Self-Driving Vehicles: What Factors Will Be Key For Consumer Adoption?

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ABSTRACT

As automotive technology continues to evolve, self-driving vehicles are on the horizon within the United States. This study tests the theoretical underpinnings of the conceptual Autonomous Vehicle Acceptance Model (AVAM) to better understand key influences of consumer adoption of future self-driving vehicles. A 27- item survey was conducted using Qualtrics (n = 358). Results show that social influence, attitude towards a self-driving vehicle, and perceived safety all directly affect the likelihood of using a self-driving vehicle. Marketing implications are discussed that should be important for enhancing consumer adoption of self-driving vehicles within the U.S.

Keywords: self-driving vehicles, autonomous technology, future automobiles

INTRODUCTION

Automotive manufacturers appear to be racing to grab a share of the self-driving vehicle market, estimated to generate a $7 trillion economic opportunity by 2050 (Macleod & Santarini, 2019). Automakers, tech giants, and specialty startups have invested at least $50 billion during the last few years to develop self-driving technology (Craig & Lofton, 2019). These technologies include electronic sensors that determine distance between the vehicle and obstacles, as well as detect lane markings, pedestrians, and bicycles. Technologies are also capable of parking the vehicle and provide navigation systems with built-in maps to guide the vehicle direction and location. They also include cameras that provide 360-degree views around the vehicle, and dedicated short-range communications to monitor road conditions, congestion, crashes, and possible rerouting (Canis, 2017).

Research exploring U.S. consumer attitudes towards self-driving vehicles have emerged in the last few years. A recent study found that 54% of U.S. drivers feel less safe at the prospect of sharing the road with a self-driving vehicle. Moreover, 58% of women were likely to feel unsafe, compared to 49% of men. On the other hand, 70% of Millennials want self-driving technology, compared to 54% of Generation X and 51% of Baby Boomers (Edmonds, 2017). Consumer perceptions of safety, reliability, and efficiency of self-driving vehicles will play a major role in the speed in which self-driving vehicles are adopted by the general public within the United States.

A 2019 J.D. Power Mobility Confidence Index Study found that almost two thirds of U.S. consumers admitted to having little to no knowledge about self-driving vehicles. Gen Z respondents indicated the most knowledge regarding self-driving vehicles, while Baby Boomers expressed the least amount of knowledge. This same article found that industry experts recognize the importance of marketing self-driving technology to consumers to build understanding, trust, and acceptance.

Hewitt et al. (2019) introduced the Autonomous Vehicle Acceptance Model (AVAM) to measure public acceptance of autonomous (self-driving) vehicles. The AVAM combines elements of the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), and the Car Technology Acceptance Model (CTAM), developed by Osswald et al. (2012). The AVAM uses nine factors to explain user acceptance of autonomous vehicles.

The AVAM's proposed relationships have not been tested empirically for predicting intention to use self-driving vehicles. However, the AVAM has shown good internal consistency for all factors in the model, as well as acceptable external validity when compared to similar study results. The AVAM research presented six levels of autonomy scenarios to allow respondents to visualize six hypothetical levels of self-driving vehicle technologies. Respondents completed six different questionnaires, one for each hypothetical autonomy level, and then assessed how ratings changed for the eight predictive variables as the level of autonomy changed.

The purpose of this study is to test the theoretical underpinnings of the AVAM to better understand key influences of consumer adoption of future self-driving vehicles when they become commercially available in the U.S. It is important to validate factors that may impact consumers' likelihood of using a self-driving vehicles if these vehicles are going to be successfully diffused into the marketplace. The U.S. automotive industry, regulatory agencies, urban planners, and marketers all need to understand what is likely to influence consumer perceptions, and ultimately the adoption of self-driving vehicles as they plan for the arrival of self-driving vehicles.

SELF-DRIVING VEHICLES

A self-driving vehicle has been commonly defined as a computer-controlled vehicle that drives itself. U.S. regulators and the Society of Automotive Engineers (SAE) have identified the following six levels/stages of driving automation:

SAE Level 0 (No automation): human driver is at the control of the driving task even when equipped with warning and/or intervention systems.
SAE Level 1 (Driver assistance): human driver performs all aspects of the dynamic driving task when automated system can assist the driver with one driver assistance system of either steering or acceleration/deceleration.
SAE Level 2 (Partial automation): human driver performs all aspects of the dynamic driving task when automated system can assist the driver with one or more driver assistance systems of both steering and acceleration/deceleration.
SAE Level 3 (Conditional automation): automated driving system performs all aspects of driving mode-specific performance; however, the human driver must be ready to take back control to a request to intervene.
SAE Level 4 (High automation): automated driving system performs all aspects of driving tasks, even if a human driver does not need to take back control to a request to intervene. However, the automated system can operate only in certain environments and under certain conditions.
SAE Level 5 (Full automation): the automated system performs all driving tasks, in any environment and under all conditions that can be conducted by a human driver.
(SAE International, 2018)

Research suggests that only 10-30% of all vehicles sold in the U.S. will be fully self-driving by 2030 (Mims, 2019). Optimistic predictions by some suggest that self-driving vehicles will be sufficiently reliable and affordable to replace human driving, provide independent mobility to non-drivers, and reduce driver stress, congestion, accidents, and pollution by 2030. However, Litman (2020) argues that many predictions of self-driving benefits are speculative and exaggerated, and often made by individuals with financial interests in the industry. Litman (2020) also suggests that self-driving technologies rely more on public infrastructure than other innovations, and as a result will involve more regulations than other new technologies to protect pedestrians, bicyclists, and public transit users. The National Highway Traffic Safety Administration has identified four potential benefits of self-driving vehicles: safety, economic and social benefits, efficiency and convenience, and mobility (National Highway Traffic Safety Administration, 2020).

Regarding safety, consumers appear torn with respect to whether self-driving vehicles should operate as utilitarian, minimizing total risk to people regardless of who they are, or as self-protective, placing greater weight on the safety of their own passengers. Individuals understand that the utilitarian approach is more ethical, but from a consumer perspective, they want the self-protective vehicles (Shariff et al., 2017). As a result, beyond the technological planning aspects of self-driving vehicles, society will need to face social and moral dilemmas (Duarte & Ratti, 2018).

Recent studies argue that municipal planning for self-driving vehicles has been minimal, with few strategies and policies being developed (Freemark et al., 2019; Guerra, 2016). For example, how self-driving vehicles will interact with the existing transportation system and the environment is not yet fully understood. Transportation planners feel that automobile travel is likely to increase with self-driving vehicles, resulting in more traffic congestion and negative environmental effects (Fraedrich et al., 2019). Fagnant and Kockelman (2015) conclude that it would be wise for policy makers and the public to seek a smooth introduction of self-driving vehicles through intelligent planning, meaningful vision, and regulatory action by: 1) expanding federally funded research for self-driving vehicles, 2) developing federal guidelines for self-driving vehicle certification, and 3) determining standards for liability, security, and data privacy.

A number of technological hurdles must also be addressed, as well as regulatory and infrastructure obstacles, but many original equipment manufacturers have indicated they plan to start selling self-driving vehicles between 2020 and 2025. However, cybersecurity concerns as to who will be liable if the vehicle crashes, and how self-driving vehicles will be insured, will all need to be addressed before self-driving vehicles will be available for sale in the U.S. to the general public (Craig & Lofton, 2019). Bellet et al. (2019) point out that the insurance industry and liability experts will be central to the move towards self-driving vehicles. Similarly, Canis (2017) suggests that liability and insurance, infrastructure and transportation funding, vehicle communication, and cybersecurity are all issues that may cause disruptions caused by self-driving vehicles.

According to the newly released government guidelines, *Ensuring American Leadership in Automated Vehicle Technologies* (2020), the U.S. federal government will provide guidance and best practices, conduct research and pilot programs, and provide other assistance to help stakeholders plan and make investments for the introduction of automated vehicle technology in the coming decades. Moreover, the U.S. federal government is actively funding automated vehicle technology research in the areas of safety, mobility, security and cybersecurity, infrastructure, and connectivity.

Consumer Acceptance of Self-Driving Vehicles

Self-driving vehicles have the potential to reduce fatal car crashes and provide additional mobility for the elderly and the disabled. However, the speed at which self-driving vehicles are adopted by consumers will depend heavily on vehicle cost, as well as the perceived level of consumer trust in vehicle security, safety, reliability, and efficiency. How these vehicle features are presented and promoted are challenges that the automotive industry will face. Educating consumers about self-driving vehicles will play a major role in their success and rate of acceptance.

Hewitt et al., (2019) found that the consuming public is not yet convinced about self-driving technologies in vehicles, finding lower levels of performance expectations and perceived ease-of-use than expected. The self-driving vehicle adoption rate is likely to be slower and more complicated than optimistic predictions. Vehicles last longer, cost more, and are more regulated than most other consumer goods. It will probably take decades for self-driving vehicles to dominate new vehicle purchases and fleets, and some motorists may resist using them all together. Optimistically, self-driving vehicles will be safe and reliable by 2025, and may be commercially available in many areas by 2030 (Litman, 2020).

Studies show trust appears to be a critical factor in consumer acceptance of self-driving vehicles (Adnan et al., 2018; Kaur & Rampersad, 2018; Planing & Dursun, 2018). Consumers must trust that the technologies in the self-driving vehicles are safe and reliable for mass use. Consumers must also trust that laws and regulations will be developed to address ethical and legal liability issues. Finally, they need to trust that urban planners and policy makers will be able to amend public infrastructure to meet the needs of changing traffic patterns and environmental concerns.

Risk attitudes also play a role in acceptability of self-driving vehicles (Dixit et al., 2019), as well as positive attitudes towards technology in general (Hardman et al., 2019). Sener et al. (2019) found that attitudes toward self-driving vehicles, performance expectations, perceived safety, and social influence were strong indicators of intent to use self-driving vehicles. In addition, Lavieri et al. (2017) report that lifestyle factors, such as younger, urban residents who are well educated and technologically savvy are more likely to be early adopters of self-driving technologies than older, suburban and rural individuals.

CONCEPTUAL FRAMEWORK AND HYPOTHESES

The AVAM is a combination of the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003), and the Car Technology Acceptance Model (CTAM) developed by Osswald et al. (2012). The AVAM incorporates eight factors from the UTAUT – Performance Expectancy, Effort Expectancy, Attitude Towards Technology, Social Influence, Facilitating Conditions, Self-Efficacy, Anxiety, and Behavioral Intentions, and Perceived Safety from the Car Technology Acceptance Model (CTAM). Performance Expectancy, Effort Expectancy, Attitude Towards Technology, Social Influence, Self-Efficacy, Anxiety, and Perceived Safety were hypothesized to directly impact Intentions to Use an Autonomous Vehicle in the AVAM. Facilitating Conditions was hypothesized to have a direct impact on Actual Use of an Autonomous Vehicle in the AVAM. Facilitating Conditions was not used as a predictor variable in this study, given that the focus was on predicting consumers' intention to use a self-driving vehicle, as well as the fact that self-driving vehicles are not currently commercially available in the U.S.

Performance Expectancy

Performance expectancy is defined in this study as the level of belief an individual has that a self-driving vehicle will help attain goals in driving performance (i.e., improved safety, better gas mileage, reduced stress). Litman (2020) explains that self-driving vehicles should lead to reduced driver stress and improved independent mobility for certain individuals. However, the performance of self-driving vehicles is seemingly hard to predict (Kaur & Rampersad, 2018). With advanced technology such as infrared sensors, inertial navigation systems, and ultrasonic sensors, the failure of any one of these technologies could cause a fatal accident.

Venkatesh et al. (2003) found performance expectancy to be a strong predictor of intention to use information technology. Osswald et al. (2012) included performance expectancy as a predictor of information technology usage in a vehicle in their theoretical car technology acceptance model (CTAM). Similarly, Nordhoff et al. (2016) also predicted performance expectancy to have a positive effect on acceptance of self-driving vehicles in their conceptual model. Moreover, Sener et al. (2019) found attitudes toward performance expectation to be strongly associated with intent to use self-driving vehicles, as did Leicht et al. (2018).

Based on prior research, and as shown in Figure 1, Hypothesis #1 is presented as:
H1: Performance Expectancy has a direct impact on Intention to Use a Self-Driving Vehicle.

Effort Expectancy

The underlying construct for effort expectancy is ease of use, used in the technology acceptance model TAM to refer to the level of belief that using specific new technology will be hassle-free and user-friendly (Davis, 1989). For this study, effort expectancy is defined as the level of perceived ease associated with the use of self-driving vehicles. Kyriakidis et al. (2014) found from a public opinion questionnaire that self-driving vehicles were perceived to be easier to use than manual driving vehicles.

Venkatesh et al. (2003) reported effort expectancy to be a strong predictor of intention to use information technology. Hewitt et al. (2019) found effort expectancy to decrease with higher levels of vehicle automation up to SAE Level 4, then slightly increase in SAE Level 5. Osswald et al. (2012) included effort expectancy as a predictor of technology acceptance in self-driving vehicles in the CTAM, as did Nordhoff et al. (2016) in their conceptual model.

Based on prior research, and as shown in Figure 1, Hypothesis #2 is presented as:
H2: Effort Expectancy has a direct impact on Intention to Use a Self-Driving Vehicle.

Self-Efficacy

Self-efficacy is defined in this study as an individual's belief that he/she has the ability and competency to use the technology. Consumers with high self-efficacy seemingly should feel they have the skills and ability to master the technology required to use a self-driving vehicle. Osswald et al. (2012) included self-efficacy as a predictor of information technology usage in a vehicle in their theoretical car technology acceptance model (CTAM). Gkartzonikas and Gkritza (2019) also reported self-efficacy to be an important factor in predicting intention to use self-driving vehicles.

Based on prior research, and as shown in Figure 1, Hypothesis #3 is presented as:
H3: Self-Efficacy has a direct impact on Intention to Use a Self-Driving Vehicle.

Social Influence

The psychological concept of social influence is rooted in the assumption that a person's behavior is heavily influenced by the behavior and presence of others. For this study, social influence refers to the extent to which members in society influence one another's behavior, and experience social pressure to perform a particular behavior. A consumer's interpersonal influences could come from a variety sources, such as neighbors, relatives, family members, and friends. Brown et al., (2002) suggest that social influences may have a greater affect in the consumer context than in workplace or educational contexts, because a consumer's adoption of technology for personal use is usually a voluntary decision, as compared to when technology choices are imposed upon individuals by management or curriculum decisions in the workplace.

Langer et al. (2016) found social influence to be a strong predictor of usage intention for driver assistance systems. Liu et al. (2019a) concluded that 'social trust' (trust in people of social circle and organizations) has a positive influence on the acceptance of self-driving vehicles. In addition, Gkartzonikas and Gkritza (2019) found social norms to be a predictor of intention to use self-driving vehicle. Barth et al. (2016) reported that social influence had equal or even stronger effect than cost-related factors in the early stages of electrical vehicle adoption.

Based on prior research, and as shown in Figure 1, Hypothesis #4 is presented as:
H4: Social Influence has a direct impact on Intention to Use a Self-Driving Vehicle.

Attitude Toward Self-Driving Vehicle

An individual's attitude towards using technology is defined as the degree to which a person has a favorable or unfavorable evaluation of using technology. Rogers (2003) found that innovation adoption decisions are determined by the overall attitude of potential users toward innovations. Charness et al. (2018) argue that attitudes towards self-driving technology can significantly impact the adoption of self-driving vehicles. Osswald et al. (2012) included attitude towards using technology as a predictor of intention to use self-driving vehicles in their theoretical model (CTAM).

Based on prior research, and as shown in Figure 1, Hypothesis #5 is presented as:
H5: Attitude Towards a Self-Driving Vehicle has a direct impact on Intention to Use a Self-Driving Vehicle.

Anxiety

Consumer anxiety may be the biggest barrier to mass self-driving vehicle adoption. The fear of the unknown is likely a big driver of the anxiety. Anxiety is defined as the concern and apprehension felt by an individual regarding the use of a self-driving vehicle. Anxiety has been shown to be a significant predictor of behavioral intention (Bandura, 1986). Hewitt et al. (2019) found anxiety level ratings by respondents to increase as the level of vehicle autonomy increased. Osswald et al. (2012) positioned anxiety as a direct predictor of actual use of self-driving vehicles in their theoretical model (CTAM).

Based on prior research, as shown in Figure 1, Hypothesis #6 is presented as:
H6: Anxiety has a indirect (negative) impact on Intention to Use a Self-Driving Vehicle.

Perceived Safety

Safe-driving vehicles are viewed as safer than human-driven vehicles (Deb et al., 2017). Many traffic accidents are caused by human error, which self-driving technologies can minimize. Surprisingly, Hewitt et al. (2019) found perceived safety of respondents to decrease from Level 1 – Level 2 scenarios, from Level 2 – Level 3 scenarios, and from Level 4 – Level 5 scenarios. Liu et al. (2019b) found that self-driving vehicles need to be safer than human-driven vehicles for consumer acceptance to occur.

Based on prior research, and as shown in Figure 1, Hypothesis #7 is presented as:
H7: Perceived Safety has a direct impact on Intention to Use a Self-Driving Vehicle.

RESEARCH METHODOLOGY

Data Collection

Data were collected from 358 respondents using Qualtrics. The demographic profile of respondents appears to be reflective of the general population. Of the sample respondents, 50.3% were men and 49.7% were women. Regarding age of respondent, 22.1% were 18-29; 24.6% were 30-44; 28.2% were 45-60; and 25.1% were 60 or older. Respondents were generally well educated, with 38.3% having a high school degree; 24.0% obtaining an associate or bachelor's degree; and 11.7% possessing at least a master's degree. Approximately 52% of respondents reported household income of $50,000 or higher.

A 27-item questionnaire was developed. The questionnaire assessed respondents' beliefs concerning self-driving vehicles. Respondents were informed that for the purpose of this research, a self-driving vehicle is defined as follows: "Your car is fully self-driving only on large, multi-lane highways. You must manually steer and accelerate/decelerate when on minor roads, but upon entering a highway the car can take full control and can steer, accelerate/decelerate and switch lanes as appropriate. The car does not rely on your input at all while on the highway. Upon reaching the exit of the highway, the car indicates that you must retake control of the steering and speed control." The above definition was used by Hewitt et al. (2019) in their description of a Level 4 autonomy scenario to survey respondents. In this study, the term "self-driving" replaced "autonomously" in the definition, as it was felt that respondents could better relate to and visualize self-driving vehicles vs. autonomous vehicles.

Measurement Scales

All variables were measured using a five-point Likert-type scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5). The measurement scales for Performance Expectancy, Effort Expectancy, Self-Efficacy, Social Influence, Attitude Towards a Self-Driving Vehicles, and Anxiety were all three item scales, while Intention to Use a Self-Driving Vehicle was a two item scale. These measurement scales were used by Hewitt et al. (2019) and adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT) to align with self-driving vehicles. Perceived Safety was also a three item scale used by Hewitt et al. (2019) that was slightly modified from the Car Technology Acceptance Model (CTAM). (See Appendix)

DATA ANALYSIS AND RESULTS

The internal reliability of the measurement scales were first assessed. The Cronbach's alpha reliabilities for each construct are as follows: Performance Expectancy (.869); Effort Expectancy (.889); Self-Efficacy (.751); Social Influence (.835); Attitude Towards a Self-Driving Vehicle (.904); Anxiety (.801); Perceived Safety (.732); and Intention to Use a Self-Driving Vehicle (.877). All reliabilities reflected excellent internal consistencies, with all values above the threshold value of .70.

The proposed theoretical model was then tested using Structural Equation Modeling (SEM). Three types of information were considered in assessing the model fit: chi-square, measurement error, and fit indices. Given that chi-square values tend to be sensitive to sample size and are likely to be significant if large datasets are utilized, chi-square is not an absolute criterion in evaluating model fit. A second criterion that was examined was measurement error, namely RMSEA (root-mean-square error of approximation) and RMR (Root Mean Square Residual). The final piece of evidence examined were the fit indices of CFI (Comparative Fit

Index), IFI (Incremental Fit Index), NFI (Normed Fit Index), and NNFI (Non-Normed Fit Index).

As shown in Table 1, the overall model fit was very good. Although the Chi-Square was significant at .01 level, the measurement error, indicated by RMSEA and RMR, was low at .08. In addition, all the fit indices, including CFI = .98, IFI = .98, NFI = .97, NNFI = .97, were all well above the acceptable cut-off values (Hu and Bentler, 1999). Therefore, the proposed theoretical model was accepted as indicated in Table 1 (Appendix)

Structural Model Analyses

Structural equation modeling (SEM) was also used to test the relationships between the theoretical constructs, as well as the hypotheses. Raw data were used as input, and the program analyzed the covariance matrix calculated from the raw data by using Maximum Likelihood (ML) estimation. Hypotheses were tested through path analysis. The significance of path coefficients in the model provides support for the hypothesized relationship (Bentler, 1989).

H1 proposed a significant positive relationship between Performance Expectancy and Intention to Use a Self-Driving Vehicle. However, as shown in Table 2, H1 was not supported ($\beta = 0.05$, p = N.S.). Similarly, H2 and H3, which proposed that Effort Expectancy and Self-Efficacy would have significant positive effects on Intention to Use a Self-Driving Vehicle, were also not supported ($\beta = 0.03$, p = N.S; $\beta = -.03$, p = N.S., respectively) as indicated in Table 2 (Appendix)

H4 postulated that Social Influence would have a significant positive effect on Intention to Use a Self-Driving Vehicle. This hypothesis was supported ($\beta = 0.41$, $p < .10$). In addition, H5 was also supported, as Attitude Towards a Self-Driving Vehicle was found to have a significant positive effect on Intention to Use a Self-Driving Vehicle ($\beta = 0.33$, $p < .10$). Anxiety was found not to have a significant effect on Intention to Use a Self-Driving Vehicle (β = 0.-.05, p = N.S.), so H6 was not supported. Finally, H7 was supported as Perceived Safety was found to have a significant positive effect on Intention to Use a Self-Driving Vehicle ($\beta = 0.98$, $p < .01$).

DISCUSSION

Self-driving vehicles will likely be available for commercial adoption in the U.S. within the next ten years. However, little is known about the extent to which consumers will embrace this new automotive technology. Initial studies indicate that early adopters of self-driving vehicles will likely be younger, higher income, highly educated consumers who spend considerable time in their vehicles and are comfortable with innovative technology.

This study examined factors that may influence consumer adoption and usage of self-driving vehicles when these vehicles become available in the U.S. The theoretical basis of this study was derived from the conceptual Autonomous Vehicle Acceptance Model (AVAM) introduced by Hewitt et al., 2019. The findings partially support the relationships proposed in the conceptual AVAM. The empirical test of hypotheses show that Social Influence, Attitude Towards a Self-Driving Vehicle, and Perceived Safety all have a direct impact on Intention to Use a Self-Driving Vehicle. However, Performance Expectancy, Effort Expectancy, Self-Efficacy, and Anxiety were not found to be significant predictors of Intention to Use a Self-Driving Vehicle.

As the results suggest, social influence likely will play a major role in the adoption of self-driving vehicles. Zhang et al. (2020) argue that since self-driving vehicles have yet to be commercialized, first-hand usage experience is not available, therefore, the evaluation of self-driving vehicles is largely influenced by media reports and opinions from friends. This assumption is supported by similar studies that show the importance of social influence on consumer acceptance of self-driving vehicles (Sener et al. 2019; Panagiotopoulos & Dimitrakopoulos, 2018). Social media can be a valuable tool for automotive manufacturers if used effectively to connect with consumers, and to influence the information shared by family and friends through the various social media platforms regarding attributes of self-driving vehicles.

Consumer attitude towards a self-driving vehicle will also be an important factor in the consumer adoption process for self-driving vehicles. Consumer attitudes are dynamic and change over time as consumers are exposed to more information through various promotional activities and word-of-mouth communication from family and friends. Research has shown that drivers who are initially passionate about driving may change their attitudes in favor of autonomous driving after additional product information (Pettersson & Karlson, 2015). Automotive marketers will need to provide ample information regarding the functionally of their vehicles to dispel potential misconceptions, and to allow consumers to make informed purchase decisions regarding self-driving vehicles.

Perceived safety also appears to be a critical factor, and possibly the most important factor, in consumer acceptance of self-driving vehicles. Safety will need to be a major focus in the promotion of self-driving vehicles. Consumers will need to trust that the automated technology driving the vehicles will protect them from crashes on the roadway. Promotional strategies will play a critical role in building that trust and in determining the speed at which consumers accept self-driving vehicles.

Although not tested in this study, another factor certain to influence consumer decisions concerning self-driving vehicles is price. An accurate estimate of consumers' willingness to pay for safer, more efficient, and less stressful driving is another critical factor in product adoption. Getting the price right is essential for all new product introductions. Early adopters act as catalysts for the diffusion and acceptance of innovation (Rogers, 2003). However, early adopters of technology are often willing to pay higher prices than the average population for innovative products (Hofstetter et al, 2013). Marketers in the automotive industry will need to assess the price sensitivity of consumers early in the adoption process and not overprice their products. Determining consumer preferences regarding vehicle attributes will likely impact the ultimate pricing of self-driving vehicles.

Finally, a supportive regulatory framework, government funding, and investment in automated vehicle technology will likely play a key role in the adoption rate of self-driving vehicles in the U.S. Self-driving vehicles have the potential to impact road infrastructure, urban planning, how automobiles are marketed, and the environment. The successful transition to fully self-driving vehicles will require the automotive industry, policy-makers, urban planning practitioners, and marketers to work together while taking into account available technologies and consumer perspectives.

CONCLUSION

The findings of this study indicate that social influence, consumer attitude towards a self-driving vehicle, and perceived safety will all play important roles in determining consumers' intention to use a self-driving vehicle. How marketers use this information should play a major role in the speed at which self-driving vehicles are accepted by U.S. consumers and adopted by the general driving population.

Some reports predict suggest that by 2030 self-driving vehicles will be replacing most human-operated vehicles. Others argue that due to the uncertainty of vehicle benefits, costs, travel impacts, deployment speed, and consumer demand, these predictions appear to be somewhat optimistic (Litman, 2020). However, it is no longer a question of if we will one day have self-driving vehicles on the road within the U.S., but rather a question of when and under what conditions. The automotive industry's challenge will be to develop self-driving vehicles that meet the needs of consumers within the regulatory guidelines established by policy makers. In addition, successfully transitioning to fully self-driving vehicles will require the automotive industry and marketers to work together while taking into account available technologies and consumer perspectives.

LIMITATIONS AND FUTURE RESEARCH

One limitation of this study is that the Autonomous Vehicle Acceptance Model (AVAM) was not tested under different respondent usage motives. For example, the intention to use a self-driving vehicle might be impacted by different factors based on whether the individual's primary motive for using this type of vehicle is for utilitarian reasons (e.g., safety, fuel efficiency, stress free driving) versus hedonic reasons (e.g., enjoyment, impressing family and friends). Another limitation is that the "intention to use" is a self-reported response that may differ significantly from actual use at a later date. The results of this study relied to a large extent on respondents' imagination regarding the operation of self-driving vehicles. Once these vehicles are commercially available, intentions and attitudes may change either more positively or negatively.

Additional research is needed to assess cultural differences that could influence the generalizability of consumer adoption models for self-driving vehicles. McCoy et al. (2007) argue that technology acceptance models, such as TAM (Davis, 1989), may not be applicable to all people, and that results may differ depending on respondents' cultural orientation. A cross-cultural analysis would be beneficial, given major automobile manufacturers market their vehicles globally. Further research should also focus on testing more complex models for predicting usage intention for self-driving vehicles. Expanding adoption models to include additional predictors, such as personality and lifestyle characteristics, should enhance the understanding of the rationale and motives influencing usage intention for self-driving vehicles. Finally, additional studies are needed to examine how intention to use may differ by gender, education level, household income, location (urban vs. rural), and driving experience.

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APPENDIX

Figure 1
Proposed Self-Driving Vehicle Acceptance Model

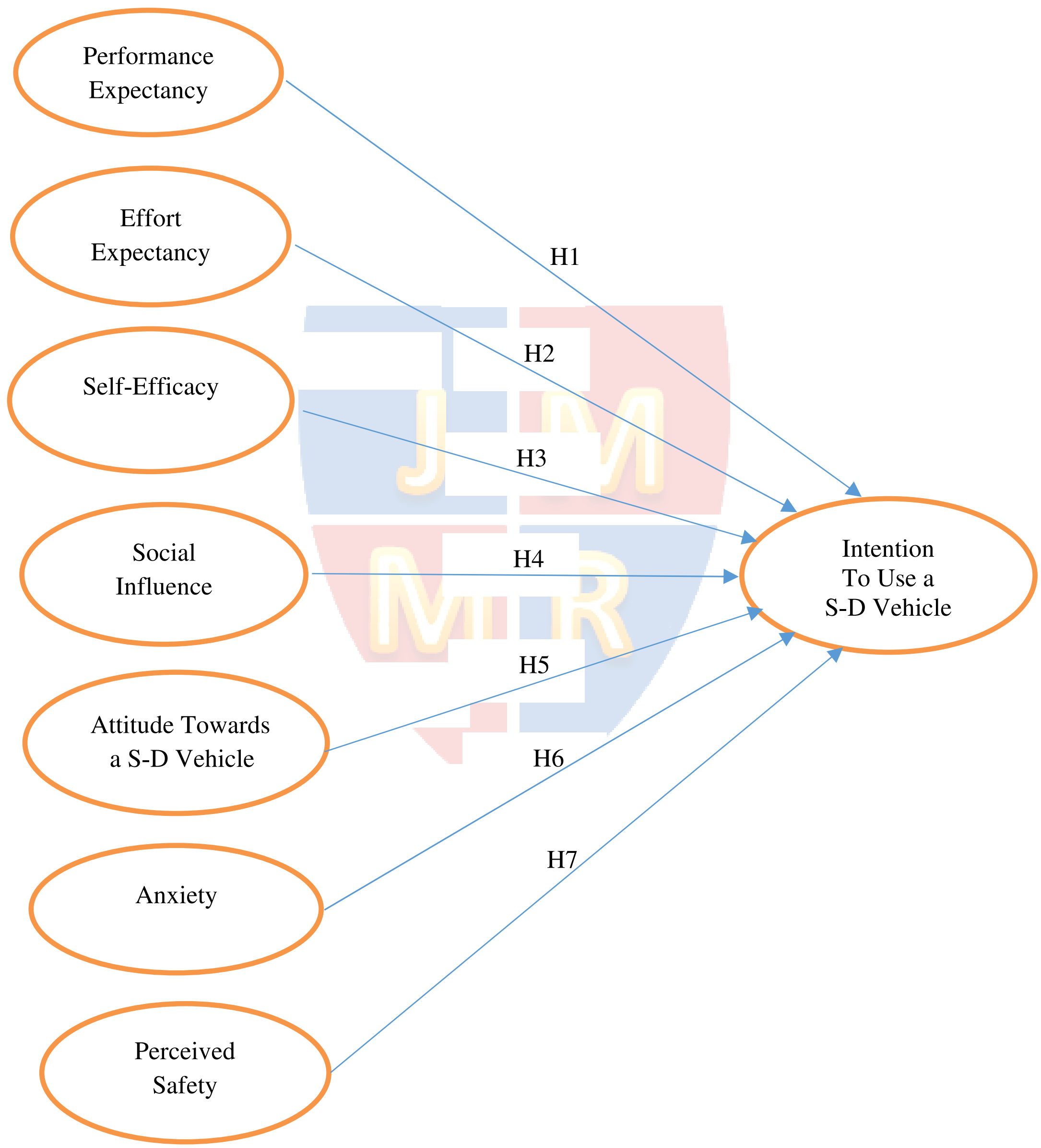

Table 1
Proposed Theoretical Model Testing

	Chi-Square	DF	Ratio	Sig.	RMSEA	RMR	CFI	IFI	NFI	NNFI	Decision
Structure Model	772.54	202	3.82	.000	.08	.08	.98	.98	.97	.97	Accept

Table 2
Hypotheses Testing

		H1	H2	H3	H4	H5	H6	H7
	Factors	Performance Expectancy	Effort Expectancy	Self-Efficacy	Social Influence	Attitude	Anxiety	Perceived Safety
Intention	Path Coefficient	.05	.03	-.03	.41*	.33*	-.05	.98**
	T-Value	.40	.19	-.18	1.92	1.77	-.93	3.68

* Significant at .10 level
** Significant at .01 level

(Measurement Scales)

Performance Expectancy*
1. Using the vehicle would enable me to reach my destination quickly.
2. Using the vehicle would enable me to reach my destination cost efficiently.
3. Using the vehicle would enable me to reach my destination safely.

(Hewitt, Politis, Amanatidis, & Sarkar, 2019)

Effort Expectancy*
1. I would find the vehicle easy to use.
2. My interaction with the vehicle would be clear and understandable.
3. It would be easy for me to learn to use the vehicle.

(Hewitt, Politis, Amanatidis, & Sarkar, 2019)

Self-Efficacy *
1. I could reach my destination using the vehicle if I had just built-in instructions for assistance.
2. I could reach my destination using the vehicle if I had no assistance.
3. I could reach my destination using the vehicle if there was someone who could help me.

(Hewitt, Politis, Amanatidis, & Sarkar, 2019)

Social Influences*
1. I would be proud to show the vehicle to people who are close to me.
2. I would feel more inclined to use the vehicle if it was widely used by others
3. I would prefer to use the vehicle with other passengers n the vehicle as well.

(Hewitt, Politis, Amanatidis, & Sarkar, 2019)

Attitude Towards a Self-Driving Vehicle*
1. Using the vehicle would be a good idea.
2. The vehicle would make driving more interesting.
3. Using the vehicle would be fun.

(Hewitt, Politis, Amanatidis, & Sarkar, 2019)

Anxiety *
1. I would have concerns about using the vehicle.
2. The vehicle would be somewhat frightening to me.
3. I am afraid that I would not understand the vehicle.

(Hewitt, Politis, Amanatidis, & Sarkar, 2019)

Perceived Safety *
1. I believe that using the vehicle would be dangerous.
2. I would feel safe while using the vehicle.
3. I would trust the vehicle.

(Hewitt, Politis, Amanatidis, & Sarkar, 2019)

Intention to Use a Self-Driving Vehicle*
1. Given that I had access to the vehicle, I predict that I would use it.
2. If the vehicle becomes available to me, I plan to obtain and use it.

(Hewitt, Politis, Amanatidis, & Sarkar, 2019)

*Likert-type items anchored by 1 = Strongly Disagree; 5 = Strongly Agree