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Know Your User: Building a Predictive Model of Consumer Preference for Driverless Cars

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KNOW YOUR USER: BUILDING A PREDICTIVE MODEL OF CONSUMER PREFERENCE FOR DRIVERLESS CARS

By

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SIGNATURE PAGE

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ABSTRACT

INTRODUCTION: This dissertation identifies factors significantly predicting participants' preference for riding in an autonomous vehicle rather than flying on a commercial aircraft. A plethora of research has investigated these two transportation industries independently; however, scarcely any research has considered the impact these two industries will have on each other. Travelers' preference for riding in an autonomous vehicle rather than a commercial aircraft was investigated through four different scenarios.

METHOD: A regression equation was created to predict participants' preferred travel method and validated through a two-stage process. Stage 1 involved the creation of the regression equation, and a total of 1,008 participants responded to an online survey, providing information on demographics, travel-related behavior, and their preference for riding in an autonomous vehicle rather than flying on a commercial aircraft. Stage 2 involved validation of the regression equation, and 1,008 participants responded to the same online survey. Stage 2 participants' scores were predicted using the regression equation created in Stage 1. Then, their predicted scores and actual scores were compared to validate the equation throughout four different travel scenarios.

RESULTS: In Stage 1, a backward stepwise regression assessed the twenty predictive factors (age, gender, ethnicity, social class, price, perceived value, familiarity, fun factor, wariness of new technology, personality (openness, conscientiousness, extraversion, agreeableness, and neuroticism), general vehicle affect, general airplane affect, vehicle comfort, vehicle external factors, airplane comfort, and airplane external factors). These factors were tested in four different scenarios, which varied only in the length of time participants would spend traveling.

CONCLUSION: A predictive model was created for each scenario, and then all four models were validated in Stage 2 using participants' predicted scores and actual scores. Models were validated using a *t*-test, correlation, and comparison of cross-validated R^2. The most robust model was for the four-hour trip, with six variables significantly predicting participants' preferred travel method, which accounted for 50.7% of the variance in the model (50.1% adjusted). Upper Social Class, Vehicle Affect, Airplane Affect, and Vehicle Comfort were the only significant predictors throughout all four scenarios. These four predictors will help other researchers and experts in the vehicle industry identify the first adopters of this new technology. The implications of the results and suggestions for future research are discussed.

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Chapter One

Introduction

Purpose Statement

As automation and technology rapidly advance in our society, industries are researching and developing both the automation and user interaction with the automation. Recently, the automotive industry has experienced a significant amount of media attention for different companies' attempts to build and introduce fully autonomous, driverless vehicles (i.e., no human driver). Research has investigated various factors influencing consumers' willingness to use fully autonomous vehicles. However, little research has investigated the impact fully autonomous cars could have on other transportation industries, such as commercial aviation. When people choose a travel method (fly or drive), there are often several factors that affect their decision, such as personal characteristics/preferences, length of trip, price, etc. Therefore, the current research seeks to explore the relatively unknown area of identifying which factors influence a person's preference for riding in an autonomous vehicle rather than flying on a commercial aircraft. This study consists of creating and validating a predictive model measuring participants' choice of preferred travel method using several different personal factors, feelings toward traveling, and feelings toward new technologies.

The current chapter discusses the background and rationale for this line of research, including operational definitions of all terms, research questions, and hypotheses to enhance understanding and future researchers interested in replicating the study. Furthermore, this chapter provides an overview of the significance offered by this study, as well as relevant limitations and assumptions that could significantly impact the findings and interpretations of this study.

Background and Rationale

The introduction of fully autonomous vehicles onto public roads opens several avenues of research, and perhaps one of the most important is consumers' acceptance and adoption of using this new technology. For years, vehicles have been increasing in their technology and automated operations, offering automated assistance ranging from passive lane departure warnings to active collision avoidance. Regardless of the automation level, humans have retained control of the vehicle, and drivers maintain awareness of the car and their environment throughout the entire trip. However, advancing research and development is poised to change the traditional interactions between humans and vehicles fundamentally.

There are five levels of vehicle automation ranging from Level One – limited automation – to Level Five – full automation (i.e., no human driver). Prominent vehicle manufacturers, such as Waymo, Uber, Tesla, etc. have been furiously competing to safely push Level Five vehicles onto the market (NHTSA, 2016; Reimer, 2014). Most companies make similar claims regarding the capabilities of this new technology, such as operating on any road and in any conditions that a human driver could negotiate; however, without any input from a human driver. Importantly, a lot of research and development has focused on ensuring the vehicle can safely and efficiently maneuver in its environment while transporting passengers and interacting with other drivers/vehicles and pedestrians. However, research often fails to equally consider consumers' behavioral intentions toward this new technology or the impact it will have on other transportation industries.

One of the most significant transportation industries involves commercial aviation. While the industry is doing well right now, fully autonomous vehicles could potentially disrupt the entire industry if travelers choose to ride to their destination rather than fly. Flying presents travelers with a stressful, time consuming, and often uncomfortable ordeal, as people navigate through traffic, airport security, and share personal space with a stranger. Flights that are only 1-2 hours can often take the same amount of time if the person had just driven to their destination (i.e., 5-6 hours of trip time). Understandably, people don't want to drive for 5-6 hours straight; thus, the lesser of two evils become flying. However, the introduction of fully autonomous vehicles now presents a third, and perhaps better, option for travelers.

If travelers don't want to go through the hassle of flying commercially, but they also don't want to drive for six hours straight, riding in an autonomous vehicle may provide the perfect solution. For the added convenience of traveling on your time schedule, stopping when you need to, having personal space, etc. travelers may even feel comfortable adding a few hours to their trip. Furthermore, since there is no need for a traditional setup inside autonomous vehicles, travelers may have a couch that pulls out to a bed and can sleep through the night while their car ferries them to their destination. Once at their destination, they now have a vehicle to use, whereas if they had flown, they would've had to rely on ridesharing services, public transportation, or a rental car.

Previous research examined travelers' opinions when asked to choose between using a driverless vehicle or commercially flying. Results indicated that almost 2/3 of participants would instead use a driverless car than fly for a midrange, 5-hour trip (Rice & Winter, 2018). Although plane tickets seem costly, airlines don't make a significant amount of money off each flight (about $10-$20 off each ticket). If airlines start losing, for example, a conservative estimate of one out of every ten passengers, they could potentially experience significant financial detriments. To offset losing money, airlines may seek other means of increasing revenue, such as increased ticket prices, higher fees for seat selection/baggage, reduced route options, etc., which may deter more customers.

Problem Statement

Although there is still some debate as to the exact date fully autonomous vehicles will be available, it is no longer a question of *if* but rather *when*. While many companies are focusing on research and development, not many industries or researchers are striving to understand the impact autonomous vehicles will have on the rest of the transportation industry. Therefore, the purpose of the current research is to understand better the impact that autonomous vehicles could have on the rest of the transportation industry, mainly commercial aviation.

Unsurprisingly, the transportation industry relies heavily on travelers to make a profit; thus, it is very much at the mercy of the traveling public's preferences. Right now, travelers tolerate commercial aviation because it is a necessary evil. Most people don't choose commercial aviation because they enjoy the experience. Flying commercial involves arriving at the airport hours early, going through security, sharing personal space with a stranger, being cramped in a tiny chair for long periods, etc. Unfortunately, it's the only reasonable method to travel long distances. Traveling via automobile is usually more comfortable because passengers have greater control over their experience. However, it can be exhausting, and therefore, dangerous to travel long distances, especially if the driver is alone or attempting to cover the entire range in one trip without stopping to rest.

Therefore, people often choose to fly commercial when traveling long distances, but the introduction of fully autonomous vehicles could potentially disrupt the commercial aviation industry. To date, only one study has investigated the impact of fully autonomous vehicles on the commercial aviation industry (Rice & Winter, 2018); however, this study did not focus on identifying predictors of passenger behavior. A better understanding of what type of traveler is most likely to choose to ride in an autonomous vehicle rather than flying on a commercial aircraft could provide crucial information for saving the commercial aviation industry and growing the driverless vehicle industry. This dissertation offers a basis for further understanding of the personal characteristics of travelers, which may influence their decision between one of two travel methods.

Operational Definition of Terms

1. *Travel Method Preference* refers to the participants' preference for riding in a fully autonomous vehicle rather than flying in a commercial aircraft for a variety of different scenarios. This is measured from the average score on the Travel Method Preference Scale (see Appendix A).
2. *Age* refers to the participant's age measured in years.
3. *Gender* refers to the social construct of the participant's gender, either male, female, or a written response for 'other.'
4. *Social Class* refers to the participant's self-identified membership within a hierarchical social grouping based on wealth, education, occupation, income, etc..
5. *Ethnicity* refers to the participant's self-identified ethnicity from the following options: 1) Caucasian, 2) African descent (e.g., African American), 3) Hispanic descent (e.g., Latin America), 4) Asian descent, 5) India (not Asian), or 6) Other.
6. *Price* refers to whether or not participants believe the cost of an airplane ticket is an essential factor for them.

7. *Perceived Value* refers to the participants' perception of how much worth they believe autonomous vehicles provide. This is measured from the average score on the Perceived Value scale (see Appendix B).
8. *Familiarity* refers to the participants' familiarity with autonomous vehicles. This is measured from the average score on the Familiarity scale (see Appendix C).
9. *Fun Factor* refers to how much entertainment or enjoyment participants believe they will experience with autonomous vehicles. This is measured from the average score on the Fun Factor scale (see Appendix D).
10. *Wariness of New Technologies* refers to the participants' fear of or hesitation in using new technology, such as autonomous vehicles. This is measured from the average score on the Wariness of new technologies scale (see Appendix E).
11. *Personality* refers to five individual variables that represent aspects of the participant's personality: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Each of these five personality traits is measured by the participants score on four questions of the Mini International Personality Item Pool (Mini-IPIP; Donnellan, Oswald, Baird, & Lucas, 2006). All five personality constructs are represented on the scale, for a total of 20 questions.
12. *General Vehicle Affect* refers to the participant's general emotional response to the hypothetical scenario about autonomous vehicles presented in the survey. This is measured from the average score on the General Affect scale (see Appendix F).
13. *General Airplane Affect* refers to the participant's general emotional response to the hypothetical scenario about commercial aircraft presented in the survey. This is measured from the average score on the General Affect scale (see Appendix F).

14. *Vehicle External Comfort* refers to the participants' overall level of comfort while traveling in a vehicle, such as space and the ability to sleep (see Appendix G).
15. *Vehicle External Factors* refers to the participants' overall satisfaction level with external factors associated with traveling in a vehicle, such as schedule flexibility (see Appendix H).
16. *Airplane Comfort* refers to the participants' overall level of comfort while traveling in a commercial aircraft, such as space and the ability to sleep (see Appendix I).
17. *Airplane External Factors* refers to the participants' overall satisfaction level with external factors associated with traveling in a commercial aircraft, such as going through TSA security (see Appendix J).

Research Questions

1. RQ1: Are any basic demographic variables (age, gender, social class, and ethnicity) significant predictors of participants' preferred travel method when controlling for all other variables?
2. RQ2: Is price a significant predictor of participants' preferred travel method when controlling for all other variables?
3. RQ3: Are current consumer perceptions (perceived value, familiarity, fun factor, wariness of new technologies), significant predictors of participants' preferred travel method, when controlling for all other variables?
4. RQ5: Are any personality traits (Big Five), significant predictors of participants' preferred travel method, when controlling for all other variables?
5. RQ6: Is vehicle affect a significant predictor of participants' preferred travel method when controlling for all other variables?

6. RQ7: Is airplane affect a significant predictor of participants' preferred travel method when controlling for all other variables?
7. RQ8: Is vehicle comfort a significant predictor of participants' preferred travel method when controlling for all other variables?
8. RQ9: Is vehicle external factors a significant predictor of participants' preferred travel method when controlling for all other variables?
9. RQ10: Is airplane comfort a significant predictor of participants' preferred travel method when controlling for all other variables?
10. RQ11: Is airplane external factors a significant predictor of participants' preferred travel method when controlling for all other variables?

Research Hypotheses

Hypothesis 1

H_{01}: Demographic variables (age, gender, social class, and ethnicity) do not significantly predict participants' preferred travel method when controlling for all other variables.

H_{A1}: At least one demographic variable (age, gender, social class, and ethnicity) will significantly predict participants' preferred travel method when controlling for all other variables.

Hypothesis 2

H_{02}: Price does not significantly predict participants' preferred travel method when controlling for all other variables.

H_{A3}: Price is a significant predictor of participants' preferred travel method when controlling for all other variables.

Hypothesis 3

H_{03}: Current consumer perceptions (perceived value, familiarity, fun factor, wariness of new technologies) do not significantly predict participants' preferred travel method when controlling for all other variables.

H_{A3}: At least one current consumer perceptions (perceived value, familiarity, fun factor, wariness of new technologies) will significantly predict participants' preferred travel method when controlling for all other variables.

Hypothesis 4

H_{04}: None of the big five personality traits significantly predicts participants' preferred travel method when controlling for all other variables.

H_{A4}: At least one of the big five personality traits is a significant predictor of participants' preferred travel method when controlling for all other variables.

Hypothesis 5

H_{05}: Vehicle Affect is not a significant predictor of participants' preferred travel method when controlling for all other variables.

H_{A5}: Vehicle Affect is a significant predictor of participants' preferred travel method when controlling for all other variables.

Hypothesis 6

H_{06}: Airplane Affect is not a significant predictor of participants' preferred travel method when controlling for all other variables.

H_{A6}: Airplane Affect is a significant predictor of participants' preferred travel method when controlling for all other variables.

Hypothesis 7

H_{07}: Vehicle Comfort is not a significant predictor of participants' preferred travel method when controlling for all other variables.

H_{A7}: Vehicle Comfort is a significant predictor of participants' preferred travel method when controlling for all other variables.

Hypothesis 8

H_{08}: Vehicle External Factors is not a significant predictor of participants' preferred travel method when controlling for all other variables.

H_{A8}: Vehicle External Factors is a significant predictor of participants' preferred travel method when controlling for all other variables.

Hypothesis 9

H_{09}: Airplane Comfort is not a significant predictor of participants' preferred travel method when controlling for all other variables.

H_{A9}: Airplane Comfort is a significant predictor of participants' preferred travel method when controlling for all other variables.

Hypothesis 10

H_{10}: Airplane External Factors is not a significant predictor of participants' preferred travel method when controlling for all other variables.

H_{10}: Airplane External Factors is a significant predictor of participants' preferred travel method when controlling for all other variables.

Significance of Study

The push for integrating autonomous vehicles onto America's public roadways has received a plethora of attention from different media outlets, research organizations, and consumer safety reports. However, all of these different avenues of investigation and information dissemination have yet to consider the impact autonomous vehicles could have on the commercial aviation industry. Currently, the commercial aviation industry is financially performing well. However, they have a historically low-profit margin per flight (McCartney, 2018) and travelers don't typically experience high levels of enjoyment from this mode of transportation (Kloppenborg & Gourdin, 1992; Nadiri, Hussain, Ekiz, & Erdogan, 2008; Young, Cunningham, & Lee, 1994).

Several consumer reports have begun speculating as to the impact autonomous vehicles will have on the transportation industry. The overarching conclusion being that as autonomous cars become more available, affordable, and safe, travelers will increasingly choose them over other modes of transportation, mostly because of the increased comfort and convenience they will offer. On the other hand, only one scientific study has investigated the potential impact autonomous vehicles will have on the commercial aviation industry (Rice & Winter, 2018).

Therefore, the practical significance of the current research involves the exploration of factors potentially influencing travelers' decision to choose one method of travel over the other. If enough travelers view autonomous vehicles as a preferred alternative mode of travel over commercial aircraft, then this could have tremendous negative implications for the success of the commercial aviation industry. The current study investigates factors that may predict travelers' preferred travel method. The findings from this study can help both the autonomous vehicle industry and the commercial aviation industry better understand their customers and identify important factors to prioritize when building and maintaining customer support. However, as previously stated, this is a relatively unexplored area of research. Therefore, future research should replicate and build upon the current study to better understand travelers' behavioral intentions between these two modes of transportation.

Study Limitations and Delimitations

Limitations

Unfortunately, research is unable to account for every single possible variable and external factor; thus, there are a few limitations associated with the project. Potentially one of the most significant limitations is the fact that I collected data via an online convenience sampling technique from Amazon's Mechanical Turk® (MTurk). I utilized MTurk because it provides researchers with access to a large pool of participants for a relatively small financial cost and is optimal for survey distribution. Fortunately, recent research has indicated that data collected from MTurk has reliability ratings comparable to traditionally collected laboratory data (Buhrmester, Kwang, & Gosling, 2011; Germine et al., 2012; Rice, Winter, Doherty & Milner, 2017).

Another limitation associated with this research is that participants will receive monetary compensation for completing the survey. Paying participants to complete the survey may tempt them to rush through the questions so that they can finish and move on to the next task. The nature of this research assumes that participants are taking their time to understand the scenarios and provide thoughtful responses. Fortunately, MTurk attempts to mitigate some of this concern by providing a type of reliability rating for each participant that researchers can access. MTurk users who consistently provide thoughtful and careful responses to HITs (Human Intelligence Tasks) have higher reliability ratings than users who speed through tasks or provide inaccurate data (i.e., skipping questions, "Christmas-treeing" responses, guessing, etc.). To ensure high-quality data collection for this study, MTurk participants were required to have at least a 98% approval rating and have completed more than 100 HITs before completing the current survey.

Furthermore, the nature of survey data means that it is almost entirely dependent upon self-reports, which relies on participants' accuracy of self-awareness. Unfortunately, many external factors could influence participants' response bias, thus affecting their responses. For example, if a participant was recently in a car crash, then their opinion of vehicles may be abnormally more negative than usual; however, the researchers are not privy to that information. Also, individuals may have varying understandings of the survey scale prompts, *Agree*, and *Strongly Agree* or the difference between them. Fortunately, the nature of online surveys also allows for large amounts of data collection, which helps minimize variance.

Delimitations

I placed certain boundaries upon the accessible participant population, background literature, procedures, and analyses. For the accessible population, only participants who are 18 years of age or older and who have internet access were allowed to participate in the study; thus, the results are not necessarily generalizable to younger travelers or those without internet access. Furthermore, because fully autonomous vehicles are not yet legal, we cannot ask participants about their past behavior or even conduct experimental in-person research. Instead, we must entirely rely on participants' perceived behavioral intentions.

Although participants have probably never traveled in a fully autonomous vehicle, I assumed that most people have probably experienced riding in modern cars and traveling via commercial aircraft; thus, they can make reasonable comparisons about their experiences. Furthermore, because this line of research is interested in participants' perceived behavioral intentions, we can collect data from *potential* travelers as well as people who have traveled in the past. Thus, there was no need to limit the survey to only people who indicated a history of traveling, as this research was also interested in future travelers' behavioral intentions.

Finally, several scales were either adapted or created for this particular research. Before scale creation, I conducted an extensive literature review to ensure there were no pre-existing instruments that could measure the same constructs within a reasonable time frame. Both I tested the adapted scales and the newly created scales for reliability and validity using Cronbach's Alpha and Guttman's split-half tests. All the results from these analyses indicated medium-high reliability and validity (see Table 1 for an overview of results and related appendices).

Assumptions of Regression

The current line of research utilizes multiple regression as the data analysis technique and model fitting, which allows for the creation and validation of a sound prediction model. As with any statistical procedure, there are certain assumptions of the data are required to ensure appropriate analysis. The assumptions for multiple regression are as follows:

1. There is one continuous dependent variable.
2. There are two or more independent variables.
3. Observations are independent.
4. A linear relationship between the dependent variable and independent variables, individually and collectively.
5. There is homoscedasticity in the data.
6. There is no multicollinearity in the data.
7. There are no significant outliers in the data.
8. The residuals (errors) are normally distributed.

The first two assumptions are concerned with study design and the design of the survey instruments representing the independent variables. For this study, there is only one dependent variable, travel method preference, thus satisfying the first assumption. Furthermore, there are 20 independent variables, thus fulfilling the second assumption, as well.

Assumption three states that the observations should be independent, meaning that the errors of each observation should not be correlated with each other (if they were then another type of analysis might be more appropriate). Independence of observations is tested using the Durbin-Watson statistical output produced by SPSS or by assessing the scatterplot of the residuals. The residuals scatterplot can also assist with verifying the fourth assumption, which states that there should be a linear relationship between the independent variables and dependent variables, both individually and collectively. The fifth assumption is concerned with ensuring there is homoscedasticity in the data, which means that the variance of error terms should be similar across the values of the independent variables. A plot of standardized residuals versus predicted values can show whether points are equally distributed across all values of the independent variables.

The sixth assumption is concerned with ensuring there is no multicollinearity within the data, meaning that the independent variables are not highly correlated with each other. The presence of multicollinearity can be tested through SPSS using Tolerance/Variance Inflation Factor (VIF) values and correlation values. Assumption seven states that there should be no outliers in the data, as this can interfere with accurate regression analysis. Before analysis, I screened the data to identify any outliers. I removed these outliers from the final analysis (all data modified or removed from the final analysis will be stored in a separate folder so as not to be erased). Finally, assumption eight states that the residuals (errors) should be normally distributed. This assumption can be checked by comparing the residual plot to a superimposed normal curve or a P-P plot.

Summary

Chapter One identified the problem area that the current research addresses and outlines the background information and rationale behind the present study. To this end, I provide a detailed description of the study’s operational definitions, research questions, hypotheses, and practical significance. As with all research, acknowledgment of limitations and assumptions of the appropriate statistical procedure are highlighted. In the following chapter, a thorough description of relevant literature will be explored, thus providing rationale as to the inclusion of the independent variables as well as the adaption/creation of the scales used within the survey.

Chapter Two

Review of Related Literature

Introduction

Understanding and reporting human behavior can be challenging compared to other disciplines because the primary objects of interest – humans – are continually changing and evolving. As technology and automation continue rapidly advancing in our society, particularly in the aviation and automotive industry, accurately interpreting and predicting consumers' behavior will offer insights into the success or failure of these potentially competing industries. As autonomous vehicles grow in their capabilities, safety, and accessibility, they introduce the potential to disrupt the commercial airline industry, encroaching upon commercial aviation's current customer base (Nishimoto, 2018; Rice & Winter, 2018). Previous research on user acceptance of autonomous automobiles has offered different definitions, models, and measures of acceptance; however, researchers have yet to consider the impact of the autonomous vehicle industry on the commercial aviation industry.

The purpose of this dissertation is to understand better what type of person would choose to ride in an autonomous vehicle rather than fly in a commercial aircraft. Ultimately, my goal is to build a prediction model, which will assist researchers in understanding the different personal factors affecting a person's decision when they must choose between two different, competing technologies. Previous research and rationale for each factor will be provided, in addition to the discussion of regression and prediction models, particularly for the research within this dissertation.

Sources

Compilation of this literature review involved collating a variety of sources from two main search engines, Google Scholar and Embry-Riddle Aeronautical University's Hunt Library portal, which allowed access to journals and databases not freely available on Google Scholar. Databases mined for the information included SpringerLink, ScienceDirect, IEEE Xplore, Sage, NIH NCBI, among others. Within these databases, I collected data from peer-reviewed journal articles, books, conferences, papers/proceedings, and news reports. Keywords and phrases related to the research-specific variables were used, including gender, age, affect, wariness of new technology, technology acceptance model, fear of flying, autonomous vehicles, comfort while traveling, customer satisfaction, fun and modern technology, regression analysis, prediction models, and model fit.

Dependent Variable: Preferred Travel Method

For this study, the dependent variable will consist of participants' preferred travel method, which indicates their level of preference for riding in an autonomous vehicle rather than flying on a commercial flight. However, it is essential to note that fully autonomous vehicles (no human involvement) are not yet legal. Thus participants will only be asked to indicate their perceived preferred travel method and will not be asked to ride in a fully autonomous vehicle or commercial airline flight. Travel method preference was measured using a scale created explicitly for this research, Travel Method Preference Scale (see Appendix A). I ran a pilot study to determine the reliability and validity of this scale, revealing a Cronbach's alpha of .93, indicating high internal consistency and a Guttman's split-half of .92, indicating high reliability.

Predictive Factors

This dissertation considers 20 different factors that may significantly predict a participant's preference for riding in a fully autonomous (driverless) vehicle. I considered these factors because the current line of research strived to build a prediction model that focused on personal factors related to the participant, rather than external factors outside of the participant's control. These factors include age, gender, social class, ethnicity (individualistic and collectivistic), price, perceived value, familiarity, fun factor, wariness of new technology, personality (openness, conscientiousness, extraversion, agreeableness, and neuroticism), general vehicle affect, general airplane affect, vehicle comfort, vehicle external factors, airplane comfort, and airplane external factors.

Consumer Travel Behavior

The U.S. Department of Transportation recently released the 2017 National Household Travel Survey (NHTS), which contains the most comprehensive national household travel data since 2009, thus allowing insights into America's current travel trends. While this survey provides a massive amount of data regarding travel behavior, perhaps one of the most interesting findings is the downward trend in trip rates per capita appears to be continuing, as compared to the previous surveys in 2009 and 2001 (Mcguckin, 2018; Polzin, 2018; U.S. Department of Transportation, 2018). While this particular survey did not investigate the reasons behind this continued downward trend (but suggested that future research further explore these trends and causal factors), it did provide information on other factors that may be influencing this downward trend in travel.

In particular, advanced technology has allowed people to substitute traditional communication methods for a multitude of new behaviors, "such as teleworking, e-commerce, social media networking instead of in-person social interactions, distance learning, and electronic transfer of documents, media, music, information, and more” (Polzin, 2018, para. 6). In general, people appear to be using technology and the Internet more to accomplish tasks previously completed in person, thus reducing long travel time. According to the survey, e-commerce is growing exponentially, which could potentially account for the decline in Vehicle Miles Traveled (VMT; Polzin, 2018; U.S. Department of Transportation, 2018).

Since people seem to be moving more toward online work, transactions, and communications, it will be interesting to see the effect that autonomous vehicles will have upon travelers’ behavior. If travelers are no longer tasked with actual driving, but can continue working, shopping, and communicating online, will the trend in VMT start revealing an increase? While autonomous vehicles may seem like transportation technology for the future, reputable vehicle companies, such as General Motors, Nissan, Toyota, and Tesla, have already been investing in research and development of autonomous vehicles for several years, if not decades (Eden, Nanchen, Ramseyer, & Evéquoz, 2017; Lavieri et al., 2017; Yadron, 2016). Many of these companies expect to have fully autonomous, self-driving vehicles on the roads within a few years. Tesla states all their vehicles “come standard with advanced hardware capable of providing Autopilot features today, and full self-driving capabilities in the future – through software updates designed to improve functionality over time” (Tesla, 2019, para. 1).

Researchers developed a mathematical model (Bass diffusion) to predict ‘market penetration’ and ‘market saturation’ of fully autonomous vehicles using historical data on the adoption of hybrid electric cars and internet/cell phone adoption in the United States (Lavasani, Jin, & Du, 2016). This model assumes that autonomous vehicles will be available by 2025 and points out that market saturation occurs when 75% of U.S. households have purchased an autonomous vehicle, which is forecasted to happen in 2059. A market analysis conducted by the Center for Automotive Research interviewed more than 25 senior technologists, automotive industry experts, academics, and government officials. The report concluded that

> technological change toward full automation is inevitable given market dynamics and social, economic, and environmental forces. It is considered that the marketplace (i.e., consumers) will be the engine pulling the industry forward. The transitions to [autonomous vehicles are] framed as a radical revolution in the way we interact with vehicles and the future design of roads and cities that will need several technological, regulatory, and societal factors to successfully align to be achieved.
>
> Clark et al., 2016, p. 11

Autonomous vehicles offer the possibility of revolutionizing the way individuals travel and use their cars. If companies like Tesla are correct in their predictions of autonomous vehicle capabilities', passengers may have the option of being chauffeured between origins and destinations in a demand-responsive manner. Tesla describes the feature of 'Enhanced Summon,' which allows the "car [to] navigate complex environments and parking spaces, maneuvering around objects as necessary, [and] come find you anywhere in a parking lot" (Tesla, 2019, para. 3). With these capabilities, ridesharing services, such as Uber, Lyft, Zipcar, etc. could be operated with autonomous vehicle fleets (Lavieri et al., 2017).

For example, a study conducted in Ulm, Germany, concluded that participants' membership in the carsharing service, car2go, significantly increased their willingness to forego the purchase of a private car (Firnkhorn & Müller, 2011; Lavieri et al., 2017). More recently, researchers surveyed 10,000 respondents on their acceptance of driverless vehicles and sociodemographic variables through a 94-item online questionnaire. Results indicated that scores on the questionnaire were explained through factors pertaining to the following variables: perceived usefulness of driverless vehicles, perceived ease of use, pleasure/fun in using driverless vehicles, familiarity with driverless vehicles, and being comfortable with technology (Nordhoff, de Winter, Kyriakidis, van Arem, & Happee, 2018). Many of these variables, and the aforementioned research, influenced the research design and variables investigated for the current study. However, it's important to remember that autonomous vehicles are only one side of this debate over travelers' preferred mode of transportation; thus, it's equally important to consider commercial aviation travel, as well.

Researchers have already begun acknowledging and investigating the impact that driverless vehicles could have on the commercial aviation industry (Fairs, 2015; Goldstein, 2017; Radfar, 2017; Rice & Winter, 2018). Representatives of large vehicle companies have stated that self-driving cars could disrupt the airline and hotel industries, particularly for short-haul flights, as the hassle of commuting to and from the airport will be eliminated (Fairs, 2015; Goldstein, 2017; Radfar, 2017; Rice & Winter, 2018). Commercial aviation may experience this encroachment upon their customer base as travelers opt to ride in driverless vehicles rather than take a traditional short-haul flight.

Currently, the commercial aviation industry seems to be experiencing a robust economic period as airlines are making meaningful profits within the United States (International Air Transport Association, 2018; Stalnaker, Usman, Taylor, & Alport, 2018). However, this increase in airline profit often results from an increased cost leveled at the consumer (Graham, 2018). For example, to maintain low airfares, and thus an adequate customer base, many airlines charge for amenities that were once included, such as carry-on or checked luggage, onboard food, selecting seats, and boarding order. Furthermore, after the terrorist attacks of 9/11, airport security measures were increased significantly (although whether or not this increased safety is up for debate). This heightened security created an additional increase in travel time, in some cases doubling the actual trip time (Barros & Tomber, 2010; Rice & Winter, 2018).

One previous study has begun quantitatively investigating the impact of driverless vehicles on the commercial aviation industry (Rice & Winter, 2018). Over 2,000 participants responded to an online survey detailing varying travel scenarios that differed in trip length time and asked participants to indicate if they would prefer to fly commercial or ride in an autonomous vehicle. In general, an increase in travel time positively correlated with an increase in the percentage of customers who would prefer to fly commercial. However, in all cases, when participants were told that they would need a vehicle at their destination, and flying commercial would require them to rent a vehicle at their destination, willingness to fly commercial decreased. In one scenario, the total travel time was 5 hours for both the drive and the flight. When participants had to rent a vehicle at their destination, only 26% of participants indicated that they would still want to fly commercial (Rice & Winter, 2018).

To date, the study mentioned above is the only research quantitatively investigating the impact of driverless vehicles on the commercial aviation industry, particularly with a focus on consumer traveler behavior. Thus, there is a wide range of variables explored in the current research, as this still an incredibly new field that research has yet to determine influencing factors. However, the technology and advancements within the automotive industry are continuing to advance – regardless of whether or not there is comprehensive consumer behavior research and information. Therefore, it’s vital to continue exploring what factors will influence future customers’ decisions when asked to choose between flying commercial or riding in an autonomous vehicle

Automated Vehicles

Technological advancements have been growing exponentially in modern society, particularly within the automotive industry, with the advent of automated, driverless cars. Automated ground vehicles offer many benefits, including increased safety (Bansal, Kockelman, & Singh, 2016; Diels, 2014; Fagnant & Kockelman, 2015; Manyika et al., 2013; Maccubin et al., 2008). There were over 37,000 fatalities from vehicle crashes in 2016 alone (National Highway Transportation Safety Administration [NHTSA], 2016), which are often due to human error (NHTSA, 2015).

> Autonomous vehicles are those where the full-time performance is undertaken by an automated driving system for all aspects of the dynamic driving task, which includes the operational (steering, braking, accelerating, monitoring the vehicle and roadway) and tactical (responding to events, determining when to change lanes, turn, use signals, etc.) aspects of the driving task under all roadway and environmental conditions that can be managed by a human driver.
>
> Meng et al., 2018, p. 105

Depending upon the manufacturer, fully autonomous vehicles maneuver through the environment using a few different mechanisms; however, all Level 4 systems – and the majority of Level 3 – acquire and maintain situational awareness and “self”-awareness (Jo, Kim, Kim, Jang, & Sunwoo, 2014; Karagiannis et al., 2011). Maintaining active situational awareness and self-awareness is often achieved through two main procedures, localization and mapping or simultaneous localization and mapping (Elbanhawi, Simic, & Jazar, 2015; Meng et al., 2018). Thus, facilitating road lane following and obstacle avoidance (Alves de Lima & Victorino, 2016).

Previous research has identified ten different levels of automation within the industry that range from full human involvement (Level One – No Automation) to no human involvement (Level Ten – Full Automation). According to the NHTSA, there are six different levels of automated vehicle systems that range from providing simple driver assistance to controlling the majority of driving functions (NHTSA, 2016; Reimer, 2014).

The first, Level 0, is classified as ‘No Automation’ because the driver must perform all driving-related tasks without help from the technological system. Level 1 is classified as ‘Driver Assistance’ because the driver still completes all driving-related tasks; however, the driver may receive some assistance from the technology, such as forward collision warning, lane departure warning, and blind-spot alerts (NHTSA, 2016; Reimer, 2014). However, vehicular systems within this level do not offer any automated assistance, so the driver must remain alert and in control at all times. Level 2 systems include ‘Partial Automation,’ which combines some automation functions, like adaptive cruise control, imminent collision braking, and lane-keeping; however, the driver is still expected to maintain awareness and responsibility for the vehicle (Reimer, 2014).

Level 3 automated systems contain ‘Conditional Automation’ because they encompass two or more functions that tend to be slightly more advanced than the versions offered with Level 2 automation (NHTSA, 2016). For example, some vehicles provide lateral and longitudinal control of the vehicle in traffic jams or on highways (Rajamani, Tan, Law, & Zhang, 2000; Reimer, 2014). Vehicles with Level 3 automated systems will provide some self-driving features and allow the driver to delegate full control of all critical operational functions to the computerized system. Mostly, the human driver will not have to maintain constant awareness of the system or roadway while driving but will still retain the option to manually take over, if they wish – or if the environment is not appropriate for Level-3 driving (Reimer, 2014).

Drivers can expect to see ‘High Automation’ within Level 4 systems meaning that the vehicle will be capable of performing the majority of critical driving functions under certain conditions (NHTSA, 2016). Those situation-dependent conditions will vary among manufacturers, such as weather, road terrain, traffic, etc. Finally, Level 5 automation will consist of ‘Full Automation,’ such that the vehicle is entirely capable of performing all driving-related functions without any input from the driver. The interior of cars at this stage of automation may look altogether different from our vehicle interiors today. There will no longer be a need for the setup we currently have in vehicles (i.e., front seat/back seat configuration, steering wheel, dashboard, etc.).

Instead, level five vehicles may resemble luxurious train cars or private jets, such as Volvo’s 360c. This car conceptualizes “passengers entering through a wide gullwing door, which could lead to a spacious living room setup with a seat that can convert to a bed, or a mobile conference room with an interactive table and coffee makers…and the windows double as augmented reality displays” (Nishimoto, 2018, para. 3). The interior design will resemble social, work, and entertainment spaces allowing the passenger to engage in non-driving tasks, such as checking emails, reading books, watching movies, face to face conversations, etc. (Diels, 2014). When questioned, individuals noted several positive attributes of driverless vehicles. Driverless vehicles have improved fuel efficiency, shorter journey times, and in some cases, increased productivity because the passenger(s) no longer has to monitor the external environment (Clark, Parkhurst, & Ricci, 2016).

While the automotive industry has steadily researched and developed autonomous vehicles, as of now, it is still illegal to operate a fully autonomous vehicle on public roadways. At the federal level, the NHTSA has published a 'preliminary statement of policy concerning automated vehicles' (NHTSA, 2015) after multiple states requested clarification and guidance on conducting safe trials of automation vehicles on public roads. Within this legislation, NHTSA focused on three main areas of

> technological development: 1) in-vehicle crash avoidance systems (either warning the driver or involving automation to control the vehicle), 2) vehicle to vehicle communications (developed for crash avoidance), and 3) self-driving vehicles, [which] are view viewed along a continuum of automation,
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> Clark et al., 2016, p. 10

similar to the hierarchy of automation published by the Society of Automotive Engineers International (2014). While these features increase safety and consumer confidence within fully autonomous vehicles, there are still several different personal factors potentially influencing consumers' decision-making process.

Personality

Our personality can often play a significant role in our perceptions, feelings, and, ultimately, the adoption of new technology. The Big Five personality scale (or OCEAN) is a widely used tool for measuring different aspects of peoples' personalities because it facilitates the prediction of behavioral intentions and offers the rationale behind people's actions. This scale is composed of the components, Openness to experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, of which participants score along a continuum indicating their propensity to display that trait.

Previous research has investigated participants' "perceptions of user acceptance of, concerns about, and willingness to buy AV [autonomous vehicle] technology" (Clark et al., 2016, p. 17). However, personality traits only weakly correlate with these different perceptions of autonomous vehicles (Clark et al., 2016; Kyriakidis, Happee, & de Winter, 2015). On the other hand, research has also demonstrated that individuals with high levels of Extraversion are often more likely to have high levels of initial trust in a machine, which can positively influence behavioral intentions (Merritt & Ilgen, 2008). Therefore, the literature cannot definitively state that personality will affect consumers' decisions in one direction as personality may or may not influence participants' decision-making process.

Gender

While differences between males and females are not as vast as scientists once believed, there are still important distinctions between these two genders, particularly regarding their decision-making process. The majority of our knowledge regarding gender differences in decision-making comes from the financial and economic domain (Charness & Gneezy, 2012; Fonseca, Mullen, Zamarro, & Zissimopoulos, 2012; Francis, Hasan, Park, & Wu, 2014; Powell & Ansic, 1997). Researchers studied these differences before the field of psychology began equally representing female participants (Liu & Mager, 2016). However, subsequent research in other areas has continued to explore gender differences, thus replicating and supporting several previous findings.

In general, women tend to be more risk-averse than men. When faced with an identical situation, women tend to choose the safer outcome (Borghans, Heckman, Golsteyn, & Meijers, 2009; Byrnes, Miller, & Schafer, 1999; Charness & Gneezy, 2012; Fehr-Duda, de Gennaro, & Schubert, 2006; Rice & Winter, 2019). Scientific literature has replicated this finding on financial decision-making, lifestyle choices, social situations, etc. For example, previous research demonstrates that when participants rate their perceived willingness to fly on autonomous aircraft (Rice & Winter, 2019), undergo robotic dentistry (Anania et al., 2018b), or walk across the street in front of a driverless vehicle (Winter et al., 2019), women responded with significantly lower rates of perceived willingness than men.

However, it's important to note that the research mentioned above contains the underlying assumption that the hypothetical scenario presented to participants entails a certain level of risk (i.e., participants did not read completely harmless situations). Previous research indicates that flying in a commercial aircraft represents a certain level of risk (Clemes, Gan, Kao, & Choong, 2008; Mehta, Rice, Winter, & Eudy, 2017). "Male passengers were more satisfied with the safety and security dimensions than female passengers" (Clemes et al., 2008, p. 59). Interestingly, researchers do not fully understand why women tend to make more risk-aversive choices, although evolutionary psychology has proposed a plausible cause.

While researchers cannot empirically test theories generated from evolutionary psychology, they do attempt to provide some iota of an explanation into human behavior. This research can be beneficial as people are notoriously bad at accurately explaining *all* the factors affecting their behavior and decisions (Donaldson & Grant-Vallone, 2002; Paulhus & Vazire, 2007). Often, when participants subjectively recount their motivations, thoughts, and desires, they fail to account for or misrepresent the impact of specific stimuli (Lelkes et al., 2012; Paulus

& Vazire, 2007). Thus, researchers can only account for a piece of the whole picture, which usually results in researchers seeking out objective ways to collect as much information as possible.

Historically, during our species' hunter-gatherer days, women typically stayed near the home, foraging for vegetables and fruit and caring for the children, while the men ventured out to hunt for wild game (Trivers, 1972). Thus, women were not exposed to as many potentially risky situations as men and often erred on the side of caution. Furthermore, because women were mostly in charge of childcare, they were predisposed to making safer choices, which would hopefully ensure the safety and survival of their offspring – and the continuation of their family (Buss, 2003; Harris, Jenkins, & Glaser, 2006). On the other hand, men were often faced with unavoidable risky scenarios as they traveled through uncivilized terrain and hunted wild game.

Evolutionarily, our modern environment and technology are still incredibly new, and our brains have not yet evolved, meaning that we still have the same mind as our hunter-gatherer ancestors (Kaas, 2013; Neubauer, Hublin, & Gunz, 2018). Therefore, in general, women tend to be predisposed to making relatively safer choices compared to men, and previous research has indicated that men show more positive perceptions of advanced technology like autonomous vehicles (Byrnes et al., 1999; Kyriakidis et al., 2015; Payre, Cestac, & Delhomme, 2014). However, it's important to note that while gender could influence someone's behavior, there are also a lot of other causal factors that could interfere with someone's decision-making process, regardless of gender.

Age

In American society, a person's age typically represents specific actions someone may not accomplish. For example, citizens can't legally drink until they are 21 years old, and citizens can’t legally drive by themselves until they are 18 years old. As we get older, we often lose privileges, such as living independently or driving ourselves. While many of these age-related barriers stem from legitimate reasons (for example, more drivers in their mid-60s and older start experiencing fatal vehicular crashes; Li, Braver, & Chen, 2003; NHTSA, 2015), they often result in limiting older individuals’ freedom and mobility. Cessation of driving due to age-related obstacles (i.e., slower reaction time, poor eyesight, reduced mobility, etc.) often leads to an increased reliance on the assistance of others or increased isolation. Increased isolation can also exacerbate depression symptoms (Marottoli et al., 1997; Ragland, Satariano, & MacLeod, 2005). Therefore, older people may view autonomous vehicles as avenues to help maintain or increase levels of autonomy and freedom because they no longer have to rely on another person to drive them (Harper, Hendrickson, Mangones, & Samaras, 2016; Howard & Dai, 2014).

Furthermore, financial means often increase as we age, as well, making it more feasible to purchase new technology that may help maintain or increase our freedom and mobility, such as automated, driverless vehicles (Reimer, 2014). On the other hand, previous research has indicated that older adults express higher levels of satisfaction when flying commercial aviation than younger adults (Clemes, Gan, Kao, & Choong, 2008). However, it’s important to note that financial freedom again plays a vital role as older adults may be able to afford flying with higher quality airlines or to pay for upgrades, which positively enhances their overall experience.

In contrast, younger people, especially those living in urban areas, were more likely to have positive perceptions of autonomous vehicles compared to other groups (Hulse, Xie, & Galea, 2018). Recent research investigated the effect of age on participants’ perception of risk of different types of vehicles, finding that younger participants viewed vehicles as riskier than older participants (Hulse et al., 2018). However, this effect disappeared when the participants were prompted with risk perceptions of an autonomous vehicle, perhaps because none of the groups had any experience with autonomous cars; thus, there were no preconceived notions of potential risk (Hulse et al., 2018). Therefore, the current study will consider age as a predictive factor; however, the literature is still undecided as to the direction of the relationship between age and perception of using an automated vehicle.

Ethnicity

Unsurprisingly, the environment and society can often have a significant impact on our worldview and our mentality. Researchers categorized societies according to different aspects of their culture. Culture is "the collective programming of the mind that distinguishes the members of one group or category of people from others" (Hofstede, 2011, p. 3). Primarily, it describes a group of people in general terms as characteristics of individuals are often displayed along a bell curve. Thus the majority of individuals that fall along the middle make up the characteristics of that culture (Hofstede, 2011). Certain aspects of our culture, such as societal and national norms, are more deeply rooted in the human mind. These aspects have a more significant effect on our behavior than other elements, such as the culture found within our occupation, different hobbies, pop culture, etc. (Hofstede, 2011).

Previous research divided national cultures into individualistic or collectivistic dimensions along a scale (Hofstede, 2011). This scale "relates to the integration of individuals into primary groups" (Hofstede, 2011, p. 8). In individualistic cultures, people are often focused on their immediate wellbeing and potentially the wellbeing of their immediate family. They tend to focus on promoting themselves and achieving individual success without considering the needs or what is best for overall group success. On the other hand, citizens of collectivistic cultures are more integrated with each other, and there are often large, extended family units who are incredibly loyal to each other and focus on promoting the success of the overall group without concern for individual desires (Hofstede, 2011).

Western cultures (e.g., the United States of America and Europe) tend to identify more strongly with Individualism as compared to Eastern communities (e.g., Asia and the Middle East), which tend to identify more strongly with Collectivism. Ethnographical research indicates that ethnicity influences people's emotional reactions and behavioral intentions toward autonomous technology (Mehta et al., 2017; Srite & Karahanna, 2006). In particular, participants from collectivistic societies tend to be more trusting of new technology and are more likely to use the latest technology, especially if it could potentially benefit the rest of their community (Haboucha, Ishaq, & Shiftan, 2017; Hofstede, 1980, 2001; Markus & Kitayama, 1991; Mehta et al., 2017). On the other hand, people from individualistic societies tend to be less trusting of new technology and less willing to use the latest technology, regardless of whether or not it offers societal-wide benefits (Hofstede, 1980, 2001; Markus & Kitayama, 1991; Mehta et al., 2017).

While ethnicity and culture are two separate concepts, previous research has indicated they are strongly related, with ethnic identity acting as an essential determinant of cultural norms, values, and preferences (Desmet, Ortuño-Ortín, & Wacziarg, 2017). Therefore, the currents study asks participants to provide their ethnicity and categorized as individualistic or collectivistic. The categorization of cultures is following Hofstede's list of countries and their classification of individualism or collectivism (Hofstede & Bond, 1984). However, it is essential to note that other factors, such as individuals' income, have been shown to influence levels of individualism and collectivism, thus prompting the need for exploration of additional factors.

Social Class

Several different variables comprise the overarching category of social class or socioeconomic status (SES), such as income, education level, type of employment, etc. (Ames, Go, Kaye, & Spasojevic, 2011). As a whole, these variables may influence a person's willingness to use or acceptance of technology, particularly new or potentially risky technology. Sociologists often define social class as a group of individuals within a society that share similar features related to their economic status, such as income (adjusted for cost of living), education, job type, neighborhood type, etc.

There is some debate as to the exact breakdown of social classes within America; however, the majority of experts agree that there are five main categories: Upper Class, Upper Middle Class, Lower Middle Class, Working Class, and Lower Class (Poor). According to the Pew Research Center, 19% of American adults comprise Upper Class with annual household income more than double the national median (Elkins, 2019; Kochhar, 2018). Previous research has indicated that those within higher social classes tended to view technology more positively and have considerably more experience using technology than other groups (Maldifassi & Canessa, 2009; Porter & Donthu, 2006). Although several different factors comprise social class, previous research has demonstrated that income can impact awareness and acceptance of technology.

While income itself is a relatively straightforward factor, it can significantly influence peoples' perceptions and behavioral intentions. In particular, individuals with high levels of self-reported income seem to be the most receptive to using new technologies and reflects actual usage behavior (Choi & DiNitto, 2013; Junco, Merson, & Salter, 2010). Individuals with higher incomes may have easier access to new technology, thus increasing their familiarity and perceived usefulness of the technology, which positively influences their acceptance and usage of the technology (Davis, 1989).

The majority of research considering the impact of income on technology use and adoption has focused on differential rates of Internet subscriptions and use. Research suggests that the cost to access to the Internet, along with other demographic factors, significantly influences participants' likelihood of using the Internet, such that individuals with lower income are less likely to use Internet technology (Greenhow, Walker, & Kim, 2014; Jensen, King, Davis, & Guntzviller, 2010; Junco et al., 2010; Porter & Donthu, 2006).

Results from exploring the relationship between Internet subscription and actual usage behavior may extrapolate to other new technologies, such as autonomous vehicles; and a few studies have investigated the influence of participants' income on their perceptions of autonomous vehicles (Nordhoff et al., 2018; Howard and Dai, 2014; Levin & Boyles, 2019). Regarding acceptance and use of new technology, individuals' income typically represents a significant predictor of participants' preference as those with higher levels of income indicated a higher perceived likelihood of using autonomous vehicle technology (Nordhoff et al., 2018; Howard and Dai, 2014; Levin & Boyles, 2019). Because higher income is associated with upper-level social classes, a participants' self-identified social class may influence their thoughts about new technology. However, it's important to note that there are still many other factors potentially affecting participants' acceptance of modern technology.

Technology Acceptance

While autonomous vehicles are increasing in their sophistication, the availability of technology is not always positively correlated with consumer acceptance and usage of technology. For example, consider the unfortunate fates of highly-touted technological products, such as Google Glass, Sony Betamax, and Microsoft Zune, to name a few (Gilbert, 2019). Previous research has investigated different theories of human behavior regarding the acceptance of new technology (Ajzen, 1991; Legris, Ingham, & Collerette, 2003; Davis, 1985; Venkatesh, Morris, Davis, & Davis, 2003). The Unified Theory of Acceptance and Use of Technology (UTAUT) explores and identifies several factors affecting a person's behavioral intentions and actual acceptance and use of new technology (Venkatesh et al., 2003).

The UTAUT resulted from a comprehensive review and synthesis of several theoretical models exploring participants' behavioral intentions and actual behavior. These models included the Theory of Reasoned Action, the Technology Acceptance Model, the Theory of Planned Behavior, and the Model of Personal Computer Utilization (Ajzen, 1991; Davis, 1989; Davis, Bagozzi, & Warshaw,1989; Fishbein & Ajzen, 1975; Thompson, Higgins, & Howell, 1991; Venkatesh et al., 2003). These models explain participants' acceptance and use of information systems and information technology. The aforementioned models explained between 17% - 70% of the variance in behavioral intentions (Venkatesh et al., 2003).

One of the main factors that separate the UTAUT from other models is that it contains four key elements (performance expectancy, effort expectancy, social influence, and facilitating conditions). Venkatesh and colleagues (2003) have identified *performance expectancy* as the extent to which consumers believe using a particular technology will provide them with benefits in completing a specific activity. *Effort expectancy* is the level of physical or mental effort the users think they will have to exert while using the technology. Social influence entails the extent to which consumers believe that their peer group (e.g., friends or family) will find a technology beneficial and express a desire or likelihood also to use the technology. *Facilitating conditions* refer to the consumers' perceptions of the support services offered in conjunction with the technology in the case of a problem or failure (Venkatesh, Thong, & Xu, 2012).

Also, the model includes four moderators (gender, age, experience, and voluntariness), which help add predictive power (Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2017; Venkatesh et al., 2003). However, these moderators are often used on a case by case basis as they are not always relevant for every situation. For example, if a company mandates that employees must use a specific piece of technology, then voluntariness as a moderator is not particularly applicable. Some factors that evolved from the Technology Acceptance Model include individuals' perceived usefulness of the new technology (i.e., performance expectancy) and perceived ease of use of the latest technology (i.e., effort expectancy).

Perceived usefulness is "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). Technology with a high degree of perceived usefulness provides the user with some type of desired advantage, performance, or service. Previous research indicates that a person's perceived performance highly correlates with actual system usage (Robey, 1979).

Perceived ease of use is "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). While people are often willing to work harder for services or products they desire, this usually occurs through a cost-benefit analysis. When determining whether or not to use new technology, if it will cost us more resources (e.g., time, money, mental/physical effort, etc.) than we'll gain, we often choose not to use the technology.

Earlier studies attempting to predict users' acceptance of new technologies using these different factors have consistently found significant results from using a mixture of these different models (Larue, Rakotonirainy, Haworth, & Darvell, 2015; Henzler, Boller, Buchholz, & Dietmeyer, 2015; Osswald, Wurhofer, Trösterer, Beck, & Tscheligi, 2012; Rahman, Lesch, Horrey, & Strawderman, 2017). Recently, researchers used a combination of these different models to measure participants' acceptance of using Adaptive Driver Assistance Systems (ADAS), such as lane assist, collision avoidance, adaptive cruise control, etc. Results indicated that attitude, perceived usefulness, perceived ease of use, performance expectancy, and effort expectancy were all significant predictors of participants' behavioral intention (Rahman et al., 2017).

A comparison of predictive ability among the different models indicated that TAM (Davis, 1985) exhibited the highest adjusted R^2, performing better than the TPB and the UTAUT (Rahman et al., 2017). While comprehensive, these published scales were too lengthy for the current research, potentially causing survey fatigue, which can lead to corrupted data. Thus, to measure the different aspects that were consistent throughout the aforementioned models, the study utilized shortened scales that encompassed participants' familiarity with the technology, perceived value of the technology, and anticipated fun factor (i.e., enjoyment from using) of the new technology. Researchers previously validated these scales; however, the statements changed to reflect the appropriate scenario presented in the current dissertation. Before implementation, I validated the scales' internal consistency and reliability and reported the results in Table 1.

Perceived Value

According to the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology, participants' perceived usefulness of technology is a strong predictor of actual user behavior. An individuals' perceived value often determines usefulness in a particular product or service. The perceived value represents "the consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given" (Zeithaml, 1988, p. 14). This concept often contains different aspects that either have utilitarian (functional values, efficiency values, economic values, etc.) or hedonic (recreational values, aesthetic values, playfulness values, etc.) features within the product or service (Mathwick, Malhotra, & Rigdon, 2001; Jones, Reynolds, & Arnold, 2006; Chai, Malhotra, & Alpert, 2015).

For this dissertation, I used a five-statement Likert-scale which had ratings from Strongly Disagree (-2) to Strongly Agree (2), with a neutral option of 0. The statements on this scale were: 1) I think driverless vehicle technology is useful, 2) A driverless vehicle would be something valuable for me to own, 3) There would be value in using a driverless vehicle, 4) If driverless vehicles were available, I think it would be beneficial to use one, and 5) A driverless vehicle would be beneficial to me. I provide the relevant psychometrics for this scale in Appendix B.

The majority of the statements on this scale relate to ways that participants may infer or perceive the driverless vehicle to benefit them in some manner or provide some type of value. Intuitively, if a person believes that a technological product has a high value, they will probably be more likely to use the technology (Venkatesh et al., 2003; Davis, 1989; Turel, Serenko, & Bontis, 2007). While the concept of 'value' can be somewhat vague, research has focused on aspects, such as monetary, emotional, social, and performance dimensions associated with the technology, indicating that consumers' perceived value of technology significantly affects their intentions to use the technology (Turel et al., 2007).

Also, marketing and consumer behavior researchers have found various constructs related to hedonic motivation (i.e., enjoyment or perceived value) are essential predictors of consumers' technology use (Brown & Venkatesh, 2005; Holbrook & Hirschman, 1982; Nysveen et al., 2005). Consumers often use judgments of perceived value to make a comparison within and across products (Oliver, 1997). However, it's important to note that perceived value often influences a person's experience with the technology. For example, age is often a significant predictor of users' acceptance of smartphone technology because younger people have grown up with this technology and have more experience with smartphones than older people; thus, they are more familiar with the technology (Fozard & Wahl, 2012; Kang et al., 2010; Klimova & Poulova, 2018).

Familiarity

Previous research on consumer behavior has investigated the impact of familiarity with a specific product or task. As a person's experience and knowledge about a product increase, this leads to the development of mental heuristics, which facilitate the decision-making process (Alba & Hutchinson, 1987; Bozinoff, 1981; Kinard, Capella, & Kinard, 2009). Familiarity may be described as our acknowledgment and comprehension of an external stimulus, whether that's another person or a piece of machinery. Familiarity is often associated with a positive connotation; however, being familiar with something does not always guarantee that we experience positive feelings or that we trust the external stimulus to act appropriately. Furthermore, if you are unfamiliar with an external stimulus, then you may also be less likely to trust the system as you are unsure of its reliability and any potential risk factors. Therefore, familiarity with a system can have a significant impact on a user's propensity to trust and use the system.

While there are many different forms of trust (Kramer, 1999), previous research has identified two types that significantly influence human-machine interactions, dispositional trust, and history-based trust (Merritt & Ilgen, 2008). Dispositional trust is more generalizable because it encompasses our level of trust in other persons or machines upon our first encounter before a significant interaction even occurs (Kramer, 1999; Merritt & Ilgen, 2008). On the other hand, history-based trust establishes as we experience more interactions between ourselves and the other person – or machine. Both our preconceived notions about someone else or a piece of machinery, and our continued interactions can influence our propensity to trust the external system.

Research suggests that if a person is more familiar with a particular situation/product/task, and they've had positive experiences, this may increase positive emotional responses and correlates with behavioral intentions (Gefen, 2000). Furthermore, a survey investigating public opinion regarding driverless vehicles found that participants' who reported higher levels of familiarity with autonomous vehicles correlated with increased expectations of safety benefits and a more efficient fuel economy. Participants with high levels of familiarity were less concerned over learning how to use an autonomous vehicle, "and less concerned about self-driving vehicles moving around while unoccupied…and they were more interested in having this technology on their vehicle(s)" (Schoettle & Sivak, 2014, p. 20).

For this dissertation, I used a five-statement Likert-scale which had ratings from Strongly Disagree (-2) to Strongly Agree (2), with a neutral option of 0. The statements on this scale were: 1) Driverless vehicles have been of interest to me for a while, 2) I have a lot of knowledge about driverless vehicles, 3) I have read a lot about driverless vehicles, 4) I know more about driverless vehicles than the average person, and 5) I am familiar with driverless vehicles. I provide the relevant psychometrics for this scale in Appendix C.

Fun Factor

As previously noted, hedonic motivation can significantly influence consumers' willingness and intentions to use a product. Specifically, the perceived level of enjoyment or fun they will experience while using technology predicts behavioral intentions. Research investigating factors that would predict participants' acceptance of driverless vehicles discovered that individuals' "gave high ratings for thinking that they would enjoy taking a ride in a driverless vehicle…[and] higher ratings for believing that people important to them would like it when they use driverless vehicles" (Nordhoff et al., 2018, p. 5).

On the other hand, individuals reporting on their use of ADAS, such as Adaptive Cruise Control noted that they experienced "feelings of losing control as well as reduced autonomy and competence" (Eckoldt, Knobel, Hassenzahl, Schumann, 2012; Meschtscherjakov et al., 2015, p. 2414). Furthermore, additional research has shown that as autonomy increases within vehicles, drivers/passengers experienced decreased perceived enjoyment, as well (Meschtscherjakov et al., 2015; Rödel, Stadler, Meschtscherjakov, & Tscheligi, 2014). Therefore, it's important to note that participants' perceived fun or enjoyment can affect their willingness to ride in a driverless vehicle. Participants may view driverless cars as more fun (potentially because of the new technology) or being less fun (because they are no longer in control).

For this dissertation, I used a five-statement Likert-scale which had ratings from Strongly Disagree (-2) to Strongly Agree (2), with a neutral option of 0. The statements on this scale were: 1) I am interested in trying out a driverless vehicle, 2) I like the idea of driverless vehicles, 3) I think it would be cool to use a driverless vehicle, 4) I've always wanted to use a driverless vehicle, and 5) I think it would be fun to use a driverless vehicle. See Appendix D for relevant psychometrics of this scale.

Wariness of New Technology

Technology-wise, Western society has developed more in the last 50 years than the previous two centuries combined (Berman & Dorrier, 2016), in large part due to unprecedented advancements in the fields of science, technology, engineering, and mathematics. These advancements have resulted in impressive contributions to our society; however, technology often advances so quickly that we don't have time to understand all of its facets and potential drawbacks fully. When confronted with new technology, people often question their safety, reliability, and potential risk. This uncertainty can affect users' levels of trust (Merritt & Ilgen, 2008) within the system and, ultimately, their willingness to use the new technology (Lee & Moray, 1992; Lee & See, 2004; Muir, 1987; Riley, 1989).

Within the aviation industry, consumer perception of risk influences a multitude of varying factors, such as "financial risk, social risk, and psychological risk" (Ringle Sarstedt, & Zimmerman, 2011, p. 460). Even though air travel is reportedly one of the safest ways to travel – and accident rates have fallen over the past 20 years – passengers often "perceive air travel as more risky than is justified from an objective point of view because individuals generally overassess [*sic*] the risk associated with low-probability events" (Ringle et al., 2011, p. 460; Viscusi, 1985). However, this perception of risk is influenced by the media because they highly publicize the accidents, which causes people to overestimate the probability of the event happening again (Folkes, 1988). Furthermore, our perceptions of risk influence affect – or emotion – that is either elicited from the external stimulus or based upon our experience (Peters, Burraston, & Mertz, 2004), particularly when faced with new technology, such as autonomous vehicles.

General Affect

Traditionally, researchers studied people's decision-making process in the financial field as economists, marketing, and industry endeavored to discover how people thought out complex decisions and made choices throughout their daily life (Frydman & Camerer, 2016; George & Dane, 2016; Sokol-Hessner, Raio, Gottesman, Lackovic, & Phelps, 2016). The most efficient decision-making process would consist of the organism considering the advantages and disadvantages of every choice and then selecting the most economical option (i.e., more benefits compared to disadvantages; Frydman & Camerer, 2016; Slovic, Peters, Finucane, & MacGregor, 2005). While this style of decision-making is effective, researchers quickly realized that people don't typically operate with this type of objective thought process (Tversky & Kahneman, 1986). Research has uncovered a significant factor affecting humans' rational and objective decision-making process – affect (Lerner, Li, Valdesolo, & Kassan, 2015; Peters, Västfjäll, Gärling, & Slovic, 2006; Slovic et al., 2005; Zajonc, 1980).

Previous research continuously indicates that affect – or emotion – plays a significant role in peoples' decision-making process (Lerner et al., 2015; Peters et al., 2006; Schwarz & Clore, 2003; Slovic et al., 2005). When people may not have a lot of knowledge about the situation, or they feel unsure about a situation, thus relying on their mental heuristics (Slovic, Finucane, Peters, & MacGregor, 2007). Mental heuristics primarily consist of "short-cuts" that our brain takes when making decisions, which help us move throughout our day more efficiently. If we stopped and thought out the pros and cons of every single decision, our day would collapse with this time-consuming process, and it would take a long time to accomplish anything meaningful. Therefore, our brain tends to make quick judgments/decisions to help speed along this process and help us progress through the day.

Often, these mental short-cuts or snap decisions are created from the emotions elicited from our current situation/dilemma or based on our prior experiences (Damasio, 1994; Kahneman, 2011; Lerner et al., 2014; Volz & Hertwig, 2016). Emotions represent a relatively dynamic mental state that can change throughout the day and occur automatically (Slovic et al., 2005). Emotions depend upon our current situation and what we are experiencing (compared to our 'mood,' which tends to be relatively stable, and changes are only made slowly over time). Evolutionarily, emotional decision-making probably helped our ancestors survive potentially dangerous situations where they didn't have a lot of information, or they didn't have time to think through all the possible advantages and disadvantages (Slovic et al., 2005). Thus, erring on the side of caution and allowing negative emotions, such as fear, anger, disgust, etc. to guide their behavior and decisions may have helped them survive.

Customer Satisfaction

Two of the largest travel industries of the modern society include commercial aviation and automobiles (U.S. Department of Transportation, 2017). These two industries have a lot at stake when building and retaining a strong customer base, although, until recently, they weren't really in competition with each other. The length of time it takes to complete a trip plays a significant role in travelers' decision to fly or drive. Previous research has indicated that as travel time/length increases for a journey, people are more likely to choose to fly because driving for that long would simply be too exhausting (Gronau, 1970). However, when the trip is shorter, people often prefer driving to their destination because automotive travel provides more comfort than commercial airline travel. Riding in a vehicle saves the traveler from dealing with airports (and airport traffic), lack of freedom in choosing departure/arrival time, airplane food, sitting next to strangers, etc. (Kloppenborg & Gourdin, 1992; Nadiri et al., 2008; Young, Cunningham,

& Lee, 1994). Therefore, passengers' perceived level of comfort can significantly affect their preferred travel method, autonomous vehicle, or commercial airliner.

Traditionally, commercial aviation travel faced onerous regulations as to where airlines could operate and what services they could offer (Piercy, 2001). However, the 1978 Airline Deregulation Act allowed airlines to begin customizing features offered to passengers, which ultimately influenced the price passengers paid for an airline ticket (Koklic, Kukar-Kinney, & Vegelj, 2017; Levin, 1987). Competition between airlines drove down ticket prices (Loureiro & Fialho, 2016). This competition also enticed airline companies to lure in more customers through obtaining high customer satisfaction levels and offering high-quality service. Thus allowing the airline to reasonably charge for a higher ticket price and increase profitability (Keeton, 2010; Smith, 2004).

Many airlines began offering incentives, such as frequent flyer programs, free carry-on luggage, increased legroom, etc., to attract and retain loyal customers (Fornell, 1992; Miller, 1993). Growing a loyal customer base was important because loyal customers are more likely to continue using a particular service (Cronin & Taylor, 1992; Forgas, Moliner, Sánchez, & Palau, 2010; Fornell, 1992; Oliver, 1997). The main point behind these additional features was to increase customer satisfaction, which "directly affects customers' future behavioral intentions" (Clemes et al., 2008, p. 52; Koklic et al., 2017); therefore, many airline companies began investigating how they could positively influence customer satisfaction.

Passengers often report perceived comfort while traveling as one of the main contributors to their overall satisfaction levels (Clemes et al., 2008; Jacobson & Martinez, 1974). Comfort while traveling entails factors, such as adequate knee and legroom, comfortable seating, neighboring travelers (Kloppenborg & Gourdin, 1992; Nadiri et al., 2008; Young et al., 1994), “vibrations, noise, temperature, and air quality measurement systems” (Elbanhawi, Simic, & Jazar, 2015, p. 5; Han, 2013). Passengers’ perceived levels of comfort while traveling on an airplane or ground vehicle are influenced by similar factors. However, a significant difference is that passengers have control over many of these factors when traveling via ground vehicles.

Vehicle manufacturers focusing on designing and developing fully autonomous automobiles have consistently cited the increased level of comfort afforded passengers and their desire to replace short-haul flight (Nishimoto, 2018). Once travelers factor in travel time for short-haul flights, such as driving to the airport, going through security, actual flight time, retrieving luggage, and time to drive to the destination from the airport, it can often take the same amount of time, if not slightly longer, than if the traveler had just driven there (Nishimoto, 2018). Furthermore, travelers must experience all of the negative factors that accompany air travel. On the other hand, autonomous vehicles potentially offer travelers all of the comfort of traveling via ground vehicle transportation without the adverse effects of driving for long periods.

Thi study considered two different methods of travel, commercial aviation, and driverless vehicles. While several various factors influence a person’s willingness to choose a specific method, comfort while traveling impacts passengers’ choice, which includes elements, such as appropriate sitting room, fellow passengers, etc. (Clemes et al., 2008; Kloppenborg & Gourdin, 1992; Jacobson & Martinez, 1974). Importantly, passenger comfort levels positively correlate with higher customer satisfaction levels, which also positively influence customer loyalty and their likelihood to continue using that particular service (Cronin & Taylor, 1992; Forgas et al., 2010; Fornell, 1992; Koklic et al., 2017; Oliver, 1997). Therefore, perceived comfort may significantly predict a person’s preferred travel method, particularly if they believe that one mode of transportation may offer higher levels of comfort than another mode of travel (i.e., autonomous vehicle vs. commercial aircraft).

For this research, I created four different scales designed to measure participants' overall perceived satisfaction/comfort of traveling in a vehicle or a commercial aircraft. I used factor analysis to condense over 30 travel-related variables into the four scales, Vehicle Comfort, Vehicle External Factors, Airplane Comfort, and Airplane External Factors. These scales range from three to five statements on a 5-point Likert scale from Strongly Disagree to Strongly Agree. The two comfort scales measured participants' overall feeling of comfort while traveling with that specific method, such as "I enjoy sleeping while traveling in a vehicle" or "I enjoy sleeping while on traveling in an airplane." The two external factors scales measured participants' satisfaction with their overall experience of traveling with that specific method, such as "I enjoy having schedule flexibility (the ability to leave when I want)" or "I enjoy waiting in the airport before I leave my departure point." Appendices G-J provides the full scales.

Regression and Prediction Models

The purpose of this research is to build a prediction model for understanding what type of person would choose to ride in an autonomous vehicle rather than fly in a commercial airliner. I assessed 20 different factors according to their level of significant contribution to the overall model. These factors include age, gender (male and female), social class, ethnicity, price, perceived value, familiarity, fun factor, wariness of new technology, personality (openness, conscientiousness, extraversion, agreeableness, and neuroticism), general vehicle affect, general airplane affect, vehicle comfort, vehicle external factors, airplane comfort, and airplane external factors. I included inclusion justification for each factor in the previous sections; therefore, the current section will review an explanation of research design methodology as supported by similar topics in the scientific literature.

Although several different scientific models measure consumers' acceptance of new technology, many of these models comprise factors that are outside of the users' control, such as facilitating conditions, social influence, external factors, etc. For this research, the objective was to build a model primarily based upon participant demographics (i.e., individual characteristics that the participant either has control over or views as a part of their identity). Therefore, using the most recent UTAUT model would be inappropriate because it considers many elements outside of the users' control. Furthermore, the current research was not explicitly exploring participants' acceptance of new technology, but rather their choice between two different technologies. Despite the multitude of varying technology acceptance/planned behavior models, none measured this specific variable. Thus, the current research uses demographic data and smaller scale items (Perceived Value scale, Familiarity scale, Fun Factor scale, and the comfort/external factors scales) to accurately measure participant-specific traits.

Previous research attempting to model human behavioral intentions has frequently used regression analyses, similar to the methodology and design in the current study. Investigation of willingness to interact with driverless vehicles (Anania et al., 2018a; Howard & Dai, 2014; Hulse et al., 2018; Milner et al., 2019), willingness to fly in autonomous airplanes (Rice, Winter, Mehta, & Ragbir, 2019), and predictors of behavior (Beck & Ajzen, 1991; Rahmati-Najarkolaei, Rahnama, Fesharaki, & Behnood, 2016) used prediction models and regression analyses to assess different predictors affecting participants' behavioral intentions.

This line of research is comprised of two separate stages to facilitate the creation and validation of a prediction model. The first stage uses participant data to build a regression equation that predicts what type of person would choose to ride in an autonomous vehicle rather than fly on a commercial aircraft. The second stage utilizes a secondary set of data to test the validity of the model created in the first stage. Because this model involved multiple variables, and previous research has successfully used similar, sound methodology, a multiple linear regression was the appropriate statistical technique to utilize (Harrell, 2015).

Summary

The purpose of Chapter 2 is to explore previous literature relevant to the variables considered in the current study. This review facilitates a general understanding of the different factors, how they may or may not be related, and identifies any gaps in the literature/research. A review of the literature highlights a hole in the intersection of autonomous vehicle research and commercial aviation research, particularly concerning factors affecting consumers' decision-making and their preferred mode of travel. Moving forward, Chapter 3 will describe the current study's methodology, including information about the population, sample, instrumentation, procedures, variables, design, and analyses. The information presented in Chapter 3 contains sufficient detail so that future researchers may easily replicate the study, provided access to adequate resources.

Chapter Three

Methodology

Introduction

The current section provides a detailed account of the methodology used to research this study. The purpose of this chapter is to provide sufficiently detailed information so that future researchers may easily replicate the procedure, assuming they have access to adequate resources. Therefore, I discuss details regarding the specific steps, tools/instruments, and research design. Within these areas of foci, I focus on participant parameters, such as the population and sample. Furthermore, there will be a thorough description of the procedures and methods utilized for data collection, variables, and estimated statistical power for analyses. Lastly, I address legal and ethical measures taken to protect participants' anonymity and confidentiality throughout the research.

Research Design

The purpose of this research was to develop a model depicting what type of personal characteristics determine a person's likelihood of choosing to ride in an autonomous vehicle rather than fly on a commercial aircraft. This goal was achieved primarily through a quantitative research study using a correlational design with multiple linear regression as the preferred statistical procedure for data analysis. This design and analysis are the most appropriate method for prediction and model fit, which is the goal of this research.

Linear regression presents the opportunity to explore factors affecting participants' decision to ride in a fully autonomous vehicle rather than fly in a commercial aircraft. The current research study will not attempt to examine differences between groups; thus, there is no need for statistical analyses comparing groups, such as *t*-tests or Analysis of Variance

(ANOVA). Furthermore, the current study design lends itself to data collection via a survey as naturalistic observation and archival research would either be impossible or insufficient, especially because fully autonomous vehicles are not yet available or street legal. Therefore, the current study used a survey-based correlational quantitative design with multiple linear regression as the analysis.

Population and Sample

Population

The current research study seeks to build a prediction model to determine what type of person is likely to choose to ride in a fully autonomous vehicle rather than flying on a commercial aircraft. Once fully autonomous vehicles become legal and available to the public, the results of this study will hopefully be generalizable to the target population, which includes any people wishing to travel and faced with choosing between using an autonomous vehicle or flying commercial. Accurately understanding consumer behavior, particularly regarding new technology, could have a significant impact on industries introducing this new technology and industries that may be threatened by the latest technology. Unfortunately, it is implausible to gather data from every single person in the target population. Therefore, I collected data from a representative sample of the accessible population. Because this research consists of an online survey, the accessible population includes any travelers who have access to the internet and use Amazon’s MTurk platform. Only participants aged 18 years or older were considered as part of the accessible population.

Sample

Data was collected via convenience sampling techniques from participants recruited using MTurk. Participants received 50 cents for their participation in the study, which required about 5-10 minutes of their time. This research study encompassed two different stages to facilitate the building of the prediction model and then testing the model fit; thus, the study required two separate sets of participants.

While convenience sampling may be viewed as a limitation, prior research has indicated that online survey data is as reliable and valid as traditional laboratory data (Berinsky, Huber, & Lenz, 2012; Buhrmester, Kwang, & Gosling, 2011; Coppock, 2018; Deutskens, de Jong, Ruyter, & Wetzels, 2006; Germine et al., 2012; Rice, Winter, Doherty, & Milner, 2017). Furthermore, I strived to eliminate possible bias that may arise from the convenience sampling technique. I ensured that the survey was available to anyone who has internet access, is 18 years or older, and remaining open for several hours so that participants from multiple time zones have the opportunity to participate.

Power Analysis

A determination of a priori sample size was conducted to guarantee the validity of the relationships among the variables, thus allowing for causal inference. The program G*Power 3.1.9.2 was used to perform these analyses. With a small effect size of .05, power (beta) of .99, and an alpha level of significance .05, and 20 predictors, each stage of the study needed a minimum sample size of 818 participants.

As previously mentioned, the study was conducted twice to allow for the creation of the model/regression equation and then testing and validation of the model. At a minimum, each stage needs a total of 818 participants to build and test the model within the given parameters accurately. However, to account for the additional cases required to run a backward stepwise regression, possible missing data, outliers, or other potential issues, approximately 1,000 participants were surveyed for each stage, thus requiring a total of 2,000 participants for the entire line of research.

Research Methodology

As previously stated, participants were recruited online using Amazon's MTurk, which provides an online platform that allows users to complete tasks, such as responding to surveys, for monetary compensation. MTurk has certain contingencies in place, thus preventing the use of robots, scripts, or other automated methods to complete tasks. Participants have an online profile that allows them to see requests to complete tasks, such as responding to surveys. Once they select a task, they are sent a link with specific instructions for completing the task. For this study, participants received a link to a Google Forms survey.

The survey consisted of two sections such that one of the sections asks participants about autonomous vehicles, and the other section asks participants about commercial flights (these sections were counterbalanced). Once participants access the survey, they read the posted instructions and responded to the multiple-choice questions and the open-response prompt. Participants responded to the same survey in Stage 1 and Stage 2.

In the autonomous vehicles section, participants read the following scenario, "*Imagine a time in the future where driverless cars are available to the general public and they have a safety record equal to, or better than, regular cars. You have to travel from one major city to another for work related business, but the autopilot would do all the work and you could even sleep along the way.*" Then, participants responded to a general affect scale (see Appendix F), the Vehicle Comfort scale (see Appendix G), Vehicle External Factors scale (see Appendix H), Wariness of New Technology scale (see Appendix E), Fun Factor scale (see Appendix D), Perceived Value scale (see Appendix B), and the Familiarity scale (see Appendix C).

In the commercial flight section, participants read the following scenario, "*Imagine you have to travel from one major city to another for work related business. You decide to take a commercial flight.*" Participants proceeded to answer the same scales from those mentioned above, except mentions of 'autonomous vehicle' were be replaced with 'airplane,' and they responded to the Airplane Comfort scale (see Appendix I) and the Airplane External Factors scale (see Appendix J). In each section, scale order was randomized by Google Forms® for each participant, and items within scales were presented in a randomized order. The instructions for responding to the scales read, "*Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.*"

To capture participants' preferred travel method, participants read the following scenario, "*Imagine a time in the future where autonomous cars are available to the general public and they have a safety record equal to, or better than, regular cars. You have to travel from one major city to another for work related business. The autopilot would do all the work and you could even sleep along the way. The alternative would be to take a regular commercial flight*." and responded to the Travel Method Preference Scale (see Appendix A).

However, to determine if the length of the trip (i.e. the total time it would take to travel from origin to destination) affected participants' response, they were also prompted with the following scenario before responding to the Travel Method Preference scale, "*Imagine the drive will take you about 4 hours. The airline flight itself will take about 1 hour gate to gate; however, this does not encompass travel to/from the airport, security, baggage collection, etc. Given this information, which method of travel would you prefer?*" Participants responded to this scenario four times, with the only difference being the schedule presented (i.e., the time it would take to complete the drive and time it would take to fly (gate to gate)). The four different time schedules are as follows:

- 4-hour drive/1-hour flight
- 8-hour drive/1.5-hour flight
- 12-hour drive/2-hour flight
- 16-hour drive/2.5 hour flight

Once completing their responses to the varying time schedules, participants responded to the open-ended question, "*Are there any other factors that affected your choice of preferred method of travel?*" Participants' responses to this prompt may provide insight into factors that should be considered for future research, whether as mediating variables or additional predictors of behavioral intentions.

Finally, participants provided demographic data to capture information related to the proposed predictors in the study (see Appendix K). This survey was the only instrument used to collect data for the current research. As previously stated, participants were recruited online using Amazon's ® MTurk and compensated for their participation. This line of research consisted of two stages, allowing for the creation of the prediction model and validation of the prediction model (using a new set of data). Both stages used the same instrument. After completing the survey, participants received instructions on receiving their monetary compensation.

Pilot Study

Because this is exploratory research, I considered a multitude of factors as potentially influencing participants' choice of preferred travel method. To help narrow the scope of the project, I conducted two pilot studies to explore many of these factors and determine which ones were most significant, and thus, included in the final study. The first pilot study used a series of 5-point Likert-type scales (from Strongly Disagree to Strongly Agree) to measure participants' responses on a variety of travel-related factors. There were 252 (90 female) participants, and the average age was 34.92 (*SD* = 10.83).

The 22 items from the survey were subjected to principal components analysis (PCA). Before performing the PCA, the suitability of the data for factor analysis was assessed. Inspection of the correlation matrix revealed the presence of 119 coefficients of .3 and above. The Kaiser-Meyer-Olkin value was .84, exceeding the recommended value of .6 (Kaiser, 1970, 1974), and Bartlett's Test of Sphericity (Bartlett, 1954) reached statistical significance, supporting the factorability of the correlation matrix.

Principal components analysis revealed the presence of five components with eigenvalues exceeding 1, explaining 27%, 42%, 50%, 56%, and 61% of the variance, respectively. Interestingly, an inspection of the scree plot revealed a clear break after the fourth component. However, a Parallel Analysis showed only three components with eigenvalues exceeding the corresponding criterion values for a randomly generated data matrix of the same size (22 variables x 250 respondents). The PCA was rerun with the fixed number of factors set to three, which explained 50% of the variance.

Because of the relatively small difference in variance explained and the fact that this was exploratory, I decided to compromise between the results from the first PCA and the Parallel Analysis and retain only four components. Furthermore, the results from Cattell's (1966) scree test also suggested the use of four components. These four components explained 56% of the variance with Component 1 contributing 27.33%, Component 2 contributing 15.15%, Component 3 contributing 7.76%, and Component 4 contributing 5.9%. To aid in the interpretation of these components, I performed an oblimin rotation. The rotated solution revealed the presence of strong loadings and the majority of variables loading substantially on one component (see Tables 1 and 2 for the related Pattern Matrix and Structure Matrix)

After conducting the factor analysis, the most influential factors tended to relate to participants' characteristics of travel preferences rather than factors unrelated to them, such as food options in an airport/airplane. Furthermore, the factor analysis indicated which items ran together and allowed for the creation of four subscales designed to measure participants' travel preferences, which were named 1) Vehicle Comfort, 2) Vehicle External Factors, 3) Airplane Comfort, and 4) Airplane External Factors.

For the second pilot study, only factors measuring participants' personal characteristics were considered. Ultimately, 20 factors were used as the independent variables with the potential to predict the dependent variable – participants' preferred travel method. These predictors were 1) Age, 2) Gender, 3) Social Class, 4) Ethnicity, 5) Price, 6) Perceived Value, 7) Familiarity, 8) Fun Factor, 9) Wariness of New Technology, 10) Openness, 11) Conscientiousness, 12) Extraversion, 13) Agreeableness, 14) Neuroticism, 15) Vehicle Affect, 16) Airplane Affect, 17) Vehicle Comfort, 18) Vehicle External Factors, 19) Airplane Comfort, and 20) Airplane External Factors.

The majority of these factors were measured on 5-point Likert scales (from Strongly Disagree to Strongly Agree). There were 247 (98 female) participants, and the mean age was 37.57 (*SD* = 12.26). After data collection, a backward stepwise regression was conducted to determine the factors significantly predicting the dependent variable. A backward stepwise regression begins with a fully saturated model (all factors are considered) and then, through an iterative process, gradually eliminates the weakest variables from the model until only the strongest predictors remain (which are usually statistically significant). SPSS considers the significance of factors using an entry alpha value of .05 and .10 as the elimination threshold. This type of stepwise approach is useful because it gradually reduces the number of predictors, which reduces the problem of multicollinearity and helps avoid overfitting the model. However, it's also important to note that when using this approach, once variables are removed from the model, they are never reconsidered.

Participants responded to four different scenarios, designed to measure changes in participants' responses based on length of trip (i.e., how long it takes to travel from origin to destination). A backward stepwise regression was conducted for each scenario. While there were slight differences, most final models included these significant predictors: Vehicle General Affect, Vehicle Comfort, Fun Factor, Plane Comfort, Gender, and Age (see tables 3 – 7 for a tabular reporting of the results). These models accounted for 13% - 44% of the adjusted variance in the criterion. These two pilot studies provide strong evidence of the impact of these specific independent variables on participants' preferred travel method.

Therefore, moving forward, only factors deemed as personal characteristics (or directly impacting participants' travel experience) were considered for the current study. Focusing on personal attributes/experiences will provide industry, researchers, and designers with a better understanding of what type of person is most likely to choose to ride in an autonomous vehicle rather than flying on a commercial aircraft without worrying about the influence of external factors on their decision. As a Human Factors professional, one of the main goals is to understand what type of user is interested in a product/service and to ensure that the product/service is designed to fit their needs and wants. Too often, Human Factors professionals are considered in the last stage of R&D (and perhaps even later). Thus it becomes challenging to enact real change, and the consumer forced to adapt themselves to the product/service. Therefore, this line of research strives to consider the consumer at the beginning of the process to provide the vehicle industry and aviation industry with a better understanding of their potential customer base.

Variables

Independent Variables

This research seeks to build a prediction model. The independent variables consist of all the predictors used for model development and prediction of the dependent variable. As previously detailed, only factors pertaining to participants' personal characteristics or personal travel preferences were considered in light of the findings from the previous pilot studies. These factors include age, gender, social class, ethnicity, price, perceived value, familiarity, fun factor, wariness of new technology, personality (openness, conscientiousness, extraversion, agreeableness, and neuroticism), vehicle affect, vehicle comfort, vehicle external factors, airplane affect, airplane comfort, and airplane external factors. Table 8 provides an overview of all independent variables, including question type, measurement type, and referenced appendices. Also, reliability estimates – calculated from the aforementioned pilot study – are provided, as well.

Table 8. Overview of Independent Variables

Independent Variable	Question Type	Measurement Type	Cronbach's Alpha	Guttman's Split Half	Appendix
Age	Free response	Interval			
Gender	Multiple choice/ free response	Nominal			
Social Class	Free response	Interval			
Ethnicity	Multiple choice/ free response	Nominal			
Price	Multiple choice	Nominal			
Perceived Value	Likert scale	Interval	.905	.892	Appendix B
Familiarity	Likert scale	Interval	.847	.841	Appendix C
Fun Factor	Likert scale	Interval	.918	.872	Appendix D
Wariness of New Technologies	Likert scale	Interval	.859	.831	Appendix E
Openness to Experience	Subscale of Mini-IPIP (Donnellan et al., 2006)	Interval	.767	.851	
Conscientiousness	Subscale of Mini-IPIP (Donnellan et al., 2006)	Interval	.711	.553	
Extraversion	Subscale of Mini-IPIP (Donnellan et al., 2006)	Interval	.770	.629	
Agreeableness	Subscale of Mini-IPIP (Donnellan et al., 2006)	Interval	.800	.624	
Neuroticism	Subscale of Mini-IPIP (Donnellan et al., 2006)	Interval	.727	.562	
General Affect	Likert-type scale	Interval	.947	.941	Appendix F

Independent Variable	Question Type	Measurement Type	Cronbach's Alpha	Guttman's Split Half	Appendix
Vehicle Comfort	Likert-type scale	Interval	.766	.465	Appendix G
Vehicle External Factors	Likert-type scale	Interval			Appendix H
Airplane Comfort	Likert-type scale	Interval			Appendix I
Airplane External Factors	Likert-type scale	Interval			Appendix J

Rather than break the variable of age into groups, it was treated as a continuous variable, allowing for any response in the free-response prompt. Gender was developed as a categorical variable with three choices, 1) male, 2) female, and 3) other. This was presented as multiple-choice; however, if participants choose 'other,' they were prompted to provide further detail in the free-response. Similarly, social class and ethnicity were measured as categorical variables with multiple-choice options. Price was presented as a continuous variable, a 7-point scale with options ranging from "Not at all important" (-3) to "Extremely important" (3). This variable measures whether or not the cost of an airplane ticket is important to participants.

The independent variables, Perceived Value, Familiarity, Fun Factor, Wariness of New Technology, and Personality are measured via Likert scales, which are traditionally considered as an ordinal measurement. However, for this research, each scale is indexed to produce a single number, thus allowing for interval scale of measurement (Boone & Boone, 2012; Joshi, Kale, Chandel, & Pal, 2015; Rickards, Magee, & Artino, 2012; Sullivan & Artino, 2013).

Perceived value was measured as the participant's score averaged from their response to five statements, designed to capture how much they believe autonomous vehicles would provide some type of benefit to them or society. Participants responded to five statements on a 5-point scale ranging from “Strongly Disagree” (-2) to “Strongly Agree” (2) with a zero-neutral point. The scale of measurement for this variable – and all other continuous variables – is ordinal; however, as previously mentioned, it will be treated as an interval scale of measurement. Familiarity was measured as the participant’s score averaged from their response to five statements, which are designed to measure their self-perceived level of knowledge or experience with autonomous vehicles. Participants responded to five statements on a 5-point scale ranging from “Strongly Disagree” (-2) to “Strongly Agree” (2) with a zero-neutral point. Fun factor was measured as the participant’s score averaged from their response to five statements, which are designed to estimate how much entertainment they believe autonomous vehicles would offer. Participants responded to five statement on a 5-point scale ranging from “Strongly Disagree” (-2) to “Strongly Agree” (2) with a zero-neutral point.

Personality factors were measured as five discrete variables, which average participants’ responses to the different areas of Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. The Mini-International Personality Item Pool (Mini-IPIP; Donnellan et al., 2006), a 20-item survey, prompts participants to provide their responses on a 5-point scale to a series of different statements that describe aspects of their personality. Participants have options ranging from “Very Inaccurate” (-2) to “Very Accurate” (2) with a zero-neutral option “Neither accurate nor inaccurate.” Where appropriate, items are reverse scored, and the sum of all responses represents the final value for participant’s score on that particular factor.

Affect was measured as participants’ average score across seven statements designed to assess their overall mood while responding to the survey. Response prompts are on a five-point scale ranging from “Strongly Agree” (-2) to “Strongly Agree” (2) with a zero-neutral point. For this research, participants responded to the General Affect scale twice, once in the autonomous vehicles section and once in the commercial airplanes section.

The four remaining variables were designed to capture the participant’s overall satisfaction levels with different methods of transportation, autonomous vehicles, and commercial aircraft. The four scales (1) Vehicle Comfort, 2) Vehicle External Factors, 3) Airplane Comfort, and 4) Airplane External Factors) uniquely measure participants’ feelings about using a specific mode of travel and travel preferences that may also influence their decision. Overall, there are 14 items, and response prompts are on a 5-point scale ranging from Strongly Disagree (-2) to Strongly Agree (2). Participants’ responses will be averaged to provide their overall score for each scale.

Dependent Variable

For this research, the dependent variable is the participants’ preference for riding in an autonomous vehicle rather than flying on a commercial aircraft (see Appendix A). This was measured as participant’s average score on a four statement, a 5-point Likert scale with responses ranging from “Strongly Disagree” (-2) to “Strongly Agree” (2) with a zero-neutral point. Similar to the independent variables, the scale of measurement is technically ordinal; however, as is common in the field, it will be treated as interval data in the analysis (Boone & Boone, 2012; Joshi et al., 2015; Rickards et al., 2012; Sullivan & Artino, 2013).

As previously mentioned, participants responded to four different time schedules, which represent the four different scenarios. The purpose of these scenarios is to determine if the length of the trip (i.e., the total time it would take to travel from origin to destination) affects participants’ responses. They read the following scenario before responding to the Travel

Method Preference scale, "*Imagine the drive will take you about 4 hours. The airline flight itself will take about 1 hour gate to gate; however, this does not encompass travel to/from the airport, security, baggage collection, etc. Given this information, which method of travel would you prefer?*" Participants will respond to this scenario four times, with the only difference being the schedule presented.

Data Analysis

For this dissertation, a correlational design using multiple linear regression was employed for analyzing Stage 1 data. Stage 2 employed model fit testing upon a new set of data to determine the validity of the previously developed model. As previously noted, using standard multiple linear regression allows for the most appropriate analysis of the relationship between the independent variables and the dependent variable. Using this method for Stage 1 analysis, a regression equation was developed, including coefficients for each independent variable significantly correlated to participants' choice of traveling via an autonomous vehicle rather than a commercial flight. Stage 2 utilized a secondary set of data to test the model by predicting participants' preferred travel method scores (from the equation created in Stage 1) and comparing the predicted scores against participants' actual preferred travel method scores. Specifically, the regression equation was tested for model fit using a *t*-test, correlation, and cross-validated R^2.

First, the model fit was tested by conducting a t-test on the two sets of data (actual scores on the Preferred Travel Method scale and the predicted scores calculated from the stage 1 regression equation). If there is a strong model fit, then there will be no statistically significant difference between the scores for the dependent variables. Therefore, I may infer that the predicted scores do not vary from the actual scores, thus validating the original equation.

Second, model fit was tested by conducting correlation analyses on the two sets of data. If there is strong model fit, then there will be a statistically significant correlation between the scores. This will allow me to infer that the predicted scores correlate with the actual scores, thus further supporting evidence of model fit.

Third, model fit was tested using cross-validated R^2. The cross-validated R^2 = 1-(1-R^2)[(n+k)/(n-k)], where R^2 is overall R^2 from the initial model, n is the sample size of the stage 1 sample, and k is the degrees of freedom. A cross-validated R^2 helps avoid the issue of overfitting the model and shows how well the model would apply to other samples from the population. If there is little to no difference between the overall R^2 and the cross-validated R^2, this is further evidence indicating the presence of model fit.

Other methods of analysis were considered; however, because the primary purpose of this research is to build a predictive model, it was determined that linear regression was the most appropriate method rather than statistical techniques that compare groups. Particularly, standard multiple regression is pertinent for this line of research rather than hierarchical multiple regression as there lacks a theoretical basis for organizing the independent variables in a particular order during analysis. Furthermore, because the dependent variable is an interval scale of measurement, rather than dichotomous, logistical regression would have been inappropriate, as well.

The current research employed a multiple regression analysis, which explores the influence of several independent variables on one continuous dependent variable. Furthermore, this particular analysis allows for considering the impact of one independent variable on the dependent variable while controlling for all other independent variables. The model developed from this analysis will help researchers better understand what factors predict participants' preferred travel method between fully autonomous vehicles and commercial airplanes.

Participant Eligibility Requirements

Following appropriate ethical regulations, participants needed to be at least 18 years of age or older. At the beginning of the survey instrument, participants responded to a dichotomous choice question ('Yes' or 'No') ensuring that they meet age requirements – and if not, they were automatically directed to a separate page, thus removing any chance to participate. The survey instrument and research methods have been designed to ensure that participants do not experience any harm or undue stress. All aspects of the research, including the protocol, instrumentation, and relevant materials, were assessed for approval by Embry-Riddle Aeronautical University's Institutional Review Board (IRB) for transparency and appropriate care of participants. The IRB application and approval notice are included in Appendix L.

Participants' Protection

The current study used an online convenience sample provided by Amazon's ® Mechanical Turk ® (MTurk). MTurk protects all participants' confidential information, and the researchers do not have access to it. Specifically, no names, contacting information, or otherwise identifying information is provided to researchers, which helps guarantee participants' responses are kept anonymous and confidential. While participants' responses were used for model construction and validation, they were only used in aggregated data analyses, and individual responses will not be published or available to the public.

Legal and Ethical Consideration

The human participants in this study were not exposed to any risk. As previously mentioned, MTurk was used to gather participants, and MTurk is responsible for screening all participants to verify they have provided the correct information. Following ethical protocol, the current study only collected data from participants who indicated that they are at least 18 years old and ensured that study procedure and survey instrument did not cause participants any physical, physiological, emotional, or legal risks. The IRB at Embry-Riddle Aeronautical University reviewed the overall study, methodology, and survey instrumentation before data collection.

Summary

Chapter Three provides a detailed description of the methodology that was used for conducting this study, including the experimental design, procedures, participants, variables, and ethical considerations. If interested, future researchers should have enough detail and information to replicate this study successfully. Furthermore, the current chapter describes data analysis techniques to facilitate the interpretation of future results. The following sections will cover the performed data analyses and resulting statistics.

Chapter Four

Results

Introduction

The goal of the current research was to create and validate a regression model predicting participants' preference for riding in an autonomous vehicle rather than a commercial aircraft through four different scenarios. Each scenario was identical except for the length of the trip, which included a four hour, eight hour, twelve hour, and sixteen hour travel scenario. This was primarily achieved by conducting a regression analysis and model fitting, which is the focus of the current chapter. Chapter four will detail the statistical analyses performed, including descriptive and inferential statistics. All data analyses were conducted using Microsoft Excel and the statistical analysis software, IBM SPSS.

General Design

The current research used a correlational design with multiple linear regression as the data analysis technique, which allowed for the creation of a model predicting participants' preference for riding in an autonomous vehicle rather than flying on a commercial aircraft. Overall, 20 independent variables were tested for their impact on participants' preferred travel method. These variables were: age, gender, social class, ethnicity, price, perceived value, familiarity, fun factor, wariness of new technology, personality (openness, conscientiousness, extraversion, agreeableness, and neuroticism), vehicle affect, vehicle comfort, vehicle external factors, airplane affect, airplane comfort, and airplane external factors. The dependent variable was the participants' preference for riding in an autonomous vehicle rather than flying in a commercial aircraft. In the first stage, the data was used to build the regression equation. The second stage used a secondary data sample to test the regression equation through three different model fitting procedures.

Research Tool and Instrument

The most efficient method of collecting data for this study was through Google Forms® (see Appendix L for the entire instrument). Questions on the survey ranged from multiple choice, free response, to Likert/Likert-type scales. As previously mentioned, there were two versions of the survey, with the only difference being which section was presented to participants first (autonomous vehicle section or commercial aircraft section); however, the order and details of all other questions remained precisely the same. The surveys were administered once, and then the data were randomly split into two groups (before any data cleaning or analyses) for the two separate stages. Amazon's MTurk® facilitated the recruitment of participants, and all participants were paid US$0.50 as monetary compensation for completing the survey.

Descriptive Statistics

The current line of research involved two separate stages, which allowed for the creation of the regression equation and validation of the equation. The resulting regression equation was designed to predict which type of person would prefer to ride in an autonomous vehicle rather than fly on a commercial aircraft. The total sample size included 2,016 participants (1,099 females).

Missing and Excluded Data

For Stages 1 and 2, data were excluded if it met the following criteria. For the scales measuring Affect, Comfort, External Factors, Wariness, Fun Factor, Value, and Familiarity, if participants skipped two or more responses, they were removed. One missing response was considered manageable as the average was taken to indicate the overall score. For the personality scales, if participants missed at least one answer, they were removed from the final analysis. Participants with at least one missing data point were excluded because personality was measured with summative data. Thus, any missing points would result in an unrepresentative overall score. Furthermore, to accurately create the formula for detecting outliers (Mahalanobis Distance), there could be no missing data; therefore, all other variables (gender, ethnicity, age, and social class) with missing responses were removed.

Although it is impossible to discern why specific questions were missed (either participants simply didn't notice the question, or they did not understand what was being asked), no clear patterns were detected in missing data points. Furthermore, the Institutional Review Board states that survey questions cannot be required. Thus participants have the freedom to bypass any questions they don't understand or don't wish to answer. Lastly, to adequately satisfy the assumptions of regression, outliers were removed prior to data analysis. The details of outlier identification and removal are provided in the Assumptions section.

Table 9 provides an overview of the full data set for Stage 1 and Stage 2, including frequency counts and percentage of excluded or missing data (Stage 1 N = 1,008 prior to data exclusion and Stage 2 N = 1,008 prior to data exclusion). From Stage 1, 129 data points were excluded due to the aforementioned exclusion criteria and 46 due to outliers, resulting in 863 total participants for Stage 1. From Stage 2, 95 data points were excluded due to the aforementioned exclusion criteria and 30 due to outliers, resulting in 882 total participants for Stage 2.

Table 9
Summary of Missing and Excluded Data

Variable		Stage 1	Stage 2
Preferred Travel Method		21 (2.08%)	22 (2.18%)
Perceived Value		10 (.99%)	11 (1.09%)
Familiarity		4 (.39%)	8 (.79%)
Fun Factor		8 (.79%)	11 (1.09%)
Wariness		6 (.59%)	8 (.79%)
	Openness	21 (2.08%)	15 (1.48%)
	Conscientiousness	23 (2.28%)	18 (1.78%)
Personality	Extraversion	22 (2.18%)	18 (1.78%)
	Agreeableness	22 (2.18%)	18 (1.78%)
	Neuroticism	13 (1.28%)	20 (1.98%)
Vehicle General Affect		4 (.39%)	13 (1.28%)
Airplane General Affect		10 (.99%)	11 (1.09%)
Vehicle Comfort		5 (.49%)	4 (.39%)
Vehicle External Factors		3 (.29%)	6 (.59%)
Airplane Comfort		10 (.99%)	7 (.69%)
Airplane External Factors		3 (.29%)	2 (.19%)
Age		31 (3.07%)	
Total		185 (18.35%)[a]	192 (19.04%)[a]

a. Total is not the sum of all missing data, as some cases had multiple missing data points; does not include removal of outliers

Stage 1

After excluding data that did not meet the requirement and data outliers, the sample size for Stage 1 was N = 863, which included 457 females (53%). Participants' mean age was 38.77 (SD = 11.95). A summary of the descriptive statistics for Stage 1 is available in Table 10.

Table 10
Summary of Stage 1 Descriptive Statistics

	Variable	N	M	SD
	Age	863	38.77	11.95
Gender	Male	406 (47%)		
	Female	457 (53%)		
Social Class	Upper Class	6 (0.7%)		
	Upper Middle Class	233 (27%)		
	Lower Middle Class	357 (41.4%)		
	Working Class	213 (24.7%)		
	Lower Class	54 (6.3%)		
Ethnicity	Caucasian	684 (79%)		
	African descent	61 (7.1%)		
	Asian descent	52 (6%)		
	Hispanic descent	42 (4.9%)		
	Indian	8 (0.9%)		
	Other	16 (1.9%)		

Stage 2

After excluding data that did not meet the requirement and data outliers, the sample size for Stage 2 was N = 882, which included 512 females (56%). Participants' mean age was 38.18 (SD = 11.92). A summary of the descriptive statistics for Stage 2 is available in Table 11.

Table 11
Summary of Stage 2 Descriptive Statistics

	Variable	N	M	SD
	Age	882	38.19	11.92
Gender	Male	387 (44%)		
	Female	495 (56%)		
Social Class	Upper Class	7 (0.8%)		
	Upper Middle Class	242 (27.4%)		
	Lower Middle Class	379 (43%)		
	Working Class	212 (24%)		
	Lower Class	42 (4.8%)		
Ethnicity	Caucasian	638 (72.3)		
	African descent	76 (8.6%)		
	Asian descent	87 (9.9%)		
	Hispanic descent	52 (5.9%)		
	Indian	6 (0.7%)		
	Other	23 (2.6%)		

Sample Sizes, Effect Size, and Observed Power

Due to the nature of online surveys, a convenience sample technique was utilized via Amazon's Mechanical Turk. Appropriate apriori sample sizes provided adequate recommendations for sample sizes. Using G*Power 3.1.9.4, a minimum of 818 participants was necessary to adequately complete each stage of the study, with a small effect size of .05, an alpha level of .05, a power of .99, and 20 predictors. As noted earlier, both stages meet the minimum sample size requirements.

Assumptions of Regression

In total, there are eight assumptions associated with regression which need to be addressed before conducting inferential analyses. Chapter 1 detailed these assumptions, and the current section will review these assumptions regarding the specific data set that was used for analysis. Each assumption will be evaluated and whether or not it satisfactorily met the requirements. Because the same dataset was used for all four scenarios, the assumptions were only tested once using the four-hour trip as the dependent variable. Therefore, these assumptions also account for the data used in the eight-hour, twelve-hour, and sixteen-hour scenarios. As a reminder, the regression assumptions are as follows:

1. There is one, continuous, dependent variable.
2. There are two or more independent variables.
3. There is independence of observations.
4. There is a linear relationship between the dependent variable and each of the independent variables, both individually and collectively.
5. There is homoscedasticity in the data.
6. There is no multicollinearity in the data.
7. There are no significant outliers in the data.
8. The residuals (errors) are normally distributed.

Assumption 1 was satisfied because although the dependent variable is technically ordinal, it will be treated as continuous, or interval, during the analysis, which is a common practice in the field (Boone & Boone, 2012; Joshi et al., 2015; Rickards et al., 2012; Sullivan & Artino, 2013). The dependent variable averaged participants' scores on a four-item Likert-type scale to obtain one overall score for each participant (Brown, 2011). Assumption 2 was also met as there were 20 independent variables, the majority of which were continuous. Assumption 3 (regarding the independence of observations) was also met as the Durbin-Watson statistic was 1.966, which meets the recommended range (1.5 – 2.5) for Durbin-Watson statistics (Field, 2009).

In addition, Assumption 4 was met as there was a linear relationship between the dependent variable and independent variables, both individually and collectively. The Partial Regression plots for the variables included in the final regression model were included in the analysis output, and all indicated a linear relationship. For the four-hour trip, the variables included in the final regression model included Vehicle Affect, Fun Factor, Value, Plane Affect, Plane Comfort, Extraversion, and Asian. See figures 1 – 6 for the partial regression plots for the quantitative variables.

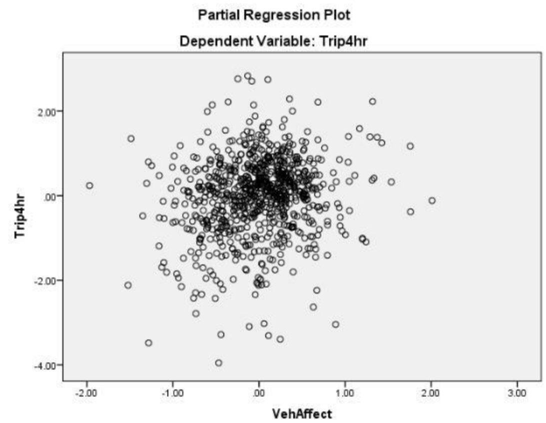

Figure 1: Partial Regression Plot - Vehicle Affect

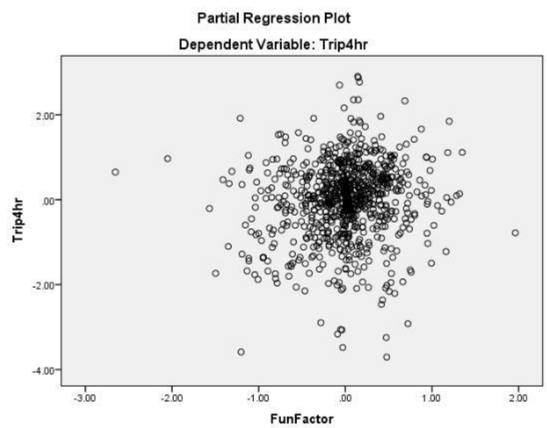

Figure 2: Partial Regression Plot - Fun Factor

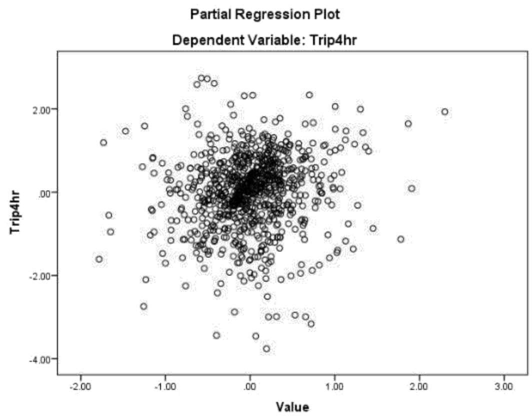

Figure 3: Partial Regression Plot - Value

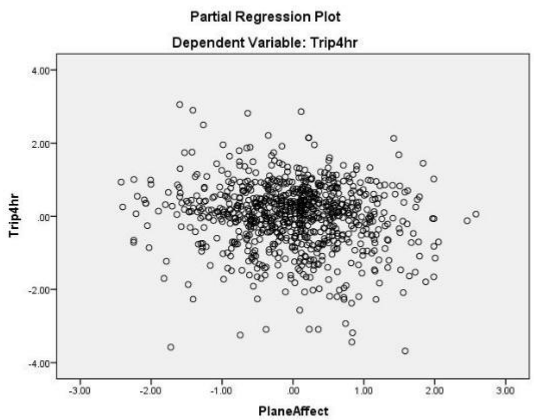

Figure 4: Partial Regression Plot - Plane Affect

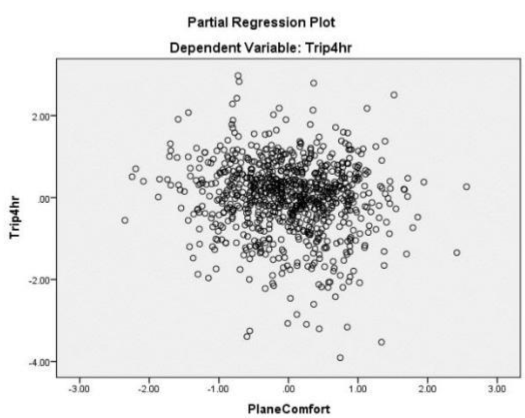

Figure 5: Partial Regression Plot - Plane Comfort

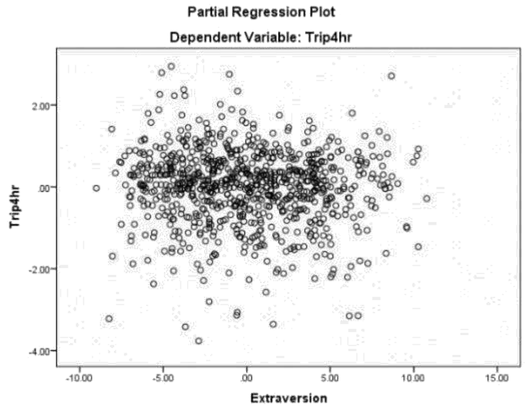

Figure 6: Partial Regression Plot - Extraversion

Assumption 5 is concerned with homoscedasticity and ensuring that the variance of errors (residuals) is constant across all the values of the independent variable. This assumption can be checked by inspection of a plot of standardized residuals against the predicted values (see Figure 7). Because the points on the scatterplot did not exhibit a pattern or funnel shape, the data was determined to have homoscedasticity.

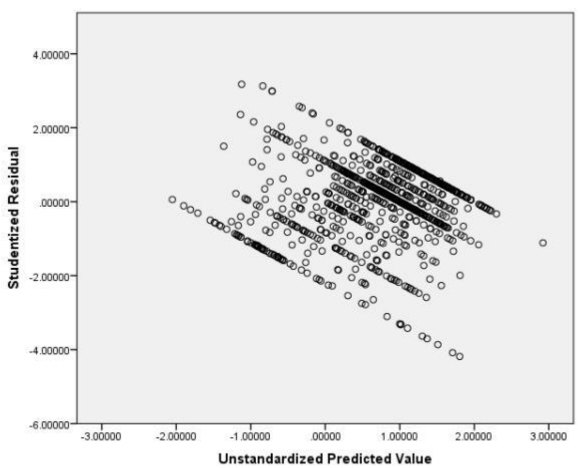

Figure 7: Scatterplot for homoscedasticity

The sixth assumption revolves around no multicollinearity within the data. Multicollinearity can cause issues with understanding which variable contributes to the variance and creating a parsimonious model. For this data set, the Tolerance/VIF values were assessed to ensure there were no violations (data violating this assumption will have a Tolerance value less than 0.1 and a VIF value of greater than 10). Fortunately, none of the variables in the final model violated this assumption (see Table 12 for an overview of the specific variable values for the 4hr model).

Table 12
Summary of Collinearity Statistics

Model	Collinearity Statistics	
	Tolerance	VIF
(Constant)		
Vehicle Affect	.221	4.521
Fun Factor	.175	5.717
Value	.209	4.777
Plane Affect	.618	1.618
Plane Comfort	.611	1.637

Assumption 7 is concerned with the detection and removal of outlying data points. An outlier is an observation that does not follow the usual pattern of data points, which may negatively affect the model fit of the regression equation. For this data set, outliers were detected using Mahalanobis Distance to indicate statistically significant outliers, $\alpha = .001$. In total, 76 cases were removed (46 from Stage 1 and 30 from Stage 2), which represents 3.7% of the data sample due to outliers. Researchers have suggested that within a normally distributed population, there is a 1% chance that you will get an outlying data point (Osborne & Overbay, 2004). Therefore, some of the outliers from the current data sample may be a result of other factors, such as data errors, misreporting, sampling error, standardization error, etc., and were appropriately removed.

Assumption 8 is based upon the premise that residuals (errors) are normally distributed. This can be investigated by looking at a histogram with a superimposed normal curve and a P-

Plot. Figure 8 provides an overview of the histogram, and although the residuals aren't entirely normal, they are sufficiently distributed to satisfy this assumption. However, for further consideration, the normal probability plot (P-Plot) should also be considered. If the residuals are normally distributed, the points will be aligned along the diagonal line; however, these points will rarely perfectly align; thus, some deviation is acceptable (Laerd Statistics, 2015). Figure 9 provides an overview of the P-Plot, which indicates that the residuals do not deviate far from the diagonal line. Observation of these two tests provides evidence that the requirements for this assumption were adequately met.

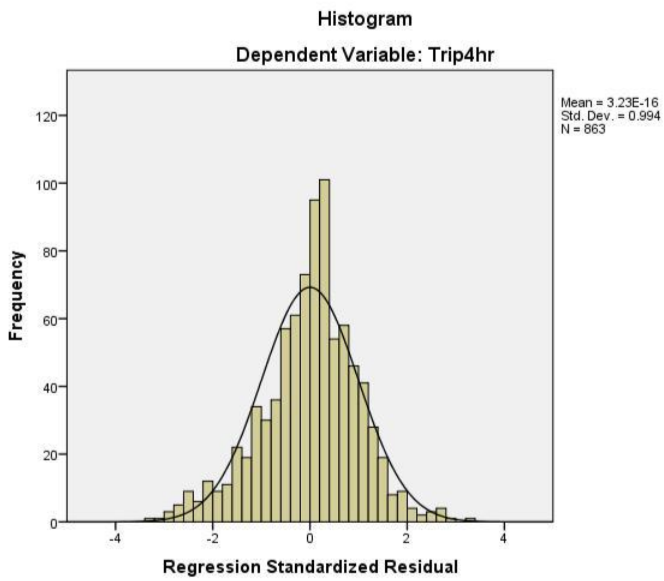

Figure 8: Frequency Distribution Histogram of Residuals

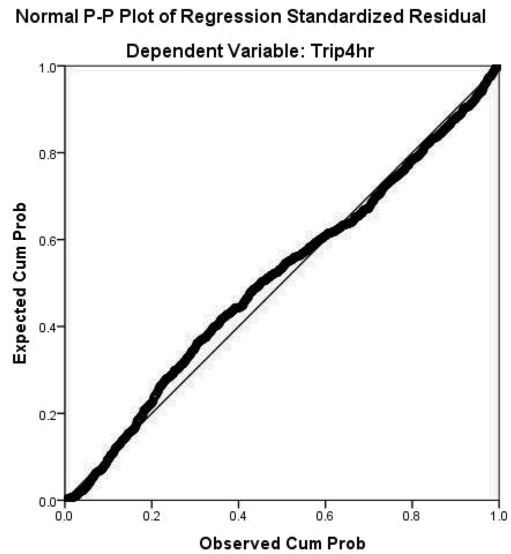

Figure 9: Normal Probability Plot (p-plot)

Stage 1

Stage 1 was conducted to build the regression equation necessary for predicting participants' preferred travel method. There were 20 total predictors used for this analysis, including age, gender, social class, ethnicity, price, perceived value, familiarity, fun factor, wariness of new technology, personality (openness, conscientiousness, extraversion, agreeableness, and neuroticism), vehicle affect, vehicle comfort, vehicle external factors, airplane affect, airplane comfort, and airplane external factors. A backward stepwise regression was utilized to determine which variables significantly predicted participants' preferred travel method. Through an iterative process, a backward stepwise regression eliminates statistically insignificant predictors until the final model represents the statistically significant predictors. Participants' preferred travel method was measured across four different scenarios, which represented the different travel length times: four-hour, eight-hour, twelve-hour, and sixteen-hour. The final model for each scenario is detailed below.

Four-Hour Trip

For the four-hour trip, the final model included ten significant predictors: Vehicle Affect, Fun Factor, Value, Plane Affect, Vehicle Comfort, Extraversion, Openness, African, Asian, and Upper Class. The resulting regression equation was:

$$Y = .169 + .297X_1 + .229X_2 + .290X_3 - .106X_4 - .106X_5 - .020X_6 + .016X_7 - .222X_8 - .302X_9 - .670X_{10}$$

where Y is participants' preference for riding in an autonomous vehicle, and X_1 – X_9 are Vehicle Affect, Fun Factor, Value, Plane Affect, Vehicle Comfort, Extraversion, Openness, African, Asian, and Upper Class, respectively. This model resulted in an $R^2 = .507$ (adjusted $R^2 = .501$), thus accounting for roughly 50% of the variance in participants' preferred travel method. This model was statistically significant, $F(10, 852) = 87.549$, $p < .001$. The overall model summary and ANOVA can be found in appendices, M and N, respectively.

The final model for the four-hour trip included ten significant predictors with the coefficients listed in Table 13. According to the unstandardized B coefficients, when holding all other variables constant, for every unit increase in Vehicle Affect, participants' preference for traveling in an autonomous vehicle increases .297 units on average, the coefficient was significant, $t(852) = 5.102$, $p < .001$. Holding all other variable constant, for each unit increase in Fun Factor, participants' preference for traveling in an autonomous vehicle increases .229 units on average, the coefficient was significant, $t(852) = 3.859$, $p < .001$. Holding all other variable constant, for each unit increase in Value, participants' preference for traveling in an autonomous vehicle increases .290 units on average, the coefficient was significant, $t(852) = 4.953$, $p < .001$. Holding all other variable constant, for each unit increase in Plane Affect, participants' preference for traveling in an autonomous vehicle decreases .106 units on average, the coefficient was significant, $t(852) = -2.978$, $p = .003$. Holding all other variable constant, for each unit increase in Vehicle Comfort, participants' preference for traveling in an autonomous vehicle decreases .106 units on average, the coefficient was significant, $t(852) = -2.627$, $p = .009$. Holding all other variable constant, for each unit increase in Extraversion, participants' preference for traveling in an autonomous vehicle decreases .020 units on average, the coefficient was significant, $t(852) = -2.768$, $p = .054$. Holding all other variable constant, for each unit increase in Openness, participants' preference for traveling in an autonomous vehicle increases .016 units on average, the coefficient was significant, $t(852) = 1.186$, $p = .070$. Holding all other variable constant, for each unit increase in African ethnicity, participants' preference for traveling in an autonomous vehicle decreases .222 units on average, the coefficient was significant, $t(852) = -1.943$, $p = .052$. Holding all other variable constant, for each unit increase in Asian ethnicity, participants' preference for traveling in an autonomous vehicle decreases .302 units on average, the coefficient was significant, $t(852) = -2.513$, $p = .012$. Holding all other variable constant, for each unit increase in Upper Class, participants' preference for traveling in an autonomous vehicle increases .670 units on average, the coefficient was significant, $t(852) = -1.943$, $p = .052$.

Table 13
Regression Coefficients for four-hour trip (Model 18)

Model[a]		Unstandardized Coefficients B	Unstandardized Coefficients Std. error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part
18	(Constant)	.169	.146		1.157	.248			
	VehicleAffect	.297	.058	.259	5.102	.000	.630	.172	.123
	FunFactor	.229	.059	.220	3.859	.000	.647	.131	.093
	Value	.290	.058	.258	4.953	.000	.659	.167	.119
	PlaneAffect	-.106	.035	-.091	-2.978	.003	-.068	-.102	-.072
	PlaneComfort	-.106	.040	-.081	-2.627	.009	-.097	-.090	-.063
	Extraversion	-.020	.007	-.070	-2.768	.006	-.040	-.094	-.067
	Imagination	.016	.009	.045	1.816	.070	.097	.062	.044
	African	-.222	.114	-.048	-1.943	.052	-.081	-.066	-.047
	Asian	-.302	.120	-.061	-2.513	.012	-.032	-.086	-.060
	UpperClass	.670	.345	.047	1.943	.052	.075	.066	.047

a. Dependent Variable: Preferred Travel Method

Eight-Hour Trip

For the eight-hour trip, the final model included thirteen significant predictors: Vehicle Affect, Vehicle Comfort, Wariness of New Technology, Value, Familiarity, Plane Affect, Plane Price, Agreeableness, Conscientiousness, Gender, African, Asian, and Upper Class. The resulting regression equation was:

$$Y = .552 + .367X_1 + .094X_2 + .088X_3 + .221X_4 - .196X_5 - .291X_6 - .100X_7 - .023X_8 - .021X_9 - .203X_{10} - .390X_{11} - .391X_{12} + 1.367X_{13}$$

where Y was participants' preference for riding in an autonomous vehicle, and $X_1 – X_{13}$ is Vehicle Affect, Vehicle Comfort, Wariness of New Technology, Value, Familiarity, Plane Affect, Plane Price, Agreeableness, Conscientiousness, Gender, African, Asian, and Upper Class, respectively. This model resulted in an R^2 = .333 (adjusted R^2 = .322), thus accounting for roughly 32% of the variance in participants' preference for riding in an autonomous vehicle. This model was statistically significant, $F(13, 849) = 32.544$, $p < .001$. The overall model summary and ANOVA can be found in appendices, O and P, respectively.

The final model for the eight-hour trip included thirteen significant predictors with the coefficients listed in Table 14. According to the unstandardized B coefficients, when holding all other variables constant, for every unit increase in Vehicle Affect, participants' preference for traveling in an autonomous vehicle increases .367 units on average, the coefficient was significant, $t(849) = 5.592$, $p < .001$. Holding all other variables constant, for every unit increase in Vehicle Comfort, participants' preference for traveling in an autonomous vehicle increases .094 units on average, the coefficient was significant, $t(849)$, 1.823, $p = .069$. Holding all other variables constant, for every unit increase in Wariness of New Technology, participants' preference for traveling in an autonomous vehicle increases .088 units on average, the coefficient was significant, $t(849) = 2.172$, $p = .030$. Holding all other variables constant, for every unit increase in Value, participants' preference for traveling in an autonomous vehicle increases .221 units on average, the coefficient was significant, $t(849) = 3.685$, $p < .001$. Holding all other variables constant, for every unit increase in Familiarity, participants' preference for traveling in an autonomous vehicle increases .196 units on average, the coefficient was significant, $t(849) = 4.527$, $p < .001$. Holding all other variables constant, for every unit increase in Plane Affect, participants' preference for traveling in an autonomous vehicle decreases .291 units on average, the coefficient was significant, $t(849) = -7.966$, $p < .001$.

Holding all other variables constant, for every unit increase in Plane Price, participants' preference for traveling in an autonomous vehicle decreases .100 units on average, the coefficient was significant, $t(849) = -2.966$, $p = .003$. Holding all other variables constant, for every unit increase in Agreeableness, participants' preference for traveling in an autonomous vehicle decreases .023 units on average, the coefficient was not significant, $t(849) = -2.042$, $p = .041$. Holding all other variables constant, for every unit increase in Conscientiousness, participants' preference for traveling in an autonomous vehicle decreases .021 units on average, the coefficient was significant, $t(849) = -1.872$, $p = .061$. Holding all other variables constant, for every unit increase in Gender, participants' preference for traveling in an autonomous vehicle decreases .203 units on average, the coefficient was significant, $t(849) = -2.674$, $p = .008$. Holding all other variables constant, for every unit increase in African ethnicity, participants' preference for traveling in an autonomous vehicle decreases .390 units on average, the coefficient was significant, $t(849) = -2.768$, $p = .006$. Holding all other variables constant, for every unit increase in Asian ethnicity, participants' preference for traveling in an autonomous vehicle decreases .391 units on average, the coefficient was significant, $t(849) = -2.623$, $p = .009$. Holding all other variables constant, for every unit increase in Upper Class, participants' preference for traveling in an autonomous vehicle increases 1.367 units on average, the coefficient was significant, $t(849) = 3.191$, $p = .001$.

Table 14
Regression Coefficients for eight-hour trip (Model 15)

Model[a]		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations		
		B	Std. error	Beta			Zero-order	Partial	Part
15	(Constant)	.552	.228		2.422	.016			
	VehicleAffect	.367	.066	.302	5.592	.000	.455	.188	.157
	VehicleComfort	.094	.051	.061	1.823	.069	.229	.062	.051
	WaryTech	.088	.041	.068	2.172	.030	-.118	.074	.061
	Value	.221	.060	.186	3.685	.000	.457	.125	.103
	Familiarity	.196	.043	.144	4.527	.000	.268	.154	.127
	PlaneAffect	-.291	.037	-.237	-7.966	.000	-.142	-.264	-.223
	PlanePrice	-.100	.034	-.085	-2.966	.003	-.050	-.101	-.083
	Agreeableness	-.023	.011	-.061	-2.042	.041	-.022	-.070	-.057
	Conscientiousness	-.021	.011	-.054	-1.872	.061	-.086	-.064	-.052
	Gender	-.203	.076	-.081	-2.674	.008	.018	-.091	-.075
	African	-.390	.141	-.080	-2.768	.006	-.095	-.095	-.078
	Asian	-.391	.149	-.075	-2.623	.009	-.049	-.090	-.074
	UpperClass	1.367	.428	.091	3.191	.001	.128	.109	.089

a. Dependent Variable: Preferred Travel Method

Twelve-Hour Trip

For the twelve-hour trip, the final model included twelve significant predictors: Vehicle Affect, Vehicle Comfort, Wariness of New Technology, Familiarity, Plane Affect, Plane External Factors, Plane Price, Extraversion, Conscientiousness, Neuroticism, Asian, and Upper Class. The resulting equation was

$$Y = -.445 + .454X_1 + .132X_2 + .117X_3 + .135X_4 - .363X_5 + .111X_6 - .110X_7 + .017X_8 - .022X_9 + .027X_{10} - .339X_{11} + 1.307X_{12}$$

where Y was participants' preference for riding in an autonomous vehicle, and $X_1 – X_{12}$ are Vehicle Affect, Vehicle Comfort, Wariness of New Technology, Familiarity, Plane Affect, Plane External Factors, Plane Price, Extraversion, Conscientiousness, Neuroticism, Asian, and Upper Class, respectively. This model resulted in an $R^2 = .269$ (adjusted $R^2 = .259$), thus accounting for roughly 26% of the variance in participants' preference for riding in an autonomous vehicle. This model was statistically significant, $F(12, 850) = 26.052$, $p < .001$. The overall model summary and ANOVA can be found in appendices, Q and R, respectively.

The final model for the twelve-hour trip included twelve significant predictors with the coefficients listed in Table 15. According to the unstandardized B coefficients, when holding all other variables constant, for every unit increase in Vehicle Affect, participants' preference for traveling in an autonomous vehicle increases .454 units on average, the coefficient was significant, $t(850) = 10.141$, $p < .001$. When holding all other variables constant, for every unit increase in Vehicle Comfort, participants' preference for traveling in an autonomous vehicle increases .132 units on average, the coefficient was significant, $t(850) = 2.588$, $p = .010$. When holding all other variables constant, for every unit increase in Wariness of New Technology, participants' preference for traveling in an autonomous vehicle increases .117 units on average, the coefficient was significant, $t(850) = 2.797$, $p = .005$. When holding all other variables constant, for every unit increase in Familiarity, participants' preference for traveling in an autonomous vehicle increases .135 units on average, the coefficient was significant, $t(850) = 3.056$, $p = .002$.

When holding all other variables constant, for every unit increase in Plane Affect, participants' preference for traveling in an autonomous vehicle decreases .363 units on average, the coefficient was significant, $t(850) = -8.672$, $p < .001$. When holding all other variables constant, for every unit increase in Plane External Factors, participants' preference for traveling in an autonomous vehicle increases .111 units on average, the coefficient was significant, $t(850) = 2.250$, $p = .025$. When holding all other variables constant, for every unit increase in Plane Price, participants' preference for traveling in an autonomous vehicle decreases .110 units on average, the coefficient was significant, $t(850) = -3.196$, $p = .001$. When holding all other variables constant, for every unit increase in Extraversion, participants' preference for traveling in an autonomous vehicle increases .017 units on average, the coefficient was significant, $t(850) = 1.823$, $p = .069$. When holding all other variables constant, for every unit increase in Conscientiousness, participants' preference for traveling in an autonomous vehicle decreases .022 units on average, the coefficient was significant, $t(850) = 1.851$, $p = .065$. When holding all other variables constant, for every unit increase in Neuroticism, participants' preference for traveling in an autonomous vehicle increases .027 units on average, the coefficient was significant, $t(850) = 2.472$, $p = .014$. When holding all other variables constant, for every unit increase in Asian ethnicity, participants' preference for traveling in an autonomous vehicle decreases .339 units on average, the coefficient was significant, $t(850) = -2.244$, $p = .025$. When holding all other variables constant, for every unit increase in Upper Class, participants' preference for traveling in an autonomous vehicle increases 1.307 units on average, the coefficient was significant, $t(850) = 3.011$, $p = .003$.

Table 15
Regression Coefficients for twelve-hour trip (Model 16)

Model[a]		Unstandardized Coefficients B	Unstandardized Coefficients Std. error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part
16	(Constant)	-.445	.280		-1.589	.112			
	VehicleAffect	.454	.045	.385	10.141	.000	.372	.329	.297
	VehicleComfort	.132	.051	.089	2.588	.010	.216	.088	.076
	WaryTech	.117	.042	.093	2.797	.005	-.046	.095	.082
	Familiarity	.135	.044	.102	3.056	.002	.234	.104	.090
	PlaneAffect	-.363	.042	-.303	-8.672	.000	-.150	-.285	-.254
	PlaneExtFact	.111	.049	.080	2.250	.025	.015	.077	.066
	PlanePrice	-.110	.034	-.096	-3.196	.001	-.086	-.109	-.094
	Extraversion	.017	.009	.058	1.823	.069	.067	.062	.053
	Conscientiousness	-.022	.012	-.059	-1.851	.065	-.115	-.063	-.054
	Neuroticism	.027	.011	.082	2.472	.014	.078	.084	.073
	Asian	-.339	.151	-.067	-2.244	.025	-.054	-.077	-.066
	UpperClass	1.307	.434	.090	3.011	.003	.126	.103	.088

a. Dependent Variable: Preferred Travel Method

Sixteen-Hour Trip

For the sixteen-hour trip, the final model included twelve significant predictors: Vehicle Affect, Vehicle Comfort, Wariness of New Technology, Familiarity, Plane Affect, Plane External Factors, Plane Price, Extraversion, Neuroticism, Asian, Lower Class, and Upper Class. The resulting equation was

$$Y = -.946 + .431X_1 + .179X_2 + .136X_3 + .150X_4 - .356X_5 + .177X_6 - .140X_7 + .023X_8 + .030X_9 - .295X_{10} + .330X_{11} + 1.334X_{12}$$

where Y was participants’ preference for riding in an autonomous vehicle, and $X_1 – X_{12}$ are Vehicle Affect, Vehicle Comfort, Wariness of New Technology, Familiarity, Plane Affect, Plane External Factors, Plane Price, Extraversion, Neuroticism, Asian, Lower Class, and Upper Class, respectively. This model resulted in an R^2 = .267 (adjusted R^2 = .256), thus accounting for roughly 25% of the variance in participants' preference for riding in an autonomous vehicle. This model was statistically significant, $F(12, 850) = 29.260$, $p < .001$. The overall model summary and ANOVA can be found in appendices, S and T, respectively.

The final model for the sixteen-hour trip included twelve significant predictors with the coefficients listed in Table 16. According to the unstandardized B coefficients, when holding all other variables constant, for every unit increase in Vehicle Affect, participants' preference for traveling in an autonomous vehicle increases .431 units on average, the coefficient was significant, $t(850) = 9.456$, $p < .001$. When holding all other variables constant, for every unit increase in Vehicle Comfort, participants' preference for traveling in an autonomous vehicle increases .179 units on average, the coefficient was significant, $t(850) = 3.443$, $p = .001$. When holding all other variables constant, for every unit increase in Wariness of New Technology, participants' preference for traveling in an autonomous vehicle increases .136 units on average, the coefficient was significant, $t(850) = 3.198$, $p = .001$. When holding all other variables constant, for every unit increase in Familiarity, participants' preference for traveling in an autonomous vehicle increases .150 units on average, the coefficient was significant, $t(850) = 3.310$, $p = .001$.

When holding all other variables constant, for every unit increase in Plane Affect, participants' preference for traveling in an autonomous vehicle decreases .356 units on average, the coefficient was significant, $t(850) = -8.359$, $p < .001$. When holding all other variables constant, for every unit increase in Plane External Factors, participants' preference for traveling in an autonomous vehicle increases .177 units on average, the coefficient was significant, $t(850)$

= 3.536, $p < .001$. When holding all other variables constant, for every unit increase in Plane Price, participants' preference for traveling in an autonomous vehicle decreases .140 units on average, the coefficient was significant, $t(850) = -4.005$, $p < .001$. When holding all other variables constant, for every unit increase in Extraversion, participants' preference for traveling in an autonomous vehicle increases .023 units on average, the coefficient was significant, $t(850) = 2.328$, $p = .020$. When holding all other variables constant, for every unit increase in Neuroticism, participants' preference for traveling in an autonomous vehicle increases .030 units on average, the coefficient was significant, $t(850) = 2.887$, $p = .004$. When holding all other variables constant, for every unit increase in Asian ethnicity, participants' preference for traveling in an autonomous vehicle decreases .295 units on average, the coefficient was significant, $t(850) = -1.917$, $p = .056$. When holding all other variables constant, for every unit increase in Lower Class, participants' preference for traveling in an autonomous vehicle increases .330 units on average, the coefficient was significant, $t(850) = 2.168$, $p = .030$. When holding all other variables constant, for every unit increase in Upper Class, participants' preference for traveling in an autonomous vehicle increases 1.334 units on average, the coefficient was significant, $t(850) = 3.014$, $p = .003$.

Table 16
Regression Coefficients for sixteen-hour trip (Model 16)

Model[a]		Unstandardized Coefficients B	Unstandardized Coefficients Std. error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part
16	(Constant)	-.946	.191		-4.948	.000			
	VehicleAffect	.431	.046	.358	9.456	.000	.355	.309	.278
	VehicleComfort	.179	.052	.118	3.443	.001	.236	.117	.101
	WaryTech	.136	.043	.107	3.198	.001	-.022	.109	.094
	Familiarity	.150	.045	.111	3.310	.001	.250	.113	.097
	PlaneAffect	-.356	.043	-.293	-8.359	.000	-.112	-.276	-.246
	PlaneExtFact	.177	.050	.125	3.536	.000	.071	.120	.104
	PlanePrice	-.140	.035	-.121	-4.005	.000	-.116	-.136	-.118
	Extraversion	.023	.010	.074	2.328	.020	.088	.080	.068
	Neuroticism	.030	.010	.090	2.887	.004	.071	.099	.085
	Asian	-.295	.154	-.057	-1.917	.056	-.050	-.066	-.056
	LowerClass	.330	.152	.065	2.168	.030	.050	.074	.064
	UpperClass	1.334	.443	.090	3.014	.003	.130	.103	.089

a. Dependent Variable: Preferred Travel Method

Stage Two

As previously noted, the purpose of Stage 2 was to validate the regression equation that accounted for the most variance. For the current dissertation, four different scenarios were presented to participants, which represented the varying trip lengths: four hours, eight hours, twelve hours, and sixteen hours. In the following sections, the model fit for each regression equation produced will be validated. This validation was accomplished by comparing participants' predicted scores on the Preferred Travel Method scale (using the equation created in Stage 1) to their actual scores on the Preferred Travel Method scale. This comparison was accomplished through a *t*-test, correlation, and cross-validated R^2.

Four-Hour Scenario

To begin testing the predictive validity of the equation, a *t*-test was performed to compare participants' predicted scores to their actual scores of preference for riding in an autonomous vehicle rather than a commercial aircraft. This analysis resulted in a non-significant finding, $t(1762) = -.176$, $p = .860$, and is displayed in Table 17.

Table 17
T-Test between Actual and Predicted Scores of Preferred Travel Method

	Levene's Test for Equality of Variances		t-test for Equality of Means						
								95% Confidence Interval	
	F	Sig.	t	df	Sig.	Mean Difference	Std. Error Difference	Lower	Upper
Equal variances assumed	122.032	.000	-.176	1762	.860	-.00857	.04858	-.10386	.08673

Furthermore, a correlational analysis was conducted to determine the relationship of similarity between the actual and predicted scores. Interpretation of the results indicate that the scores have a strong and positive relationship, $r(880) = .653$, $p < .001$. The results of this analysis are represented in Table 18.

Table 18
Correlational Analysis Between Actual and Predicted Preferred Travel Method Scores

		Actual	Predicted
Actual	Pearson	1	.653
	Sig.		.000
	N	882	882
Predicted	Pearson	.653	1
	Sig.	.000	
	N	882	882

Lastly, cross-validated R^2 was compared to determine the validity of the regression equation. The following formula calculates the estimated squared cross-validity coefficient:

$$^{2} = 1 - \left(\frac{-1}{\quad}\right)\left(\frac{+ + 1}{\quad}\right)(1 - {}^{2})$$

$- - 1$

where N = sample size, k = number of predictors, and R^2 = observed squared multiple correlation (Pedhazur, 1997). Using the aforementioned formula, the stage two cross-validity coefficient is calculated below:

$$.484 = 1 - \left(\frac{882 - 1}{882}\right)\left(\frac{882 + 20 + 1}{882 - 20 - 1}\right)(1 - .507)$$

where N = 882, k = 20, and R^2 = .507. The cross-validity coefficient is ^{2} = .484, which indicates a good model fit because the cross-validity coefficient is similar to the R^2 found in the original model produced during Stage 1.

Eight-Hour Scenario

To begin testing the predictive validity of the equation, a *t*-test was performed to compare participants' predicted scores to their actual scores of preference for riding in an autonomous vehicle rather than a commercial aircraft. This analysis resulted in a non-significant finding, $t(1762) = .576$, $p = .564$, and is displayed in Table 19.

Table 19

T-Test between Actual and Predicted Scores of Preferred Travel Method

	Levene's Test for Equality of Variances		t-test for Equality of Means						
								95% Confidence Interval	
	F	Sig.	t	df	Sig.	Mean Difference	Std. Error Difference	Lower	Upper
Equal variances not assumed	528.738	.000	.576	1762	.564	.02806	.04870	-.06745	.12358

Furthermore, a correlational analysis was conducted to determine the relationship of similarity between the actual and predicted scores. Interpretation of the results indicate that the scores have a strong and positive relationship, $r(880) = .516$, $p < .001$. The results of this analysis are represented in Table 20.

Table 20
Correlational Analysis Between Actual and Predicted Preferred Travel Method Scores

		Actual	Predicted
Actual	Pearson	1	.516
	Sig.		.000
	N	882	882
Predicted	Pearson	.516	1
	Sig.	.000	
	N	882	882

Lastly, cross-validated R^2 was compared to determine the validity of the regression equation. The following formula calculates the estimated squared cross-validity coefficient:

$$^2 = 1 - \left(\frac{-1}{}\right)\left(\frac{+\ +1}{-\ -1}\right)(1 - {}^2)$$

where N = sample size, k = number of predictors, and R^2 = observed squared multiple correlation (Pedhazur, 1997). Using the aforementioned formula, stage two cross-validity coefficient is calculated below:

$$.301 = 1 - \left(\frac{882 - 1}{882}\right)\left(\frac{882 + 20 + 1}{882 - 20 - 1}\right)(1 - .333)$$

where N = 882, k = 20, and R^2 = .333. The cross-validity coefficient is ^{2} = .301, which indicates moderate to strong model fit because the cross-validity coefficient is similar to the R^2 found in the original model produced during Stage 1.

Twelve-Hour Scenario

To begin testing the predictive validity of the equation, a t-test was performed to compare participants' predicted scores to their actual scores of preference for riding in an autonomous vehicle rather than a commercial aircraft. This analysis resulted in a non-significant finding, $t(1762) = -.335$, $p = .737$, and is displayed in Table 21.

Table 21
T-Test between Actual and Predicted Scores of Preferred Travel Method

	Levene's Test for Equality of Variances		t-test for Equality of Means						
								95% Confidence Interval	
	F	Sig.	t	df	Sig.	Mean Difference	Std. Error Difference	Lower	Upper
Equal Variances Assumed	476.288	.000	-.335	1762	.737	-.01565	.04667	-.10717	.07588

Furthermore, a correlational analysis was conducted to determine the relationship of similarity between the actual and predicted scores. Interpretation of the results indicate that the scores have a strong and positive relationship, $r(880) = .445$, $p < .001$. The results from this analysis are represented in Table 22.

Table 22
Correlational Analysis Between Actual and Predicted Preferred Travel Method Scores

		Actual	Predicted
Actual	Pearson	1	.445
	Sig.		.000
	N	882	882
Predicted	Pearson	.445	1
	Sig.	.000	
	N	882	882

Lastly, cross-validated R^2 was compared to determine the validity of the regression equation. The following formula calculates the estimated squared cross-validity coefficient:

$$^2 = 1 - \left(\frac{-1}{\quad}\right)\left(\frac{+\ +1}{\quad}\right)(1 - {}^2)$$

$- -1$

where N = sample size, k = number of predictors, and R^2 = observed squared multiple correlation (Pedhazur, 1997). Using the aforementioned formula, stage two cross-validity coefficient is calculated below:

$$.234 = 1 - \left(\frac{882 - 1}{882}\right)\left(\frac{882 + 20 + 1}{882 - 20 - 1}\right)(1 - .269)$$

where N = 882, k = 20, and R^2 = .269. The cross-validity coefficient is ^{2} = .234, which indicates weak to moderate model fit because the cross-validity coefficient is somewhat similar to the R^2 found in the original model produced during Stage 1.

Sixteen-Hour Scenario

To begin testing the predictive validity of the equation, a *t*-test was performed to compare participants' predicted scores to their actual scores of preference for riding in an autonomous vehicle rather than a commercial aircraft. This analysis resulted in a non-significant finding, $t(1762) = -.490$, $p = .624$, and is displayed in Table 23.

Table 23

T-Test between Actual and Predicted Scores of Preferred Travel Method

	Levene's Test for Equality of Variances		t-test for Equality of Means					95% Confidence Interval	
	F	Sig.	t	df	Sig.	Mean Difference	Std. Error Difference	Lower	Upper
Equal Variances Assumed	359.161	.000	-.490	1762	.624	-.02295	.04685	-.11484	.06895

Furthermore, a correlational analysis was conducted to determine the relationship of similarity between the actual and predicted scores. Interpretation of the results indicate that the scores have a strong and positive relationship, $r(880) = .412$, $p < .001$. The results of this analysis are represented in Table 24.

Table 24
Correlational Analysis Between Actual and Predicted Preferred Travel Method Scores

		Actual	Predicted
Actual	Pearson	1	.412
	Sig.		.000
	N	882	882
Predicted	Pearson	.412	1
	Sig.	.000	
	N	882	882

Lastly, cross-validated R^2 was compared to determine the validity of the regression equation. The following formula calculates the estimated squared cross-validity coefficient:

$$^2 = 1 - \left(\frac{-1}{}\right)\left(\frac{++1}{--1}\right)(1 - ^2)$$

where N = sample size, k = number of predictors, and R^2 = observed squared multiple correlation (Pedhazur, 1997). Using the aforementioned formula, stage two cross-validity coefficient is calculated below:

$$.232 = 1 - \left(\frac{882 - 1}{882}\right)\left(\frac{882 + 20 + 1}{882 - 20 - 1}\right)(1 - .267)$$

where N = 882, k = 20, and R^2 = .267. The cross-validity coefficient is ^{2} = .232, which indicates weak to moderate model fit because the cross-validity coefficient is somewhat similar to the R^2 found in the original model produced during Stage 1.

Summary

The current research strived to build and validate a prediction equation for measuring participants' preference for riding in an autonomous vehicle rather than flying in a commercial aircraft. To achieve this objective, the research and data analysis was conducted in two different stages. In stage one, participants' responses to the Preferred Travel Method scale were used to build the regression equation. In stage two, data was collected from a new set of participants, and their predicted responses were compared to their actual responses on the Preferred Travel Method scale. This comparison was accomplished by conducting a *t*-test, correlation, and cross-validated R^2.

From stage one, the most robust model resulted from the four hour travel scenario and included ten significant predictors: Vehicle Affect, Fun Factor, Value, Plane Affect, Vehicle Comfort, Extraversion, Openness, African, Asian, and Upper Class, which accounted for 50.7% of the variance (50.1% adjusted). For the eight hour trip, the final model included thirteen significant predictors: Vehicle Affect, Vehicle Comfort, Wariness of New Technology, Value, Familiarity, Plane Affect, Plane Price, Agreeableness, Conscientiousness, Gender, African, Asian, and Upper Class, which accounted 33% of the variance (32% adjusted). For the twelve hour trip, the final model included twelve significant predictors: Vehicle Affect, Vehicle Comfort, Wariness of New Technology, Familiarity, Plane Affect, Plane External Factors, Plane Price, Extraversion, Conscientiousness, Neuroticism, Asian, and Upper Class, which accounted for 27% of the variance (26% adjusted). For the sixteen hour trip, the final model included twelve significant predictors: Vehicle Affect, Vehicle Comfort, Wariness of New Technology, Familiarity, Plane Affect, Plane External Factors, Plane Price, Extraversion, Neuroticism, Asian, Lower Class, and Upper Class, respectively, which accounted for 26% of the variance (25% adjusted). Due to the relatively exploratory nature of the current research, these models provide a foundation for future research to continue exploring. There are possibly several other factors affecting participants' preference for riding in an autonomous vehicle and participants' perceptions will likely continue evolving as autonomous vehicles become available to the public. A summary of all four models is provided below in Tables 25 – 27.

Table 25
Model Summaries of Stage 1

	Four-Hour	Eight-Hour	Twelve-Hour	Sixteen-Hour
R^2	.51	.33	.27	.26
Adj. R^2	.50	.32	.26	.25
F	87.55	32.54	26.05	25.77
df	10, 852	13, 849	12, 850	12, 850
p	< .001	< .001	< .001	< .001

Table 26
Statistically Significant Unstandardized Beta Coefficients of Stage 1

	Four Hour	Eight Hour	Twelve Hour	Sixteen Hour
Constant	.169	.552	-.445	-.946
Age				
Gender		-.203		
Lower Class				.330
Working Class				
Upper Middle				
Upper Class	.670	1.367	1.307	1.334
African	-.222	-.390		
Hispanic				
Asian	-.302	-.391	-.339	-.295
Indian				
Other				
Plane Price		-.100	-.110	-.140
Perceived Value	.290	.221		
Familiarity		.196	.135	.150
Fun Factor	.229			
Wariness Tech.		.088	.117	.136
Openness	.016			
Conscientiousness		-.021	-.022	
Extraversion	-.020		.017	.023
Agreeableness		-.023		
Neuroticism			.027	.030
Vehicle Affect	.297	.367	.454	.431
Vehicle Comfort	-.106	.094	.132	.179
Vehicle Ext. Fact				
Airplane Affect	-.106	-.291	-.363	-.356
Airplane Comfort				
Airplane Ext. Fact			.111	.177

Table 27
Model Fit Summaries using Actual Vs. Predicted Scores (Stage 2)

	T-test			Correlation		Original R^2	Cross-Validated R^2
	t	df	Sig.	R	Sig.		
Four Hour	-.176	1762	.860	.653	<.001	.507	.484
Eight Hour	.576	1762	.564	.516	<.001	.333	.301
Twelve Hour	-.335	1762	.737	.445	<.001	.269	.234
Sixteen Hour	-.490	1762	.624	.412	<.001	.267	.232

While none of the models produced the same set of predictive variables, there were a few similarities throughout the four models (see Table 28). Out of the 20 variables, only four showed up in every model: Upper Class, Vehicle Affect, Airplane Affect, and Vehicle Comfort. These findings support previous research that indicates people from upper social class tend to feel more accepting and have more favorable opinions associated with new technology (Maldifassi & Canessa, 2009; Porter & Donthu, 2006). Affect measured participants' emotional response to the idea of riding in a fully autonomous vehicle. In contrast, airplane affect measured participants' emotional response to the idea of riding in a commercial aircraft. Both these variables were significant in every travel scenario, thus demonstrating the significant impact of emotions on consumers' decision-making processes. Furthermore, participants prioritized having a comfortable experience while riding in a driverless vehicle and those from an upper social class had a higher preference for riding in a driverless vehicle.

At least one category within social class, ethnicity, and personality were also significant predictors in every scenario. Upper Class was a positive significant predictor in every scenario in addition to Lower Class, which was only significant in the sixteen-hour scenario. Personality was significant in every scenario with Openness in the four-hour with a positive coefficient. Conscientiousness had significant negative coefficient in the eight-hour and twelve-hour scenarios. Extraversion showed up in three different models, including the four, twelve, and sixteen-hour scenarios.

Interestingly, extraversion had a negative coefficient in the four-hour scenario, suggesting that as Extraversion increased, participants' preference for riding in an autonomous vehicle decreased. However, in the twelve-hour and sixteen-hour scenario, Extraversion had a positive coefficient suggesting that as levels of extraversion increased, so too did their preference for riding in an autonomous vehicle. Agreeableness was only significant in the eight-hour scenario with a negative coefficient and Neuroticism was significant in the twelve-hour and sixteen-hour scenarios with positive coefficients.

The next most common variables included Plane Price, Familiarity, and Wariness of New Technology, all of which were significant predictors in the eight, twelve, and sixteen-hour scenarios. Plane Price measured whether or not the cost of an airplane ticket was important for participants. In all three models, Plane Price had a negative coefficient, indicating that as the importance of the cost of an airplane ticket increased, participants' preference for riding in a fully autonomous vehicle decreased. Familiarity measured participant's perceived level of experience with an autonomous vehicle. Wariness of New Technology measured participants' fear or concern associated with using new technology.

For the remaining predictive variables, the majority were evenly spread out across the different models, except for gender. Gender was only significant in the eight-hour scenario, with females having a higher preference than males for riding in an autonomous vehicle. However, age was not a significant predictor in any scenario, nor was Vehicle External Factors or Airplane Comfort, in addition to a few other ethnicities and social class categories.

Table 28
Summary of Significant Predictors across all four scenarios

	Four Hour	Eight Hour	Twelve Hour	Sixteen Hour
Age				
Gender		□		
Social Class	■	■	■	■
Ethnicity	□	□	□	□
Price		■	■	■
Value	■	■		
Familiarity		■	■	■
Fun Factor	■			
Wariness		■	■	■
Personality	□	□	□	□
Vehicle Affect	■	■	■	■
Plane Affect	■	■	■	■
Vehicle Comfort	■	■	■	■
Vehicle External Factors				
Plane Comfort				
Plane External Factors			■	■

■ *Null hypothesis rejected* □ *Null hypothesis rejected for at least one of the categories*

During stage two analyses, all four models indicated statistically insignificant differences on the t-test, which is an indicator for strong model fit. All four models showed significant correlations with medium to strong relationships between the two datasets. Furthermore, all four models had cross-validated a R^2 that was similar to the respective R^2 found in Stage 1. The four-hour scenario seemed to produce the strongest model as it had a statistically insignificant t-test, strong and positive correlation, and a small difference between the original R^2 and the cross-validated R^2 when compared across all four models.

The purpose of Chapter Four was to provide a detailed description of the analyses used for the current dissertation with a summary of results. All four models indicated a strong model fit. The four-hour travel scenario arguably provided the most robust and most parsimonious model as it had the highest amount of variance accounted for with the fewest number of variables out of the four models. A detailed overview of the impact and meaning of these results will be discussed in the following section, Chapter Five.

Chapter Five

Discussion

Overview

The current research strived to understand better the factors affecting participants' preference for riding in an autonomous vehicle rather than flying in a commercial aircraft. This was accomplished through two different research stages that consisted of building a regression equation and then validating the equation through model fit. After removing missing data and outliers, there was a total of 1,745 participants (952 females) for both stages, who responded to the online survey. These participants were then split in half to facilitate the data analysis for stage one and two. In stage one, participants' responses were used to create the regression equation, and then participants from the second stage were used to validate the regression equation using model fit analyses. Participants responded to the same survey in both stages, and the detailed methodology is provided in Chapter Three.

The current research used a correlational design with multiple linear regression as the data analysis technique, which allowed for the creation of a model predicting participants' preference for riding in an autonomous vehicle rather than flying on a commercial aircraft. Overall, 20 independent variables were tested for their impact on participants' preferred travel method: age, gender, social class, ethnicity, price, perceived value, familiarity, fun factor, wariness of new technology, personality (openness, conscientiousness, extraversion, agreeableness, and neuroticism), vehicle affect, vehicle comfort, vehicle external factors, airplane affect, airplane comfort, and airplane external factors. The dependent variable was the participants' preference for riding in an autonomous vehicle rather than flying on a commercial aircraft. The following are a list of the alternative hypotheses:

Hypothesis 1

H_{A1}: At least one demographic variable (age, gender, social class, and ethnicity) will significantly predict participants' preferred travel method when controlling for all other variables.

Hypothesis 2

H_{A3}: Price is a significant predictor of participants' preferred travel method when controlling for all other variables.

Hypothesis 3

H_{A3}: At least one current consumer perceptions (perceived value, familiarity, fun factor, wariness of new technologies) will significantly predict participants' preferred travel method when controlling for all other variables.

Hypothesis 4

H_{A4}: At least one of the big five personality traits is a significant predictor of participants' preferred travel method when controlling for all other variables.

Hypothesis 5

H_{A5}: Vehicle Affect is a significant predictor of participants' preferred travel method when controlling for all other variables.

Hypothesis 6

H_{A6}: Airplane Affect is a significant predictor of participants' preferred travel method when controlling for all other variables.

Hypothesis 7

H_{A7}: Vehicle Comfort is a significant predictor of participants' preferred travel method when controlling for all other variables.

Hypothesis 8

H_{A8}: Vehicle External Factors is a significant predictor of participants' preferred travel method when controlling for all other variables.

Hypothesis 9

H_{A9}: Airplane Comfort is a significant predictor of participants' preferred travel method when controlling for all other variables.

Hypothesis 10

H_{10}: Airplane External Factors is a significant predictor of participants' preferred travel method when controlling for all other variables.

Moving forward, Chapter Five will provide a detailed description of the meaningfulness of the current research, including a summary of the results, their practical applications, limitations, and directions for future research.

Summary of Findings

As research continues to pursue the creation of a safe and efficient, fully autonomous vehicle, this new technology's successful adoption hinges on the public's perceptions of fully autonomous vehicles. Once autonomous vehicles become readily available to the public, they may have a tremendous negative impact on the commercial airline industry as people choose to ride in the autonomous vehicle rather than fly on a commercial aircraft. Therefore, understanding the type of consumer who may want to ride in an autonomous vehicle rather than fly on a commercial aircraft may provide crucial information to both fields within the transportation industry.

To investigate consumer perceptions, a predictive model was created and validated through two separate stages of data analysis (see Chapter 4 for a detailed description). In Stage 1, 20 predictors were considered as potentially impacting participants' choice for choosing to ride in an autonomous vehicle rather than fly on a commercial aircraft. Backward stepwise regression was used throughout four different scenarios to determine statistically significant predictors.

For the four-hour travel scenario, ten variables were found to significantly predict participants' preference for riding in an autonomous vehicle rather than flying on a commercial aircraft, including Vehicle Affect, Fun Factor, Value, Plane Affect, Vehicle Comfort, Extraversion, Openness, African, Asian, and Upper Class, which accounted for 50.7% of the variance (50.1% adjusted). In Stage 2, the regression equation was tested for model fit by comparing participants' predicted scores to their actual scores using a *t*-test, correlation, and cross-validated R^2. The *t*-test was not significant, $t(1762) = -.176$, $p = .860$, there was a strong and positive correlation, $r(880) = .653$, $p < .001$, and lastly the cross-validated R^2 was .484, which is similar to the original R^2, .507. When these three tests are considered together, they are all indicators of model fit and support the strength and validity of the model.

For the eight-hour travel scenario, thirteen variables were found to significantly predict participants' preference for riding in an autonomous vehicle rather than flying on a commercial aircraft, including Vehicle Affect, Vehicle Comfort, Wariness of New Technology, Value, Familiarity, Plane Affect, Plane Price, Agreeableness, Conscientiousness, Gender, African, Asian, and Upper Class, which accounted 33% of the variance (32% adjusted). In Stage 2, the regression equation was tested for model fit by comparing participants' predicted scores to their actual scores using a *t*-test, correlation, and cross-validated R^2. The t-test was significant, $t(1762) = -.176$, $p = .860$, there was a strong and positive correlation, $r(880) = .516$, $p < .001$, and lastly the cross-validated R^2 was .301, which is similar to the original R^2 was .333. When these three tests are considered together, they are all indicators of model fit and support the strength and validity of the model.

For the twelve-hour travel scenario, twelve variables were found to significantly predict participants' preference for riding in an autonomous vehicle rather than flying on a commercial aircraft, including Vehicle Affect, Vehicle Comfort, Wariness of New Technology, Familiarity, Plane Affect, Plane External Factors, Plane Price, Extraversion, Conscientiousness, Neuroticism, Asian, and Upper Class, respectively, which accounted for 27% of the variance (26% adjusted). In Stage 2, the regression equation was tested for model fit by comparing participants' predicted scores to their actual scores using a *t*-test, correlation, and cross-validated R^2. The *t*-test was not significant, $t(1762) = -.335$, $p = .737$, there was a strong and positive correlation, $r(880) = .445$, $p < .001$, and lastly the cross-validated R^2 was .234, which is similar to the original R^2, .269. When these three tests are considered together, they are all indicators of model fit and support the strength and validity of the model.

For the sixteen-hour travel scenario, twelve variables were found to significantly predict participants' preference for riding in an autonomous vehicle rather than flying on a commercial aircraft, including Vehicle Affect, Vehicle Comfort, Wariness of New Technology, Familiarity, Plane Affect, Plane External Factors, Plane Price, Extraversion, Neuroticism, Asian, Lower Class, and Upper Class, respectively, which accounted for 27% of the variance (26% adjusted). In Stage 2, the regression equation was tested for model fit by comparing participants' predicted scores to their actual scores using a *t*-test, correlation, and cross-validated R^2. The *t*-test was not significant, $t(1762) = -.490$, $p = .624$, there was a strong and positive correlation, $r(880) = .412$, $p < .001$, and lastly the cross-validated R^2 was .232, which is similar to the original R^2, .267. When these three tests are considered together, they are all indicators of model fit and support the strength and validity of the model.

General Discussion

Because this research was reasonably exploratory, there was a wide range of variables considered for inclusion, which is reflected in the different hypotheses. However, not all of the hypotheses were supported; therefore, this section will cover every hypothesis and provide rationale as to why or why not it may not have significantly predicted participants' choice.

The first hypothesis states that at least one demographic (age, gender, social class, and ethnicity) variable will significantly predict participants' preferred travel method. Age was not a significant predictor in any scenario, and gender was only significant in the eight-hour scenario. At least one category within social class and ethnicity was a significant predictor in each scenario. Previous research has suggested that people of a certain age, gender, social class, and ethnicity may prefer using a certain type of technology, or at least feel comfortable/familiar with using technology (Borghans et al., 2009; Byrnes et al., 1999; Charness & Gneezy, 2012). However, that finding was not replicated in half of the travel scenarios. This hypothesis may have only been partially supported in the current study because autonomous vehicle technology is not yet available to the public; thus, no one has had a chance to use it yet. On the other hand, people of varying demographics may recognize the benefits of autonomous vehicles. Thus one group was not more partial to them than another group.

The second hypothesis stated that the price of an airplane ticket would significantly predict participants' preference for riding in an autonomous vehicle. This hypothesis was mainly focused around the idea that riding in an autonomous car would be a cheaper alternative to flying commercial. Therefore, if the price of an airplane ticket were an important factor for participants, then they would probably prefer to ride in the autonomous vehicle. When asked about factors that affect passengers' satisfaction with flying via commercial air travel, price is often listed as a top concern (Keeton, 2010; Smith, 2004), which fueled the creation of this particular hypothesis. However, this hypothesis was not supported by the data from the four-hour travel scenario. Interestingly, as the trips got longer, the price of a plane ticket did appear to become a significant predictor, although it was always with a negative coefficient.

Due to the nature of online surveys, I was unable to ask follow-up questions; therefore, I can only speculate as to why price did not significantly predict participants' preference for riding in an autonomous vehicle in the four-hour scenario. Because participants were only traveling for about four hours in the hypothetical scenario, it's possible that they thought the price of an airline ticket for such a short flight would be roughly equivalent to how much they would spend on a road trip for the same amount of time; thus, there was no difference between the two options. Furthermore, as the length of the trip increased, the price of a ticket did become a significant predictor suggesting that trip length plays an important role.

The third hypothesis was concerned with the possibility that current consumer perceptions (perceived value, familiarity, fun factor, wariness of new technologies) would significantly predict participants' preference for riding in an autonomous vehicle. Based on research around consumers' acceptance of new technology (i.e. TAM, UTUAT, TPB), many of these factors have been identified as influencing consumers' perceptions, acceptance, and willingness to use new technology (Ajzen, 1991; Legris et al., 2003; Davis, 1985; Venkatesh, et al., 2003), which provided the rationale for inclusion in the current study. Perceived Value was significant in the four-hour and eight-hour scenario; whereas fun factor was only significant in the four-hour scenario. Interestingly, familiarity and wariness of new technology did show up as significant predictors for the remaining travel scenarios.

The factors of Perceived Value and Fun Factor significantly predicted participants' preference for riding in an autonomous vehicle while familiarity and wariness of new technology did not in the four-hour scenario. It is assumed that the earliest adopters of new technology will likely perceive some type of benefit or entertainment to using the latest technology (Chai et al., 2015; Mathwick et al., 2001; Jones et al., 2006; Eckoldt et al., 2012), thus explaining the two significant predictors. Familiarity was most likely not significant because fully autonomous vehicle technology is not yet available to the public. Therefore no one is familiar with the technology. As previously stated, early adopters of new technology are likely not concerned with the possible risks associated with using the latest technology (at least not enough to hinder their potential usage); thus, explaining why wariness of new technology was not found as a significant predictor in the four-hour scenario. However, as trip length increased, participants may have become more concerned with the amount of time they would be spending in the vehicle and its reliability, thus influencing the significant predictor of wariness.

The fourth hypothesis was concerned with at least one of the Big Five personality traits significantly predicting participants' preferred travel method. Previous research has indicated that often people who score higher on the Extraversion and Openness scale are usually more receptive to new technology and express a greater desire to use it (Merritt & Ilgen, 2008). For the current research, Openness was only significant in the four-hour scenario and Extraversion was a significant predictor in the four-hour, twelve-hour, and sixteen-hour scenarios.

Although extraversion was found as a significant predictor, it actually had a negative coefficient in the four-hour scenario meaning that as extraversion increased, preference for riding in an autonomous vehicle rather than a commercial aircraft decreased. It's possible that these participants felt that riding in a vehicle is an isolating experience compared to riding in a commercial aircraft where you are surrounded by other people and have multiple opportunities to engage in discussions with your neighbors. Whereas, when traveling in a vehicle, you are often traveling on your own; therefore, people with high levels of extraversion may have disliked that possible scenario.

The fifth and sixth hypotheses addressed whether or not Vehicle Affect and Airplane Affect, respectively, would significantly predict participants' preference for riding in an autonomous vehicle. These variables were designed to measure participants' emotional reaction to the idea of riding in an autonomous vehicle and their emotional reaction to riding in a commercial aircraft. Previous research has indicated that emotions, or affect, often play a considerable role in humans' decision-making process (Lerner et al., 2015; Peters et al., 2006; Schwarz & Clore, 2003; Slovic et al., 2005), particularly regarding unfamiliar or potentially dangerous scenarios. As expected, these particular variables were found to predict participants' preference in all four travel scenarios significantly. However, it's important to note that Airplane Affect displayed a negative coefficient, such that as participants' airplane affect decreased, their preference for riding in an autonomous vehicle rather than a commercial aircraft increased.

The seventh and eighth hypotheses were concerned with the impact that Vehicle Comfort and Vehicle External Factors would have on participants' preference. Vehicle Comfort was designed to measure participants’ experience and satisfaction with riding in a vehicle, including aspects, such as the ability to fall asleep while traveling in a vehicle. Previous research investigating consumers’ satisfaction levels while traveling in similar modes of transportation (i.e. trains, planes, public buses, etc.) have indicated these factors often influence passengers’ satisfaction levels with their trip (Kloppenborg & Gourdin, 1992; Nadiri et al., 2008; Young et al., 1994). Vehicle External Factors captured participants’ prioritization of things like schedule flexibility while traveling in a vehicle and the ability to maintain hygiene standards while traveling in a vehicle. The majority of these factors were included as they were significant in a prior pilot study.

Vehicle comfort was a significant predictor in all four scenarios, which makes sense because passengers will be in the vehicle for an extended period; thus, comfort is paramount. However, vehicle external factors was not a significant predictor in any scenario. Although participants may value these aspects of riding in a vehicle, perhaps they were not significant enough to influence their decision. For example, the ability to fall asleep in a car or schedule flexibility may not be high on participants’ priority list when imagining what factors are essential to consider when traveling in an autonomous vehicle.

The ninth hypothesis discussed whether or not the variable of Airplane Comfort would significantly predict participants’ preferred travel method. This variable was designed to measure features of passengers’ experience of riding in a commercial aircraft, such as available space to a passenger on an airplane, ability to maintain hygiene standards, and ability to fall asleep on a plane. Previous research studying consumers’ experience and satisfaction with commercial air travel have highlighted these different components as essential factors in determining consumers’ overall satisfaction level, which in turn, influences their future decision to continue using that particular airline's services (Kloppenborg & Gourdin, 1992; Nadiri et al., 2008; Young et al., 1994). Airplane Comfort was not a significant predictor in any of the scenarios, perhaps because if participants were concerned with riding in a vehicle then the comforts of an airplane aren't prioritized.

The final hypothesis was concerned with the variable, Airplane External Factors, significantly predicting participants' preferred travel method. Similar to the Vehicle External Factors, this variable measured participants' experience of riding in a commercial aircraft and the importance of factors, such as having limited schedule flexibility, sharing personal space with strangers, ability to fall asleep while on an airplane, etc. Research on travelers' preferences and factors affecting their comfort levels has cited these types of aspects (Kloppenborg & Gourdin, 1992; Nadiri et al., 2008; Young et al., 1994); thus, they were included in the current study.

However, this particular variable did not significantly predict participants' preferred travel method for the four-hour travel scenario or the eight-hour travel scenario. Still, it was a significant predictor for the twelve-hour and sixteen-hour scenario. This finding suggests that when the trips are shorter, passengers are not as concerned with travel-related features, such as the ability to fall asleep on an aircraft or sharing personal space with strangers. As a trip gets longer and takes more time to complete, different factors become important for passengers to consider and influence their preferences.

Practical Applications

Although this research merely provides a foundation for future research and is relatively exploratory, it can provide critical information for researchers in both the automotive industry and the commercial airline industry. As Human Factors practitioners, we always hope to be included at the very beginning of a design/research process so that we can better understand the end-user – their wants, needs, fears, target population, etc. If we know the end-user, then we will be more effective in designing a safe and efficient product/service that consumers will want to use. Unfortunately, human factors researchers are often brought in at the end of the process and asked to solve huge problems that would have been much more manageable if addressed at the beginning of the process rather than the end. This particular research is unique because the field of autonomous vehicle technology is still so new that we can start investigating important factors at the beginning of the design and creation process, acting proactively to address consumer concerns rather than retroactively.

One of the first steps as a Human Factors practitioner should be to understand your end-user that is exactly what this dissertation has provided – identifying what type of person would prefer to ride in an autonomous vehicle rather than fly on a commercial aircraft. Experts in the automotive industry may use this research to find their first customers and adopters of the technology. On the other hand, the commercial airline industry may use this information to better understand which customers they are going to lose first to autonomous vehicles and how they can build incentive programs to retain those customers.

The only four predictive variables that were present throughout all four of the travel scenarios were those of upper class, vehicle affect, airplane affect, and vehicle comfort. Participants from upper social class indicated the highest preference for riding in a driverless vehicle as compared to other social classes. This finding supports previous research indicating that upper social class citizens tend to view new technology more positively and are more willing to use it (Maldifassi & Canessa, 2009; Porter & Donthu, 2006). Results indicate that participants are having some type of emotional reaction to the idea of riding in an autonomous vehicle. The idea of riding in an autonomous vehicle evokes positive emotions while the idea of riding in a commercial aircraft evokes negative emotions. While my research provides some additional information as to why consumers may be happy at the idea of riding in an autonomous vehicle (i.e. they believe it will be fun or bring added value to their life), industry experts should pursue this line of research to better understand what makes consumers excited about the prospect of riding in an autonomous vehicle and how those features can be safely explored. Understandably, participants are also concerned with maintaining comfortable travel arrangements while traveling in a driverless vehicle, such as how much space is available and the ability to sleep while traveling.

On the other hand, the commercial airline industry can utilize the same information to understand better which type of consumer they are going to lose first to autonomous vehicles. If people are having an emotional reaction to entertainment and enjoyment, they will get out of riding in an autonomous vehicle, then how can commercial airlines make the experience of flying more enjoyable? Or perhaps the commercial airline industry can capitalize on the fact that for longer trips, it merely becomes more convenient to travel by air. Thus, they can focus on making their long-haul trips more comfortable and growing that customer base to compensate for the shrinking customer base using short-haul flights. The current dissertation is just one of the first steps in better understanding the impact of fully autonomous vehicles on the commercial airline industry.

Limitations

As with all research, there are some limitations to the current study that should be addressed for full transparency. One of the most critical limitations was the use of a convenience sampling technique as participants were recruited from Amazon’s Mechanical Turk (MTurk), which allowed me to collect thousands of participants in a timely manner. Although MTurk does allow for a wide range of participants, it does limit the data collection process to those who have internet access and are registered users of Amazon's MTurk, thus limiting some of the generalizability of the results. Fortunately, previous research has indicated that data collected from MTurk is as reliable as traditionally collected laboratory data (Buhrmester et al., 2011; Germine et al., 2012; Rice et al., 2017).

Furthermore, actual behavioral data were not collected or analyzed, mostly because fully autonomous vehicles do not yet exist for the public, and paying participants to travel in a vehicle or a commercial aircraft would introduce a tremendous resource burden. Therefore, only behavioral intentions, or participants' perceptions of their possible actions, were collected. While perceived actions correlate with actual behavior (Ajzen, 1991; Davis, 1989; Davis et al., 1989; Fishbein & Ajzen, 1975), they are not the same thing. Therefore, it's essential to consider the findings of the study within the light of perceptual intentions.

To date, the current dissertation is one of the only studies examining the impact of fully autonomous vehicles on the commercial airline industry and identifying what type of person would prefer to ride in an autonomous vehicle rather than fly on a commercial aircraft. Therefore, this research was fairly exploratory, and while a wide range of variables were considered, the list was certainly not exhaustive. While this is a limitation of the current study, it does provide multiple opportunities for future research to consider the impact of other variables and how this information might be manipulated to affect consumer support and willingness to use an autonomous vehicle.

Future Research

The current research provides the foundation for several different research avenues to explore the impact of fully autonomous vehicles on the commercial airline industry. The findings suggest that overall, participants are having an emotional reaction to the idea of riding in a fully autonomous vehicle rather than a commercial aircraft. Researchers from the automotive industry and commercial airline industry should explore participants' emotional reactions to understand better what factors are influencing their decision-making process. Are consumers excited by the idea of riding in an autonomous vehicle? If so, what excites them? How can these facets be capitalized? Or perhaps consumers are worried about safety and comfort during long trips. How can the automotive industry alleviate these concerns or design vehicle interiors that are more suitable for longer trips?

Likewise, the commercial airline industry can use this information to understand better participants' emotional reactions to riding in an autonomous vehicle rather than an aircraft. What specifically do they not like about riding in airplanes? Can any of those factors be improved upon to help retain some of their customer base? Or perhaps if the commercial airline industry discovers that consumers will only fly for trips over eight hours in length, how can the industry attract more customers or improve their passengers' experience so that they're more willing to continue flying with that particular airline? Because the commercial airline industry already makes a relatively small profit off of each flight, U.S. based airlines must start considering the impact on their overall success and growth.

Furthermore, findings from this research can also be extrapolated and applied to other transportation industries, such as trains, ridesharing services, boats, etc. Although the crux of this research is comparing commercial aviation to autonomous vehicles, commercial aviation is not the only other alternative mode of transportation available to travelers. Thus, understanding the impact of autonomous vehicles on different modes of transportation will probably start to provide additional information not discovered in this initial line of research. As previously mentioned, this was a fairly exploratory study designed to understand better what type of person would prefer to ride in an autonomous vehicle rather than fly on a commercial aircraft. Once the basic type of passenger is identified, researchers from both industries can start better understanding the needs and wants of their consumer base.

Conclusion

As the introduction of autonomous vehicles becomes increasingly more likely, understanding their impact on the rest of the transportation industry is crucial for the success of other transportation methods, such as commercial aviation. The current research strived to answer preliminary questions regarding consumers' acceptance and potential preference of riding in an autonomous vehicle rather than flying in a commercial aircraft. Through a series of two stages, a predictive model was created through backward stepwise regression predicting what type of person would prefer to ride in an autonomous vehicle rather than fly in a commercial aircraft. Then, this equation was tested for model fit by comparing participants' predicted scores to their actual scores using a *t*-test, correlation, and cross-validated R^2. While multiple hypothetical travel scenarios were considered, the most robust predictive model resulted from the four-hour travel scenario, accounting for 50% of the variance. Throughout the four travel scenarios, the most common significant predictors were upper social class, vehicle affect, airplane affect, and vehicle comfort, indicating the importance of emotions on consumers' decision-making process along with comfortable travel and identifying early adopters, such as upper-class citizens. While future research should be conducted, the current findings can be used by both the automotive industry and the commercial airline industry to understand their customers' preferences better while traveling in these two separate modes.

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Appendices

Appendix A – Travel Method Preference Scale

The Preferred Travel Method scale has a Cronbach's Alpha of .93 and Guttman's Split Half of .92. Correlations between items ranged from r = .69 to .88. All of the aforementioned statistics indicate high internal consistency and high reliability. Participants read the following information:

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. I would prefer the driverless car.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

2. I would be more comfortable riding in the driverless car.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

3. I would choose the driverless car.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

4. I would be happier with the driverless car.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

Appendix B – Perceived Value Scale

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. I think driverless vehicle technology is useful.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

2. A driverless vehicle would be something valuable for me to own.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

3. There would be value in using a driverless vehicle.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

4. If driverless vehicles were available, I think it would be beneficial to use one.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

5. A driverless vehicle would be beneficial to me.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

Appendix C – Familiarity Scale

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. Driverless vehicles have been of interest to me for awhile.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

2. I have a lot of knowledge about driverless vehicles.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

3. I have read a lot about driverless vehicles.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

4. I know more about driverless vehicles than the average person.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

5. I am familiar with driverless vehicles.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

Appendix D – Fun Factor Scale

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. I am interested in trying out a driverless vehicle.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

2. I think it would be cool to use a driverless vehicle.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

3. I've always wanted to use a driverless vehicle.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

4. I think it would be fun to use a driverless vehicle.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

5. I am familiar with driverless vehicles.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

Appendix E – Wariness of New Technology Scale

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. New technology scares me.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

2. In general, I am wary of new technology.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

3. I tend to fear new technology until it is proven to be safe.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

4. New technology is not as safe as it should be.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

5. New technology is likely to be dangerous.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

Appendix F – General Affect Scale

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. I feel good about this.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

2. I feel positive about this.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

3. I feel favorable about this.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

4. I feel cheerful about this.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

5. I feel happy about this.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

6. I feel enthusiastic about this.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

7. I feel delighted about this.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

Appendix G – Vehicle Comfort Scale

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. I enjoy traveling in a car if I don't have to drive.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

2. I enjoy how much space I have in a car.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

3. I enjoy sleeping while traveling in a car.

   Strongly disagree   Disagree   Neither disagree nor agree   Agree   Strongly Agree

Appendix H – Vehicle External Factors Scale

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. I enjoy the freedom to stop and eat wherever and whenever I want.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

2. I enjoy having schedule flexibility (the ability to leave when I want).

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

3. I can easily maintain my hygiene standards while traveling in a car.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

Appendix I – Airplane Comfort Scale

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. I enjoy traveling in an airplane.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

2. I am ok with how much space I have on an airplane.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

3. I can easily maintain my hygiene standards while traveling in an airplane.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

4. I enjoy sleeping while traveling in an airplane.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

5. I can easily fall asleep while traveling on an airplane.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

Appendix J – Airplane External Factors Scale

Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.

1. I enjoy waiting in the airport before I leave my departure point.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

2. I am ok having a limited choice over my departure time and arrival time.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

3. I enjoy going through TSA security.

   Strongly disagree Disagree Neither disagree nor agree Agree Strongly Agree

Appendix K – Participant Demographics Questions

1. *What is your gender?*
    - *Female*
    - *Male*
    - *Other ______*
2. *What is your ethnicity?*
    - *Caucasian*
    - *African descent (e.g., African American)*
    - *Hispanic descent (e.g., Latin America)*
    - *Asian descent*
    - *India (not Asian)*
    - *Other ______*
3. *What is your age?*
4. *What is your social class?*
    - *Upper Class*
    - *Upper Middle Class*
    - *Lower Middle Class*
    - *Working Class*
    - *Lower Class*

Appendix L – IRB Approval and Full Instrument

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

Principal Investigator: Mattie Milner

Other Investigators: Stephen Rice

Role: Student **Campus:** Daytona Beach **College:** Arts & Sciences

Project Title: Airplanes or Driverless Cars? Building a Predictive Model

Review Board Use Only

Initial Reviewer: Teri Gabriel **Date:** 09/25/2019 **Approval #:** 20-026

Determination: Exempt

Dr. Michael Wiggins
IRB Chair Signature: Michael E. Wiggins, Ed.D. Digitally signed by Michael E. Wiggins, Ed.D. DN: cn=Michael E. Wiggins, Ed.D., o=Embry-Riddle Aeronautical University, ou=Aeronautical Science Department, email=wigginsm@erau.edu, c=US Date: 2019.09.26 17:09:14 -04'00' **Date:** 09/26/2019

Brief Description:

The purpose of this study is to understand what personal factors predict the type of person who would prefer to ride in an autonomous vehicle rather than fly in a commercial aircraft. An anonymous survey through Google Forms will be used in this study.

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 M – Model Summary: 4 hour trip

Model Summary (Model 18)

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	.714	.510	.494	.83716
2	.714	.510	.495	.83666
3	.714	.510	.496	.83616
4	.714	.510	.496	.83566
5	.714	.510	.497	.83517
6	.714	.510	.497	.83469
7	.714	.510	.498	.83422
8	.714	.510	.499	.83376
9	.714	.510	.499	.83333
10	.714	.510	.500	.83291
11	.714	.510	.500	.83252
12	.714	.510	.500	.83221
13	.714	.510	.501	.83185
14	.714	.509	.501	.83167
15	.713	.509	.501	.83149
16	.713	.508	.501	.83138
17	.713	.508	.501	.83138
18	.712	.507	.501	.83169

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Indian, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Indian, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Indian, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Imagination, Age, Extraversion, VehExtFact, Conscientiousness, Agreeableness, WaryTech, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Hispanic, Gender, Imagination, Age, Extraversion, VehExtFact, Conscientiousness, Agreeableness, WaryTech, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Gender, Imagination, Age, Extraversion, VehExtFact, Conscientiousness, Agreeableness, WaryTech, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Gender, Imagination, Age, Extraversion, VehExtFact, Agreeableness, WaryTech, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Imagination, Age, Extraversion, VehExtFact, Agreeableness, WaryTech, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Imagination, Age, Extraversion, VehExtFact, Agreeableness, WaryTech, PlaneAffect, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Imagination, Age, Extraversion, Agreeableness, WaryTech, PlaneAffect, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, Imagination, Age, Extraversion, Agreeableness, WaryTech, PlaneAffect, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Asian, FunFactor, African, Imagination, Age, Extraversion, Agreeableness, WaryTech, PlaneAffect, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Asian, FunFactor, African, Imagination, Age, Extraversion, WaryTech, PlaneAffect, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Asian, FunFactor, African, Imagination, Age, Extraversion, PlaneAffect, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Asian, FunFactor, African, Imagination, Extraversion, PlaneAffect, PlaneComfort, VehicleAffect, Value

Appendix N – *F* Values and Significance: 4 hour trip

ANOVA

Model[a]		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	609.722	27	22.582	32.222	.000
	Residual	585.201	835	.701		
	Total	1194.923	862			
2	Regression	609.721	26	23.451	33.501	.000
	Residual	585.202	836	.700		
	Total	1194.923	862			
3	Regression	609.720	25	24.389	34.883	.000
	Residual	585.204	837	.699		
	Total	1194.923	862			
4	Regression	609.718	24	25.405	36.379	.000
	Residual	585.205	838	.698		
	Total	1194.923	862			
5	Regression	609.707	23	26.509	38.005	.000
	Residual	585.216	839	.698		
	Total	1194.923	862			
6	Regression	609.693	22	27.713	39.778	.000
	Residual	585.230	840	.697		
	Total	1194.923	862			
7	Regression	609.653	21	29.031	41.716	.000
	Residual	585.270	841	.696		
	Total	1194.923	862			
8	Regression	609.596	20	30.480	43.846	.000
	Residual	585.327	842	.695		
	Total	1194.923	862			
9	Regression	609.510	19	32.079	46.195	.000
	Residual	585.413	843	.694		
	Total	1194.923	862			
10	Regression	609.408	18	33.856	48.802	.000
	Residual	585.515	844	.694		
	Total	1194.923	862			
11	Regression	609.264	17	35.839	51.709	.000
	Residual	585.659	845	.693		
	Total	1194.923	862			
12	Regression	609.002	16	38.063	54.958	.000
	Residual	585.921	846	.693		
	Total	1194.923	862			
13	Regression	608.825	15	40.588	58.656	.000
	Residual	586.098	847	.692		
	Total	1194.923	862			
14	Regression	608.385	14	43.456	62.828	.000
	Residual	586.538	848	.692		
	Total	1194.923	862			
15	Regression	607.942	13	46.765	67.640	.000

	Residual	586.981	849	.691		
	Total	1194.923	862			
16	Regression	607.408	12	50.617	73.232	.000
	Residual	587.515	850	.691		
	Total	1194.923	862			
17	Regression	606.813	11	55.165	79.824	.000
	Residual	588.110	851	.691		
	Total	1194.923	862			
18	Regression	605.585	10	60.558	87.549	.000
	Residual	589.338	852	.692		
	Total	1194.923	862			

Dependent Variable: Trip4hr

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Indian, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Indian, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Indian, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Imagination, Age, Extraversion, VehExtFact, Conscientiousness, Agreeableness, WaryTech, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Hispanic, Gender, Imagination, Age, Extraversion, VehExtFact, Conscientiousness, Agreeableness, WaryTech, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Gender, Imagination, Age, Extraversion, VehExtFact, Conscientiousness, Agreeableness, WaryTech, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Gender, Imagination, Age, Extraversion, VehExtFact, Agreeableness, WaryTech, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Imagination, Age, Extraversion, VehExtFact, Agreeableness, WaryTech, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Imagination, Age, Extraversion, VehExtFact, Agreeableness, WaryTech, PlaneAffect, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, LowerClass, Imagination, Age, Extraversion, Agreeableness, WaryTech, PlaneAffect, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, Asian, FunFactor, African, Imagination, Age, Extraversion, Agreeableness, WaryTech, PlaneAffect, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Asian, FunFactor, African, Imagination, Age, Extraversion, Agreeableness, WaryTech, PlaneAffect, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Asian, FunFactor, African, Imagination, Age, Extraversion, WaryTech, PlaneAffect, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Asian, FunFactor, African, Imagination, Age, Extraversion, PlaneAffect, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Asian, FunFactor, African, Imagination, Extraversion, PlaneAffect, PlaneComfort, VehicleAffect, Value

Appendix O – Model Summary: 8 hour trip

Model Summary (Model 15)

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	.587	.345	.324	1.02553
2	.587	.345	.325	1.02491
3	.587	.345	.326	1.02431
4	.587	.345	.326	1.02371
5	.587	.345	.327	1.02329
6	.587	.344	.327	1.02303
7	.586	.344	.327	1.02292
8	.586	.343	.327	1.02302
9	.585	.342	.327	1.02304
10	.584	.341	.327	1.02325
11	.583	.340	.326	1.02356
12	.582	.338	.326	1.02401
13	.580	.336	.325	1.02495
14	.578	.335	.324	1.02580
15	.577	.333	.322	1.02669

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Extraversion, VehExtFact, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, Hispanic, PlaneExtFact, Gender, UpperMiddle, Extraversion, VehExtFact, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Other, Indian, PlanePrice, Asian, FunFactor, African, Hispanic, PlaneExtFact, Gender, UpperMiddle, Extraversion, VehExtFact, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Other, Indian, PlanePrice, Asian, FunFactor, African, PlaneExtFact, Gender, UpperMiddle, Extraversion, VehExtFact, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Other, Indian, PlanePrice, Asian, FunFactor, African, PlaneExtFact, Gender, UpperMiddle, Extraversion, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Other, Indian, PlanePrice, Asian, FunFactor, African, PlaneExtFact, Gender, UpperMiddle, Extraversion, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Other, Indian, PlanePrice, Asian, FunFactor, African, Gender, UpperMiddle, Extraversion, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Indian, PlanePrice, Asian, FunFactor, African, Gender, UpperMiddle, Extraversion, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, PlanePrice, Asian, FunFactor, African, Gender, UpperMiddle, Extraversion, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, PlanePrice, Asian, FunFactor, African, Gender, Extraversion, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, PlanePrice, Asian, FunFactor, African, Gender, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, PlanePrice, Asian, African, Gender, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Dependent Variable: Trip8hr

Appendix P – *F* Values and Significance: 8 hour trip

ANOVA

Model[a]		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	395.615	20	19.781	17.714	.000
	Residual	924.602	828	1.117		
	Total	1320.216	848			
2	Regression	395.331	19	20.807	18.650	.000
	Residual	924.886	829	1.116		
	Total	1320.216	848			
3	Regression	394.994	18	21.944	19.686	.000
	Residual	925.222	830	1.115		
	Total	1320.216	848			
4	Regression	394.542	17	23.208	20.835	.000
	Residual	925.675	831	1.114		
	Total	1320.216	848			
5	Regression	393.936	16	24.621	22.115	.000
	Residual	926.280	832	1.113		
	Total	1320.216	848			
6	Regression	392.793	15	26.186	23.520	.000
	Residual	927.423	833	1.113		
	Total	1320.216	848			
7	Regression	390.901	14	27.922	25.058	.000
	Residual	929.315	834	1.114		
	Total	1320.216	848			
8	Regression	388.561	13	29.889	26.788	.000
	Residual	931.655	835	1.116		
	Total	1320.216	848			
9	Regression	386.453	12	32.204	28.833	.000
	Residual	933.763	836	1.117		
	Total	1320.216	848			
10	Regression	385.101	11	35.009	31.336	.000
	Residual	935.115	837	1.117		
	Total	1320.216	848			
11	Regression	382.359	10	38.236	34.165	.000
	Residual	937.857	838	1.119		
	Total	1320.216	848			
12	Regression	395.615	20	19.781	17.714	.000
	Residual	924.602	828	1.117		
	Total	1320.216	848			
13	Regression	395.331	19	20.807	18.650	.000
	Residual	924.886	829	1.116		
	Total	1320.216	848			
14	Regression	394.994	18	21.944	19.686	.000
	Residual	925.222	830	1.115		
	Total	1320.216	848			
15	Regression	394.542	17	23.208	20.835	.000

Residual	925.675	831	1.114
Total	1320.216	848	

a. Dependent Variable: Trip8hr

b. Predictors: (Constant), SocialClass, Gender, PlaneAffect, Ethnicity, Imagination, PlanePrice, Age, Value, Conscientiousness, Extraversion, VehExtFactors, WarNewTech, Familiarity, Agreeableness, Neuroticism, VehComfort, PlaneExtFactors, PlaneComfort, VehAffect, FunFactor

c. Predictors: (Constant), SocialClass, Gender, PlaneAffect, Ethnicity, Imagination, PlanePrice, Value, Conscientiousness, Extraversion, VehExtFactors, WarNewTech, Familiarity, Agreeableness, Neuroticism, VehComfort, PlaneExtFactors, PlaneComfort, VehAffect, FunFactor

d. Predictors: (Constant), SocialClass, Gender, PlaneAffect, Ethnicity, PlanePrice, Value, Conscientiousness, Extraversion, VehExtFactors, WarNewTech, Familiarity, Agreeableness, Neuroticism, VehComfort, PlaneExtFactors, PlaneComfort, VehAffect, FunFactor

e. Predictors: (Constant), SocialClass, Gender, PlaneAffect, Ethnicity, PlanePrice, Value, Conscientiousness, Extraversion, VehExtFactors, WarNewTech, Familiarity, Agreeableness, VehComfort, PlaneExtFactors, PlaneComfort, VehAffect, FunFactor

f. Predictors: (Constant), SocialClass, Gender, PlaneAffect, Ethnicity, PlanePrice, Value, Conscientiousness, Extraversion, VehExtFactors, WarNewTech, Familiarity, Agreeableness, VehComfort, PlaneExtFactors, PlaneComfort, VehAffect

g. Predictors: (Constant), Gender, PlaneAffect, Ethnicity, PlanePrice, Value, Conscientiousness, Extraversion, VehExtFactors, WarNewTech, Familiarity, Agreeableness, VehComfort, PlaneExtFactors, PlaneComfort, VehAffect

h. Predictors: (Constant), Gender, PlaneAffect, Ethnicity, PlanePrice, Value, Conscientiousness, Extraversion, WarNewTech, Familiarity, Agreeableness, VehComfort, PlaneExtFactors, PlaneComfort, VehAffect

i. Predictors: (Constant), Gender, PlaneAffect, Ethnicity, PlanePrice, Value, Conscientiousness, WarNewTech, Familiarity, Agreeableness, VehComfort, PlaneExtFactors, PlaneComfort, VehAffect

j. Predictors: (Constant), Gender, PlaneAffect, Ethnicity, PlanePrice, Value, Conscientiousness, WarNewTech, Familiarity, Agreeableness, VehComfort, PlaneExtFactors, VehAffect

k. Predictors: (Constant), Gender, PlaneAffect, Ethnicity, PlanePrice, Value, Conscientiousness, WarNewTech, Familiarity, Agreeableness, VehComfort, VehAffect

l. Predictors: (Constant), Gender, PlaneAffect, Ethnicity, PlanePrice, Value, Conscientiousness, WarNewTech, Familiarity, Agreeableness, VehAffect

Appendix Q – Model Summary: 12 hour trip

Model Summary (Model 16)

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	.532	.283	.260	1.04418
2	.532	.283	.261	1.04355
3	.532	.283	.262	1.04305
4	.532	.283	.262	1.04255
5	.532	.282	.263	1.04212
6	.531	.282	.263	1.04184
7	.530	.281	.263	1.04169
8	.530	.280	.263	1.04175
9	.529	.279	.263	1.04182
10	.528	.278	.263	1.04195
11	.527	.277	.263	1.04216
12	.525	.276	.262	1.04257
13	.524	.275	.262	1.04290
14	.522	.273	.261	1.04357
15	.520	.271	.260	1.04431
16	.519	.269	.259	1.04512

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, African, LowerClass, Hispanic, PlaneExtFact, Gender, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, African, LowerClass, Hispanic, PlaneExtFact, Gender, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Gender, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Extraversion, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, African, PlaneExtFact, Extraversion, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, PlaneExtFact, Extraversion, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, PlaneExtFact, Extraversion, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect

Dependent Variable: Trip12hr

Appendix R – *F* Values and Significance: 12 hour trip

ANOVA

Model[a]		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	359.496	27	13.315	12.212	.000
	Residual	910.403	835	1.090		
	Total	1269.898	862			
2	Regression	359.493	26	13.827	12.697	.000
	Residual	910.406	836	1.089		
	Total	1269.898	862			
3	Regression	359.286	25	14.371	13.210	.000
	Residual	910.613	837	1.088		
	Total	1269.898	862			
4	Regression	359.062	24	14.961	13.765	.000
	Residual	910.836	838	1.087		
	Total	1269.898	862			
5	Regression	358.738	23	15.597	14.362	.000
	Residual	911.160	839	1.086		
	Total	1269.898	862			
6	Regression	358.141	22	16.279	14.998	.000
	Residual	911.758	840	1.085		
	Total	1269.898	862			
7	Regression	357.321	21	17.015	15.681	.000
	Residual	912.577	841	1.085		
	Total	1269.898	862			
8	Regression	356.128	20	17.806	16.408	.000
	Residual	913.770	842	1.085		
	Total	1269.898	862			
9	Regression	354.911	19	18.680	17.210	.000
	Residual	914.988	843	1.085		
	Total	1269.898	862			
10	Regression	353.602	18	19.645	18.095	.000
	Residual	916.296	844	1.086		
	Total	1269.898	862			
11	Regression	352.145	17	20.714	19.072	.000
	Residual	917.754	845	1.086		
	Total	1269.898	862			
12	Regression	350.332	16	21.896	20.144	.000
	Residual	919.566	846	1.087		
	Total	1269.898	862			
13	Regression	348.663	15	23.244	21.371	.000
	Residual	921.236	847	1.088		
	Total	1269.898	862			
14	Regression	346.397	14	24.743	22.720	.000
	Residual	923.501	848	1.089		
	Total	1269.898	862			
15	Regression	343.994	13	26.461	24.263	.000

	Residual	925.905	849	1.091		
	Total	1269.898	862			
16	Regression	341.466	12	28.455	26.052	.000
	Residual	928.433	850	1.092		
	Total	1269.898	862			

Dependent Variable: Trip12hr

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, African, LowerClass, Hispanic, PlaneExtFact, Gender, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, African, LowerClass, Hispanic, PlaneExtFact, Gender, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Gender, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, African, LowerClass, PlaneExtFact, Extraversion, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, African, PlaneExtFact, Extraversion, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, PlaneExtFact, Extraversion, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, PlaneExtFact, Extraversion, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect

Appendix S – Model Summary: 16 hour trip

Model Summary (Model 16)

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	.530	.281	.258	1.06448
2	.530	.281	.259	1.06387
3	.530	.281	.260	1.06331
4	.530	.281	.260	1.06288
5	.529	.280	.261	1.06252
6	.529	.280	.261	1.06221
7	.529	.279	.261	1.06199
8	.528	.279	.262	1.06173
9	.527	.278	.262	1.06158
10	.526	.277	.262	1.06177
11	.525	.276	.261	1.06207
12	.524	.275	.261	1.06227
13	.523	.273	.260	1.06286
14	.521	.271	.259	1.06370
15	.518	.269	.258	1.06468
16	.516	.267	.256	1.06555

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Imagination, Age, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Imagination, Age, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Age, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, African, LowerClass, Hispanic, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, African, LowerClass, Hispanic, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, African, LowerClass, Hispanic, PlaneExtFact, Gender, Extraversion, WorkingClass, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, LowerClass, Hispanic, PlaneExtFact, Gender, Extraversion, WorkingClass, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, LowerClass, PlaneExtFact, Extraversion, WorkingClass, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, LowerClass, PlaneExtFact, Extraversion, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect

Dependent Variable: Trip16hr

Appendix T – *F* Values and Significance: 16 hour trip

ANOVA

Model[a]		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	370.064	27	13.706	12.096	.000
	Residual	946.152	835	1.133		
	Total	1316.216	862			
2	Regression	370.022	26	14.232	12.574	.000
	Residual	946.195	836	1.132		
	Total	1316.216	862			
3	Regression	369.884	25	14.795	13.086	.000
	Residual	946.332	837	1.131		
	Total	1316.216	862			
4	Regression	369.522	24	15.397	13.629	.000
	Residual	946.694	838	1.130		
	Total	1316.216	862			
5	Regression	369.026	23	16.045	14.212	.000
	Residual	947.190	839	1.129		
	Total	1316.216	862			
6	Regression	368.456	22	16.748	14.844	.000
	Residual	947.761	840	1.128		
	Total	1316.216	862			
7	Regression	367.722	21	17.511	15.526	.000
	Residual	948.494	841	1.128		
	Total	1316.216	862			
8	Regression	367.050	20	18.353	16.280	.000
	Residual	949.166	842	1.127		
	Total	1316.216	862			
9	Regression	366.192	19	19.273	17.102	.000
	Residual	950.025	843	1.127		
	Total	1316.216	862			
10	Regression	364.730	18	20.263	17.974	.000
	Residual	951.486	844	1.127		
	Total	1316.216	862			
11	Regression	363.067	17	21.357	18.934	.000
	Residual	953.150	845	1.128		
	Total	1316.216	862			
12	Regression	361.578	16	22.599	20.027	.000
	Residual	954.639	846	1.128		
	Total	1316.216	862			
13	Regression	359.377	15	23.958	21.208	.000
	Residual	956.839	847	1.130		
	Total	1316.216	862			
14	Regression	356.746	14	25.482	22.521	.000
	Residual	959.470	848	1.131		
	Total	1316.216	862			
15	Regression	353.834	13	27.218	24.011	.000

	Residual	962.382	849	1.134		
	Total	1316.216	862			
16	Regression	351.124	12	29.260	25.771	.000
	Residual	965.092	850	1.135		
	Total	1316.216	862			

Dependent Variable: Trip16hr

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, VehExtFact, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, WorkingClass, Conscientiousness, Agreeableness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, UpperMiddle, Imagination, Age, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Imagination, Age, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, PlaneComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Imagination, Age, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Age, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, FunFactor, African, LowerClass, Hispanic, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, Indian, PlanePrice, Asian, African, LowerClass, Hispanic, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, African, LowerClass, Hispanic, PlaneExtFact, Gender, Extraversion, WorkingClass, Conscientiousness, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, African, LowerClass, Hispanic, PlaneExtFact, Gender, Extraversion, WorkingClass, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, LowerClass, Hispanic, PlaneExtFact, Gender, Extraversion, WorkingClass, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect, Value

Predictors: (Constant), UpperClass, Neuroticism, Other, PlanePrice, Asian, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, LowerClass, PlaneExtFact, Gender, Extraversion, WorkingClass, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, LowerClass, PlaneExtFact, Extraversion, WorkingClass, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect

Predictors: (Constant), UpperClass, Neuroticism, PlanePrice, Asian, LowerClass, PlaneExtFact, Extraversion, WaryTech, Familiarity, PlaneAffect, VehicleComfort, VehicleAffect

Table 1

Pattern Matrix produced from the first pilot study factor analysis.

Table 1

Pattern Matrix[a] from pilot study factor analysis

Variable	Component 1	2	3	4
VAR00001		.579		
VAR00002		.636		
VAR00003		.702		
VAR00004		.495		.411
VAR00005		.436		.436
VAR00006				.736
VAR00007		.635		
VAR00008		.478		.424
VAR00009			.716	
VAR00010			.856	
VAR00011	.689			
VAR00012	.725			
VAR00013	.607		.456	
VAR00014	.716			
VAR00015	.775			
VAR00016	.688			
VAR00017	.763			
VAR00018	.471			
VAR00019				.691
VAR00020	.716			
VAR00021	.573			
VAR00022	.799			

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 16 iterations.

Table 2

Structure Matrix produced from the first pilot study factor analysis.

Table 2

Structure Matrix from pilot study factor analysis

	Component			
Variable	1	2	3	4
VAR00001		.595		
VAR00002		.652		
VAR00003		.690		
VAR00004		.555		.543
VAR00005		.530		.554
VAR00006				.694
VAR00007		.614		
VAR00008		.549		.547
VAR00009			.764	
VAR00010			.801	
VAR00011	.736		.416	
VAR00012	.775			
VAR00013	.669		.559	
VAR00014	.719			
VAR00015	.744			
VAR00016	.754			
VAR00017	.734			
VAR00018	.455			
VAR00019				.691
VAR00020	.700			
VAR00021	.603			
VAR00022	.797			

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

Table 3

Regression results from the pilot study scenario 1: 4-hour road trip/ 1 hour flight.

Table 3

Pilot Study DV1: 4hr road trip/ 1hr flight

	Beta Coef.	Std. Error	*t*-value	Sig.
Constant	-.414	.219	-1.887	.060
Vehicle General Affect	.226	.090	2.945	.004*
Vehicle External Factors	.156	.088	3.028	.003*
Fun Factor	.430	.087	5.507	<.000*
Plane Comfort	-.084	.058	-1.705	.089
Gender	-.083	.121	-1.681	.094
Age	.104	.005	2.016	.045

* indicates statistical significance

Table 4

Regression results from the pilot study scenario 2: 8-hour road trip/ 1.5 hour flight.

Table 4

Pilot Study DV2: 8hr road trip/ 1.5hr flight

	Beta Coef.	Std. Error	*t*-value	Sig.
Constant	-.180	.129	-1.399	.163
Vehicle General Affect	.174	.123	1.885	.061
Vehicle Comfort	.146	.102	2.221	.027*
Fun Factor	.219	.115	2.420	.016*
Plane Comfort	-.246	.092	-3.561	<.000*
Plane External Factors	.234	.082	3.445	.001*

* indicates statistical significance

Table 5

Regression results from the pilot study scenario 3: 12-hour road trip/ 2 hour flight

Table 5

Pilot Study DV3: 12hr road trip/ 2hr flight

	Beta Coef.	Std. Error	*t*-value	Sig.
Constant	-.288	.112	-2.569	.011*
Fun Factor	.269	.075	4.224	<.000*
Familiarity	.195	.081	2.916	.004*
Plane Comfort	-.212	.087	-2.991	.003*
Plane External Factors	.217	.081	3.018	.003*

* indicates statistical significance

Table 6

Regression results from the pilot study scenario 4: 16-hour road trip/ 2.5 hour flight

Table 6

Pilot Study DV4: 16hr road trip/ 2.5hr flight

	Beta Coef.	Std. Error	*t*-value	Sig.
Constant	-.384	.116	-3.299	.001*
Fun Factor	.202	.078	3.095	.002*
Familiarity	.165	.084	2.397	.017*
Plane Comfort	-.224	.091	-3.083	.002*
Plane External Factors	.254	.084	3.449	.001*

* indicates statistical significance

Table 7

Summary of significant regression results from scenarios 1 – 4

Table 7

Summary of Significant Predictors

	DV1	DV2	DV3	DV4
Vehicle General Affect	.004*	-	-	-
Vehicle Comfort	-	.027*	-	-
Vehicle External Factors	.003*	-	-	-
Fun Factor	<.000*	.016*	<.000*	.002*
Plane Comfort	-	<.000*	.003*	-
Plane External Factors	-	.001*	.003*	.001*

* indicates statistical significance