Utilizing technology acceptance model (TAM) for driverless car technology adoption

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Abstract: This paper examines the relationship between perceived usefulness of driverless car technology, perceived ease of use of driverless car technology, years of driving experience, age and the intention to use driverless cars. This research is a cross-sectional descriptive correlational study with the Technology Acceptance Model as its theoretical framework. The primary method of data collection was an online survey. Pearson's correlation and multiple linear regression were used for data analysis. This study found significant, positive relationships between perceived usefulness of driverless car technology, perceived ease of use of driverless car technology and intention to use driverless cars. Also, there were significant, negative relationships between years of driving experience, age and intention to use driverless cars.

Keywords: driverless car technology adoption; technology acceptance model; innovation adoption; society; autonomous vehicles

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Introduction

The global automotive industry is now at a turning point for the transportation phase change due to driverless car technology (DCT), which potentially has groundbreaking economic, regulatory, and social implications (Bansal, Kockelman, & Singh, 2016; Gadepally, 2013; Howard & Dai, 2014; Knight, 2013; Maarafi, 2015). DCT represents a disruptive change that could potentially revive the concept of single occupancy cars and initiate a socio-cultural revolution (Brett, 2016). A driverless car (DC) is an unmanned vehicle that is capable of maneuvering without human input but utilizes the support of several sophisticated sub-systems and devices (Owczarzak & Żak, 2015).

DCT has its roots as far back as 1926 when Achen motors, an automotive distributor, demonstrated a 'phantom car tour' around the city of Milwaukee (Menon, 2015). However, it was not until 2005 when Stanley, the winning robot of Defense Advanced Research Projects Agency (DARPA) Urban Challenge, completed the 150-mile obstacle course and provided more realistic technological solutions regarding the feasibility of DCT (Guerra, 2016; Thrun et al., 2006).

The consumers of the automobile industry have experienced many incremental automation changes to the cars driven today (Jiang, Petrovic, Ayyer, Tolani, & Husain, 2015). Collision avoidance system, park assist, adaptive cruise control, and lane change assist are some examples of the driver assistance systems that are currently available commercially (Howard & Dai, 2014; Zindler & Geiss, 2016). These systems provide car manufacturers with building blocks that ultimately furnish the role of feeding into DCT (Howard & Dai, 2014).

Research has validated that social change is a consequence of technological change (Mohd, Ahmad, Samsudin, & Sudin, 2011). Automation cannot achieve its potential if its latent users do not adopt and if it is associated with improper reliance during early stages of implementation (Ghazizadeh, Lee, & Boyle, 2012). For DCT to be successful shortly, gaining social acceptance and anticipating factors impacting the adoption of DCT from the perspective of users has to be researched in-depth (Bansal et al., 2016; Heide & Henning, 2006; Menon, 2015; Payre, Cestac, & Delhomme, 2014). The literature shows evidence that the technology of DC is considerably ahead of the research examining the social acceptance of this technology (Guerra, 2016). Moreover, existing studies within this domain seem to differ in the results of DCT acceptance with varying demographics and geography. The leadership of automobile organizations could benefit from the new data, regarding the factors influencing acceptance of DCT, which will facilitate their decision-making and guide resources towards an appropriate direction.

The societal benefits of DCT, such as providing mobility solutions for all consumers regardless of their age, skills, and ability (Brett, 2016), warrant in-depth research into the social acceptance of this technology. Understanding the factors that influence the consumer adoption structure of DCT will guide the future research of more dependable and socially acceptable vehicles (Matthews, 2016).

The purpose of this study was to determine whether there is a relationship between the perceived usefulness of driverless car technology, perceived ease of use of driverless car technology, years of driving experience, age (independent constructs) and the intention to use driverless cars (dependent construct).

The perceived usefulness of DCT was the extent to which potential consumers of DC perceive this technology enhances their mobility, which eventually may influence their intentions to use DC. The perceived ease of use of DCT was the extent to which potential consumers of DC perceive the degree of ease associated with this technology, which eventually may influence their intentions to use DC. The intention to use DC construct represented the behavioral intention of potential consumers to adopt DC.

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Technology Acceptance Model

The Technology Acceptance Model (TAM; Davis, 1989) will continue to remain the hotspot of research as new technologies are evolving (Horton, Buck, Waterson, & Clegg, 2001; Venkatesh, Davis, & Morris, 2007). TAM is one of the most effective and widely used information systems theoretical frameworks (Holden & Karsh, 2010; Lee, Kozar, & Larsen, 2003; Li, 2010). As shown in Figure 1, TAM is a proven powerful framework for determination of early user acceptance and the original scale measures the TAM constructs within the context of different technologies across populations and is sufficiently validated (Davis & Venkatesh, 1996). An early indication of user acceptance becomes critical when huge financial implications are associated, especially with new, emerging technologies (Davis, 1993).

Figure 1. TAM model. Adapted from Davis & Venkatesh, 1996, p. 20.



The most common usage of TAM has evolved to be the determinant of the relationship between perceived usefulness (PU), perceived ease of use (PEOU), and anticipated future usage of many emerging technologies (Horton et al., 2001). The reliability of the items of the TAM constructs measured via Cronbach's alpha has been found to exceed 0.9 across numerous studies (Davis & Venkatesh, 1996; Yousafzai, Foxall, & Pallister, 2007a). TAM has found its application in various settings, such as, but not limited to, online learning, social networking media, intranet, and smartphones. For example, a study of factors influencing attitudes towards adoption of mobile commerce provided empirical evidence that the TAM model can be applied to the field of mobile commerce and provided sufficient explanation of consumer adoption intentions (Yang, 2005). Similarly, another study on the acceptance of advanced mobile services validated the application of TAM (López-Nicolás, Molina-Castillo, & Bouwman, 2008). Further, Jansson, Marell, and Nordlund (2010) explored the factors regarding consumers' adoption associated with alternate fuel eco-friendly car technology.



The research model of this study is shown in Figure 2. The current literature on DCT adoption constitutes of descriptive univariate analysis. This work attempted to apply the theoretical constructs available from TAM to the domain of DCT adoption. The study conducted by Schoettle and Sivak (2014) provides valuable information about the general perceptions of potential consumers of DCT. However, this paper aims to build more specificity by examining relational aspects between technology acceptance constructs and the intention to use DC.

Similarly, Menon (2015) pointed out that the factors influencing adoption of DCT can potentially change over time and as technology evolves. This study attempts along a similar path to ascertain consumers' perceptions in a different setting and, thus, to present new data. Further, investigating the acceptance of driverless car technology by Nees (2016) concluded that acceptance of DCT was low in older people and people with more driving experience. This study attempted to confirm these results in a different setting.





Methodology

The cross-sectional, descriptive, correlational research design was the underlying methodology of this study, which obtained quantitative data regarding consumers' perceptions of fully driverless transportation in the U.S. The research questions that are addressed in this study are as follows:

Q1: To what extent does a relationship exist between the perceived usefulness of driverless car technology and the intention to use driverless cars?

Q2: To what extent does a relationship exist between the perceived ease of use of driverless car technology and the intention to use driverless cars?

Q3: To what extent does a relationship exist between the number of years of driving experience and the intention to use driverless cars? Q4: To what extent does a relationship exist between age and the intention to use driverless cars?

Q5: To what extent do the socio-economic demographic variables (Gender, Level of Education, and Household Income) moderate the relationship between the perceived usefulness of driverless car technology and the intention to use driverless cars?

Q6: To what extent do the socio-economic demographic variables (Gender, Level of Education, and Household Income) moderate the relationship between the perceived ease of use of driverless car technology and the intention to use driverless cars?

Q7: What is the combined impact of perceived usefulness of driverless car technology, perceived ease of use of driverless car technology, number of years of driving experience, and age on the intention to use driverless cars?

Instrument

The study utilized modified versions of existing instruments and items used for each construct are discussed in Table 1.

Construct	Item					
	Adapted from Nees, 2016, p.1452.					
Intention to use DC	1. Given that I would have access to a driverless car, I foresee that I would use it.					
Intention to use DC	2. I intend to own a driverless car when they become available in the market.					
	3. I intend to add a driverless car on the list of my favorite cars.					
	Adapted from Davis and Venkatesh, 1996, p.45.					
	1. I think using a driverless car would allow me to be more productive.					
Duracian de Lla falance of	2. I believe that I would find a driverless car useful for driving.					
DCT	3. I feel using a driverless car would allow me to be safer while in the car.					
DCI	4. I think using a driverless car would reduce traffic-related problems.					
	5. I sense using a driverless car would reduce driver stress and improve driving performance.					
	6. I foresee that a driverless car would enhance the mobility of people regardless of their age, skill, and ability.					
	Adapted from Davis, 1989, p.340					
	1. I think learning to operate a driverless car would be easy for me.					
Perceived Ease of Use of	2. I believe my interaction with a driverless car would be clear and understandable.					
DCI	3. I think it would be easy for me to become skillful at using a driverless car.					
	4. I believe I would find a driverless car easy to use.					
	1. Age					
	2. Gender					
	3. The current level of education					
Additional Variables	4. Ethnicity					
Additional variables	5. Household income					
	6. The current state of residence					
	7. The current job function					
	8. Number of years of driving experience					

Table 1. tems Utilized in the Study Instrument

Participants

The employees working at a truck accessory manufacturer were the participants of this study. The organization has 13 subsidiaries located across various states within the U.S. The proportional stratified

sampling method was utilized to select the sample (n = 377) as different divisions were strata with unequal size. The sample embodied a diverse occupational background as shown in Figure 3.



Figure 3. Distribution of Study Sample by Job Function.

Data Collection

A link to Survey Monkey incorporating the study instrument was distributed via email to the sample located in all 13 subsidiaries of the selected organization across the U.S. For background information, the definition and picture of a DC along with a brief video on DCT were provided. The survey incorporated two dummy questions to assess the presence of mind of respondents. The survey remained open for ten business days. Finally, a sample of 377 out of 567 responses was included in this study due to various reasons for exclusion, such as missing values, wrong answer on dummy questions, and outlier tests.

Validity and Reliability

The reason for the selection of 13 subsidiaries of the participant organization across the U.S. was to minimize threats to external validity, which could help in cautiously generalizing across a wider population. The distribution of the sample across various states of the U.S. is shown in Figure 4.





Out of the 377 responses used for this study, 20 (5.3%) reported residing in California, 54 (14.3%) in Florida, 15 (4.0%) in Kansas, 97 (25.7%) in Michigan, 36 (9.5%) in Missouri, 48 (12.7%) in North Dakota, and 56 (14.9%) in Ohio.

Each construct was measured on a Likert-type scale of five points and five anchors. Cronbach's $\alpha > 0.7$, as per academic quantitative research standards, was used to validate the scale's internal consistency. It was determined that the items used on the instrument have appropriate internal consistency as shown in Table 2.

Table 2. Reliability Analysis of the Instrument.

Scale	Cronbach's a	Number of Items
Intention to use DC	0.902	3
Perceived usefulness of DCT	0.896	6
Perceived ease of use of DCT	0.899	4

Analysis and Results

We used the inferential statistical techniques shown in Table 3 to determine the strength and direction of the relationships between the perceived usefulness of DCT, perceived ease of use of DCT, years of driving experience, age and the intention to use DC. The Statistical Package for the Social Sciences (SPSS) 24.0 was used for performing the different statistical procedures.

Table 3. Data Analysis Approach				
Research Question	Inferential Statistical Technique			
Q1	Pearson Correlation			
Q2	Pearson Correlation			
Q3	Pearson Correlation			
Q4	Pearson Correlation			
Q5	Pearson Correlation			
Q6	Pearson Correlation			
Q7	Multiple Linear Regression			

A preliminary examination of the data revealed that the assumptions of linearity, independence of errors, normal distribution, and collinearity were reasonably met.

Demographic Analysis

Demographic data of the participants that include gender, age, education level, ethnicity, and annual household income are presented in Table 4. Even though the number of male participants was more than double the number of female participants, due to the large sample size, we had sufficient female participants to test the moderation effects of this variable. Due to the nature of the data, the moderation effects of ethnicity variable were not included in this study.

Variables		Frequency	Percentage		
Gender	Male	258	68.44%		
	Female	119	31.56%		
Age (years)	18-20	07	1.86%		
0 4 9	21-24	26	6.90%		
	25-30	67	17.77%		
	31-34	38	10.08%		
	35-40	59	15.65%		
	41-50	98	25.98%	%	
	51-60	60	15.92%		
Variables Male Gender Male Age (years) 18-20 21-24 25-30 21-24 25-30 31-34 35-40 41-50 51-60 60+ 60+ Education High School Technical Training Some College - No Degree Associate Degree Bachelor Degree Bachelor Degree Graduate Degree Ethnicity American Indian/ Alaskan Na Asian/Pacific Islander African American Hispanic Caucasian \$0 - \$24,999 \$25,000 - \$49,999 \$2000 - \$149,999 \$100,000 - \$124,999 \$100,000 - \$124,999 \$100,000 - \$124,999 \$100,000 - \$124,999 \$100,000 - \$124,999 \$100,000 - \$149,999 \$100,000 - \$124,999 \$100,000 - \$124,999 \$100,000 - \$124,999 \$100,000 - \$124,999 \$100,000 - \$124,999 \$100,000 - \$124,999 \$100,000 - \$124,999 \$100,000 - \$124,999 \$100,000 - \$124,999	60+	22	5.84%		
Education	High School	43	11.41%		
	Technical Training	17	4.51%		
	Some College - No Degree	103	27.32%		
	Associate Degree	37	9.81%		
	Bachelor Degree	144	38.20%		
Age (years) Education Ethnicity Annual Household In come	Graduate Degree	33	8.75%		
Ethnicity	American Indian/ Alaskan Native	4	1.06%		
	Asian/Pacific Islander	6	1.59%		
	African American	12	3.18%		
	Hispanic	27	7.16%		
	Caucasian	328 87.01%			
	\$0 - \$24,999	12	3.18%		
	\$25,000 - \$49,999	64	16.97%		
	\$50,000 - \$74,999	72	19.10%		
Annual Household	\$75,000 - \$99,999	Frequency Percentage le 258 68.44% nale 119 31.56% 20 07 1.86% 24 26 6.90% 30 67 17.77% 34 38 10.08% 40 59 15.65% 50 98 25.98% 60 15.92% - 22 5.84% ph School 43 11.41% hnical Training 17 4.51% ne College - No Degree 103 27.32% ocitate Degree 37 9.81% chelor Degree 144 38.20% aduate Degree 33 8.75% terican Indian/ Alaskan Native 4 1.06% an/Pacific Islander 6 1.59% icastain 328 87.01% s24,999 12 3.18% j000 - \$49,999 82 21.75% j000 - \$49,999 82 21.75%			
	\$100,000 - \$124,999	65	17.24%		
come	\$125,000 - \$149,999	28	7.43%		
	\$150,000 - \$174,999	17	4.51%		
	\$175,000 - \$199,999	11	2.92%		
	\$200,000+	26	6 90%		

Table 4. Participants' Demographics

The Result of Research Questions

Table 5 shows Pearson correlations between Perceived Usefulness of DCT, Perceived Ease of Use of DCT, Years of Driving Experience, Age and the Intention to use DC. The significance threshold for this study was set at $p \le 0.05$.

	Intention to Use DC
Perceived Usefulness of DCT	0.780***
Perceived Ease of Use of DCT	0.387***
Years of Driving Experience	-0.144**
Age	-0.123*

Note. $\dagger = p < 0.10, \, *= p < 0.05, \, **= p < 0.01, \, ***= p < 0.001, \, and \, n = 377$ for all analyses.

The results of the research questions analyses are shown in Table 6. The SPSS output reflecting an overall multiple linear regression model summary and beta coefficients examining the impact on the dependent construct is shown in Table 7 and Table 8, respectively. The beta values shown in Table 8 (B - Perceived Usefulness of DCT = 0.420; B - Perceived Ease of Use of DCT = 0.127; B - Years of Driving Experience = -0.390) represents the average change in a consumer's intentions to use DC for each increment change in the perceived usefulness of DCT, perceived ease of use of DCT, and years of driving experience, respectively. The beta value for age is not statistically significant and therefore, is not a predictor of consumer's intentions to use DC.

Research Question	Statistical Analysis Result				
Q1: To what extent does a relationship exist between the perceived usefulness of DCT and the intention to use DC?	The perceived usefulness of DCT and the intention to use DC have a strong, statistically significant positive relationship $(r = 0.780, n = 377, p < 0.001)$.				
Q2: To what extent does a relationship exist between the perceived ease of use of DCT and the intention to use DC?	The perceived ease of use of DCT and the intention to use DC have a moderate, statistically significant positive relationship ($r = 0.387$, $n = 377$, $p < 0.001$).				
Q3: To what extent does a relationship exist between the number of years of driving experience and the intention to use DC?	Years of driving experience and the intention to use DC have a weak, statistically significant negative relationship $(r = -0.144, n = 377, p < 0.01).$				
Q4: To what extent does a relationship exist between age and the intention to use DC?	Age and the intention to use DC have a weak, statistically significant negative relationship $(r = -0.123, n = 377, p < 0.05).$				
	Gender, level of education, and household income were not found to have any moderating influence on the relationship between the percei- ved usefulness of DCT and the intention to use DC.				
Q5: To what extent do the socio-economic demographic variables (Gender, Level of Education, and Household Income) moderate the relationship between the perceived usefulness of DCT and the intention to use DC?	<u>Gender as a moderator:</u> Male (r = 0.774, n = 258, p < 0.001) Female (r = 0.802, n = 119, p < 0.001).				
	<u>Level of education as a moderator:</u> Low Education (r = 0.817, n = 200, p < 0.001) High Education (r = 0.747, n = 177, p < 0.001).				
	<u>Household income as a moderator</u> . Low household income (r = 0.822, n = 148, p < 0.001) Medium household income (r = 0.729, n = 147, p < 0.001) High household income (r = 0.811, n = 82, p < 0.001).				
	Gender, level of education, and household income were not found have any moderating influence on the relationship between the per- ved ease of use of DCT and the intention to use DC.				
O6. To what extent do the socio-economic demographic variables (Gender, Level of	<u>Gender as a moderator:</u> Male (r = 0.377, n = 258, p < 0.001) Female (r = 0.407, n = 119, p < 0.001).				
Education, and Household Income) moderate the relationship between the perceived ease of use of DCT and the intention to use DC?	Level of education as a moderator: Low Education ($r = 0.406$, $n = 200$, $p < 0.001$) High Education ($r = 0.364$, $n = 177$, $p < 0.001$).				
	<u>Household income as a moderator:</u> Low household income ($r = 0.340$, $n = 148$, $p < 0.001$) Medium household income ($r = 0.446$, $n = 147$, $p < 0.001$) High household income ($r = 0.353$, $n = 82$, $p < 0.01$).				
	The multiple linear regression model sufficiently explains the dependent construct of intention to use DC				
Q7: What is the combined impact of perceived usefulness of DCT, perceived ease of use	$(R^2 = 0.622, n = 377, p < 0.001).$				
of DCT, number of years of driving experience, and age on the intention to use DC?	By evaluating R^2 , a statistical interpretation can be made that 62.2% of the variance in the intention to use DC is explained by the combination of the perceived usefulness of DCT, perceived ease of use of DCT, any years of driving experience.				

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Model	R .791	R Square 0.626	re 0.622	2.329	R Cha 0.62	Square inge	F Change 155.781	df1 4	df2 372	Sig. F Change 0.000	- Uurbin- Watson - 1.942
	Table 8. Beta Coefficients.										
		Unstandardized Coefficients		Standardized Coefficients			95.0% Con Interval for	fidence B		Collinearity Stat	istics
Model		В	Std. Error	Beta	t	51g.	Lower Bound	Upper Bound	1	Tolerance	Variance Inflated Factor
	(Constant) Perceived	-1.94	.3 0.742		-2.617	0.009	-3.403	-0.483			
1	Usefulness of DCT	f 0.42	0 0.020	0.732	21.385	0.000	0.382	0.459		0.818	1.166
	Perceived Ea of Use of DC	se 0.12	7 0.037	0.117	3.436	0.001	0.054	0.200		0.861	1.162
	Years of Driving Expe rience	e0.39	00 0.186	-0.193	-2.097	0.037	-0.756	-0.024	-	0.119	8.409
	Age	0.312	0.196	0.149	1.616	0.107	-0.069	0.702		0.119	8.418

Table 7. Multiple Regression Model Summary

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Comparative Analyses

The existing research findings have indicated that the TAM constructs of Perceived Usefulness and Perceived Ease of Use are significant factors for anticipating future usage of different technologies across various settings (Davis & Venkatesh, 1996; Dillon & Morris, 1996; Drennan, Kennedy, and Pisarski, 2005; Lee et al., 2003; Park, Kim, Shon, and Shim, 2013). These findings are consistent with the findings of this study that revealed as the perception of usefulness associated with DCT increased, the intentions of potential consumers to use DC strongly increased. Also, as the perception of ease of use associated with DCT increased, the intentions of the potential consumers to use DC moderately increased.

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Thus, due to the strongest correlation in this study, it is proposed that the perceived usefulness construct be served as a noteworthy focus area for the marketers of DCT. Also, it is speculated that once usefulness of DC technology is established, consumers may put forth the effort required to learn this technology. However, Lane and Coleman (2012) found that higher Perceived Ease of Use led to higher Perceived Usefulness, which ultimately led to higher usage of technology.

This work found that as consumers' years of driving experience increased, the intentions of potential consumers to use DC decreased slightly. Also, the data revealed that with an increase in consumers' age, the intentions of potential consumers to use DC decreased slightly. These findings are consistent with existing research that the acceptance of DCT is lower in consumers with more driving experience and with older consumers (Nees, 2016).

Conclusion and Future Studies

The regression model had sufficient explanatory power with each construct, except age, is a significant predictor of consumers' behavioral intention to use DC. The Perceived Usefulness construct was shown to be the strongest predictor of intention to use DC. The constructs of the TAM framework provided a robust theoretical base for predicting DC adoption.

In the coming years, seniors are projected to constitute the majority of the U.S. population and, hence, are one of the biggest consumer bases for automobile manufacturers in the future. Therefore, it becomes of paramount significance for DCT manufacturers to develop and implement interventions in advance that will help reduce the impact of age on the intention to use DC.

This study was limited to determining only the relationships between the constructs under examination and could not predict causation. Also, Arts, Frambach and Bijmolt (2011) cautioned that, with multifaceted technological innovations, the measured adoption behavioral intention might reflect higher levels than actual adoption.

Future studies of DCT adoption may include the construct of selfefficacy as a mediating variable between the relationship of Perceived Ease of Use of DCT and intention to use DC. The level of a person's self-efficacy may mediate the relationship between Perceived Ease of Use and behavioral intentions. Even though customer resistance to innovation was not included in this study, this construct may be significant for future studies on DCT adoption research. Also, future studies can examine the impact of a user's level of experience with currently available automotive technology, such as those specified in National Highway Traffic Safety Administration (NHTSA) level three category (e.g., lane assist, brake assist), on the intention to use DC. Moreover, a user's level of experience with currently available automotive technology may mediate the relationship between the Perceived Ease of Use of DCT and the intention to use DC. Finally, the degree to which consumers are willing to give up their driving control could be a significant factor to be considered in future studies.

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Biography

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