

Driver Perceptions of V2V and V2I for Autonomous Vehicles: A Study of Technology Acceptance Factors

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Abstract

This study will examine user acceptance towards the latest autonomous vehicle technologies with a focus on vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) technologies. An online survey was utilised to collect 203 responses (from a diverse group of people with about 35 master students). This research will predominantly utilise a quantitative research approach to study consumer views on autonomous vehicle technologies and will be conducted amongst professional and nonprofessional drivers. The technology acceptance model (TAM) by Davis represents the underlying research model of this study updated to include significant factors. Hypothesis testing is performed for three scenarios (AV, V2V, and V2I) using multiple regression analysis and ANOVA test in SPSS version 20. However, the outcomes of this study revealed that V2V exhibited the most considerable and statistically significant positive impact on the driver, as evidenced by the variables compatibility (COP) and perceived ease of use (PEOU). Besides, the study also conducted on V2I demonstrated that the most significant positive influence was observed by attitude towards using (ATU) and driver context (DC), which relates to the existing literature on pervasive computing. Furthermore, it was found that PEOU and DC variables exhibited a strong positive impact on autonomous vehicles (AV), with statistical significance.

Keywords: autonomous vehicle (AV), vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), Pervasive computing (PC), Technology Acceptance Model (TAM)

1. Introduction

The ability to wirelessly exchange information from one vehicle to another vehicle regarding the location and speed of the vehicles around them is needed because these types of self-driving vehicles to help to avoid accidents and ease congestion. These benefits can be achieved if all vehicles can communicate with each other through this technology. This type of communication helps vehicles enable speed identification and exchange addresses with other vehicles [1].

The technology used in the V2V model enables vehicles to collect one-way messages. Vehicles that have V2V software could be used to receive messages from surrounding vehicles that will help them avoid any potential collision. V2V communications have a range of about 350 meters. Sensors will enable vehicles to identify

and avoid hazards. Vehicle to infrastructure (V2I) is also another type of communication framework that enables a variety of vehicles to share information with devices implemented in the highway system. Through devices such as signs, cameras and streetlights. Software and hardware networks enable this infrastructure. V2I technology uses two-way wireless systems to improve the level of road safety [2]. Identical V2V and V2I is dedicated to short-range communications. The sensors used in the V2I are based on the intelligent transfer system. This will help capture data and problems that vehicles encounter on the road [2].

Due to the need for road safety and the increase in the number of vehicles supporting V2V and V2I technologies, there has been a growing interest in developing autonomous vehicle technologies. These technologies include emergency vehicle alerts, emergency braking, roadside alerts, lane change assistance, stop warnings, and blind-spot warnings. In this context, many works have focused on designing mechanisms and methods that improve road safety and help reduce the number of accidents and deaths [3]. However, autonomous vehicle sensors such as LiDAR, ultrasound, radar, and cameras have their limitations, therefore to fill the aforementioned gaps in this research, this study aims to investigate the potential of V2V and V2I technologies to address these issues utilising the literature on technology acceptance model (TAM) and pervasive computing (PC).

2. Related Work

Current Technology Acceptance Models

According to [4] "The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it". With these words, Weiser began his work in 1991, describing his vision of ubiquitous computing, known as pervasive computing. As mentioned by [6] the term "pervasive" refers to something that is "existing everywhere," implanted, mobile, flexible, everlasting and effective.

Pervasive computing is an evolutionary step in the technological world. It first began in the mid-1970s at a time when the computer was more interactive in society. As mentioned by [7], key academics in the field of pervasive computing believes that the idea of making a computer personal is technologically misplaced. Moreover, [7] reveal the weakness of the computer, that keeps computing separate from our lives. However, the

personal computer has not reached its full potential for its users; it was the first step to pervasive computing. It is also an important factor in the development of graphical user interfaces. The application of comprehensive computing to automotive technology is essential since vehicles have become an integral part of modern life. At present, computers are largely built into autonomous vehicles, because it allows the vehicle to have more opportunities and facilitate the activities of drivers, allowing them to enjoy better performance, comfort, and safety [8].

Regarding [9], the TAM is a theory of information systems that describes how users accept and utilise a technology. TAM describes the relationship between a person's beliefs and attitudes and their intention to undertake a behaviour. Two beliefs, perceived usefulness (PU) and perceived ease of use (PEOU), determine the willingness to adopt a technology, according to TAM. Numerous empirical investigations have demonstrated (since the development of this model) that TAM is a simple and robust model of technology adoption behaviours used in a wide range of information systems.

TAM asserts that the intention of a user utilising any technology is determined by its PU and PEOU. Prior to TAM research, intentions behaviour has been shown to modulate the influence of other possible antecedents on actual user behaviour. Utilising behavioural intention (BI) as the dependent variable (as opposed to actual usage) is especially valuable for examining the early acceptability of technological systems. The intention to use a system is determined by the user's perceptions of the system's ease of use and its perceived usefulness, [10] defined PU as the extent to which an individual believes that utilising a certain system will improve their work performance. Consistently, PU appears as the primary motivator of technology adoption. The definition of PEOU is the extent to which a person feels that using a certain technology would be effortless [10]. TAM has been utilised in several pieces of research to explain the acceptance and use of driving assistance technologies. PEOU and PU have both been cited as major determinants of the technological acceptability of autonomous vehicles.

Technology Acceptance Factors

Initially, the research model and assumptions are based on [11] original TAM concept. In reference to Davis', a user's attitude towards the system is a function of two constructs or factors: PU and PEOU (how useful they are to find the system and how simple it is to operate). PU is in turn causally affected by PEOU. On the other hand, the automation acceptance model (AAM) presented by [10], incorporated trust, and compatibility into TAM. Hence, the original TAM relationships persist in AAM, where TR&SF and COM influence behavioural intents and attitudes through perceived usefulness and perceived ease of use. There is a clear relationship between trust and behavioural intention [12]. Although AAM provides a theoretical framework for the adoption of modelling automation, the model has not been validated.

Davis' technology acceptance model was established to enhance knowledge of user acceptance of computer-based information systems; and, it has since served as a foundation for further adaptations of the model utilised in different fields. This is illustrated by the work of [9], who extended the model to study user acceptance of autonomous vehicles (AVs). This model is useful for this study since it provides a robust explanation for the phenomena of user acceptance. While seeking answers for why various aspects play a role, it is crucial to recognise that this is frequently explained by PU and PEOU.

Despite the fact that these articles have been partially successful in explaining the variation in user acceptability and have discovered several aspects that play a role, it is generally agreed upon that not all significant variables have been identified and that additional studies are necessary. The results show that unidentified factors will account for most of the variation in acceptance of autonomous vehicles, as mentioned by [9], which construct similar personality characteristics, which were not included in their model, are likely to be valuable additions. On the other hand, [13] argues that a closer look at age and driving experience should be considered. In agreement with the idea that the factors that will determine whether people would accept autonomous vehicles are mostly unknown, [14] argue that it is crucial for all users to have a say in whether or not autonomous vehicles will be widely adopted.

Besides, [15] built on study and included other components such as perceived enjoyment (PE), objective usability (OU) and attitude towards environmental protection (ENV) in his research report to corroborate the fundamental assumptions of the technological acceptance model in the context of autonomous vehicles. This demonstrates how powerful societal norms and individual experiences are in terms of technology acceptance in society. Likewise, constructs effects of technological adoption have been discovered, for example, the perceived enjoyment of electrically charged vehicles influences the acceptance of autonomous driving and automobile possession behaviour.

In addition, these models are established in the theory that peoples' beliefs and perceptions of a technology can influence its acceptance, with the behavioural intentions to use a technology and actual usage of behavioural indicators of acceptance [16]. The investigation will therefore adapt to the fundamental assumptions of the original TAM given by [10]. The research will adapt to the fundamental premises of the original TAM given by [11], which is presented from H1 to H6. In addition, the findings are consistent with earlier consumer acceptability studies in this area, such as the models presented by [12] [9] and [15], expanding their findings in the field of AVs technologies. Consequently, based on these recent studies, this research will keep up with the most recent autonomous vehicle technologies, such as V2V and V2I. This study will evaluate how these technologies can assist the autonomous industry to fulfil its success potential, as well as how users accept the technology. To do this, this study will attempt to expand the TAM model by including the externalities (hypothesised or constructed), including behavioural

intention to use (BI), perceived usefulness (PU), perceived ease of use (PEOU), attitude towards using (ATU), compatibility (COM), driver context (DC), trust&safety (TR&SF), and innovativeness (INV).

3. Theoretical Model Employed

We conducted an in-depth analysis of respondents' views and treat them as user information that will assist this study in determining how these technologies may evolve and whether any new ones have been developed expressly for autonomous vehicles. In addition, these models are established with the theory that peoples' beliefs and perceptions of a technology can influence its acceptance, in terms of the behavioural intentions to use

technology and the actual usage of behavioural indicators of acceptance [16]. The paper will utilise pervasive computing and adapt the fundamental premises of the original TAM given by [8], which is tested by the hypotheses as reported in this paper by statistic testing using regressions analysis and ANOVA.

The research framework consists of three significant stages, with distinct constructs for each stage. The first stage (referred to as TAM) contains four constructs: perceived usefulness (PU), perceived ease of use (PEOU), attitude towards use (ATU), and behavioural intention to use (BI). The second stage is a professional setting which consists of two constructs: driving context (DC) and compatibility (COP). The last stage, personal attributes, likewise have two constructs: trust&safety (TR&SF) and innovativeness (INV)

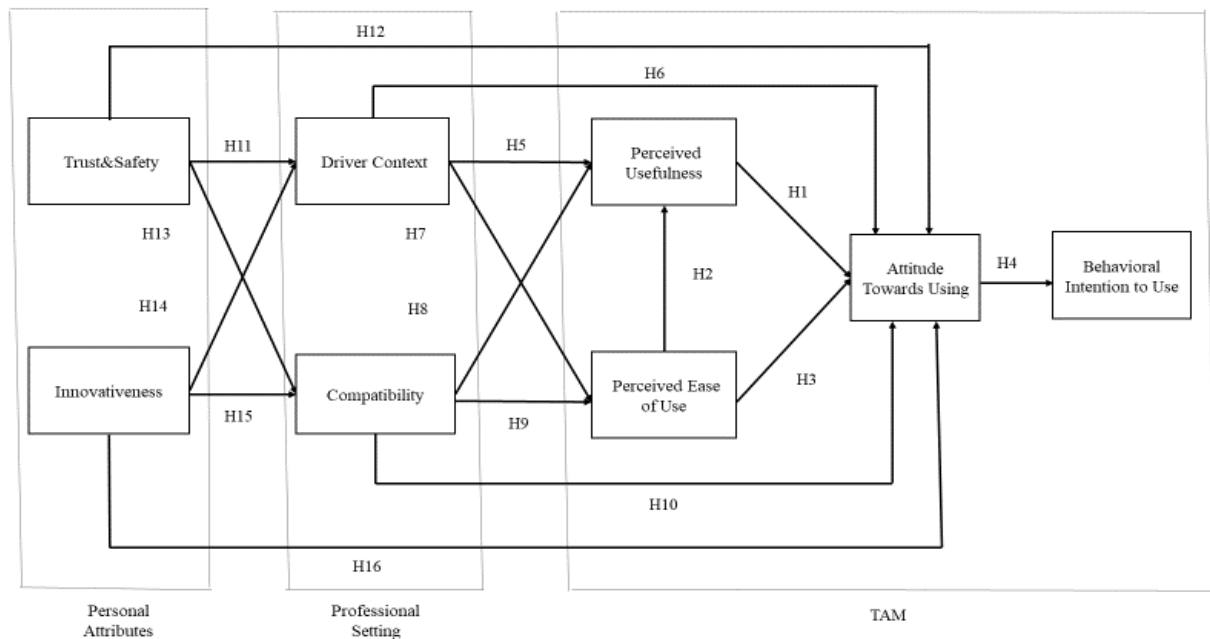


Figure 1. Research Framework for Autonomous Vehicle Technologies

3.1. Hypothesis Development

As can be seen from Figure. 1, the framework model includes eight groups of hypotheses; initially, the first group of hypotheses (H1, H2, H3 and H4) demonstrate the stages of the TAM that impacts three factors of BI, ATU, PU and PEOU. The second group of hypotheses (H5, H6, H7, H8, H9 and H10) is concerned with the effects of DC and COM, which represents the professional setting stage. The third group of hypotheses (H11, H12, H13, H14, H15 and H16) illustrates that applications based on TR&SF and INV affect the stage of personal attribute.

Stage 1: TAM

According to [17], several pieces of research contend that PEOU precedes PU and that PEOU describes a condition, whereas PU describes a process. On the other hand, [11] believes that PEOU and PU have a direct clear correlation. Moreover, [17] revealed that PEOU has a direct influence on PU regarding internet usage and

validated the important correlation between PEOU and PU in autonomous vehicle technology. As stated by [7], various research has shown PU and PEOU positively impact behavioural intention, however the significance level of these effects varies. Furthermore, PU mediates the relationship between PEOU and BI [18] and [19]. If this is the case, it stands to reason that users are more likely to accept autonomous vehicles if they find them beneficial and simple to operate.

ATU is defined by [20] as the driver's positive or negative perceptions of utilising an AV. [21] discovered that the favourable attitude of young respondents towards AVs. In addition, according to [22], a variety of research, such as [9] and [23], have demonstrated that the perceived usefulness of autonomous driving technology can increase persons' positive views about AVs and their desire to utilise AVs. As stated by [22], the behavioural intention will be positively affected by attitude. Thus, the following hypotheses were advanced:

- H1: The Perceived Usefulness of technology has a positive influence on the Attitude Towards Using.

- H2: The Perceived Ease of Use of the technology has a positive influence on its Perceived Usefulness.
- H3: The Perceived Ease of Use of the technology has a positive influence on the Attitude Towards Using.
- H4: The Attitude Towards Using of the technology has a positive influence on the Behavioural Intention to Use.

Stage 2: Professional Setting

As pervasive computing elements are well established regarding sensors [24], however, this study forces on AVs but may save time, increase road safety and improve communication. While a further scenario in which the vehicle is fully autonomous in the driving context. Typically, required sight distances rely on traffic management, intersection location, speeds on main and local routes, and manoeuvrability (behaviour of drivers) [25].

As society's concern for urban sustainability grows, AVs are increasingly in line with emerging societal ideals [26]. Therefore, driving context allows autonomous vehicles to be a cleaner alternative to conventional vehicles by reducing traffic congestion and air pollution and enhancing driver visibility. For this study pervasive computing factors and TAM [16] has been extensively utilised and expanded in driving situations to anticipate drivers' adoption and usage of technologies such as in-vehicle navigation, cruise control, and other needs of a hyphen system.

Furthermore, in the context of autonomous driving, [27] defined compatibility as the extent to which autonomous driving conforms to an individual's typical mobility behaviour in terms of daily driving or travelling. Compatibility may be the most useful predictor of adoption intention and a substantial predictor of behaviour. Whereas [28] established a positive relationship between compatibility, attitude, perceived usefulness, and intention to use. Considering the adoption of personal automobiles, the adopters of alternative fuel vehicles view autonomous vehicles as more suitable than non-adopters [29]. Hence, driver context and compatibility are incorporated into the current study model:

- H5: The Driver Context of the technology has a positive influence on its Perceived Usefulness.
- H6: The Driver Context of the technology has a positive influence on the Attitude Towards Using.
- H7: The Driver Context of the technology has a positive influence on its Perceived Ease of Use.
- H8: The Compatibility of the technology has a positive influence on its Perceived Usefulness.
- H9: The Compatibility of the technology has a positive influence on its Perceived Ease of Use.
- H10: The Compatibility of the technology has a positive influence on the Attitude Towards Using.

Stage 3: Personality Attributes

It is a well-established fact that trust is a crucial driver of dependence on (and acceptance of) automation, standing between a user's ideas about automation and their intention to use it [30]. According to [31] noted that trust in AVs is a significant predictor of the primary appraisal of AV use for travel. [16] point out that relatively little attention has been devoted to the role of trust in determining whether users would accept AVs or not, although a lack of faith in AV technology is the most often cited reason for not adopting it [32]. The majority of the few studies that have examined trust as a predictor of driver acceptance of autonomous vehicles (AVs) have concluded that trust is a positive and substantial indicator of drivers' positive attitudes towards AVs [33], [9], [34].

Chan and Lee theorised that an individual is inventive if they embrace an invention significantly earlier than their peers. As mentioned by [36], innovativeness is described as the user's willingness to adopt and experiment with new information technologies. This personal attribute has been shown to boost the individual's confidence and trust in the new technology. Hence, a person's level of innovativeness influences adoption intention, perceived benefits, and perceived dangers positively for both present and prospective adopters of AV technology. According to [15], Perceived usefulness and perceived ease of use are positively affected by the elements in the case of autonomous vehicles, as demonstrated by innovative users' more favourable positive perceptions and greater adoption rates. Hence, the following possibilities are proposed:

- H11: Trust and Safety have a positive influence on the Driver Context of the technology.
- H12: Trust has a positive influence on the Attitude Towards Using.
- H13: Trust and Safety have a positive influence on the Compatibility of the technology.
- H14: Innovativeness has a positive influence on the Driver Context of the technology.
- H15: Innovativeness has a positive influence on the Compatibility of the technology.
- H16: Innovativeness has a positive influence on the Attitude Towards Using.

4. Methodology

For the most part, this study uses a quantitative research approach to the topic of autonomous vehicle technology; the study was performed online in the form of a survey using 7-point Likert scale with both professional and nonprofessional drivers. After receiving approval from the Brunel University Research Ethic Committee, Google Forms survey were developed and data collecting took place between November 2022 and January 2023. In addition, individual emails were sent out to each potential participant. To survey participants both professional and nonprofessional drivers with a minimum

age of eighteen years old and master students.

Besides, this study tests the hypothesis by checking the relationship between different independent variables and our dependent variables. Hypothesis testing was performed using multiple regression and single regression in SPSS version 20, the statistical software used in this study. Before performing a regression analysis, it is important to describe the demographic profile of the participants and check for outliers, box plots and normality in the data. Furthermore, the reliability of the measurement scale will also be tested in this study. The proposed model's overall fit was then assessed using both multiple regression and single regression techniques examine the hypotheses.

4.1. Participants and Data Collection

Participants were asked for their demographic information in this survey with ages responses and categorised into four groups. Participants were between the ages of 18-24 at 34% whereas the age group of 25-34 consisted of 31%, and 28.1% of participants age were above 55. As per gender divergence, the percentage of males was 70.4% and females accounted for only 29.6%. In addition, the survey categorised participants according to different areas, the participants who came from urban areas were more interested compared with other areas. The participants that belong to urban areas accounted for 50.7%, while those in suburban areas accounted for 31% and the participants that related to rural areas represented 18.3%.

Additionally, participants were categorised on an accidental basis as it showed that participants that were involved in car accidents involving minor damage accounted for 38.9% of those surveyed. Accidents that involved an injury accounted for 18.2%; accidents that involved major damages to the car accounted for 7.4%, and lastly, 35.5% of those surveyed represented drivers who had never been involved in an accident. The survey categorises interested participants on the basis of driving activities and the participants who relate and that commute to work is more than compared to others. Therefore, the participants that commute to work

represent the highest percentage at 41.4%, journeys/travel represent 35%, leisure at 21.2%. Other different minor categories stand at 2.4% such as attending university, commuting to a farm and dropping children off to their child minder.

The professional drivers are then further divided into six mains: 22.1% are local courier drivers, 20.8% were local haulage drivers, national courier drivers accounted for 16.9%, international haulage drivers at 5.2%, national haulage drivers at 9.7% whereas the remaining categories were of an aggregate 25.3%. Further, the survey has demonstrated that most of them used an automatic parking driving assistance system the second largest group 27.6% used blind spot detection, and thirdly, 21.7% used automatic braking systems, collision avoidance systems had been used by 9.4% drivers, while the remaining categories account for just 13.2% which consists of people who use all the driving system above and the cruise control lane.

4.2. Data Analysis Handling

An online survey questions needed to be answered, therefore the research did not reveal any missing numbers when checked. Regarding outlying values, this research has identified twelve scores outside the minimum and maximum values. Box plots indicate the range of possible scores for each construct.

Table 1 shows the means and standard deviations of the constructs. In addition, the descriptive statistics reveal that all items of the constructs had a mean score of larger than 2.5 and a small standard deviation, indicating that most participants agreed with them. Additionally, the reliability test was determined by calculating Cronbach's alpha using SPSS version 20. A Cronbach's alpha value 0.90 is regarded as great reliability [37]. As shown in Table 1, Cronbach's alpha scores for all factors in the various technologies indicate that all factors received a score more than 0.7, indicating that all factors are highly reliable. While the lowest reliabilities are between 0.697, 0.693 and 0.668 and the highest scores of AV, V2V and V2I reliabilities are at 0.886, 0.890 and 0.871, indicating high reliability for each factor of these technologies.

Table 1. Reliability Test for Model Factors

Test factor (n=191)	Tech	Mean	SD	α
BI	AV	5.13	1.39	0.853
	V2V	5.02	1.46	0.890
	V2I	5.30	1.38	0.868
ATU	AV	5.30	1.39	0.886
	V2V	5.37	1.35	0.885
	V2I	5.47	1.35	0.868
PU	AV	5.00	1.32	0.853
	V2V	5.01	1.34	0.871
	V2I	5.16	1.27	0.830
DC	AV	4.84	1.52	0.697
	V2V	4.92	1.39	0.693
	V2I	5.15	1.38	0.668

PEOU	AV	5.19	1.38	0.877
	V2V	5.23	1.27	0.873
	V2I	5.34	1.25	0.859
INV	AV	5.04	1.37	0.854
	V2V	4.98	1.34	0.872
	V2I	5.10	1.34	0.871
COP	AV	4.76	1.20	0.778
	V2V	4.75	1.14	0.765
	V2I	4.94	1.13	0.749
TR&SF	AV	5.05	1.38	0.7780.77
	V2V	4.99	1.37	2
	V2I	5.10	1.31	0.760

Linearity uses Pearson's correlations or scatter plots. All independent factors show a substantial and positive correlation (P-value 0.001) with the dependent variable, according to the findings of Pearson's correlations test. In addition, as stated by [38], the Pearson's correlation of the

independent variables reveals that none of the independent variables show at 0.90 or higher. This indicates that there are no multicollinearity concerns with the data. Table 2 displays the findings Pearson's correlation test.

Table 2. Pearson's Correlation Matrix for V2V

	BI-V2V	ATU-V2V	PU-V2V	DC-V2V	PEOU-V2V	INV-V2V	COP-V2V	TR&SF-V2V
BI-V2V	1							
ATU-V2V	.810**	1						
PU-V2V	.722**	.776**	1					
DC-V2V	.663**	.672**	.805**	1				
PEOU-V2V	.618**	.734**	.623**	.648**	1			
INV-V2V	.686**	.719**	.729**	.655**	.562**	1		
COP-V2V	.628**	.647**	.623**	.606**	.564**	.650**	1	
TR&SF-V2V	.630**	.721**	.661**	.614**	.555**	.692**	.751**	1

5. Hypothesis Testing Results

Three different stages such as TAM, professional setting and personal attributes were created to test the model hypotheses regarding pervasive computing and TAM.

5.1. TAM

TAM stage effects on attitude towards using by perceived usefulness, and perceived ease of use which were tested in the first section of the model.

Table 3 indicates that the results of the multiple regression analyses show that the model is statistically significant (P value < 0.05). The adjusted R-square, PU was observed to be responsible for 62.1% of the variance in ATU. The results of PU regression analyses show that AV and V2I significantly affected ATU with p-values of (0.007 and 0.008) which are below the level of

significance when p-value < 0.05, while V2V had no significant effect on ATU at p-value of 0.078. Moreover, the standardised Beta coefficients of the model show that V2I was the most influential factor towards ATU with a percentage (33.4%) when compared to AV with a percentage (24.3%).

Additionally, the results of the regression analyses of PEOU show that AV and V2V significantly influenced on ATU. V2I had no significant effect on ATU. In addition, V2V was the most influential factor towards ATU at Beta value (44.1%) when compared to AV at Beta value (30.4%). While the adjusted R-square, PU was observed to be responsible for 58% of the variance in ATU.

Likewise, the results of the regression analyses of ATU towards BI demonstrate that AV and V2I significantly affected BI. However, V2V had no significant influence on BI. Besides, the standardised Beta coefficients of the model show that V2I was the most influential factor towards BI (40.5%) when compared to AV (32.8%).

Table 3. Multiple Regression of Stage 1

Construct	Tech	Beta	P-value	Result	Adjusted R Square
H1 (PU --> ATU)	AV	0.249	0.007	Sig	0.621
	V2V	0.247	0.078	Insig	
	V2I	0.330	0.008	Sig	
H2 (PEOU --> PU)	AV	0.395	0.001	Sig	0.416
	V2V	0.326	0.080	Insig	
	V2I	-0.053	0.760	Insig	
H3 (PEOU --->ATU)	AV	0.325	0.002	Sig	0.58
	V2V	0.434	0.006	Sig	
	V2I	0.030	0.837	Insig	
H4 (ATU --> BI)	AV	0.328	0.000	Sig	0.715
	V2V	0.165	0.120	Insig	
	V2I	0.405	0.000	Sig	

5.2. Professional Setting

The impact of the professional setting on attitude towards using was tested in the model's second stage including on driver context and compatibility, as shown in the (Table 4).

According to the adjusted R square, DC was observed to be responsible for 70.5% of the variance in PU. The results of the regression analyses of DC show AV, V2V and V2I significantly influenced PU. In addition, the results of DC towards PEOU indicate that AV and V2I

significantly affected PEOU. V2V had no significant effect on PEOU. While DC towards ATU had a significant impact on AV and V2I.

Regarding COP towards PU, the results of the regression analyses show that V2V and V2I significantly influenced PU. AV had no significant effect on PU. However, COP towards PEOU shows V2V significantly affected PEOU. AV and V2I had no significant effect on PEOU. With respect to COP towards ATU, the results were only significant for V2V. While AV and V2I had no significant impact on ATU.

Table 4. Multiple Regression of Stage 2

Construct	Tech	Beta	P-value	Result	Adjusted R Square
H5 (DC --> PU)	AV	0.286	0.001	Sig	0.705
	V2V	0.254	0.005	Sig	
	V2I	0.361	0.001	Sig	
H6 (DC --> ATU)	AV	0.381	0.001	Sig	0.559
	V2V	0.193	0.080	Insig	
	V2I	0.232	0.020	Sig	
H7 (DC --> PEOU)	AV	0.290	0.002	Sig	0.45
	V2V	0.112	0.360	Insig	
	V2I	0.324	0.004	Sig	
H8 (COP --> PU)	AV	0.153	0.208	Insig	0.433
	V2V	0.865	0.000	Sig	
	V2I	-0.385	0.007	Sig	
H9 (COP --> PEOU)	AV	0.059	0.655	Insig	0.322
	V2V	0.436	0.021	Sig	
	V2I	0.094	0.546	Insig	
H10 (COP --> ATU)	AV	0.054	0.661	Insig	0.423
	V2V	0.503	0.004	Sig	
	V2I	0.113	0.431	Insig	

5.3. Personal Attributes

The third part of the model examined the stage effect of personal attributes stage including trust&safety and innovativeness which influence driver context, compatibility, and attitude towards using.

Table 5 indicates The results of the regression analyses of TR&SF show that AV and V2V significantly influenced DC. Moreover, TR&SF demonstrates AV, V2V and V2I had significant impact on COP.

Finally, Table 5 also indicates essential findings of TR&SF towards ATU, which had a significant influence

on AV and V2V, in contrast that there was only a significant impact on ATU by V2V in terms of INV.

Table 5. Multiple Regression of Stage 3

Construct	Tech	Beta	P-value	Result	Adjusted R Square
H11 (TR&SF --> DC)	AV	0.265	0.007	Sig	0.459
	V2V	0.299	0.021	Sig	
	V2I	0.158	0.197	Insig	
H12 (TR&SF --> ATU)	AV	0.268	0.003	Sig	0.541
	V2V	0.352	0.003	Sig	
	V2I	0.162	0.152	Insig	
H13 (TR&SF --> COP)	AV	0.298	0.000	Sig	0.619
	V2V	0.300	0.006	Sig	
	V2I	0.240	0.021	Sig	
H14 (INV --> DC)	AV	0.245	0.073	Insig	0.472
	V2V	0.372	0.023	Sig	
	V2I	0.096	0.469	Insig	
H15 (INV --> COP)	AV	0.238	0.091	Insig	0.440
	V2V	0.178	0.289	Insig	
	V2I	0.279	0.041	Sig	
H16 (INV --> ATU)	AV	0.154	0.224	Insig	0.547
	V2V	0.424	0.005	Sig	
	V2I	0.188	0.126	Insig	

5.4. Theoretical Model Developed

Figure 2 displays the V2V results as an example of the regression analyses, indicating that compatibility variable indicated the strongest significant positive effect on PU and ATU variable, as can be seen by its Beta value of 0.865 and 0.503. While V2I also indicated the highest

significant positive effect was between ATU and DC towards BI and PU with Beta values 0.405 and 0.361. Whereas AV results found that the variables PEOU and DC demonstrated a statistically significant positive influenced towards PU and ATU with Beta values 0.395 and 0.381.

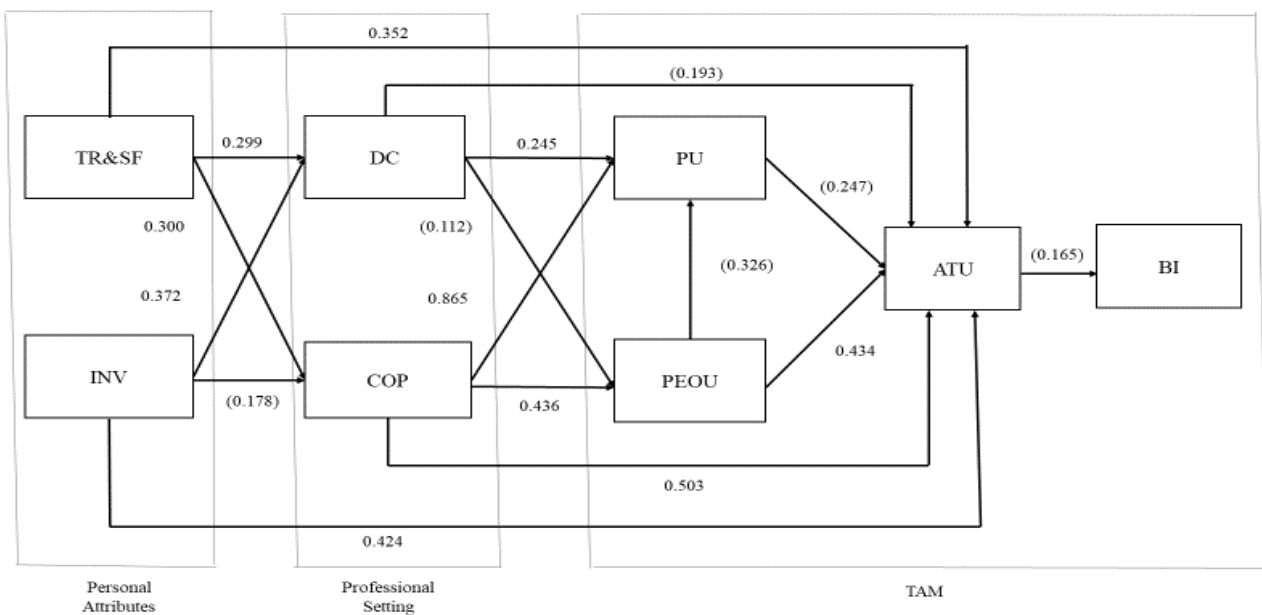


Figure 2. Regression Analyses with Beta Value for V2V

5.5. Segmentation basing on Users' Age Groups

Figure 3 shows that PEOU and TR&SF were influenced by the results of the level of significance at (p

< 0.05) for autonomous vehicle technologies on different age groups that were analysed using ANOVA.

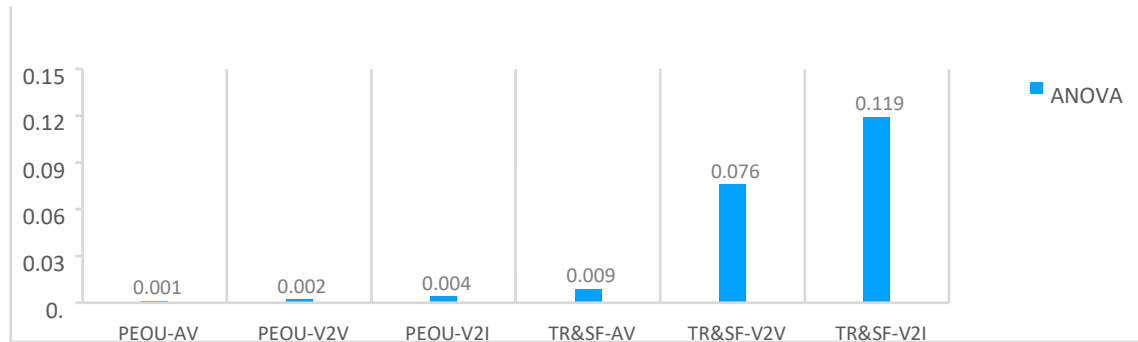


Figure 3. ANOVA of Age Group

As shown in the (Table 6) that the results of the Post Hoc test using Tukey HSD, in terms of PEOU and TR&S in different age groups. The following table shows the results for PEOU at the level of significance at ($p < 0.05$) in different age groups for AV, V2V, and V2I. While V2V and V2I regarding TR&SF show different results, which are no significant at different age groups, which p -values > 0.05 .

Table 6. Tukey HSD of Age Group

Dependent Variable	Age group 1	Age group 2	P-value	Result
PEOU-AV	18-24	25-34	0.019	Sig
PEOU-AV	35-54	25-34	0.001	Sig
PEOU-V2V	18-24	25-34	0.010	Sig
PEOU-V2V	35-54	25-34	0.002	Sig
PEOU-V2I	18-24	25-34	0.045	Sig
PEOU-V2I	35-54	25-34	0.004	Sig
TR&SF-AV	35-54	18-24	0.007	Sig
TR&SF-AV	35-54	25-34	0.044	Sig
TR&SF-V2V	35-54	18-24	0.062	Insig
TR&SF-V2V	35-54	25-34	0.571	Insig
TR&SF-V2I	35-54	18-24	0.075	Insig
TR&SF-V2I	35-54	25-34	0.506	Insig

6. Discussion

The literature relates to pervasive computing is supported with the results of this study where both professional and non-professional drivers' respondent's data indicate that driver context supports well across the three technologies of AV, V2V and V2I by showing a positive effect on most variables (especially TAM). As stated by [39] under adverse driving conditions, the

accident rate of AVs was high when visibility was low, however, [26], require that sighting distances are 10 to 40 meters shorter for AVs than for conventional vehicles to avoid any possibility of accidents. Furthermore, [40] noted that driver inattention and vehicle automation interact in a complex way and must be considered when designing future vehicles.

Further, this study shows that the results of compatibility differed in the effects on TAM, indicating positive support with V2V but not for AV and V2I which support the finding of [41] that established a positive relationship between compatibility, attitude, perceived usefulness, and intention to use. According to a piece of research done by [42], compatibility greatly determines PU and BI. [43] discovered that those who utilise driver assistance systems are more inclined to embrace AVs, implying that the user's previous behaviour will predict their future behaviour intentions. Nevertheless, the influence of the compatibility and driving context constructs on the TAM constructs is ambiguous, according to [27], and further study is required [43].

Regarding the TAM stage of this study, it shows a strong positive influence in particular H1 to H4 which agrees with the studies [15] related to PU, PEOU and ATU for independent AV. While differences between V2V and V2I technologies can be seen in the influences of H1 to H4. On the other hand, there was a positive effect in terms of PU and ATU, unlike PEOU concerning V2I. This further research supplements the extent literature concerning a gap between respondents' willingness to use technology and their actual ability to do so [15].

Additionally, trust and safety have a positive influence on DC and ATU, and also indicates that the participants believe that AV and V2V can provide more convenience in its use and more reliability. This contributes to the research gap identified by [44] who believed that the subject is not sufficiently developed and the public lacks understanding. Across all the respondents the influence of personal innovativeness is supported for V2V in terms of DC and ATU, whereas the factor was unsupported for AV and V2I. These results concern the personal attitudes stage as discussed by [43] paper states that autonomous driving is perceived as less secure than human driving.

7. Conclusion

Our study shows that the three stages of the theoretical framework identified differences in the adoption factors for AVs towards V2V and V2I technologies. The importance of the factors for the different technologies will help automotive manufacturers to focus on the key areas that concern users and need to be addressed during car design.

The theoretical framework of three stages is a key output from this research where Stage 1 (TAM) is focused on well-established adoption factors; Stage 2 (Professional Setting) comprises key contextual factors concerning autonomous driving and Stage 3 (Personality Attributes) takes into consideration user characteristics and technology attitudes.

The results from the survey of professional and non-professional drivers indicates that attitudes to autonomous driving vary according to age and driver context which signifies the relevance of pervasive computing as an underlying theoretical basis.

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