Collegiate Aviation Review International

Volume 39 | Issue 1 Peer-Reviewed Article #4

3-19-2021

What Type of Person Would Prefer Driverless Cars Over Commercial Flight?

Mattie N. Milner
Embry-Riddle Aeronautical University

Sean R. Crouse
Embry-Riddle Aeronautical University

Stephen Rice
Embry-Riddle Aeronautical University

Scott R. Winter
Embry-Riddle Aeronautical University

Prior research has investigated ground and air transportation industries independently; however, few people have considered the impact driverless cars will have on commercial aviation. This study created a regression equation to predict what type of individual would prefer driverless cars over commercial flights. Participants (n = 2,016) provided demographic information, individual travel behavior, and preference for the two travel modes in two stages. Stage 1 created an equation through backward stepwise regression. In Stage 2, participants' scores were predicted using the Stage 1 equation compared to their actual scores to validate the Stage 1 equation through the four scenarios. Significant predictors from all scenarios were Upper Social Class, Vehicle Affect, Airplane Affect, and Vehicle Comfort. These factors accounted for nearly half the variance from the data. The equation was then tested in Stage 2 tested using a t-test, correlation, and comparison of cross-validated R^2. The model fit was demonstrated to be strong in all scenarios. These predictors will aid in identifying possible early adopters of autonomous vehicles. Implications of the findings with suggestions for future research are discussed in detail in this study.

Recommended Citation:
Milner, M.N., Rice, S., Winter, S.R., & Crouse, S.R., (2021). What Type of Person Would Prefer Driverless Cars Over Commercial Flight? *Collegiate Aviation Review International,* 39(1), 64-89. Retrieved from http://ojs.library.okstate.edu/osu/index.php/CARI/article/view/8119/7476

As technology matures at an ever-increasing rate, industries evolve with processes that develop automation rapidly. The new technology is formed simultaneously with user interactions, directly molding the designs. The automotive industry has created a focal point in their *drive* for a fully autonomous vehicle (AV) (i.e., driverless). While most research has focused on the usability, functionality, and factors that influence a consumer's willingness to adopt the technology, limited research has looked at other transportation industries' impact. Individuals often choose travel methods after exploring several factors: personality, preferences, travel distance, price, etc. This study explores consumers' preferences and attempts to identify factors that possibly influence their penchant for AVs or commercial aircraft (CA). The study creates and validates a model to predict the participants' choice (AV or CA) using several factors backed by literature.

Literature Review

According to the National Highway Transportation Safety Administration (NHTSA), there are six accepted vehicle automation levels in current standards: 0 – No automation, 1 – Driver Assistance, 2 – Partial Automation, 3 – Conditional Automation, 4 – High Automation, and 5 – Full Automation. Leading automobile manufacturers, such as Tesla, Waymo, and Uber, have been attempting to deliver a safe and effective level five vehicle to the general public (NHTSA, 2015; Reimer, 2014). A common claim among these companies is the technology will function in every condition a human could negotiate, but without the human. Research and development have focused on safe and effective systems that can carry passengers and safely interact with other vehicles on the road, their drivers, and pedestrians. This research often does not consider a consumers' behavioral intentions towards automated vehicles or the technologies' impact on other transportation industries.

Existing research has explored travelers' opinions on the preferred mode of travel, with over 2/3 of participants preferring driverless cars over a commercial flight on a 5-hour, midrange trip (Rice & Winter, 2018). Despite airline tickets' perceived costliness, companies only profit $10-$20 from each ticket. Conservatively, if airlines lose 1 in 10 passengers, there would be severe financial ramifications. To mitigate the losses, airlines may be forced to increase ticket prices, reduce the number of routes, or add additional micro-transactions to make up for this loss, resulting in a higher number of customers finding alternative travel.

Currently, in the United States, travelers have limited efficient options for traveling. CA travel brings with it many drawbacks for travelers. Customers must arrive early to go through security screening, travel through crowded airports, cram into a small seat surrounded by strangers, all for the convenience of shortened travel. Furthermore, recent health concerns around the COVID-19 pandemic have further decreased the public's willingness to fly and cast a foreboding cloud on commercial aviation's future success (Lamb, Winter, Rice, Ruskin, & Vaughn, 2020; Whitley, 2020). Travel in an automobile usually can provide more comfort due to the traveler's control of setting their schedule. However, long-distance car travel can be exhausting and dangerous. Drivers may attempt to cover their trip without stopping, which can cause mental and physical exhaustion increasing the inherent risk in driving. Understanding the types of travelers who would likely choose an AV over CA could provide a litany of information to the industries.

The push for integrating autonomous transportation is the main narrative through the media, research organizations, and consumer safety reports (Rice, Winter, Mehta, & Ragbir, 2019). Despite this push, there is little consideration into the effect of AV on commercial aviation. Historically, the commercial aviation industry financially performed well, although the current economic crisis created from COVID-19 has negatively impacted the aviation industry (International Civil Aviation Organization (ICAO), 2020). Aviation is approaching an interesting period with its lowest recorded profit per flight (McCartney, 2018) and consumer enjoyment levels down (Kloppenborg & Gourdin, 1992; Nadiri, Hussain, Ekiz, & Erdogan, 2008; Young, Cunningham, & Lee, 1994).

Many speculative reports predict the impact of AV on the transportation industry. Thus far, the main conclusion is that as AV technology matures, travelers will opt for AVs over other transportation types. This outcome may be due to the increased level of comfort and convenience they can provide. However, only a single prior study investigated AVs' possible impact on CA (Rice & Winter, 2018).

Predictive Factors

This study considered 20 factors that could predict an individual's preference for riding in an AV. These factors vary from demographic information (age, gender, social class, and ethnicity) to financial questions (price and perceived value), as well as technology-based questions (familiarity, fun factor, wariness of new technology). Other identifying factors include individual personality (based upon openness, conscientiousness, extraversion, agreeableness, and neuroticism), and finally, vehicle and airplane specifics (comfort, affect, external factors). A summary and justification of these predictors follow.

Age. Age brings about physical and mental obstacles (i.e., delayed reaction, reduced mobility, reduced vision, etc.) that often increase an individual's dependency on others or causes them to isolate themselves. Increased isolation can harm mental health (Marottoli et al., 1997; Ragland, Satariano, & MacLeod, 2005). With this in mind, senior citizens may view AVs as a way to remain independent and keep their freedoms without relying on other individuals for transportation (Harper, Hendrickson, Mangones, & Samaras, 2016; Howard & Dai, 2014). It can be assumed that they generally earn more as one ages, making it easier to purchase newer technologies that may increase individual freedoms and mobility, such as an AV (Reimer, 2014).

Gender. When faced with the same situations, women often shy on the side of caution (Borghans, Heckman, Golsteyn, & Meijers, 2009; Byrnes, Miller, & Schafer, 1999; Charness & Gneezy, 2012; Fehr-Duda, de Gennaro, & Schubert, 2006; Rice & Winter, 2019). This finding has been replicated in numerous scientific studies on financial decisions, social situations, lifestyle choices, and others. For example, Rice and Winter (2019) showed women were less willingness to fly aboard an autonomous aircraft. Anania et al. (2018) showed the same results for robotic dentistry, and Winter et al. (2019) found the same results for walking in front of a driverless vehicle.

Social class. Social class is comprised of several variables (income, education level, employment, etc.) that define the individual's social-economic status (SES) (Ames, Go, Kaye, & Spasojevic, 2011). Each of the individual variables that determine a person's SES could increase the likelihood of a person's willingness to accept new technology or use it, in particular high-risk technology. Prior studies show the higher an individual's social status, the more positively they view newer technologies and have more experience using more recent technologies (Maldifassi & Canessa, 2009).

Ethnicity. Cultural identity is tied to the inherent personality traits of individuals in a community. Western cultures (i.e., United States) are much more individualist than Eastern cultures' collectivism (e.g., Asian and the Middle East). Individuals' emotional responses and behaviorisms towards autonomous technology have been identified through ethnographical research (Mehta, Rice, Winter, & Eudy, 2017; Srite & Karahanna, 2006). Specifically, collectivistic societies generally will trust newer technology and are more willing to adopt it so long as it benefits the community as a whole (Haboucha, Ishaq, & Shiftan, 2017; Hofstede, 1980, 2001; Markus & Kitayama, 1991; Mehta et al., 2017).

Perceived value. According to the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology (UTAUT), an individual's perceived usefulness of a specific technology is generally a strong prognosticator of user behavior. Perceived value can often determine how useful a product or service is to an individual. The perceived value, in theory, is "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).

Familiarity. Previous consumer behavior research explored familiarity and its impact on a product. As the individual's experience and knowledge with the product grow, they develop a set of heuristics for decision-making (Alba & Hutchinson, 1987; Bozinoff, 1981; Kinard, Capella, & Kinard, 2009). Therefore, the understanding of external stimuli, such as technology, is familiarity.

Fun factor. As mentioned earlier, hedonic motivation is often a significant influencer in a consumers' willingness to use a product and their intent. An individual's perceived level of enjoyment while using technology can predict behavioral intention. Nordhoff, de Winter, Kyriakidis, van Arem, & Happee (2018) 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" (p. 3).

Wariness of new technology. Technology has matured faster in the last 50 years than the previous two hundred in Western society (Berman & Dorrier, 2016). This acceleration can be attributed to the significant advancements in science, technology, engineering, and mathematics. One disadvantage of this rapid development of technology is that many individuals cannot keep up with these continually evolving areas and lack understanding in many breakthroughs. When presented with new technology, it is normal for individuals to question potential risks from this technology. The lack of knowledge can affect the users' trust (Merritt & Ilgen, 2008) and lead to their wariness of adopting the technology in question (Lee & Moray, 1992; Lee & See, 2004; Muir, 1987; Riley, 1989).

Personality. Existing research has examined "perceptions of user acceptance of, concerns about, and willingness to buy AV technology" (Clark, Parkhurst, & Ricci, 2016, p. 17). However, it should be noted that an individual's personality traits only show a weak correlation with AVs' perceptions (Clark et al., 2016; Kyriakidis, Happee, & de Winter, 2015). Other research has identified that highly extroverted people are more likely to initially trust new technology, which can have a positive effect on behavioral intent (Merritt & Ilgen, 2008). With this in mind, there is no specific literature to support that personality will affect consumers' decisions either way since personality positively affects the decision-making processes.

Technology acceptance. Despite AV technology maturing and becoming more available, one cannot assume that availability positively correlates with a consumer accepting and using the technology. The Unified Theory of Acceptance and Use of Technology (UTAUT) lists several factors that affect an individual's behavioral intent and how they accept the new technology and its uses (Venkatesh, Morris, Davis, & Davis, 2003). A recent study used these factors to measure how accepted the various adaptive driver assistance systems (i.e., lane assist, collision avoidance, adaptive cruise control, etc.) were. The findings displayed perceived usefulness and ease of use, the performance and effort expectancy, and attitude all were predictors of behavioral intention in an individual (Rahman, Lesch, Horrey, & Strawderman, 2017).

General affect. Researchers traditionally studied individual decision-making processes in finance due to economist, marketers, and the industry's desire to understand how the consumer made complex decisions and choices (Frydman & Camerer, 2016; George & Dane, 2016; Sokol-Hessner, Raio, Gottesman, Lackovic, & Phelps, 2016). It is known that the most efficient process would be the individual to consider every advantage and disadvantage, and only then selecting the best choice (Frydman & Camerer, 2016; Slovic, Peters, Finucane, & MacGregor, 2005). Despite this highly effective process, research shows that emotion plays a seemingly significant role when an individual makes a decision (Lerner, Li, Valdesolo, & Kassam, 2015; Peters, Västfjäll, Gärling, & Slovic, 2006; Schwarz & Clore, 2003; Slovic et al., 2005). Without experience or knowledge of the technology or situation, individuals may rely on their emotions to guide their decisions.

Current Study

The purpose of the current study was twofold. First, to build a regression equation that accurately described the data. Second, to validate a predictive model that could be used to predict future datasets accurately. Participants were presented a series of questions through an electronic survey instrument. The dataset was then randomly divided into two stages. The first dataset used in Stage 1 created the regression equation, while the second dataset for Stage 2 was used to test for model fit and validation.

Methods

Participants

Two thousand and sixteen people (54.5% female) participated in this study with a mean age of 38.48 (*SD* = 11.94) years. The data was collected via convenience sampling techniques through Amazon's ® Mechanical Turk ®. Previous research has shown that this data is as valid as data collected through in-person surveys (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). Participants who completed the survey were compensated for their time with a payment of 50 cents.

Materials and Procedure

Participants were presented with an electronic consent form to begin the study and then were provided with instructions. In the AV section of the survey, 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*." Next, participants were asked to respond to the Perceived Value scale, Familiarity scale, Fun Factor scale, Wariness of New Technology scale, a General Affect scale, the Vehicle Comfort scale, and Vehicle External Factors scale (see Appendix B for a complete listing of these scales).

In the CA 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.*" Next, participants were asked to respond to the same questions from the previous section, except 'AV' was replaced with 'airplane,' and they also were presented two additional scales (Airplane Comfort scale and the Airplane External Factors scale (see Appendix B for a complete listing of these scales). Google Forms ® randomized each section's order for each survey, and items within each scale were randomized. The scale's instructions read, "*Please respond to each of the statements below indicating how strongly you agree or disagree with each statement.*"

To understand the preferred travel method, participants were presented with 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 then were asked to respond to the Travel Method Preference Scale (see Appendix A). This scale consisted of four statements and was answered with a five-point scale anchored from Strongly Disagree to Strongly Agree with a neutral option. Since the scale demonstrated extremely high internal consistency, as measured by Cronbach's alpha values, an average of these four statements was calculated to be used as the main DV for each of the four statistical models.

To determine if the duration of the trip affected the participants' responses, they were presented the following 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 were presented this scenario four different times, with the time schedules changing in each instance (4-hour drive/1-hour flight, 8-hour drive/1.5-hour flight, 12-hour drive/2-hour flight, and 16-hour drive/2.5-hour flight).

Lastly, participants provided their demographic data. After completing the survey, participants received instructions to claim their monetary compensation. Before the main data analysis, the data sample was randomly divided into two groups to facilitate the two-stage processes of building a regression equation and assessing model fit. After the initial data analysis and halving the dataset, the first stage (N = 863) was used to construct the regression equation, and the second stage (N = 882) was used for assessing the model fit and validation.

Proposed Data and Statistical Analyses

The purpose of Stage 1 was to develop the regression equation needed to predict the preferred travel methods of the participants. Before data analysis, data were tested and satisfied the regression's required assumptions, described in the Initial Data Analysis section below. To determine which variables significantly predicted participants' preferred travel method, a backward stepwise regression was used. This method removes statistically insignificant predictors until the model only is left with statistically significant predictors. While there are several methods researchers may select when conducting regression, backward stepwise was determined to be the most appropriate for two reasons. First, due to the exploratory nature of the current study, and without a robust theoretical aspect to ground the entry/exit method of variables, stepwise conduct these processes based on statistical assessments. Second, due to dummy-coded categorical predictors, all dummy coded variables must be entered in the analysis at the same step, which occurs when using backward stepwise regression. Preferences from the participants' survey were used across the four scenarios based upon travel times as described above.

The purpose of Stage 2 was to validate the regression equations generated in Stage 1. This validation was accomplished by calculating the participants' predicted score for Preferred Travel Method using the regression equation from Stage 1 then comparing it to their actual scores in Stage 2. This assessment was accomplished by conducting a t-test, Pearson's correlation, and then cross-validating the R^2.

Limitations to the Study

The first limitation was the use of Amazon's ® Mechanical Turk ® (MTurk). Despite the large group of individuals on MTurk, it significantly limits the generalizability of the results to members of MTurk. Despite this, other research has shown that data collected from MTurk is as valid as data collected through in-person surveys (Buhrmester et al., 2011; Germine et al., 2012; Rice et al., 2017).

Another limitation is that participants could not provide behavioral data to be collected and analyzed due to the limited availability of AVs in the general public. This limitation resulted in only behavioral intentions and perceptions to be collected. Despite actual and intentions not being the same thing, perceived actions correlate with an individual's actual behavior (Ajzen, 1991; Davis, 1985; Davis, Bagozzi, & Warshaw, 1989; Fishbein & Ajzen, 1975). Therefore, it is crucial to consider this study within the limit of perceptual intentions.

Results

Initial Data Analysis

Missing or Incomplete Data. An initial review of the data was completed to examine for excessive missing data. For summed scales, such as the personality scores, a single missing response resulted in the inability to calculate a correct score, and thus these cases were removed. More than two missing answers were considered excessive and removed for items on reflective scales that were averaged, such as familiarity or fun factor. Due to missing or incomplete data, 99 cases in Stage 1 and 96 cases from Stage 2 were removed.

Assumptions of Regression. When conducting regression, several assumptions must be met. For each model, there is one continuous, dependent variable. This assumption was satisfied by taking the average score for the dependent variable (justified due to the high Cronbach's alpha values). Of note, while Likert items may technically be ordinal, several studies cite the ability to treat these values as interval (Boone & Boone, 2012; Joshi, Kale, Chandel, & Pal, 2015; Rickards, Magee, & Artino, 2012; Sullivan & Artino, 2013), and also, the advantage of taking the average score helps ensure a continuous-like value for each participant (Brown, 2011). At least two or more independent or predictor variables was satisfied through the 20 independent variables used in the study. The independence of observations is measured by the Durbin-Watson statistic. Values are suggested to be between 1.5-2.5 (Field, 2009), and the current studies have values close to 2. Next, one must ensure that there are no issues with multicollinearity between variables. This assumption was determined to be met by examining each model's output and ensuring all VIF values were less than 10. An assessment of outliers was reviewed based on Mahalanobis Distance. Seventy-six cases (or 3.7%) of the data were determined to exceed this cutoff value and were removed (46 from Stage 1 and 30 from Stage 2). All other assumptions were verified to be met, and an example of normality is found in Figure 1.

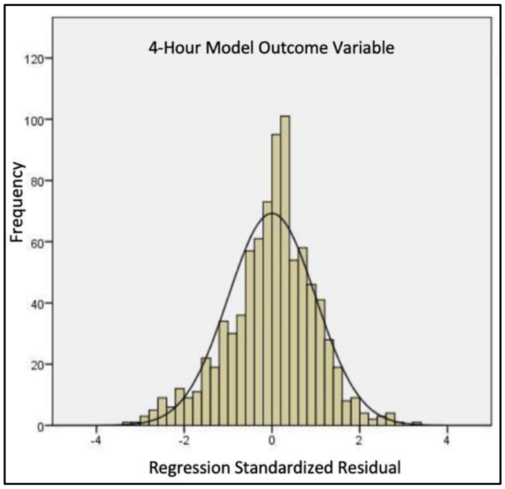

Figure 1. Histogram of the standardized residuals demonstrating normality for the dependent variable for the 4-hour model.

Descriptive Statistics

Stage 1. After removing incomplete or missing data and outliers, N = 863 for Stage 1, which included 406 males (47%). The mean age of participants was 38.77 (SD = 11.95) years. The descriptive statistics for Stage 1 are summarized in Table 1.

Table 1
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 removing incomplete or missing data and outliers, N = 882 for Stage 2, which included 387 males (44%). The mean age of participants was 38.19 (SD = 11.92) years. The descriptive statistics for Stage 2 are summarized in Table 2.

Table 2
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%)		

Inferential Statistics

Stage 1. Table 3 summarizes the regression analysis, while Table 4 identifies the significant regression coefficients for each model. Each of the four models is described below, and Appendix C presents the full regression output.

Four-hour trip. The final model for this scenario included ten significant predictors: Vehicle Affect, Fun Factor, Perceived Value, Plane Affect, Vehicle Comfort, Extraversion, Openness, African, Asian, and Upper Class. The resulting regression equation was:

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

Y is participants' preference for riding in an autonomous vehicle, and $X_1 – X_{10}$ are Vehicle Affect, Fun Factor, Perceived 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), accounting for roughly 50% of the participants' preferred travel method variance. This model was statistically significant, $F(10, 852) = 87.549$, $p < .001$.

Eight-hour trip. The final model for this scenario 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:

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

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, $F(13, 849) = 32.544$, $p < .001$.

Twelve-hour trip. The final model for this scenario 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

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

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, $F(12, 850) = 26.052$, $p < .001$.

Sixteen-hour trip. The final model for this scenario 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

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

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, $F(12, 850) = 29.260$, $p < .001$.

Table 3
Analysis of Regression Model Summaries from Stage 1.

	Four-Hour	Eight-Hour	Twelve-Hour	Sixteen-Hour
R^2	.507	.333	.269	.267
Adj. R^2	.501	.322	.259	.256
F	87.55	32.54	26.05	29.26
df	10, 852	13, 849	12, 850	12, 850
p	< .001	< .001	< .001	< .001

Table 4
Statistically significant regression coefficients from Stage 1.

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

Stage Two

Table 5 shows these values for all four scenarios. From this table, we can see that all *t*-tests were non-significant, all correlations were highly significant, and all cross-validated R^2 values were nearly identical. These results indicate a strong model fit for all four regression equations.

Table 5
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

Discussion

Continued efforts to deliver a safe and efficient AV require the adoption of public perceptions to make it a success. Once AVs become available to the general population, they will significantly impact other transportation industries such as commercial air. Many consumers will choose to ride in an AV over flying on a CA. Therefore, it is paramount to understand the consumer's motives who would prefer an AV over other transportation modes to assist the industries in future operational planning.

A predictive model was created to investigate consumer perceptions towards AV and CA. This study was accomplished in a two-stage approach. The first stage consisted of 20 predictive factors that could impact users' choice of using an AV rather than CA. Participants were presented with four scenarios then backward stepwise regression was used to create the equations. Stage 2 tested the equations for model fit by comparing the calculated scores against their actual scores using a *t*-test, Pearson's correlation, and cross-validating the R^2.

Since this research is exploratory, it included a large number of variables to explore. A breakdown of each of the variables in the study follows.

Age, Social Class, and Ethnicity. Age was not significant in any scenario, and gender only showed significance in the 8-hour scenario. Social class and ethnicity predictors showed at least one item as significant for each of the scenarios. Previous research suggests that certain people may prefer using technology or feel comfortable with it based upon ethnicity, social class, age, and gender (Borghans et al., 2009; Byrnes et al., 1999; Charness & Gneezy, 2012).

Perceived Value, Fun, Wariness of New Technology, and Familiarity. The research focused on the acceptance of new technologies (i.e., TAM, UTUAT, TPB) provided factors that may influence a consumers' perception, willingness to use, and overall acceptance of new technology (Ajzen, 1991; Davis, 1985; Legris, Ingham, & Collerette, 2003; Venkatesh et al., 2003). Perceived value was significant during the 4-hour and 8-hour scenarios. Only the 4-hour scenario showed fun as significant. All scenarios except the 4-hour one showed wariness of new technology and familiarity as a significant predictor. One can assume that those who adopt technology at early stages likely perceive a benefit or enjoy using the latest technology (Chai, Malhotra, & Alpert, 2015; Eckoldt, Knobel, Hassenzahl, & Schumann, 2012; Jones, Reynolds, & Arnold, 2006; Mathwick, Malhotra, & Rigdon, 2001), which could explain these significant predictors.

Personality Factors. Existing research indicates that highly extroverted and open people are typically more welcoming of newer technology and show more yearning to use it (Merritt & Ilgen, 2008). This research found openness significant in the 4-hour scenario, while extroversion was significant in the 4-, 12-, and 16-hour scenarios. Despite extroversion being significant, it displayed a negative coefficient in the 4-hour trip, signaling that as an individuals' extroversion increased, their preference for an AV over CA decreased. A possible reason for this is that riding in an AV means being in isolation vs. a CA, where they can engage with other people throughout their journey.

Affect. Vehicle and plane affect were included to measure a users' emotional reaction to riding in an AV and CA. Prior research indicates that an individual's emotions can play a significant role in their decision-making (Lerner et al., 2015; Peters et al., 2006; Schwarz & Clore, 2003; Slovic et al., 2005), predominantly when in a seemingly dangerous, unfamiliar situation. These variables were all significant predictors in all four scenarios. However, an important finding was that airplane affect showed a negative coefficient, meaning that as the affect decreased, their preference for AVs over CA increased.

Comfort and Price. Vehicle comfort attempted to capture users' satisfaction and experience of riding in the vehicle, such as the ability to fall asleep. Previous research showed that a consumer's satisfaction with their trip was influenced by the vehicle comfort in other modes of transportation (i.e., trains, planes, public buses, etc.) (Kloppenborg & Gourdin, 1992; Nadiri et al., 2008; Young et al., 1994). All four scenarios displayed vehicle comfort as a significant predictor, likely due to consumers wanting to be comfortable while traveling for an extended amount of time. Additionally, the importance of the plane ticket price was significant in the eight- twelve- and sixteen-hour conditions, but inversely. Suggesting that participants' level of importance over plane ticket price increased, participants' willingness to prefer a driverless vehicle decreased.

Plane External Factors. Airplane external factors focused on the users' experience while riding in a CA and how different factors, such as limited schedules, sharing space with strangers, ability to rest on the plane, etc., influenced a consumer. Previous research focusing on consumer preferences and the factors that affect a traveler's comfort level concentrate on these areas (Kloppenborg & Gourdin, 1992; Nadiri et al., 2008; Young et al., 1994); ergo, the inclusion into this study. This variable was significant in the 12-and 16-hour scenario. This finding can be interpreted in that passengers are not as concerned with plane external factors for shorter trips, but as the trip increases in time, these factors are more important for travelers.

Summary of Significant Variables in All Models. The four variables present in all scenarios were individuals identifying as upper social class, vehicle and airplane affect, and vehicle comfort. Those identifying as an upper social class had the highest indication of selecting an AV compared to the other classes. This result supports other research that discovered upper social class citizens look at technology more positively and are more accepting of it (Maldifassi & Canessa, 2009; Porter & Donthu, 2006). An emotional reaction is indicated by traveling in an AV; positive emotions for riding in an AV where negative emotions are evoked for CA travel. Industry experts could focus on this research to understand why consumers are enthusiastic about riding in an AV to understand better their intended users' profile or ways to adapt CA to fit those user needs.

Practical Applications

Despite this research being exploratory, it can prove beneficial to both the automotive and aviation industries. Understanding the users will enable companies' design teams to tailor a product that will appeal to consumers. This research is unique in that AV technology is still relatively new, so any investigations will assist the design process from the beginning, resulting in a more mature product upon release.

The aviation industry can use this research to account for consumers who will switch to AV technology and adapt to their preferences. Consumers show an emotional reaction to AV technology's use through the entertainment and enjoyment of the ride. How can the airlines increase the enjoyment of flying for consumers to retain their business? It may result in the aviation industry capitalizing on the convenience factor of longer trips. Thus, they can adapt long-haul flights to be increasingly comfortable and focus on those customers to counteract short-haul users' loss.

Conclusions

As autonomous vehicles become readily available for consumers, it is pivotal to understand and plan for the impact they will most assuredly have on others in the industry. The current research focused on acceptance and preference of the technology over CA travel. This two-stage approach developed a predictive model of an equation to determine the type of person who would prefer to ride in an AV over CA through backward stepwise regression. The equation was then tested to verify model fit by comparing predicted scores to actual scores using a *t*-test, Pearson's correlation, and cross-validating R^2. The best predictive model was developed from the four-hour scenario, which accounted for 50% of the variance. The most common predictors throughout all scenarios 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. Future research should be conducted from this study, but its results will contribute to the automotive industry and CA industry's understanding of consumer preferences while traveling via these two methods.

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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 – Other Scales Used in the Study

All scales provided responses to each of the statements below using a 5-point Strongly Disagree to Strongly Agree, and a Neither disagree nor agree option.

	SD	D	N	A	SA
Perceived Value Scale					
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.					
5. A driverless vehicle would be beneficial to me.					
Familiarity Scale					
1. Driverless vehicles have been of interest to me for awhile.					
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.					
5. I am familiar with driverless vehicles.					
Fun Factor Scale					
1. I am interested in trying out a driverless vehicle.					
2. I think it would be cool to use a driverless vehicle.					
3. I've always wanted to use a driverless vehicle.					
4. I think it would be fun to use a driverless vehicle.					
5. I am familiar with driverless vehicles.					
Wariness of New Technology Scale					
1. New technology scares me.					
2. In general, I am wary of new technology.					
3. I tend to fear new technology until it is proven to be safe.					
4. New technology is not as safe as it should be.					
5. New technology is likely to be dangerous.					
General Affect Scale					
1. I feel good about this.					
2. I feel positive about this.					
3. I feel favorable about this.					
4. I feel cheerful about this.					
5. I feel happy about this.					
6. I feel enthusiastic about this.					
7. I feel delighted about this.					
Vehicle Comfort Scale					
1. I enjoy traveling in a car if I don't have to drive.					
2. I enjoy how much space I have in a car.					
3. I enjoy sleeping while traveling in a car.					
Vehicle External Factors Scale					
1. I enjoy the freedom to stop and eat wherever and whenever I want.					
2. I enjoy having schedule flexibility (the ability to leave when I want).					
3. I can easily maintain my hygiene standards while traveling in a car.					
Airplane Comfort Scale					
1. I enjoy traveling in an airplane.					
2. I am ok with how much space I have on an airplane.					
3. I can easily maintain my hygiene standards while traveling in an airplane.					
4. I enjoy sleeping while traveling in an airplane.					
5. I can easily fall asleep while traveling on an airplane.					
Airplane External Factors Scale					
1. I enjoy waiting in the airport before I leave my departure point.					
2. I am ok having a limited choice over my departure time and arrival time.					
3. I enjoy going through TSA security.					

Appendix C – Full Regression Output for the Four Models

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

Regression Coefficients for eight-hour trip (Model 15)

Model[a]		Unstandardized Coefficients B	Unstandardized Coefficients Std. error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations 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

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

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