Deleted Residual	-822.733	837.352	-.008	403.582	1387
Stud. Deleted Residual	-2.040	2.078	.000	1.001	1387
Mahal. Distance	.107	15.946	2.998	2.253	1387
Cook's Distance	.000	.008	.001	.001	1387
Centered Leverage Value	.000	.012	.002	.002	1387

a. Dependent Variable: ID

Extreme Values

			Case Number	ID	Value
MAH_M_Normality Mahalanobis Distance for M Normality	Highest	1	2	652	15.94626
		2	597	1049	15.94626
		3	294	940	12.88725
		4	301	710	12.88725
		5	329	1354	12.88725[a]
	Lowest	1	1385	1069	.10701
		2	1384	462	.10701
		3	1381	638	.10701
		4	1366	912	.10701
		5	1270	849	.10701[b]

a. Only a partial list of cases with the value 12.88725 are shown in the table of upper extremes.

b. Only a partial list of cases with the value .10701 are shown in the table of lower extremes.

Chi-Square (χ^2) Distribution

Area to the Right of Critical Value

Degrees of Freedom	0.995	0.99	0.975	0.95	0.90	0.10	0.05	0.025	0.01	0.005
1	—	—	0.001	0.004	0.016	2.706	3.841	5.024	6.635	7.879
2	0.010	0.020	0.051	0.103	0.211	4.605	5.991	7.378	9.210	10.597
3	0.072	0.115	0.216	0.352	0.584	6.251	7.815	9.348	11.345	12.838
4	0.207	0.297	0.484	0.711	1.064	7.779	9.488	11.143	13.277	14.860
5	0.412	0.554	0.831	1.145	1.610	9.236	11.070	12.833	15.086	16.750
6	0.676	0.872	1.237	1.635	2.204	10.645	12.592	14.449	16.812	18.548
7	0.989	1.239	1.690	2.167	2.833	12.017	14.067	16.013	18.475	20.278
8	1.344	1.646	2.180	2.733	3.490	13.362	15.507	17.535	20.090	21.955
9	1.735	2.088	2.700	3.325	4.168	14.684	16.919	19.023	21.666	23.589
10	2.156	2.558	3.247	3.940	4.865	15.987	18.307	20.483	23.209	25.188
11	2.603	3.053	3.816	4.575	5.578	17.275	19.675	21.920	24.725	26.757
12	3.074	3.571	4.404	5.226	6.304	18.549	21.026	23.337	26.217	28.300
13	3.565	4.107	5.009	5.892	7.042	19.812	22.362	24.736	27.688	29.819
14	4.075	4.660	5.629	6.571	7.790	21.064	23.685	26.119	29.141	31.319
15	4.601	5.229	6.262	7.261	8.547	22.307	24.996	27.488	30.578	32.801
16	5.142	5.812	6.908	7.962	9.312	23.542	26.296	28.845	32.000	34.267
17	5.697	6.408	7.564	8.672	10.085	24.769	27.587	30.191	33.409	35.718
18	6.265	7.015	8.231	9.390	10.865	25.989	28.869	31.526	34.805	37.156
19	6.844	7.633	8.907	10.117	11.651	27.204	30.144	32.852	36.191	38.582
20	7.434	8.260	9.591	10.851	12.443	28.412	31.410	34.170	37.566	39.997
21	8.034	8.897	10.283	11.591	13.240	29.615	32.671	35.479	38.932	41.401
22	8.643	9.542	10.982	12.338	14.041	30.813	33.924	36.781	40.289	42.796
23	9.260	10.196	11.689	13.091	14.848	32.007	35.172	38.076	41.638	44.181
24	9.886	10.856	12.401	13.848	15.659	33.196	36.415	39.364	42.980	45.559
25	10.520	11.524	13.120	14.611	16.473	34.382	37.652	40.646	44.314	46.928
26	11.160	12.198	13.844	15.379	17.292	35.563	38.885	41.923	45.642	48.290
27	11.808	12.879	14.573	16.151	18.114	36.741	40.113	43.195	46.963	49.645
28	12.461	13.565	15.308	16.928	18.939	37.916	41.337	44.461	48.278	50.993
29	13.121	14.256	16.047	17.708	19.768	39.087	42.557	45.722	49.588	52.336
30	13.787	14.953	16.791	18.493	20.599	40.256	43.773	46.979	50.892	53.672
40	20.707	22.164	24.433	26.509	29.051	51.805	55.758	59.342	63.691	66.766
50	27.991	29.707	32.357	34.764	37.689	63.167	67.505	71.420	76.154	79.490
60	35.534	37.485	40.482	43.188	46.459	74.397	79.082	83.298	88.379	91.952
70	43.275	45.442	48.758	51.739	55.329	85.527	90.531	95.023	100.425	104.215
80	51.172	53.540	57.153	60.391	64.278	96.578	101.879	106.629	112.329	116.321

Method 2. The kurtosis values using AMOS, tend to have more effect on the model. All Kurtosis values < 1 (which is < 3 for acceptance for multivariate normality).

Variable	min	max	skew	c.r.	kurtosis	c.r.
G2_Convenience	1.000	5.000	-.394	-5.997	-.227	-1.726
G3_TTravel_Time	1.000	5.000	-.376	-5.725	-.192	-1.459
G4_Value_Time	1.000	5.000	-.415	-6.311	-.109	-.827
C3_Income	1.000	5.000	-.071	-1.073	-.975	-7.416
C4_Tprice	1.000	5.000	-.497	-7.557	-.452	-3.436
C5_Economic	1.000	5.000	-.365	-5.556	-.155	-1.179
H1_Eff	1.000	5.000	-.503	-7.647	.572	4.348
H3_SelfEff	1.000	5.000	-.258	-3.925	.028	.213
H5_Satisfaction	1.000	5.000	-.305	-4.645	-.086	-.652
H6_Trust	1.000	5.000	-.493	-7.494	.372	2.828
H7_Hedonic	1.000	5.000	-.569	-8.651	-.140	-1.066
B2_Moral	1.000	5.000	-.503	-7.649	-.040	-.308
B4_SN1	1.000	5.000	-.503	-7.644	.036	.275
B5_SN2	1.000	5.000	-.505	-7.685	-.095	-.721
C1_Fear	1.000	5.000	-.441	-6.709	-.285	-2.169
C2_Variance	1.000	5.000	-.194	-2.952	-.507	-3.854
Multivariate					36.228	28.119

Appendix I

Linearity Assumption and Discriminant Validity Tests

Correlations																
	B2	B4	B5	C1	C2	H1	H3	H5	H6	H7	C3	C4	C5	G2	G3	G4
B2	1															
B4	.544**	1														
B5	.595**	.559**	1													
C1	.308**	.299**	.357**	1												
C2	.310**	.256**	.270**	.444**	1											
H1	.128**	.129**	.187**	.116**	0.044	1										
H3	.127**	.139**	.133**	0.007	.053*	.265**	1									
H5	.139**	.187**	.185**	.060*	.049*	.423**	.305**	1								
H6	.185**	.193**	.141**	0.029	.077**	.401**	.332**	.397**	1							
H7	.217**	.221**	.255**	.089**	.113**	.275**	.284**	.261**	.247**	1						
C3	.157**	.164**	.201**	.142**	.259**	-0.011	.067**	-0.028	-0.022	.085**	1					
C4	0.033	.085**	.082**	-0.042	.068**	.100**	.098**	0.032	.060*	.193**	.302**	1				
C5	.218**	.254**	.348**	.262**	.161**	.124**	.121**	.104**	.129**	.185**	.314**	.217**	1			
G2	.142**	.171**	.166**	.101**	0.043	.279**	.219**	.333**	.215**	.168**	-0.038	0.031	.094**	1		
G3	.144**	.155**	.183**	.113**	.121**	.160**	.154**	.173**	.251**	.047*	.129**	.109**	.206**	.305**	1	
G4	.152**	.203**	.220**	.156**	.099**	.259**	.237**	.249**	.231**	.253**	.124**	.155**	.208**	.329**	.324**	1

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Note. Linearity indicated by 91% of all bivariate correlations being significant.

Appendix J

Homoscedasticity / Homogeneity of Variance

The Pearson Correlation of –.254 and Spearman Correlation of –.206 are both statistically significant at the .01 level. The assumption of homoscedasticity has not been satisfied.

Correlations

		ZPR_1 Standardized Predicted Value	ZRE_1_abs
ZPR_1 Standardized Predicted Value	Pearson Correlation	1	-.254**
	Sig. (2-tailed)		<.001
	N	1388	1388
ZRE_1_abs	Pearson Correlation	-.254**	1
	Sig. (2-tailed)	<.001	
	N	1388	1388

**. Correlation is significant at the 0.01 level (2-tailed).

Nonparametric Correlations

Correlations

			ZPR_1 Standardized Predicted Value	ZRE_1_abs
Spearman's rho	ZPR_1 Standardized Predicted Value	Correlation Coefficient	1.000	-.206**
		Sig. (2-tailed)	.	<.001
		N	1388	1388
	ZRE_1_abs	Correlation Coefficient	-.206**	1.000
		Sig. (2-tailed)	<.001	.
		N	1388	1388

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix K

Multicollinearity Assessment

General guidelines:

- Variance Inflation Factor (VIF) < 10
- Condition index > 15 = collinearity is suspected
- > 30 = serious multicollinearity

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.288	.034		67.067	.000		
	GFT_Norm	.080	.037	.062	2.165	.031	.857	1.167
	GFT _Hedonic	-.174	.036	-.135	-4.825	<.001	.900	1.111
	COVID_Financial	.141	.035	.110	3.985	<.001	.928	1.078
	GFT_Gain	.043	.036	.033	1.190	.234	.905	1.105

a. Dependent Variable: FUTURE MAIN MODE of Transportation for Inter-regional Travel

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions				
				(Constant)	GFT_Norm	GFT _Hedonic	COVID_Financial	GFT_Gain
1	1	1.604	1.000	.00	.18	.15	.10	.13
	2	1.000	1.267	1.00	.00	.00	.00	.00
	3	.964	1.290	.00	.04	.12	.55	.24
	4	.750	1.463	.00	.02	.70	.00	.48
	5	.682	1.534	.00	.76	.03	.35	.15

a. Dependent Variable: FUTURE MAIN MODE of Transportation for Inter-regional Travel

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions					
				(Constant)	C2_Variance C2 - I think COVID and its variances will get worse.	H1_Eff H1 - Generally, my main transport mode for inter-regional travel is efficient.	C3_Income C3 - My disposable income has increased since COVID started.	H3_SelfEff H3 - I believe issues that may pop up during my travels can be resolved.	G4_Value_Time G4 - When I travel, I value my time doing something nice or useful, such as watching a movie, working, or sleeping.
1	1	1.953	1.000	.02	.02				
	2	.047	6.445	.98	.98				
2	1	2.915	1.000	.00	.01	.00			
	2	.068	6.555	.03	.88	.14			
	3	.017	13.229	.97	.11	.85			
3	1	3.815	1.000	.00	.01	.00	.01		
	2	.102	6.105	.02	.02	.06	.91		
	3	.067	7.545	.02	.91	.11	.03		
	4	.016	15.418	.96	.06	.83	.04		
4	1	4.779	1.000	.00	.00	.00	.01	.00	
	2	.111	6.570	.01	.00	.04	.85	.02	
	3	.072	8.140	.00	.94	.03	.11	.03	
	4	.025	13.773	.00	.00	.66	.01	.60	
	5	.013	18.940	.99	.06	.27	.03	.35	
5	1	5.739	1.000	.00	.00	.00	.00	.00	.00
	2	.116	7.043	.00	.01	.03	.81	.02	.02
	3	.074	8.789	.00	.93	.01	.15	.01	.02
	4	.033	13.220	.01	.00	.11	.00	.12	.92
	5	.025	15.096	.00	.00	.65	.01	.56	.00
	6	.013	21.015	.98	.05	.20	.02	.29	.04

a. Dependent Variable: MODE_Future FUTURE MAIN MODE of Transportation for Inter-regional Travel

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.776	.113		15.677	<.001		
	C2_Variance C2 - I think COVID and its variances will get worse.	.155	.033	.126	4.740	<.001	1.000	1.000
2	(Constant)	2.550	.206		12.405	<.001		
	C2_Variance C2 - I think COVID and its variances will get worse.	.161	.032	.132	4.966	<.001	.998	1.002
	H1_Eff H1 - Generally, my main transport mode for inter-regional travel is efficient.	-.211	.047	-.119	-4.496	<.001	.998	1.002
3	(Constant)	2.338	.214		10.900	<.001		
	C2_Variance C2 - I think COVID and its variances will get worse.	.132	.033	.108	3.948	<.001	.931	1.075
	H1_Eff H1 - Generally, my main transport mode for inter-regional travel is efficient.	-.207	.047	-.117	-4.435	<.001	.998	1.002
	C3_Income C3 - My disposable income has increased since COVID started.	.098	.029	.091	3.327	<.001	.932	1.073
4	(Constant)	2.718	.252		10.766	<.001		
	C2_Variance C2 - I think COVID and its variances will get worse.	.134	.033	.110	4.026	<.001	.930	1.075
	H1_Eff H1 - Generally, my main transport mode for inter-regional travel is efficient.	-.171	.048	-.097	-3.534	<.001	.927	1.078
	C3_Income C3 - My disposable income has increased since COVID started.	.103	.029	.096	3.509	<.001	.929	1.077
	H3_SelfEff H3 - I believe issues that may pop up during my travels can be resolved.	-.140	.049	-.078	-2.838	.005	.924	1.082
5	(Constant)	2.509	.263		9.554	<.001		
	C2_Variance C2 - I think COVID and its variances will get worse.	.129	.033	.105	3.872	<.001	.927	1.079
	H1_Eff H1 - Generally, my main transport mode for inter-regional travel is efficient.	-.200	.049	-.113	-4.061	<.001	.885	1.129
	C3_Income C3 - My disposable income has increased since COVID started.	.094	.029	.088	3.211	.001	.919	1.088
	H3_SelfEff H3 - I believe issues that may pop up during my travels can be resolved.	-.164	.050	-.091	-3.287	.001	.897	1.115
	G4_Value_Time G4 - When I travel, I value my time doing something nice or useful, such as watching a movie, working, or sleeping.	.120	.043	.079	2.822	.005	.887	1.128

a. Dependent Variable: MODE_Future FUTURE MAIN MODE of Transportation for Inter-regional Travel

Appendix L

MNL Models: Likelihood Ratio Tests

Table L1

MNL Model 1

Likelihood Ratio Tests

	Model Fitting Criteria			Likelihood Ratio Tests		
Effect	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	4329.200	4412.970	4297.200	453.362	4	<.001
F1 GFT_Norms_COVID_Fear	3916.535	4000.305	3884.535	40.697	4	<.001
F2 GFT _Hedonic	3913.679	3997.449	3881.679	37.841	4	<.001
F3 COVID_Financial	3917.247	4001.017	3885.247	41.409	4	<.001
F4 GFT_Gain	3888.488	3972.258	3856.488	12.650	4	.013

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Table L2

Table MNL Model 2

Likelihood Ratio Tests			Likelihood Ratio Tests		
Effect	Description	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept		3682.365	11.757	4	0.019
F1	GFT_Norms_COVID_Fear	3692.617	22.009	4	<.001
F2	GFT _Hedonic	3685.456	14.847	4	0.005
F3	COVID_Financial	3679.818	9.209	4	0.056
F4	GFT_Gain	3680.970	10.361	4	0.035
MODE_Pre_COVID	Current MAIN MODE for Inter-regional Trav	3740.627	70.018	4	<.001
Gender	Gender	3678.849	8.241	4	0.083
Age	Age	3674.923	4.314	4	0.365
Education	Highest Level of Education	3678.335	7.726	4	0.102
HH_Income	Total Household Income	3681.596	10.987	4	0.027
Children_#	Number of Children Living at Home	3673.744	3.135	4	0.536
Cars_#	Number of Cars Owned by Household	3676.463	5.854	4	0.210
HH_DL_#	Number of Driver's License in Household	3677.817	7.208	4	0.125
Years_DL	Years with Driver's License	3680.631	10.022	4	0.040
Drive_Freq	Drive Frequency	3675.564	4.956	4	0.292
Fly_Miles	Annual Miles Flown within the US	3673.936	3.327	4	0.505
Urban_Rural	Neighborhood Type	3678.468	7.860	4	0.097
Car_Injury	Car Accident when someone was Injured	3675.346	4.738	4	0.315
Mobility_Issue	Family or Self with Mobility Issue	3678.762	8.153	4	0.086
COVID_W_Home	% of Time working from Home during COVII	3675.367	4.758	4	0.313
Biz_Travel_	Freq Business Travels Pre-COVID	3679.791	9.182	4	0.057
COVID_Vac	Vaccinated against COVID	3677.749	7.141	4	0.129
COVID	Have/Had COVID	3676.748	6.139	4	0.189
COVID_Air	Traveled by Air during COVID	3688.723	18.115	4	0.001
Airport_Dist	Distance from Home to the Nearest Airport	3671.841	1.233	4	0.873
Dir_Fl_pc	% Direct Flights: Home Airport and Destinat	3671.307	0.698	4	0.952

Note. The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model.

Table L 3

MNL Model 3

Effect	-2 Log Likelihood of Reduced Model	Likelihood Ratio Tests Chi-Square	df	Sig.
Intercept	3256.593a	0.000	0	.
B2 - I feel moral obligation to protect the environment.	3263.698b	7.105	4	0.130
B4 - People who are important to me tend to care about the environment.	3265.495b	8.902	4	0.064
B5 - It is important for me to be a role model for my family in environmental protectic	3263.996b	7.402	4	0.116
C1 - I am concerned with getting COVID when I travel.	3268.570b	11.977	4	0.018
C2 - I think COVID and its variances will get worse.	3275.416b	18.823	4	<.001
H1 - Generally, my main transport mode for inter-regional travel is efficient.	3271.808b	15.214	4	0.004
H3 - I believe issues that may pop up during my travels can be resolved.	3276.548b	19.955	4	<.001
H5 - Most of the time, I am happy with the transportation I use when I travel to other ci	3267.985b	11.392	4	0.022
H6 - In general, I trust my main inter-regional transport mode is safe.	3258.652b	2.059	4	0.725
H7 - Traveling is fun for me.	3260.465b	3.872	4	0.424
C3 - My disposable income has increased since COVID started.	3261.897b	5.304	4	0.258
C4 - Even during COVID, I could be tempted to travel by air if the ticket price was low	3263.864b	7.271	4	0.122
C5 - I think the economy is gradually recovering.	3261.473b	4.880	4	0.300
G2 - Convenience is very important to me when I travel.	3259.008b	2.415	4	0.66
G3 - I usually try to minimize my total travel time.	3267.582b	10.989	4	0.027
G4 - When I travel, I value my time doing something nice or useful, such as watching a movie, working, or sleeping.	3270.885b	14.292	4	0.006
Gender	3265.093	8.500	8	0.386
Age	3296.983b	40.389	24	0.019
Highest Level of Education	3276.179b	19.586	16	0.239
Total Household Income	3290.013b	33.420	20	0.030
Number of Children Living at Home	3263.167b	6.574	12	0.884
Number of Cars Owned by Household	3277.951b	21.358	12	0.045
Number of Driver's License in Household	3271.675b	15.082	12	0.237
Years with Driver's License	3289.847b	33.254	16	0.007
Drive Frequency	3279.179b	22.586	16	0.125
Annual Miles Flown within the US	3277.371b	20.778	12	0.054
Neighborhood Type	3279.327b	22.733	12	0.030
Car Accident when someone was Injured	3261.279b	4.686	4	0.321
Family or Self with Mobility Issue	3267.811b	11.218	4	0.024
During COVID, estimated % of Time working from Home	3285.691b	29.098	20	0.086
Business Travels Pre-COVID	3264.235b	7.641	12	0.812
Vaccinated against COVID	3264.907b	8.314	4	0.081
Have/Had COVID	3259.713b	3.120	4	0.538
Traveled by Air during COVID	3265.305b	8.712	4	0.069
Current MAIN MODE of Transport for Inter-regional Travel	3442.670b	186.076	12	<.001
Distance between Home and the Nearest Airport	3278.172b	21.579	16	0.157
% of Direct Flights between Home Airport and Destination	3275.865b	19.272	16	0.255

Note. The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

[a] This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

[b] The unexpected singularities in the Hessian matrix are encountered. This indicates that either some predictor variables should be excluded, or some categories should be merged.

Appendix M

aMoD Clusters: Similarities

A non-significant variable indicates that the clusters are similar for that attribute.

Demographic and Trip Characteristics	Cluster 1[a] Suburban Rural Drivers	Cluster 2[b] Urban Educated Flyers	Chi-Square Results		
	%		χ^2	*df*	*p*
Sex			2.683	2	0.261
Female	36%	42%			
Male	64%	58%			
Age			6.038	6	0.419
18-24	3%	5%			
25-34	42%	39%			
35-44	29%	33%			
45-54	18%	13%			
55-64	7%	7%			
> 64	3%	3%			
Number of Driver's Licenses in Household			5.514	3	0.138
0	2%	0%			
1	27%	22%			
2	55%	64%			
3 or more	16%	14%			
Number of Cars Owned by Household			3.816	3	0.282
0	4%	2%			
1	44%	50%			
2	41%	40%			
3 or more	12%	9%			
Years with Driver's License			7.399	4	0.116
No driver’s license	4%	3%			
< 3 years	7%	9%			
3-8 years	20%	27%			
9-15 years	24%	26%			
> 15 years	46%	35%			
Weekly Drive Frequency			4.099	4	0.393
I do not drive	4%	4%			
< 1 time per week	8%	7%			
1-2 times per week	10%	16%			
3-5 times per week	30%	32%			
> 5 times per week	48%	42%			

Demographic and Trip Characteristics	Cluster 1[a] Suburban Rural Drivers	Cluster 2[b] Urban Educated Flyers	Chi-Square Results		
	%		χ^2	*df*	*p*
Car Accident When Someone was Injured			0.425	1	0.514
Yes	30%	33%			
No	70%	68%			
Distance from Home to Nearest Airport			7.361	4	0.118
< 15 minutes	8%	6%			
15-30 minutes	36%	44%			
31-45 minutes	35%	35%			
46-60 minutes	14%	7%			
>1 hour	8%	7%			
Traveled by Air during COVID			2.932	1	0.087
Yes	47%	55%			
No	53%	45%			
Have/Had COVID			0.683	1	0.408
Yes	22%	25%			
No	78%	75%			
aMoD Timing in U.S.			7.877	5	0.163
Within 3 years	9%	16%			
3-5 years	28%	30%			
6-10 years	38%	34%			
11-20 years	20%	17%			
Over 20 years	5%	3%			
Never	0%	0%			

Note. aMoD = Autonomous mobility-on-demand; EV = electric vehicles; SF = commercial short-haul flight. [a] Cluster 1: $n = 255$ (51.2%). [b] Cluster 2: $n = 243$ (48.8%).

Appendix N

SF Clusters: Similarities

A non-significant variable indicates that the clusters are similar for that attribute.

Non-Significant Demographic and Trip Characteristics	Cluster 1 [a] Apathetic Travelers	Cluster 2 [b] Loyal Habitual Flyers	Chi-Square Results		
	%		χ^2	*df*	*p*
Age			8.606	6	0.197
18-24	5%	1%			
25-34	49%	44%			
35-44	19%	30%			
45-54	20%	17%			
55-64	7%	5%			
> 64	2%	3%			
Education			3.696	3	0.296
Attended high school	0%	0%			
High school diploma	14%	20%			
Bachelor’s degree	59%	59%			
Master's degree	26%	19%			
PhD/Postdoc	2%	3%			
Household Income			1.505	5	0.912
< $30,000	10%	12%			
$30,001 to $50,000	23%	27%			
$50,001 to $100,000	47%	45%			
$100,001 to $150,000	13%	10%			
$150,001 to $200,000	5%	4%			
> $200,000	2%	3%			
# Children in Household			7.107	3	0.069
0	44%	35%			
1	32%	27%			
2	22%	32%			
3 or more	2%	6%			
# Driver's License in Household			5.399	3	0.145
0	0%	2%			
1	32%	24%			
2	58%	60%			

Non-Significant Demographic and Trip Characteristics	Cluster 1 [a] Apathetic Travelers	Cluster 2 [b] Loyal Habitual Flyers	Chi-Square Results		
	%		χ^2	*df*	*p*
3 or more	10%	14%			
# Cars Owned by Household			3.222	3	0.359
0	4%	5%			
1	49%	39%			
2	36%	42%			
3 or more	11%	15%			
Years with Driver's License			7.684	4	0.104
No Driver’s license	0%	3%			
< 3 years	8%	11%			
3-8 years	33%	24%			
9-15 years	24%	23%			
> 15 years	35%	39%			
Weekly Drive Frequency			7.048	4	0.133
I do not drive	2%	4%			
< 1 time per week	10%	8%			
1-2 times per week	20%	11%			
3-5 times per week	21%	26%			
> 5 times per week	48%	51%			
MODE_Current			4.979	3	0.173
Drive	20%	15%			
SF	72%	74%			
Inter-regional Bus	7%	7%			
Inter-regional Train	8%	4%			
Neighborhood			2.902	3	0.407
A city	35%	41%			
A suburb	40%	41%			
A small city	13%	11%			
Rural/Village	13%	8%			
Car Accident when someone was Injured			2.859	1	0.091
Yes	29%	38%			
No	71%	62%			
Mobility Issue			0.228	1	0.633
Yes	23%	20%			
No	77%	80%			
Distance Home to Nearest Airport			2.195	4	0.700

Non-Significant Demographic and Trip Characteristics	Cluster 1 [a] Apathetic Travelers	Cluster 2 [b] Loyal Habitual Flyers	Chi-Square Results		
	%		χ^2	*df*	*p*
< 15 minutes	5%	7%			
15-30 minutes	42%	42%			
31-45 minutes	34%	29%			
46-60 minutes	14%	14%			
>1 hour	6%	9%			
% Direct Flights from Home Airport			6.773	4	0.148
0%-20%	10%	8%			
21%-40%	29%	22%			
41%-60%	38%	38%			
61%-80%	11%	21%			
Over 80%	12%	11%			
Annual Miles Flown			0.099	3	0.992
< 5,000 mi	35%	36%			
5,000–10,000 mi	52%	51%			
10,001–25,000 mi	11%	11%			
> 25,000 mi	2%	2%			
Fly if over a certain Drive			10.351	5	0.066
3 hr	10%	20%			
4 hr	23%	22%			
5 hr	33%	29%			
6 hr	21%	14%			
7 hr	5%	3%			
8 hr	8%	13%			
Business Travels			1.559	3	0.669
Once a year	14%	13%			
2-6 times a year	51%	52%			
7 or more times a year	21%	17%			
Did not travel for Business	14%	18%			
Vaccinated against COVID			2.097	1	0.148
Yes	80%	86%			
No	20%	14%			
Have/Had COVID			2.23	1	0.135
Yes	20%	28%			
No	80%	72%			

Non-Significant Demographic and Trip Characteristics	Cluster 1 [a] Apathetic Travelers	Cluster 2 [b] Loyal Habitual Flyers	Chi-Square Results		
	%		χ^2	*df*	*p*
Traveled by Air during COVID			1.342	1	0.247
Yes	62%	56%			
No	38%	44%			
% Work from home @ COVID			6.485	5	0.262
100%	25%	35%			
75%	37%	25%			
50%	16%	13%			
25%	11%	12%			
0%	9%	11%			
I do not work	3%	3%			
Inter-regional Bus Used			1.203	1	0.273
Yes	61%	67%			
No	39%	33%			
Inter-regional Train Used			1.061	1	0.303
Yes	70%	75%			
No	30%	25%			
aMoD Timing in U.S.			9.006	5	0.109
Within 3 years	6%	15%			
3-5 years	29%	23%			
6-10 years	38%	30%			
11-20 years	19%	21%			
Over 20 years	5%	8%			
Never	5%	4%			
Timing when 50% Cars are aMoD			3.833	4	0.429
By 2030	22%	29%			
By 2040	39%	34%			
By 2050	21%	17%			
Beyond 2050	9%	13%			
Never	9%	7%			