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Empirical Analysis of Barriers Affecting User Adoption of Autonomous Vehicles

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Empirical Analysis of Barriers Affecting User Adoption of Autonomous Vehicles

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DECLARATION

I, Mohammed Lawal Ahmed declare that this thesis is my own work and has never been previously submitted for the award of a degree or diploma in any institution either by myself or anyone else.

Every part of this thesis which contains other materials have been dully acknowledged and referenced where necessary.

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DEDICATION

This research work is dedicated to:

The memory of my father, Alhaji Mikail Ahmed, who pushed me to embark on a PhD degree, but sadly, didn’t live to see me finish.

The memory of my father in-law, Engr. M. B. Momoh, who was part of the journey when it started and was particularly interested in my research but departed before I got to the finished line.

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ABSTRACT

This research seeks to investigate the inherent concerns held by future users of AV by conducting a multi-population survey to obtain how their specific concerns will affect the uptake of AV. An 11-point Likert scale survey instrument with 34 items questions was developed and distributed using different online channels to targeted road users in the UK. The survey population, a total number of 235 people, belong to different demographic segments of road-user population. An initial data processing and analysis was conducted using the SPSS statistical tool to examine the various components of the data based on demography. The pre-analysed data were modelled using machine learning algorithms and fuzzy logic inference tool in MATLAB/Simulink to develop a Fuzzy Logic Autonomous Vehicle Adoption Model (FLAVAM). The data was divided into training and testing sets according to the different categories of concerns held by each user. From the review of literature, safety, trust, privacy, accessibility, and ethics were identified to act as the most predominant concerns that will affect the adoption of AV.

There are several contributions of this research; firstly, the research identified and quantified the impact of diverse causal factors on the adoption of autonomous vehicles and the effect of perceived causal factors on user degree of adoption. Secondly, computational model was developed based on user opinion and perception, which supports effective visualisation of relationship between user adoption and the causal factors under investigation. Thirdly, a custom fuzzy logic model to forecast user adoption of autonomous vehicles which achieved superior performance compared to standard machine learning techniques.

The FLAVAM model provides a new understanding of how inherent/perceived concerns affect the degree of AV adoption autonomous vehicles.

Keywords – autonomous vehicles, technology acceptance and adoption, fuzzy logic, machine learning

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ACRONYMS

ACES	Autonomy, Connectivity, Electrification and Sharing
AV	Autonomous Vehicles
AVAM	Autonomous Vehicle Acceptance Model
CACS	Comprehensive Automobile Traffic Control System
CCAV	Centre for Connected and Autonomous Vehicles
CVM	Contingent Valuation Method
DARPA	Defence Advanced Research Project Agency
DIT	Diffusion Innovation Theory
EDI	Electronic Data Interchange
ELROB	European Land Robot Trials
ERGS	Electronic Route Guidance System
ERC	European Research Council
EU	European Union
FIS	Fuzzy Logic Inference System
FLAVAM	Fuzzy Logic Adoption Models of Autonomous Vehicles
FTC	Future Transport and Cities
IEEE	Institute for Electrical and Electronic Engineers
IVHS	Intelligent Vehicle Highways Systems
IT	Information Technology
ITS	Intelligent Transport Systems
GPS	Global Positioning System
HAVEit	Highly Automated Vehicles for Intelligent Transport
KMO	Kaiser Meyer Olkin
LIDAR	Light Detection and Ranging
MAE	Mean Absolute Error
MIMO	Multi-Input Multi-Output
MIQ	Machine Interface Quotients
MIS	Management Information Systems
MISO	Multi-Input-Single-Output
MLP	Multilayer Perceptron
MOD	Moving Object Detection
MOT	Movable Object Tracking
MTurk	Mechanical Turk (Amazon)
NHTSA	National Highway Traffic Safety Administration

NNSFC	National Natural Science Foundation of China
PCS	Pre-Crash Safety
PAV	Private Autonomous Vehicle
PBC	Perceived Behaviour Control
PROMETHEUS	Program for EU Traffic System with Higher Efficiency and Unprecedented Safety
PTAV	Public Transport Autonomous Vehicle
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
RACS	Road Automobile Communication System
RADAR	Radio Detection and Ranging
R&D	Research and Development
RMSE	Root Means Square
SAE	Society of Automotive Engineers
SAV	Shared Autonomous vehicle
SCAS	Self-driving Car Acceptance Scale
SISO	Single-Input-Single-Output
SPSS	Statistical Program for Social Science
TAM	Technology Acceptance Model
UK	United Kingdom
UNEP	United Nation Environmental Protection
UTAUT	Universal Theory of Acceptance and Use of Technology
TRA	Theory of Reasoned Action
TPB	Theory of Planned Behaviour
WEF	World Economic Forum
WEKA	Waikato Environment for Knowledge Analysis
WHO	World Health Organisation
WTP	Willingness to Pay
WTA	Willingness-to-Accept
XCON	Expert Configuration

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CHAPTER ONE

INRODUCTION

1.1 INTRODUCTION

In the last decades, efforts to disrupt the traditional mode of transport have begun to yield results capable of changing the entire landscape of transportation and mobility. The movement of passengers, goods and services in the last century has begun to face unprecedented challenges due to some associate problems which includes traffic congestions, vehicle collisions and greenhouse gas emissions. For instance, in many parts of the world, the annual cost of traffic congestion is estimated in several billion US Dollars in economic losses. In the US alone, traffic congestion cost the economy about $88 billion in 2019 with an average per driver at $1,377 (McCarthy, 2020). It is projected to increase to $2.8 trillion with each driver losing $2,300 by 2030 (INRIX, 2014). The UK is no different; the economy loses of traffic congestion was estimated at £6.9 billion in 2019 with an average of £894 loss per driver (INRIX, 2019). One of the major problems associated with human driving is reckless and drink-driving. According to World Health Organisation an estimated 1.3 million people die of vehicle accidents every year due to reckless driving, while another 20 – 50 million people are injured costing about $500 billion to the global economies (WHO, 2017). Until recent history, nearly all vehicles were powered by fossil fuels. Global emissions from fossil fuels continue to increase with an attendant increase in the use of motorised vehicles (Albuquerque, et al., 2020). Fossil fuels from vehicles release harmful greenhouse gasses that cause atmospheric changes (Clarke and Ainslie, 2019). In the US, transportation accounts for nearly 29 percent of all greenhouse gas emission (EPA, 2019). Similarly, in Europe, road transport accounts for nearly 72 percent of all greenhouse gas emissions (EEA, 2019).

The problems associated with conventional vehicles have become a major worry which has provoked radical approach towards the future of transport and mobility. Therefore, numerous initiatives to minimise the negative consequences of conventional vehicles have propelled the development of more sustainable mode of transport for the next century. The introduction of autonomous vehicles (AV) on city roads has become one of the considerations by several research and development institutes, automotive manufacturers, and the academia and recently city planners have joined the fray to curtail the problems associated with conventional vehicles. Although, autonomous driving is still at the initial stage of development, it has been acclaimed to be one technology with significant potentials to impact urban mobility. The research community affirms that autonomous driving is a mobility option that will reduce traffic congestion, accidents and pollution whilst increasing access to mobility and efficient utilization of transportation infrastructures (Fagnant and Kockelman, 2015; Litman, 2015; Bagloee et al., 2016; Baruch, 2016; Bonneau et al., 2017; Bosch, 2018; Zhao et al., 2018). From the development in the automotive industry and major IT companies, autonomous vehicles are expected to be in practical use within the next decade (Nakagawa et al., 2017; Bagloee et al., 2016). Since the Defence Advanced Research Project Agency (DARPA) challenge and Google's self-driving vehicle trials, many automotive companies, research institutions, governments, and IT companies have been stimulated to join the race in bringing autonomous vehicles to the market. The KPMG (2018) report on business marketing strategies for automobile companies forecasted that there will be an increased yearning for innovative mobility solutions which takes into consideration improved safety and security features, weather sensing applications, as well as leisure and premium experiences in the near future. These reports and others such as that of Statista on promotional marketing are pitching the potential demands for autonomous vehicles.

However, autonomous vehicle is likely to suffer some impediments arising from scepticism towards the new technology. As often the case with every new technology, a large proportion of the public always demonstrates a certain level of distrust and resistance based on inherent concerns. According to Bansall et al. (2016) these concerns will be principal impediments to the adoption of autonomous vehicles. To safely travel from origin to destination over a distance autonomously on public roads continues to generate debates amongst the general public. In spite of the numerous discussions, interests and optimism on autonomous vehicles, there are still divergent opinions concerning substituting human driving. Safety and security concerns as well as remarkable increase in the costs of acquisition may hinder user acceptance (Bonneau et al., 2017). Several automotive manufacturers, high-tech companies, policy organisations and research institutions agree that these apprehensions are warranted; as such, they will determine the success or failure of autonomous vehicles (UMTRI, 2015, AAA foundation, 2016; Maurer et al., 2016; KPMG, 2018).

Literature is replete with studies on autonomous vehicles and user acceptance, however, most of these studies are majorly promoted by consulting firms or government sponsored studies (McKinsey, 2019; KPMG, 2018). The debate has therefore generated several questions and concerns regarding the new technology. Security, safety, ethics, and privacy are some of the areas raising significant concerns. The purpose of this research is to examine the conditions under which autonomous vehicles will be accepted by the general public. The research will provide the background understanding on the main factors that will impact the adoption of autonomous vehicles which will be relevant to policy makers, government, and automotive manufacturers.

1.2 RESEARCH AIM

The advent of autonomous vehicles as a future means of mobility will impact drivers, pedestrians, and other road users. Therefore, their acceptance will be determined by the perception of users based on several factors. The aim of this research is to examine the barriers that are likely to affect the adoption of autonomous vehicles by users based on perceived concerns. This research models the various concerns using machine learning approaches. To achieve the research aim, the research focused on the following objectives presented in section 1.3:

1.3 RESEARCH OBJECTIVES

1. To conduct in-depth critical analysis of autonomous driving technologies and state-of-the-art approaches.
2. To examine the barriers concerning the adoption of autonomous driving technologies from road users.
3. To perform a user study in order to examine the adoption of autonomous vehicles by road users.
4. To apply machine learning to user stated preference to build autonomous vehicle adoption model.
5. To evaluate the model using proven evaluation techniques

1.4 RESEARCH QUESTIONS

To achieve the research objectives, the following research questions have been formulated:

1. What factors influence user adoption of autonomous vehicles?
2. How will these factors determine the level of adoption of autonomous vehicles?

1.5 RESEARCH PROBLEM

Global estimates project that by 2035, there will be about 2 billion vehicles around the world, with majority of them being in cities (Voelcker, 2014). Many cities across the world are faced with the problems associated with conventional vehicles such as traffic congestion, accidents and environmental pollution which are due to numerous people trying to provide their own mode of transportation. As the population of cities continue to grow, there is a concomitant increase in the number of vehicle ownership. It is projected to become further exacerbated considering the predictions that more people would relocate to the cities leading to severe consequences on the economy, environment, and social aspects of cities.

Mobility in today's world is undergoing considerable changes as a result of technologies which affect the ways inhabitants and goods move between locations. According to McKinsey (2019) report, Autonomy, Connectivity, Electrification and Sharing (ACES) are the major components of future mobility. However, the current conventional mobility options have become unsustainable considering the problems of land use, accident, congestion, and pollution associated with them (Fagnant and Kockelman, 2013; Paden et al., 2016). Studies have presented some interesting results concerning conventional vehicles and their uses (Morris, 2016; RAC Foundation, 2012). These studies reveal that 95 percent of the times, vehicles are packed; with only 5 percent utilization. Same studies revealed that 95 percent of road accidents are caused by human errors and road transport contributes about 25 – 30 percent of greenhouse gas emission. Personal mobility is therefore faced with unprecedented disruptions based on these recent research and developments in the automotive industry.

Several efforts are currently being focused on the production of entirely autonomous vehicles using artificial intelligence, sensors, and cameras as well as positioning technologies that will remove the control of vehicles from the hands of human drivers. Some modern vehicles have begun to embed different forms of autonomous technologies such as adaptive cruise control, lane change assistance, steering automation, and self-parking features. However, the aim is to make vehicles completely autonomous and independent of human drivers in the future. The champions of driverless cars argue that these technologies foretell several benefits for different categories of users such as the elderly, disabled and other excluded segments of the public (Kyriakidis et al., 2015; Kaur and Rampersad, 2016). For example, mobility of the elderly and the disabled is currently limited due to the complexities involved in the current transportation alternatives. By 2030, it is projected that nearly 74 million people will be over the age of 65 and many elderly drivers voluntarily relinquish their drivers' licence when they become cognisant of their weakening ability to drive due to age, illness, and disability. (Huff et al., 2019; Lutin et al, 2013). These groups of people still have mobility needs that must be fulfilled, but their mobility needs are currently underserved. However, the advent of autonomous vehicles will transform the lives of those currently unable to maximise the full potential of mobility due to physical impediments.

Despite the promises of driverless cars, major reservations bordering on the readiness of the public to adopt this technology have revealed critical concerns. These relate to safety, security, trust, privacy, ethics, liability, and others. These are major concerns that are equally important to the technology itself. Daimler and Benz Foundation, one of the major stakeholders in the automotive industry states that the automation of vehicles by itself is insufficient to realize automated driving on city roads as intended by different stakeholders in the transport, automotive and mobility industries (Maurer et al., 2016).

1.6 RESEARCH MOTIVATION

The autonomous vehicle has recently become one of the most widely discussed topics by various stakeholders in the transportation industry, automotive manufacturers, research community, technology companies, government, and policy think-tanks. Recent developments in the automotive industry starting from the DARPA challenge and Google driverless car trials have altered automotive technology forever resulting in a projection to put cars with autonomous driving capabilities on the road before 2025. In a bid to be part of the AV revolution, numerous companies in the automotive, technology, research and government establishments have continued to expend resources in research and development, policies as well as infrastructures. Bagloee et al. (2016) contend that major car manufacturers and IT companies have invested around €77 billion in autonomous technologies to gain market-leading advantages and remain competitive. According to market forecast, there are enormous market potentials in AV technologies which is estimated to be around $200 billion leading to $1.9 trillion USD from 2025 if an average of 15% of all vehicles becomes fully or semi-autonomous (Manyika et al., 2013). By 2040, AVs are predicted to make up about 50 % of vehicle sales, 30 % of all vehicles plying urban roads and 40 % of all travels on the motorway.

The adoption of any new technology is always fraught with uncertainties and anxiety on the part of users due to inadequate knowledge and information. In most cases, the decisions to adopt are made under non-deterministic conditions. Several frameworks have been developed to support new technology adoption according to aspects of human behaviours. Extensive works have been conducted in the adoption and acceptance of technologies; prominently amongst the several works are Diffusion of Innovation (Rogers, 1962); Theory of Reasoned Behavior (Fisherben and Ajzen (1975); Technology Acceptance Model (Davis, 1986); Technology Implementation Process (Leonard-Barton, and Deschamps, 1988); Theory of Planned Behavior (Ajzen, 1991); Unified Theory of Acceptance and Use of Technology (Venkatesh, 2003). Further research studies have been derived from these pioneering works on the acceptance and adoption of different technologies including mobile and smartphones (Park and Chen, 2007; Hubert et al., 2017); automated teller machine and e-banking (Lee, 2009; Lai and Zainal, 2015; Lai, 2016;); e-learning (Cheung and Vogel, 2013; Tran, 2016); e-government (Lin et al., 2011; Rana and Dwivedi, 2015); e-commerce (Guzzo et al., 2014; Biswas and Mishra, 2019); e-health (Ward, 2013; Maillet et al., 2015); electric vehicles (Abouee-Mehrizi and Chen, 2018; Park et al., 2018); smart home technologies (Yang et al., 2017; Hubert et al., 2019); self-service technologies (Blut et al., 2016).

Heffner et al. (2007) contend that every technology has a problem of acceptance, which will not be different for autonomous vehicles. The events surrounding the automobile and technology industries suggest that CAVs are the future of mobility; it is therefore imperative to plan for the eventual consequences by recognizing the challenges of user adoption which are likely to act as barriers to the potential opportunities. Autonomous vehicles have the potential to disrupt not only the automotive industry, but also the way cities function. Therefore, understanding and analysing the triggers for adoption (or non-adoption) will successfully guide the successful introduction into the marketplace.

1.7 RESEARCH GAP

In a survey conducted in 2014 by the Institute for Electrical and Electronic Engineers (IEEE), the foremost global professional body for the advancement of technology, more than 200 experts on autonomous vehicles concluded that the three biggest obstacles for driverless cars to reach mass adoption are government regulations, legal liability and user acceptance

(Rosenzweig and Bartl, 2015). The physics and engineering of autonomous vehicles is an area of research which has begun to trigger the interests of researchers. However, studies based on user perception, acceptance and adoption are relatively new research discipline yet to gain the required prominence. Understanding the interaction between users and autonomous driving has become a crucial research component within the Connected and Autonomous Vehicles (CAV) discipline (Hengstler et al., 2016; Jafary et al., 2018; Penmetsa et al., 2019). Several studies which have investigated user acceptance and adoption of AV adopted the generic technology acceptance models (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) as test models based on socio-demographic and socio-economic factors (Kaur and Rampersad, 2016; Koul and Eydgahi, 2018; Hewitt et al., 2019). Some others are descriptive and opinionated but lacking rigorous scientific exploration (Penmetsa et al., 2019; Nordhoff et al., 2018; Konig and Neumar, 2017; Bansall et al., 2016; Schoettle and Sivak, 2014; Lavasini et al., 2016). Although, most of these studies have provided relevant contributions towards understanding acceptance of autonomous vehicles upon which this research gained initial background knowledge.

This research aims to collect data from potential drivers and road users regarding their perception and adoption of autonomous vehicles. The focus is to identify varying potential barriers that affect user adoption of AV by taking multiple factors into consideration. Current research investigates the subject against the background that users are acquainted with AV technologies due to its popularity in the news media, industry event and automobile shows. This research conducts a survey of different road users to investigate the topic from their perspective based on different factors facilitating adoption. Most research on acceptance of AVs have been conducted with respect to either demographic, economic or one of the different indicators of either ethics, safety, privacy, or trust (Litman, 2015; Bansall et al., 2016; Lavasini et al., 2016). This research attempts to use demographic indicators whilst measuring the concerns of potential users against a combination of indicators. The data generated from this research are analysed using multiple tools, SPSS, WEKA, and fuzzy logic (artificial intelligence) algorithm which helps in modelling decision-making to develop insightful knowledge aimed at stimulating the emerging AV technologies.

This research aims to identify adoption category according to user preference which would provide a profound understanding of the barriers based on a multi-population user relevant to the future development of the AV adoption discipline.

1.8 RESEARCH SCOPE

Autonomous vehicles have been touted as one solution in tackling the problems arising from the use of conventional vehicles. However, being a new technology, it will require general acceptance as a mobility option by users. At this nascent stage of its development, there are general concerns and apprehension regarding autonomous technologies. Some of these concerns have to do with the safety and reliability of the technologies. In addition, security, privacy, trust, ethics, cost, and a host of other considerations are equally competing for users' attention.

It is projected that in the next decade, tangible improvement will have been made in advancing driverless cars as an option for mobility in cities. To achieve this reality, the driving public will have to jettison vehicle ownership and adopt the technology. The scope of this research is to investigate the literature on the intended use and adoption of autonomous vehicles as a mode of transport in the future. From the literature, vehicle users and city dwellers have begun to express some concerns regarding the impending technology. This research evaluates those concerns which are expected to act as obstacles to the adoption and acceptance of the technology. Part of the research scope is to investigate the readiness of the public to adopt autonomous vehicles as a replacement alternative for conventional vehicles despite the general concerns. A quantitative data collection approach is adopted in collecting user data via a web-based multi-population survey administered to the public. The responses obtained are essential in addressing the research questions.

The research data collected examined various components related to the concerns that have the potentials to affect the adoption of autonomous vehicles and the results are analysed using statistical tools, machine learning algorithms in WEKA and fuzzy logic in MATLAB/Simulink. The model is evaluated using a 5-fold cross-validation technique and the performance accuracy of the models reveals a significant association between the variables.

1.9 RESEARCH CONTRIBUTIONS

This research contributes to the body of knowledge in autonomous vehicles adoption specialization. The research findings indicate that autonomous vehicles will face adoption and acceptance challenges. This research therefore contributes to knowledge by:

a. Identifying and enumerating the impact of diverse causal factors on the adoption of autonomous vehicles.

b. Understanding the effect of perceived causal factors on user degree of adoption.

c. Computational modelling of expert and user opinion; and support effective visualisation of the underlying relationship between user adoption and the causal factors under investigation.

d. Applying custom fuzzy logic model able to account for the uncertainty and noise in user opinion data.

2.0 SCHEMATIC DIAGRAM FOR THIS RESEARCH

This research set about investigating the adoption of autonomous vehicles from the perspective of road users including drivers, commuters, pedestrians, cyclists and the general members of the public who will be affected by the advent of AV. This requires that opinion, attitudes and behaviour data are collected from users and a model of adoption predicted from their perception and stated intention. The schematic diagram in figure 1 below shows the procedures adopted in actualizing the research objectives and questions.

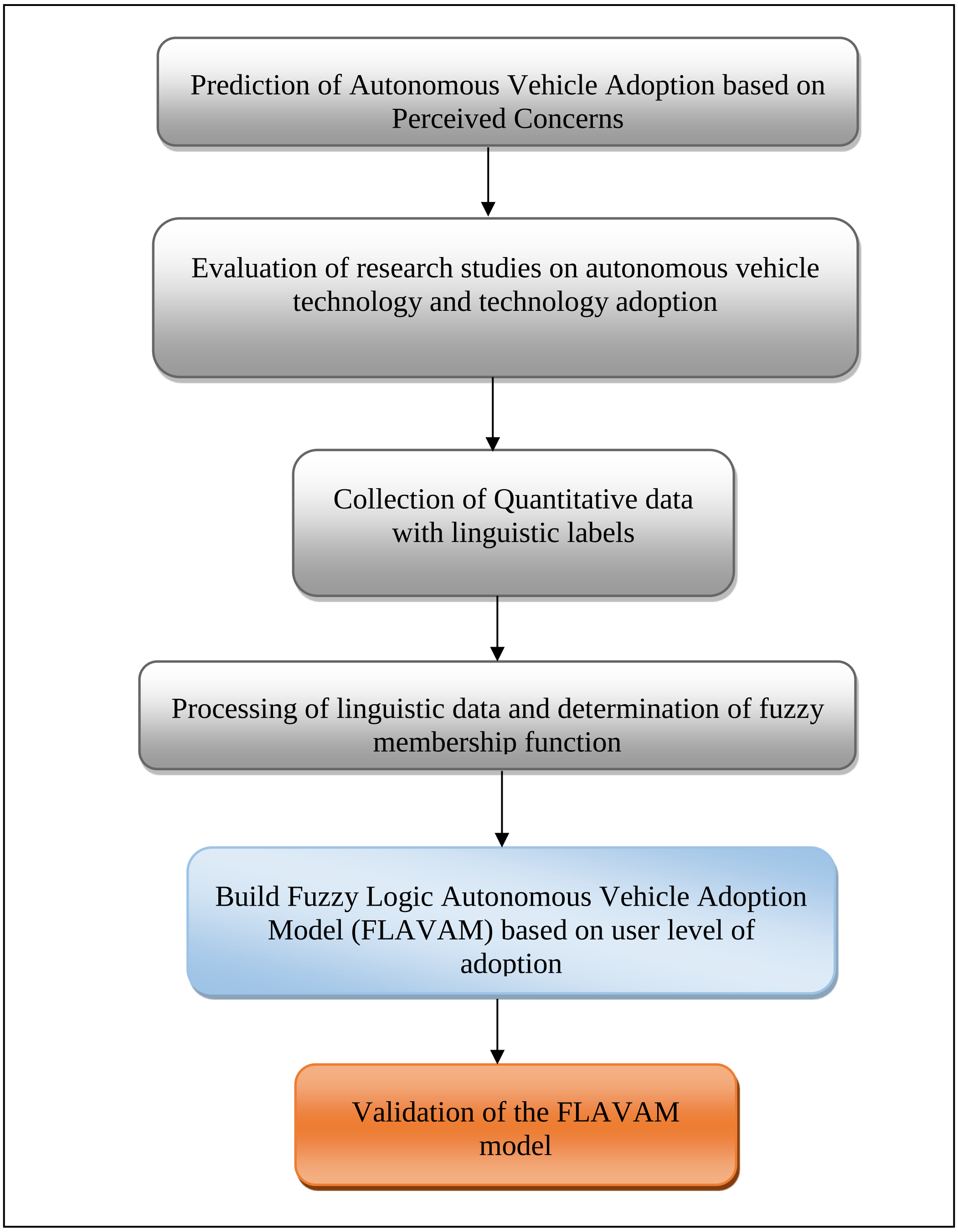

Figure 1: Schematic diagram of research model development

2.10 THESIS OUTLINE

This thesis is conducted to achieve specific objectives and examine research questions. The entire thesis is segmented into 7 chapters.

Chapter one presents an extensive introduction of the research which sets the background for the entire research by discussing the various research components. The chapter presents the aim and objectives of the research, research questions, research problem, motivation, gaps, scope, and contributions of the research.

Chapter two – literature review, presents an elaborate description of the trends and themes within the research discipline of autonomous vehicles as a subset of intelligent transport. It presents the works of other researchers in the academia and industry to provide a robust understanding for readers on the contemporary issues in autonomous vehicle and its adoption.

Chapter three – discusses theories of acceptance and adoption of technologies, previous studies in technology acceptance are discussed according to different pioneering works in user behaviours and attitudes towards new technologies. This chapter also provides literature review of studies in the acceptance of autonomous vehicles based on the findings of various authors to provide this research with the research gaps and directions.

Chapter four – presents the research methodology, provides the rationale behind the philosophical underpinning of this research methodology. In this chapter, the steps undertaken in population sampling, pilot design and method of data collection are discussed.

Chapter five – data analysis and research findings are presented in this chapter. This chapter presents the preliminary descriptive data analysis of the sample, the demography and data distribution. The chapter also provides answers to some of the research questions and the testing of preliminary machine learning models

Chapter six – in this chapter, fuzzy logic is discussed, and the major component adopted in building the adoption model in this research are presented. This chapter presents the evaluation of linguistic terms as a function of reasoning and perception in human interaction. In this chapter, the IF-THEN rules of antecedents and consequents in human reasoning are presented. The chapter discusses the fuzzy logic AV adoption model by predicting AV adoption model using (FLAVAM). This chapter provides the conceptual FLAVAM model based on user adoption which is determined by inherent and stated preference of each respondent. The chapter also presents the limitation of the model.

Chapter seven – the conclusion and recommendations of the thesis are presented in this chapter and areas of possible future research directions.

CHAPTER TWO

LITERATURE REVIEW

2.0 INTELLIGENT TRANSPORT SYSTEMS

2.1 INTRODUCTION

Transportation plays an important role in the lives of people on a daily basis in ways which affects their socio-economic activities thereby making it a fundamental aspect of cities. Therefore, it must be efficient, convenient, safe and environmentally sustainable. On one hand, the growth in population and the continuously dwindling budgetary allocation of most cities has opened up new ways of thinking about transportation using technology. On the other hand, city dwellers have become increasingly more mobile, demanding real time information regarding transport as well as the expectation for goods and services to reach their point of consumption as soon as they are produced. In a bid to address these societal changes, efforts are being made to continuously manage the problems facing transportation networks. One way to achieve these is the application of intelligence using computer technologies, sensors, and satellite communication in transportation systems.

2.2 INTELLIGENT TRANSPORT SYSTEMS

According to Grant-Muller and Usher (2014) the integration of information and communication technologies within transportation infrastructure is collectively known as intelligent transport systems (ITS). Wang et al. (2017) considers ITS as the toolbox where cutting-edge technologies are collectively deployed within the transportation network. Evidence from real life projects has been ascertained that ITSs are transport technologies that use advanced ICT to achieve reduction in accidents, congestions, and increased safety (Coronado et al., 2012). Therefore, the adoption of ITS in cities has become commonplace such that highways, bus stops, parking and toll gates are replete with ITS applications. It is projected that ITS will transform the entire landscape of transportation from design, operation, and consumption.

ITS has evolved over the years through different stages from the 60s starting in Japan with Comprehensive Automobile Traffic Control System (CACS); then the Electronic Route Guidance System (ERGS) from the United States; Autoguide from the UK and ALI-SCOUT from Germany (Giannopoulos et al., 2012; Ersoy, and Boruhan, 2015). The major focus of these initiatives was on route guidance and transport data processing. By the turn of the 80s congestion became a major challenge for most developing countries and this gave way to Road/Automobile Communication System (RACS) and Intelligent Vehicle Highways Systems (IVHS). These initiatives gave birth to present day navigation system. As ITS gained popularity, integrated research projects such as the Program for EU Traffic System with Higher Efficiency and Unprecedented Safety (PROMETHEUS) was established in partnership with auto manufacturers, researcher centres and universities (Catling, 1994 cited in Ersoy and Boruhan, 2015). In the 90s, the European community established the Dedicated Road Infrastructure for Vehicle Safety (DRIVE I and DRIVE II) intended to promote road transport and advanced transport telematics (ibid). Between 2000 and 2010, government and highway operators invested massively in most ITS projects such as communication systems, data collection equipment, digital mapping, control centres and other crucial equipment to build public ITS infrastructures (Wang et al., 2017; Wang et al., 2006). The expansion in ITS infrastructures continued to grow with respect to new business models in the transport, mobility, and automobile industries in the areas of driverless cars, autonomous vehicles, electric vehicles, ride and share. It is expected that from 2020, the proportion of ITS will increase significantly to meet market driven requirements (Walker, 2015).

Generally, the whole spectrum of information technology has been instrumental to the development in ITS driven by the abundance of data in every aspect of modern-day cities (Zhu et al., 2018; Ngo, 2017; Zhang et al., 2011). Data from GPS receivers, traffic sensors, smart cards, CCTV footage, social media, inductive-loop, and many other data sources readily provides data for ITS for superior transportation information services. Zhu et al. (2018) contend that the amount of data generated for ITS has moved from terabyte to petabyte which can only be processed using data analytics tools. Several systems within the ITS range collect and process huge amount of data to provide relevant information for traffic management, route prediction, journey patterns, accidents as well as transportation assets for decision and policies. Grant-Muller and Usher (2014) believes that the increase in internet connectivity and ubiquitous computing has powered most ITS applications aimed at tracking movements across the transportation channel, capture and process information, and then communicate the information in real-time to transport users and/or traffic managers, thereby facilitating efficient transportation networks. The information may usually be diverse to assist drivers and/or riders to make informed alternatives whilst travelling within the transportation network.

In recent times, more attention has been given to the use of ITS technologies in developed countries to improve their transportation network (Wang, et al., 2017). The application of ITS in transportation in cities includes, but not limited to, traffic lights, traffic control centres, navigation systems, payment and ticketing platforms, safety, controls and others. ITS continues to play significant role in transport telematics by providing new services for passengers, drivers and public administrators with real time information of traffic infrastructure, capacity utilization and maintenance needs. For example, Gordon (2012) used the daily smart card records of passengers from London Metro and iBus vehicle location system to obtain the boarding, alighting and transfer information of passengers regarding their trips on the various public transportation types. The author then established complete journey matrices from the data which were authenticated by traditional origin – destination matrices.

2.3 THE CHANGING NATURE OF MOBILITY IN FUTURE CITIES

Even though cities occupy only about 2 percent of the total global geographic space, they currently accommodate nearly 50 percent of the global population (La Greca and Matrinico, 2016). Urban population currently consumes almost 80 percent of global energy produced, contributes up to 75 percent of carbon emission and natural resources (UNEP, 2013 cited in Zvolska et al., 2018). This requires new thinking in terms of managing land resources, infrastructure, and the environment in an efficient and sustainable manner. The new paradigm of smart and intelligent cities which requires the unlimited utilization of smart technologies to power different aspects of city living, emphasises the automation and use of less resources. According to Zvolska et al. (2018) one concept that has generated different interests in future cities is the sharing economy. In an EU working paper presented by Gori et al. (2015) they contend that cities are a natural atmosphere for sharing economic services which focuses on the interests of users, proximity and availability driven by connectivity and enabling technologies.

Mobility has always been at the centre of human interaction whilst technology plays critical influence for economic and social engagement within the wider society. Mobility is not only about the movement of people, goods, and services, but also the movement of ideas from one point to another. According to McKinsey Quarterly report, mobility in future cities will be driven by four key developments and trends; tagged – ACES: Autonomous driving, Connectivity, Electrification of vehicles and Shared mobility (McKinsey, 2019). The report suggest that the revolution of future mobility has the potential to disrupt the entire landscape of transportation including ancillary services and value chain. The main focus for the future is the association of mobility with an assortment of positive societal benefits such as a safer transport system, sustainability, reduced cost as well as enabling an extended degree of mobility for the non-ambulatory – disabled and elderly as well as to those within the lower economic brackets of the society.

Autonomous driving being amongst the major disruptions in the mobility and transportation engineering possess the potential to change the entire transportation landscape in the next decade compared to the previous centuries (Manyika et al., 2013). It will change the nature of driving by switching the roles of drivers from being active participant with total control of the vehicle to becoming a passive participant with only partial or no control. This has been made possible with the advance application of information and communications technologies in vehicles. Bagloee et al. (2016) contend that the increased automation in vehicle manufacturing is due to the improved sensing accuracy, computing processing power, software engineering and artificial intelligence. The autonomous vehicle is touted as safe, convenient, accessible, and economic by proponents who believe that the proposed level of intelligence, will help users achieve true social mobility thereby, making movement within urban areas much more inclusive to all dwellers in the future.

The efficient movement of people and goods from point to point depends on the existence of critical transport infrastructure. With the changing nature of driving in the future, it is expected that government at various levels will play significant roles to shape the discourse of mobility either by enacting supporting laws and policies to herald autonomous driving or build new infrastructure whilst making adjustments to existing transport facilities. Several municipal and national governments have recognised the unprecedented challenges presented by the advent of autonomous driving. For example, countries like the US, UK, Germany, China, and others have begun to legislate laws to regulate the new wave of advancement brought by autonomous vehicles in the areas of testing, insurance, and land use (Bagloee et al., 2016; Anderson et al., 2016).

The changing nature of mobility has seen the entrants of technology companies into the automotive sector. Technology companies operating in the ICT sector are exploring new market opportunities and recognizing the collaborations between their capabilities and those required for vehicles with innovative capabilities (McKinsey & Company, 2016). Google, Tesla, Apple, and Uber are the most visible players, whilst several others, including Microsoft, Intel and Nvidia, are entering the market to supply software and hardware components. These players have begun to disrupt the sector with innovative technical solutions and business models – for instance, providing software at no cost to automakers in exchange for access to data, used for advertisements, marketing or other consumer insights.

2.4 THE ADVENT OF AUTONOMOUS DRIVING

The advancement in communications technologies in the last decade has shown that autonomous driving will become a possibility in the near future. This has been further accelerated by the increased research and developments in robotics and artificial intelligence in the automotive industry. Autonomous vehicles also known as connected vehicles, driverless or self-driving cars are expected to be in practical use before 2025 (Guerra, 2016; Nakagawa et al., 2017; Bagloee et al., 2016). The concept of autonomous driving is the partial or complete movement of a vehicle with little or no human assistance. According to Bonneau et al. (2017) modern vehicle users have begun to experience some level of autonomy in new model vehicles. For example, several major auto manufacturers now equip vehicles with parking assistant, cruise control, automatic seat, steering adjustment and ambient control features.

Although, recent development in autonomous driving has attracted many interests, the idea had existed for decades. Much of the development in autonomous driving were pioneered in the US, Europe, and Japan. One of the earliest examples is in 1939, at the General Motors Highways and Horizons exhibition in New York World’s Fair, where visitors were enthralled with the possibility of autonomous cars which would drive families across the U.S. safely and efficiently without human control (Geddes, 1940 cited in Bosch, 2018). In 1941, Robert Heinlein began publishing series of science fiction stories of a high-tech society with advanced technologies where cars would drive themselves to any desired location of the passenger (Martinez, 2017). In a 1957 advert of RAND Policy report cover, a picture of a family was shown playing dominoes while their car travelled effortlessly along the motorway (Anderson et al. 2016). These were only ideas and concepts which fascinated futurists and creative individuals who were ahead of their time.

With the recent advancement in computer processing, satellite position location, image and sensing devices, this long-cherished dream is gradually becoming a probable reality. In 2004, DARPA organized a self-driving car challenge which took place in the Mojave Desert region in the United States with the aim of crossing a 240-km stretch of the desert. Fifteen teams participated in this first challenge, however, no team succeeded in completing the task that year. In 2005, five teams completed the task of crossing a 150-mile obstacle course meant to test autonomous vehicles and stimulate novel technological innovations with the first team completing within 6 hours and 54 minutes. The 2005 challenge broke new grounds and the third challenge which was held in 2007 was an urban challenge to test the urban road environment (Thrun, 2010). In Europe, the European Land-Robot trial (ELROB) conducted autonomous vehicle trials in 2006 which occurred in the infantry training region near Hammelburg in Germany (Zhao et al., 2018). Unlike the DARPA, European Robotics was a linkage between industry and research in the area of ground robotics. It was later extended into gaming, which included combat and non-combatant subsequently held every year thereafter (Zhao et al., 2018). In September 2011, the University of Berlin accomplished a driverless car trail tagged "Made in Germany" which travelled nearly 20 kilometres, including 46 traffic lights and two roundabouts from the Brandenburg gate through the Berlin International Conference Centre and returned back to the point of departure successfully.

The National Natural Science Foundation of China (NNSFC) commenced the China Smart Car Future Challenge with a major research plan; a visual-auditory information cognitive computing research from 2008 – 2015 (Li and He, 2018). The main components of the NNSFC research study were to collaborate in a real physical environment; test the research progress of "visual-auditory information cognitive computing; examine the efficiency calculation model and expand the capability of computers to understand complex and diverse information as well as processing efficiency; and encourage the research plan to achieve its original innovation which is a crucial part of the overall initiatives. Part of the initial challenge included a detailed road test of about 15 kilometres of highway and suburban road and in a closed environment in 2014. The performance of the challenge where tagged 4S; safety, smartness, smoothness, and speed (Li and He, 2018).

In 2010, Google announced the recruitment of engineers from the numerous winning teams who contested in the DARPA driverless challenges and developed a semi-autonomous vehicle that has driven more than a million miles on urban streets and freeways (Waldrop, 2015). That announcement spurred many automotive companies, government, and researchers to accelerate their efforts in self-driving technologies. Several major car manufacturers and IT companies of which about 46 as at the end of 2018 had committed huge investments in the development of autonomous vehicle with many futuristic capabilities (Cho and Jung, 2018; Smiechowski, 2014). In the race to achieve full autonomy, it is estimated that around €77 billion has been spent in research and development (R&D) by the global automotive players in the development of vehicle autonomy (Bagloee et al., 2016).

Autonomous driving promises to revolutionize transportation and mobility through safer roads, efficient fuel consumption and traffic-flow efficiency (Waldrop, 2015). It presupposes that due to the limited human intervention in autonomous driving, the susceptibility of humans to driving errors, disregard for traffic rules, slow response and fatigue which currently contributes to more than 70 percent of road accidents will be eradicated (Singh, 2015; Brummelen et al., 2018). In the same vein, the looming autonomous driving technologies have the likelihood of altering the transport and mobility landscape by rapidly changing the entire industry and the way people move around. According to several research publications, vehicle automation is considered as one of the top ten disruptive technologies of the future (Manyika et al., 2013; Pinjari et al., 2013; WEF, 2016). It is therefore expected that vehicle automation will enhance some industries whilst negatively impacting others.

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Figure 2.1: Stanford Stanley – The 2005 winner of the DARPA Grand Challenge (Hickey, 2005)

Table 2.1: History of Autonomous Vehicles Development

PHASE	ACTIVITY	YEAR
Concept Development	New York World Fair Ford Model	1939
	Robert A. Heinlein publishing series of science fiction stories of a high-tech society	1941
	Early infrastructure guided self-driving vehicles	1950 – 1980
	RAND policy report advert	1957
Research Funding	US Defence Department funds DARPA Autonomous Land Vehicles Project	1980
	European Commission funds 800 million EUREKA Prometheus Project on Self-driving Vehicles	1987
Early Lab Tests	Mercedes Benz achieves 620 miles in Paris	1994
	Carnegie Mellon University achieve 3200 miles	1995
	Alberto Broggi 1200 mile in Italy	1996
Real Highway Tests	DARPA competition Stanford University won $2 million prize	2004
	DARPA competition Carnegie University won	2007
	Google launched self-driving project using map data, radars and LIDAR	2009
	ERC transportation of goods over 13,000 km Parma, Italy to Shanghai, China	2010
	Nissan LEAF 360 test drive in California and Kanagawa	2013
Envisioning Early Commercial Models	Google launches first short-range complete AV in California	2015
	Long-haul highway trucks commence testing in the US, Europe and Japan	2017
	Partnerships and collaborations between auto manufacturers, systems developer, academia, government to actualize 2020-21 launch of self-driving vehicles. Legal and legislative framework for operations and infrastructural development for self-driving vehicles in the UK, EU and US	2019
	Vehicle type approval regime under EU regulation 2018/858 to increase quality, independence, testing and accreditation of autonomous vehicle for EU market Advanced safety performance technology in AV approved at the Global ministerial conference on road safety held in Stockholm	2020

(Stanley, 2013, enhanced by the author)

2.5 THE TECHNOLOGIES OF AUTONOMOUS VEHICLES

The Autonomous vehicle (AV) also known as driverless or self-driving car is a vehicle that can move itself with little or no human intervention using advanced robotic and algorithm dependent on 'sense-plan-act' design (Anderson et al., 2016). They sense their immediate environment to classify different objects and interpret the information using sensory techniques such as cameras, GPS, RADAR, LIDAR, and computer vision to identify appropriate navigation paths subject to traffic rules (Zhao et al., 2018). The self-driving car is a complex engineering machines as depicted in the block diagram in figure 2.3, with numerous inter-operating systems; path planning, environment perception, navigation system and vehicle control (Brummelen et al., 2018). Rodriguez-Castano et al. (2016) contend that so far, navigation in several autonomous vehicle tests have been able to achieve autopilot through the combination of artificial intelligence, in-vehicle sensors, vehicle-to-vehicle, and vehicle-to-infrastructure communication.

Path planning is a part of quadratic programming usually composed of mission, path and longitudinal path planner (Kim et al., 2013). The task of the path planner is for vehicle control decisions by directing the vehicle to follow traffic rules using the road map and avoid detected objects along the path. Using the best path acquired from origin to destination without collision, the path planner uses the lane maintaining and changing capability for structured road driving. The main objective of the path planner is for making decisions involving acceleration, deceleration or manoeuvre from obstacle using a control strategy (Kim et al., 2013). The planning algorithm is integrated into the navigation middleware system for situation awareness and collision-free driving (Hu et al., 2018). The path planning algorithm is divided into two stages; local and global planning; where the local path is for information obtained from surrounding cameras or radar while the global path is for digital map information (Ozguner et al., 2007). To minimize the possible negative constraints such as overshoot, oscillation, and instability; non-linear optimisation techniques and path deformation algorithms are deployed to smoothen the path (Bevan et al., 2010).

The ability of any vehicle to drive autonomously over a distance is the core of autonomy and it is only possible when vehicles understand the driving environment which is vital to the optimum performance of AV technologies. The knowledge of the environment is critical to ensure a collision-free travel. This involves environmental perception where the road is scanned for possible vehicular and non-vehicular obstacles such as traffic lights, pedestrians, cyclist, caution signs and other possible obstacles on the motorway (Rosique et al., 2019).

The environment is mapped using sensors and cameras for different input and output operations. The task of measuring and interpreting the environment is known as localization (Cui et al., 2016). Robust localization is essential even in the absence of satellite navigation usually occasioned by the loss of signal or multipath effect. The vehicle must be able to sense its entire environment including moving object detection (MOD) and movable object tracking (MOT) for pre-crash safety (PCS) operation (Rosique et al., 2019). In environment perception operation, the camera, LIDAR and RADAR sensors complements one another with respect to their specific strengths and weaknesses. The camera sensor has the advantages of rich information including the colour and shape of objects, although it is susceptible to variation in illumination and weather conditions. The radar sensor, a more robust alternative, provides accurate distance information even in poor weather conditions but provides poor information about the shape and velocity of objects. On the other hand, the LIDAR sensor offers accurate shape and distance information with performance that is independent of variation in illumination. However, it is very expensive and requires additional processing algorithms for obtaining sequential measurement data (Iwasaki et al., 2013; Zhang et al., 2014).

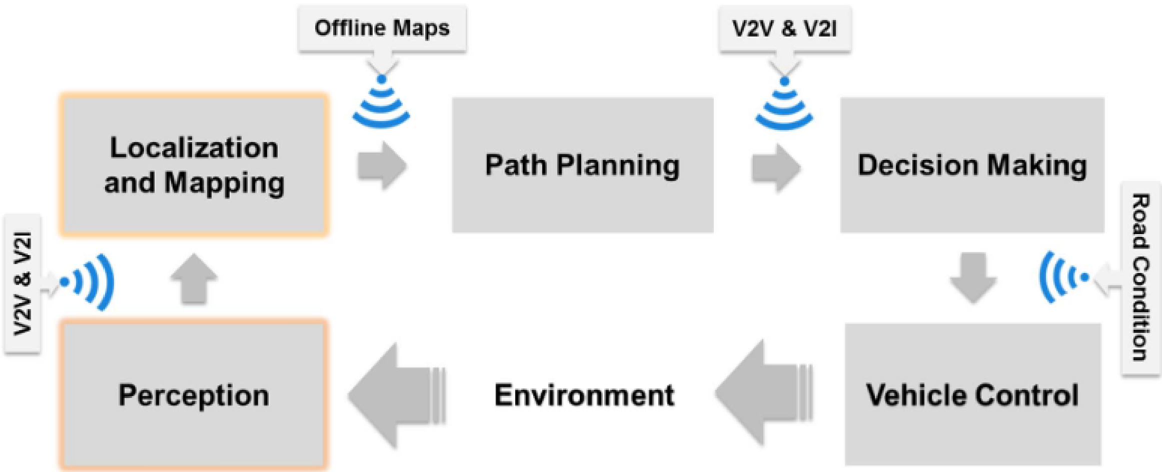


Figure 2.2: Navigation process of Autonomous vehicle (Brummelen et al., 2018)

2.6 DIFFERENT LEVELS OF AUTONOMY IN AUTONOMOUS VEHICLES

Despite the increasing advancements in vehicle automation, fully autonomous vehicles are still some years away. Generally, a car is considered to be autonomous if it navigates from the point of origination to destination with little or no human intervention by means of the information collected by the sensors and cameras for path planning and vehicle control

(Baruch, 2016; Litman, 2015). As of today, automated vehicle technologies comprise of lower-level systems that support vehicle control (e.g. lateral and longitudinal moment-to-moment inputs), excluding operational decisions (Abraham et al., 2016). Notable vehicle manufacturers currently produce vehicles with state-of-the-art features like self-parking, lane-departure warning, automated braking, and variable-speed cruise control. A large number of these vehicles are able to operate partially autonomously under specific conditions, however, several technical and environmental conditions must be satisfied before full autonomy in all conditions can be attained.

The classification of vehicle autonomy is subject to the extent of human control and participation. The Society of Automotive Engineers (SAE) has established the definition of autonomous vehicles based on the increasing levels of vehicle automation from level 0 – 5 (SAE, 2014). The growing levels in automated technology are generally categorized using the six classifications provided in International standard J3016. This has become widely accepted standard in the industry and has also been integrated into the federal policy of the National Highway Traffic Safety Administration in the United States (NHTSA, 2016). The difference between the levels of automation ranges from no automation with full driver control at level 0 to full automation without driver assistance at level 5 as shown in table 2.2. The categorization of level of autonomy as provided by the SAE is detailed below:

i. Level 0 – No Automation means the driver performs all parts of the dynamic driving task (DDT) aided by warning or intervention systems. At this level, the driver is in complete and total control which is found in conventional vehicles.
ii. Level 1 – Driver Assistance mode automation is known for sustained functional design domain performance of any of lateral or longitudinal vehicle motion tasks. At this stage, the driver executes all lane holding or changes while the vehicle is fitted with systems to control one or more specific functions using information about the driving environment in anticipation that the human driver accomplishes all other parts of the DDT. Examples of this involves stability control and pre-charged brakes.
iii. Level 2 – Partial Automation is similar to level 1 and designed to execute both lateral and longitudinal vehicle motion control subtasks of DDT. At this stage, the vehicle performs lane holding and lane changes in specific applications whilst the driver must constantly monitor the system. Examples of these are adaptive cruise control and autopilot capabilities along certain driving conditions.

iv. Level 3 – Conditional Automation allows the vehicle to perform all features of the DDT in anticipation that the human driver will react at the appropriate instance upon a request to act. The vehicle detects its environment by automatically driving with no assistance but needs to be continuously monitored to take over when required. For example, a system performing lane holding and changing in specific cases and automatic overtaking of slower vehicles. The vehicle seeks permission from the driver with sufficient warning when required.

v. Level 4 – High Automation level ensure that the vehicle accomplishes all aspects of the dynamic driving task without assistance from a human driver. The vehicles do not require a driver to intervene in special situations. The automated systems can manoeuvre in all driving conditions.

vi. Level 5 – Full Automation is when the vehicle activates complete automated driving system in all aspects of the DDT under all road and environmental conditions that can be managed by a human driver. At this stage, the intervention of the driver is not required at any time. The vehicle is able to perform all essential driving functions safely with the ability to monitor driving conditions for an entire trip even in the absence of a driver.

According to Krisher and Durbin (2016) Tesla is one of the earliest entrants with the Model S and X with level 3 autonomous features already existing in the market. However, recent mishaps have instigated fears concerning the drivers' understanding and competence in using the technology safely.

Table 2.2: Categorization of vehicle autonomy

Level	Name	Definition	Execution of steering and acceleration	Monitoring of driving environment	Fallback performance of dynamic driving task	System capability (driving modes)
Human driver monitors the driving environment						
0	No automation	Full-time performance by the human driver of all aspects of the dynamic driving task, even when enhanced by warning or intervention systems	Human Driver	Human Driver	Human Driver	N/A
1	Driver Assistance	The driving mode-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the human driver performs all remaining aspects of the dynamic driving task	Human and system	Human Driver	Human Driver	Some driving modes
2	Partial Assistance	The driving mode-specific execution by one or more driver assistance system of both either steering or acceleration/deceleration using information about the driving environment and with the expectation that the human driver performs all remaining aspects of the dynamic driving task	System	Human Driver	Human Driver	Some driving modes
Automated driving (system) monitors the driving environment						
3	Conditional Automation	The driving mode-specific performance by an automated driving system of all aspects of the dynamic driving task with the expectation that the human driver will respond appropriately to a request to intervene	System	System	Human Driver	Some driving modes
4	High Automation	The driving mode-specific performance by an automated driving system of all aspects of the dynamic driving task even if human driver does not respond appropriately to a request to intervene	System	System	System	Some driving modes
5	Full Automation	The full-time performance by an automated driving system of all aspects of the dynamic driving task under all roadway and environmental conditions that can be managed by a human driver	System	System	System	All driving modes

Source (SAE International, 2014)

2.7 ASSESSING THE BEHAVIOUR OF AUTONOMOUS VEHICLES

Driving is a complex task which entails the performance of physical and rational activities simultaneously. The driver needs to react to different behaviours of the vehicle, other motorists, pedestrians and different road composition as well as weather conditions. Conventional vehicles require drivers to be attentive and responsive to these different activities on and around the motorway. For instance, in certain instances, drivers communicate their intentions to navigate directions or blend into moving traffic using gestures. In other instances, drivers and pedestrians establish eye contact before negotiating an activity on the road. This may be a nod, wave, or just a smile to reassure the road user to act. How road users react to the behaviour of other drivers, vehicles and pedestrians is important to direct the design of automated driving systems. Conventionally, drivers evaluate each traffic scene through observation and interpretation of the behaviours of other vehicles or ‘animate human-vehicles (Portouli et al., 2014).

Emmenegger et al. (2016) argue that driving as a social activity includes communication of intent which autonomous vehicles lack. Rhetorically, they ask how driverless cars will recognize nod, wave and smile when other road users attempt to cross or negotiate a bend. Autonomous vehicles are highly intelligent machines programmed to take over driving control by mimicking the human driver’s behaviour in the best ways possible. This is known as anthropomorphism, the attribution of human behaviour to inanimate or non-human object (Zlotowski et al., 2015). Autonomous vehicles are therefore anthropomorphic since they require the relinquishment of partial or total driving control with the aid of technology. Anthropomorphism has been applied in the design of robots which perform human-like duties in areas where technology and human behaviours are interwoven. However, there are several problems associated with anthropomorphism in human-machine interaction (Niu et al., 2018). According to Mori et al. (2012) the problem of uncanny valley phenomenon where the acceptability of robots increases to the point where robots become almost like real human beings, leads humans to develop a strong negative emotional reaction.

Smoothness of path and obstacle avoidance are highly essential in motion planning in an AV design (Wei et al., 2013). In the driving behaviours of AV, it is important that driving is implemented as natural as possible; unambiguous and straightforward which is understood by pedestrians, passengers of the vehicle and other vehicles; and not merely part of a mechanical process of travelling from origin to destination. There is difference between travelling in an automated “pod” driving at 15mph and in a conventional vehicle at motorway speeds. AV requires real-time traffic, weather and road condition information to function; whilst human driver will adjust the driving experience according to observed and perceived conditions for speed and comfort. Due to extreme precautionary safety standards, current AV prototypes drive painstakingly and very moderately slow down in front of a crossing because they conjecture that other drivers may desire to proceed. This action makes AV timid and other road users could take advantage of their diffidence.

In AV, situational adaptation, such as lane change, speed adjustment, overtaking and obstacle avoidance is determined by algorithms. Depending on the situation, handing control over to drivers requires that drivers take back control in certain driving conditions in a partial automation vehicle. Under full automation, drivers will lack the option of taking control even when things go wrong. Under these conditions, drivers will need to accept these realities and learn new behaviours associated with AV driving.

2.8 GOVERNANCE AND LEGISLATIONS ON AUTONOMOUS VEHICLES

Autonomous vehicles are considered as game-changer which will radically change the way and manner people and goods move within cities due to their convenience, safety and sustainability (Fagnant and Kockelman, 2015; Paden et al., 2016; Zhao et al., 2018; McKinsey, 2019). This mode of transport and mobility will generate huge concerns due to the direct impact on the economy, social and environment of cities (Ambrosinoa et al., 2016; Gossling, 2016). It is imperative to create the right environment where different stakeholders such as users, manufacturers, service providers, insurance companies and those who will be impacted by the arrival of autonomous vehicles to engage in deliberations on their functionality. Several countries have identified the forthcoming economic opportunities that will be generated from the advent of AV technologies. The advancement in AV technologies as well as its associated technologies has led to the increasing involvement of government departments and agencies through legislation to establish legal frameworks, guidelines and regulations in most developed countries in North America, European Union and Asia (Anderson et al., 2016). Decision makers, planners and practitioners in these jurisdictions have taken profound interest in the development within the autonomous vehicle technologies; as such, they have begun to promulgate laws and policies to herald the new wave of mobility expected to ply city roads from 2025. This is expected to have numerous consequences on transport infrastructures, land use, parking, mass-transit, insurance and several other areas.

Dignum (2017) concludes that as the capabilities for autonomous technologies grow, it is important for all stakeholders to rethink responsibilities by developing new frameworks to deal with vehicle autonomy, design choices, ethics, modulate the influence of artificial intelligence systems, safeguard data stewardship and help individuals control the extent of their participation. Several governments both local and national in technologically advanced countries have gradually begun to enact laws and policies for these purposes. In a research conducted in Sydney, Australia, published by Porter et al. (2018) they opined that for fear of being left behind, governments across the world are scrambling to enact regulations for AV trials, legal and liability concerns which may arise when machine replaces human drivers. In the United Kingdom, the government continues to take steps to position the UK as one of the leading nations with a promise to introduce AV on the motorway by 2021 (Kolirin, 2019). The government of the United Kingdom instituted the Centre for Connected and Autonomous Vehicles in England and Scotland to advance CAVs trials and other related technologies with an investment of £1 billion (Dept. for Transport, 2019). The government has funded more than 200 companies in over seventy AV-related projects under the Centre for Connected and Autonomous Vehicles (CCAV) across England, Scotland, and Wales (Autovista Group, 2019). Several other initiatives to herald the arrival of CAVs have been adopted, such as the reviews and amendments of transportation policies and laws. For instance, the three-year law review conducted by the Law Commission of England, Wales and Scotland is adjusting traditional traffic and transport laws to herald self-driving vehicles. The Commissions announced the code of practice for the commercial deployment of highly automated driving systems. In 2018, both Houses of Parliament passed the Automated and Electric Vehicles Act into law amongst others; to ensure infrastructural and insurance readiness for the transport revolution of the future (House of Commons, 2018). Under the new code of practice, CAV trials are permissible on all UK roads provided the safety and trial performance reports as well as risks assessments are published before trials. With these initiatives, the CAV market in the UK is estimated to be worth about £52 billion by 2035 (Gov. UK, 2017). According to the ministers of Future of Mobility; Jesse Norman and Automotive; Richard Harrington, these are major boosts to new investments in transportation with consequential impact on the UK economy.

Similarly, other governments around the world have begun to legislate on the frameworks for autonomous vehicles to operate. The EU Commissioner for Research, Science and Innovation, Carlos Moedas, opine that the EU needs to provide the right framework to stimulate the progress required to drive AV and CAV. In 2017, Germany enacted AV bill to modify existing road traffic act by defining the requirements for partial and fully automated vehicles whilst redefining the rights of drivers and other road users. In 2019, France established legislative framework that allows the testing of autonomous vehicles with the intent to allow fully automated vehicles by 2020 and 2022. The EU, being a major player in global policies, as well as some of its member states being the largest exporters of vehicles and allied technologies, consider CAV technology as an opportunity for economic development, environmental sustainability and reduction in road accident fatalities. Projection by the Commission estimates that by 2030, autonomous vehicle will become commonplace in the EU and the industry will generate revenues exceeding €620 billion for the EU automotive industry and €180 billion for the EU electronic industry (EU Commission, 2018). According to Kiilunen (2018) CAVs in the EU context is not only about transportation, but also technology, data, liability, safety and robotics. An initial study conducted on the acceptance of self-driving cars; 58 percent of EU citizens indicated their willingness to ride in a self-driving vehicle (WEF, 2016). In 2018, the Commission announced an investment of €450m in road infrastructure and telecoms networks to support driverless cars (Campbell, 2018). Several projects being funded under the Horizon 2020 program, an umbrella funding initiative for cities and mobility continue to partner with universities and tech companies across member states to develop systems and services that are compatible with the EU frameworks. The EU agenda for CAV is comprehensive, clear, futuristic and ambitious with common vision to support actions for the development and deployment of key technologies, services and infrastructures (EU Commission, 2018). The third Mobility Package, the Vision Zero and the European Automotive – Telecom Alliance are some of the frameworks geared towards redefining the regulatory and operational guidelines for autonomous mobility. These legal and policy framework supports the deployment of safe connected and automated mobility whilst addressing societal and environmental concerns. Several member states, such as Netherlands, France, Germany, UK, Sweden and others have adopted these policies for large-scale testing and implementation of CAV technologies in line with the EU guidelines. Most of these initiatives have increased the participation of the EU member states in the race for driverless mobility. This could be seen to be demonstrated in the KPMG autonomous driving readiness index shown in figure 3.8 with Netherlands and several other Europeans countries taking the lead over USA, Canada and China (KPMG, 2019).

Similar legislation continues to be enacted in the US; with more than 41 states promulgating laws related to AV since 2012 (NCSL, 2019). In the United States, President Obama unveiled a 10-year $4 billion government funding to promote the development and adoption of fully autonomous vehicles (Tarpley et al., 2017). Thereafter, agencies within the Department of Transportation embarked on reviewing existing policies and regulations that could hinder the roll-out of CAVs. The National Highway Traffic Safety Administration (NHTSA) released the Federal Automated Vehicle Policy to harness the transformative benefits of CAVs in addition to a proposed Standard 150 (ibid). The policy delineates industry best practices for pre-development design, testing of CAVs; recommendations for the implementation at states level and regulatory tools for manufacturers to change the automotive environment. This policy applies to all individuals and manufacturers involved in the designing, testing and planning to sell CAVs in the United States. With the steady advancement in AV technologies, the congress began deliberation on the American Vision for Safer Transportation through Advancement of Revolutionary Technologies Act (AV Start Act) bill to create legislature for testing and deployment (Marshall, 2018). About 37 member states of the National Conference of States Legislatures in the US have so far legislated and/or issued executive orders governing CAVs (NCSL, 2019).

According to Mervis (2017) despite the numerous government deliberations, legislations and regulations for self-driving cars, experts still admit that there is substantial technical progress required before full automation will be approved. This is reinforced by the recent publication by the Victoria Transport Policy Institute, which contends that the claims and promises made by the automobile and big tech players in the commercialization of fully autonomous cars cannot happen before 2035-2040 (Litman, 2019). There are several teething challenges facing the autonomous car industry in the aspect of consumer acceptance primarily on ethics, security, privacy and liability in addition to high cost of sensors development, dwindling budgetary and funding for research and development as well as the impact of weather conditions.

2.9 INDUSTRY DEVELOPMENT AND TESTING OF AV

The development in autonomous vehicles technology and associated areas continue to uncover new grounds with no sign of decline. The case of autonomous driving is only a few years away before self-driving cars will be seen on the motorway. With the substantial developments within the CAV domain, several states, national governments and policymakers have begun to promulgate laws and establish policy framework to guide the operation and testing of AV as seen in the prior section (Gov. UK, 2017; EU Commission, 2018; Dept. of Transport, 2019; NCSL, 2019). The European Research Council (ERC) partly funded a 13,000 kilometres trip of autonomous vehicle carrying goods from Parma, Italy to Shanghai, China (Bimbraw, 2015). This was to demonstrate the possibility of autonomously transporting goods between continents. Volkswagen, using its Temporary Autopilot (TAP) system controlled an Audi TTS semi-autonomously at a speed of up to 130 km/h as part of trials in the European Union $40 million Highly Automated Vehicles for Intelligent Transport (HAVEit) operated several driver-assist features like safer lane changing to prevent accidents caused by distracted drivers (Okuda, 2014).

The pace of automated vehicle technology has accelerated in the past few years. In the race to become leading players in the industry, countries continue to provide funding, infrastructures and favourable rules for autonomous trials. As of now, several traditional roads have been converted to test tracks for testing autonomous vehicles as proving grounds. There are dedicated testing facilities for autonomous vehicles proving grounds specifically designed for autonomous vehicles such as the Mobility Transformation Centre of the University of Michigan, USA. The UK government launched a driverless car competition in 2014 with invitation for cities, academia and businesses to collaborate and host trials. That competition was won by Greenwich, Milton Keynes, Coventry and Bristol and an investment of £19 million was provided to continue the development in AV (Department for Transport, 2015). In 2016, the Centre for Connected & Autonomous Vehicles (CCAV) invested up to £100m in new UK CAV testing infrastructure along the London-Birmingham M40 motorway corridor in the West Midlands, covering Coventry, Birmingham, Milton Keynes, plus Oxford and London. In the efforts to make trials easier for testing companies in the UK, the government has only mandated insurance to be arranged with little or no need for permits (Department for Transport, 2015). The state of California is one of the prominent states at the forefront of autonomous vehicle technology trials by encouraging manufacturers to conduct tests on public roads. However, one of its core requirements mandates every manufacturer testing vehicle on public roads to submit an annual report detailing the number of disengagements experienced during testing. These reports are expected to be submitted by first of January every year (Etherington, 2017).

The actualization of fully autonomous vehicles is still some distance away as indicated by several industry players and experts. For instance, the Director of Michigan Mobility Transformation Centre, Huei Peng reiterated that for a vehicle to successfully drive itself safely at any speed on any road in any weather, is still a few decades away (Truett 2016). On a similar note, the CEO of Toyota Research Institute, Gill Pratt posited that as much as AV is a wonderful goal, no automobile or IT companies is near accomplishing full level 5 autonomy yet (Ackerman 2017). The Director of Uber self-driving vehicle lab, Raquel Urtasun prescribes a piecemeal approach to the introduction of self-driving cars on public roads at a smaller scale, on a small set of roads. He warned that nobody has a solution to introduce driverless cars on an uber scale that will be reliably safe enough to work everywhere (Marowits 2017). For the purpose of safety, most autonomous trials must be conducted under the supervision of a human driver; as testing of the technology prove viable and safe, these regulations will evolve.

Company	*Demonstration/Testing Description*
Audi	**Level 3**: 50,000 miles of testing. Accomplished 500-mile Level 4 drive from Palo Alto to Las Vegas
Bosch	**Level 3**: 6,000 miles of testing in Germany, U.S., and Japan
Daimler	**Level 4**: Drove 100 km route in Germany on a Mercedes-Benz S500 prototype
Delphi Automotive	**Level 4**: Cross-country U.S. trip (Delphi Automotive system installed on a Audi SQ5)
Fiat-Chrysler	**Level 4**: Testing Google technology in 100 Chrysler Pacifica minivans
Ford	**Level 4**: Testing 30 Ford Fusion midsize sedans in California, Arizona, and Michigan, in snow and night without headlights
GM	**Level 4**: Chevy Bolts in Arizona and California. Deploying Chevrolet Volts for employees on Detroit campus in 2017
Google/Waymo	**Level 4**: Over 2 million test miles on fleet of Lexus RX SUVs and prototypes
Honda/Acura	**Level 4**: Demonstrated at Intelligent Transportation Systems World Congress 2013. Testing at GoMentum Station
Hyundai/Kia	**Level 4**: Plan to run tests at American Center for Mobility facility in Willow Run
Nissan	**Level 4**: Testing zero emission vehicle fleet at the National Aeronautics and Space Administration Ames Research Center
Uber	**Level 4**: Ford Fusion (purchased off dealer lot and instrumented) and Volvo XC90 (partnership with Volvo) taxis in Pittsburgh
Volvo Cars	**Level 4**: See Uber testing. Also placing vehicles into use by real drivers for testing on-road; 100 in China and 100 in Sweden

Figure 2.3: Tests of Connected and Automated Vehicles (EIA, 2017)

2.10 CHAPTER SUMMARY

This chapter provides a systematic review of existing literature with an extensive coverage of the various concepts and trends in the autonomous vehicle technology to establish a robust background for the entire research. The review starts by considering intelligent transport as the umbrella of autonomous vehicle and the history dating back to the conceptual stages when it was a futuristic fictional idea to the beginning of the technical conceptualisation of driverless cars starting with the DARPA, ELROB and other initiatives around the world. The engineering, vehicle dynamics, industry participation, and government policies are equally presented in this chapter. The literature review chapter provided a focus upon which the entire research was conducted. The background knowledge obtained from the publications of different authors within the AV adoption discipline assisted in shaping the research.

The next chapter discusses the theoretical models in the adoption of new technologies from behavioural science perspective. The technology adoption models focus on the motivations and performance expectations responsible for user adoption and acceptance of technologies.

CHAPTER THREE

3.0 THEORIES OF ACCEPTANCE AND ADOPTION OF TECHNOLOGY

3.1 INTRODUCTION

The perpetual advancement in technology implies that user will continue to accept new systems and technologies according to features ranging from improved functionality to relevance in relation to their specific tasks. The adoption of new technology by individuals and organisations have been widely researched over the years (Davis, 1989; Goodman and Griffith, 1991; Chau, 1996; Venakatesh et al., 2003; Pavlou, 2003). One of the factors responsible for the extent of research in the technology acceptance domain is to understand user behaviour as well as the factors leading to adoption. To understand the broad area of this research, it is important to investigate the theories on technology acceptance/adoption which have been conducted in different or similar disciplines.

Technology is pivotal to human existence, whereas its adoption by individuals and organisations on a regular basis is based on its ability to meet specific objectives. There are extensive literatures on the acceptance of technology including models, however, the majority of these studies has been conducted within the information technology and systems (ITS) domain. There is a need to examine some of these models and their application in the Connected and Autonomous Vehicle (CAV) domain.

This chapter explores the various technology acceptance models and their application in different areas of research disciplines.

3.2 THEORIES OF ACCEPTANCE MODELS

Several theories and models exist in technology adoption and acceptance; including the Technology Acceptance Model (TAM), Universal Theory of Acceptance and Use of Technology (UTAUT), Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB), Diffusion Innovation Theory (DIT) and several others.

3.21 TECHNOLOGY ACCEPTANCE MODEL

TAM was developed by Davis (1986) for a PhD thesis in Management Information Systems (MIS) which investigated the theoretical model that influence systems phenomenon on user acceptance of computer-based information systems. The framework was developed to improve the overall understanding of user acceptance processes, provide successful novel underpinnings to the design and implementation of information systems in addition to offering the theoretical base for practical user-acceptance testing methodology. At the same time, to aid systems designers to appraise system functionality prior to implementation. According to the research, one of the objectives of prior studies in MIS was to advance understanding of variables that impact the successful design and deployment of IT and IS systems in organisations; actual usage, user attitudes and performance impacts (Bailey and Pearson, 1983; Ginzberg, 1981; Ives et al., 1983 cited in Davis, 1986).

The TAM model was conceived as an extension of the Theory of Reasoned Action (TRA) by Fishbein and Ajzen (1975) as its theoretical model to explain the voluntary use of IT/IS systems with respect to the perceived ease of use and perceived usefulness as the key motivators for adoption. Hallegatte and Nante (2006) posited that TAM being one of the most important acceptance models for information systems and information technology has been widely scrutinized, tested and validated. The model concludes that the overall attitude of a potential user of an IT/IS system is determined by their willingness to use the technology and that the attitude towards using is a function of two factors: perceived usefulness and perceived ease of use.

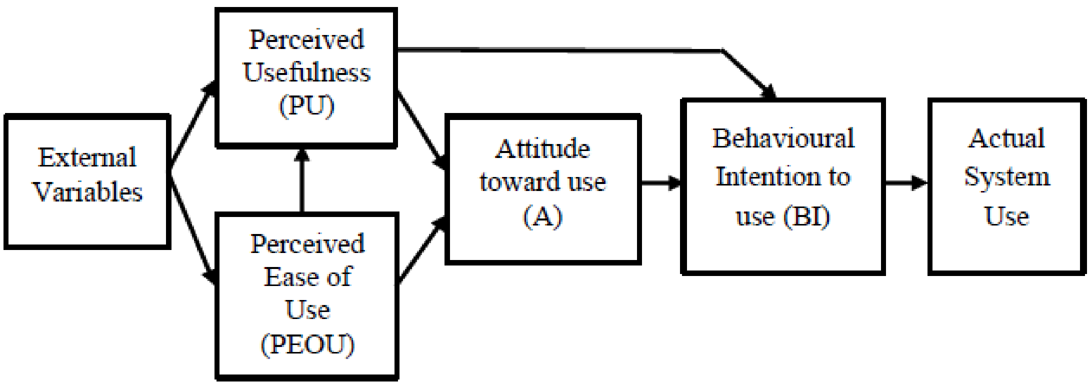


Figure 3.1: Technology Acceptance Model (TAM) (Davis, 1989)

The model has a series of interconnected constructs that explain the user's actual use and/or intention to use a technology where the perceived ease of use has a causal effect on perceived usefulness. Davis (1986) developed four equations for the model as follows:

$$EOU = \sum \beta\ iXi + \varepsilon\ n\ i \qquad (1)$$

$$USEF = \sum \beta\ i\ Xi + \beta\ n{+}1\ EOU + \varepsilon\ n\ i \qquad (2)$$

$$ATT = \beta\ 1\ EOU + \beta\ 2\ USEF + \varepsilon \qquad (3)$$

$$USE = \beta\ 1\ ATT + \varepsilon \qquad (4)$$

where:

X i = design feature i = 1, n
EOU = perceived ease of use
USEF = perceived usefulness
ATT = attitude towards using
USE = actual use of the system
$\beta\ i$ = standardized partial regression coefficient
ε = random error

The model considers the actual usage of a given technology/system for a specific purpose whereas attitude is the degree of evaluation a user subjects the intended technology/system for fitness of purpose. Attitude in this context is measured using behavioural criteria recommended in Fishbein and Ajzen (1977 cited in Davis, 1986). Perceived usefulness is the extent of conviction a user places in the fact that adopting the intended technology/system would ultimately improve performance. On the other hand, perceived ease of use is the degree a user believes that using the intended technology/system would be free of physical and mental efforts.

Since its development, TAM, has found application in different research scenarios; medicine and healthcare technology (Hu et al., 1999; Holden and Karsh, 2010); education and e-learning (Hong et al., 2001; Siegel et al., 2017; Joo et al., 2018); nutrition and agriculture (Noyango and Nayga, 2004; Han and Harrison, 2007; Costa-Font and Gill, 2008); national cultural values (Srite and Karahanna, 2006; Teo et al., 2008; Ashraf et al., 2014); internet and ecommerce (Pavlou, 2003; Irani et al., 2009); governance (Jung, 2019; Mayasari et al., 2017; Sebetci, 2015; Al-Hujran et al., 2013). Recently, researchers have begun to apply the model to automotive and vehicle technologies (Hamidu, 2015; Ambak et al., 2016; Koul and Eydgahi, 2018; Hewitt et al., 2019). Some of these researches start off by using TAM as a starting point and continue by including additional determining factors for adaptation and modification. For example, Choi and Ji (2015) combined the TAM model with trust in automation and identified 10 constructs that significantly affect acceptance of autonomous vehicles. In the work of Nees (2016) the author developed the Self-driving Car Acceptance Scale (SCAS) by using the extended versions of the TAM Model as idealized versus realistic portrayal by introducing respondents to a short scenario vignettes with a 24-item measurement scale to measure acceptance. In Koul and Eydgah (2018), the authors found a positive correlation between Perceived Ease of Use (PEOU), Perceived Usefulness (PU), year of driving experience, age and the intention to use a driverless car. As the research on autonomous vehicle continue to develop, Hewitt et al. (2019) recently developed the Autonomous Vehicle Acceptance Model (AVAM) using generic technology acceptance models, car acceptance models and level of autonomy. The research found lower acceptance for higher vehicle autonomy levels.

3.22 UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY

The use of any technology is primarily accompanied by a process of consideration of its desired features before adoption. Theories on technology acceptance have been propounded for generic and IT technologies (Davis, 1989, Hu et al., 1999; Venkatesh et al, 2003). According to prior research in IT/IS acceptance models, the unified theory of acceptance and use of technology (UTAUT) is an offshoot of the Fisherben and Ajzen (1975) theory of reasoned action (TRA) and Ajzen (1991) theory of planned behaviour (TPB) which explains the intention to use technology. The UTAUT shown in figure 3.2 was developed based on four criteria: performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). It unified eight acceptance models and proposed that the four criteria are influenced by four moderators: experience, voluntariness, age and gender before the intention and actual use of technology (ibid). The UTAUT model has been extensively used in technology acceptance research as a theoretical basis for empirical evaluation of adoption and user behaviours (Osswald et al., 2012; Williams et al., 2015; Sarfaraz, 2017; Dwivedi et al., 2017).

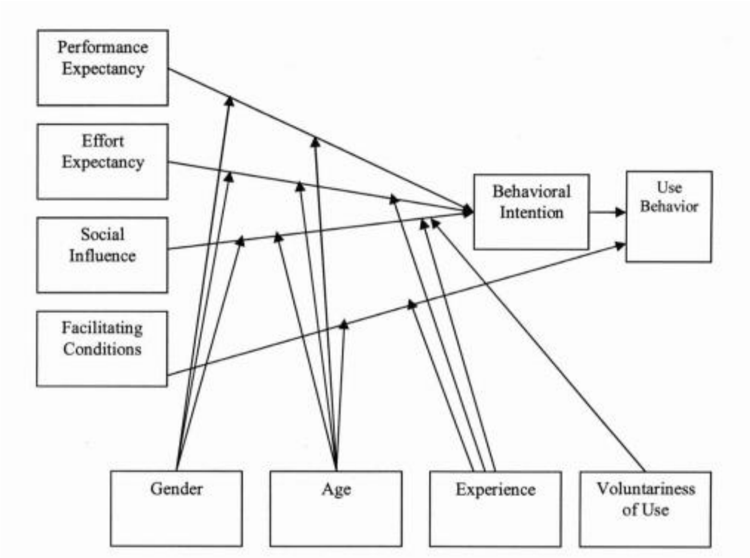


Figure 3.2: Unified theory of acceptance and use of technology (Venkatesh et al., 2003)

The exclusive feature of the UTAUT model is its inclusion of the moderating criteria which aims to improve the predictive efficiency. The four constructs (performance expectancy, effort expectancy, social influence and facilitating conditions) of the UTAUT influence the intention and usage of technology. Performance expectancy is the extent a user believes that a technology will aid in achieving significant performance, with the strongest effect in younger males. Effort expectancy is the ease associate with the use of technology, and it is major criteria for older females. The extent a user perceives the influence of others on technology usage is referred to as the social influence and it is strongest with older females within early phase of experience. The facilitating conditions are determined by the conviction that external conditionality exist to support the use of technology and it is profound in older users.

However, despite the extent the UTAUT has been used, no study except Williams et al. (2015) has reviewed its performance to explore its limitations. Their work revealed that a significant part of the model excluded the role of the individual behaviour which influence adoption of technology. In the same instance, Dwivedi et al. (2017) proposed that there may be an opportunity to reconsider the model as the adoption of IS/IT system may be an organisational decision with little or no recourse to individual users, thus making the voluntariness as a moderating component invalid.

3.23 THEORY OF REASONED ACTION AND PLANNED BEHAVIOUR

Behavioural studies have been conducted to understand and predict the behaviour of individuals in relation to actions leading to making decisions. The two most commonly used theories in adoption decisions are the Theory of Reasoned Action (TRA) and Theory of Planned Behaviour (TPB) (Cooke and French, 2008; Teo and van Schaik, 2012; Mishra et al., 2014; Nguyen et al., 2019). TRA is aimed at factors that influence the motivation behind specific decisions individuals make in relation to behaviour, attitudes and intentions (Fishbein, 1967). The underlining principle of TRA is that voluntary behaviour is considered upon an evaluation of beliefs, intentions and consequences of a given action (Fishbein and Ajzen, 2010; Berglund and Kvale, 2011; Conner et al., 2013). In order to predict behaviour leading to an action, it is important to understand the attitude towards that action. Chang (1998) observed that TRA is determined by rational, volitional and systemic behaviour which the individual has control over. Contextually, it is affected by time, outcome, action and attitude. According to Fishbein and Ajzen (1975) before an individual performs any action, the action is rationalized, and its implication weighed. They posit that behavioural intention is a function of subjective norms which are determined by normative beliefs. Mathematically, TRA is a function of behaviour, intention, attitude and subjective norms according to defined weights. Attitude towards the behaviour is a function of beliefs which are evaluated according to weights of social norms (Belleau et al., 2007).

$$BI = A_B (W_1) + SN(W_2) \quad (1)$$

$$SN = \sum (NBj.MAj) \quad (2)$$

$$A_B = \sum (biei) \quad (3)$$

Where: BI – behavioural intention

A_B – attitude towards behaviour

SN – subjective norm

W – weight of factor

NBj – perceived expectation of the jth referent

MAj – motivation to comply with the jth referent

bi – expectation of the ith outcome

ei – evaluation of the ith outcome

TRA can sufficiently predict behaviours that are rather straightforward, however, it was found to be deficient if the behaviour of the individual is not under complete volition and control (Sheppard et al., 1988; Armitage and Conner, 2001). Two problems were readily identified; firstly, the prediction of behaviour from intention is challenging as a result of various factors in addition to one's intentions to determine whether the behaviour is performed. Secondly, there is no provision in the model for assessing either the probability of failing to perform one's behaviour or the consequences of such failure in determining one's intentions (Armitage and Conner, 2001). TRA does not include behaviours that are spontaneous, habitual, impulsive, cravings or mindlessness because they are not based on careful considerations (Langer 1989 cited in Dillard and Pfau, 2002). Accordingly, any behaviours that require certain skills, techniques or opportunistic advantage are equally excluded (ibid). In order to address the limitation of the predictive validity of TRA, Ajzen (1991) extended TRA to the Theory of Planned Behaviour (TPB) shown in figure 3.3 to account for situations in which individuals cannot fully control. The TPB was extended to include perceived behavioural control to determine both behavioural intention and behaviour. This added significantly to the prediction of intention and behaviour to compensate for conditions beyond the volition of the individual in which case, that are out of his immediate control (ibid).

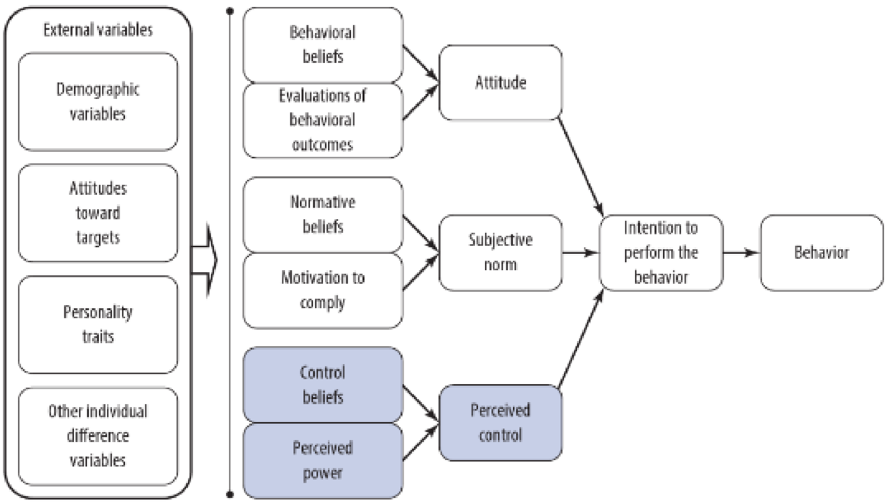


Figure 3.3: Theory of reasoned action and planned behaviour (Glanz et al., 2015)

TPB was developed to complement the weakness of TRA in decisions outside the volition of an individual (Ajzen, 1991; Armitage and Conner, 2001; Teo and van Schalk, 2012). The revised model included a new construct, Perceived Behaviour Control (PBC) to represent the subjective degree of control over performance of the behaviour itself using controllability and self-efficacy (Ajzen, 2002). In the revised model, internal and external factors act as predictor of behaviour.

3.24 DIFFUSION OF INNOVATION THEORY

The Diffusion Innovation Theory (DIT) has a long history which dates back to the 1903 when a French Sociologist, Gabriel Tarde likened diffusion to a phenomenon of social change in his book, The Laws of Imitation (Toews, 2003 cite in Kaminski, 2011). In the book, he demonstrated how opinion leadership shaped the behaviour of others. However, Katz (1957) and Rogers (1983) popularized and advanced the concept by sharing information as well as communication between opinion leaders and followers using media as a channel of influence (Dearing and Meyer, 2006). Diffusion is the process involved in the adoption of a new technology, idea, product, services, ideology, culture et al., including the process by which it is transmitted from person to person (ibid). The principle behind DIT is that every new idea, concept, technology or a way of life is usually characterised by early adopters who utilize and influence others by spreading the technology until it gradually becomes mainstream and attracts the critical mass. Communication plays a significant role in the spread of innovation or a new concept and it could take various forms, such as verbal, visual or observation. Rogers (2003) encapsulate the process of innovation diffusion as behavioural where early adopters or opinion shapers socio-metrically influence others within their network or sphere of influence.

However, becoming an early adopter of any technology, idea or concept requires that the potential adopter must invest in resources such as time and money according to its consequential benefits. The popularity of DIT has resulted in its application to several areas of research in different disciplines (Rogers, 2003; Dearing and Meyer, 2006; Chen et al., 2008; Chang, 2015; Dube and Gumbo, 2017). Attewell (1992) contend that the higher the benefits of innovation, the faster the rate of diffusion. At the same time, the higher the cost of adoption, the slower the rate of diffusion. Several factors have been found to affect the rate of diffusion: social network, communication process, interest of promoters, and adopter innovativeness such as accessibility, experimentally, status, relative advantage, compatibility, observability and product complexity (Dearing and Meyer, 2006).

The concept of DIT has been graphically represented as an S-shaped sigmoid curve, shown in figure 3.4 below which relates the rate of adoption with time. Predictably, time plays a very significant role in the lifespan of innovation adoption (Lyytinen 2001). Burt (1987 cited in Attawell, 1992) argue that on the S-curve, distinctive mechanisms of diffusion are structural equivalence and cohesion. Structural equivalence suggests that similar adopters are situated on the curve at any point in time and cohesion is when adoption results from direct communication between prior and potential adopters. In the beginning, early adopters champion the adoption of innovation until it reaches a point of saturation when it has been generally diffused to late adopters over time.

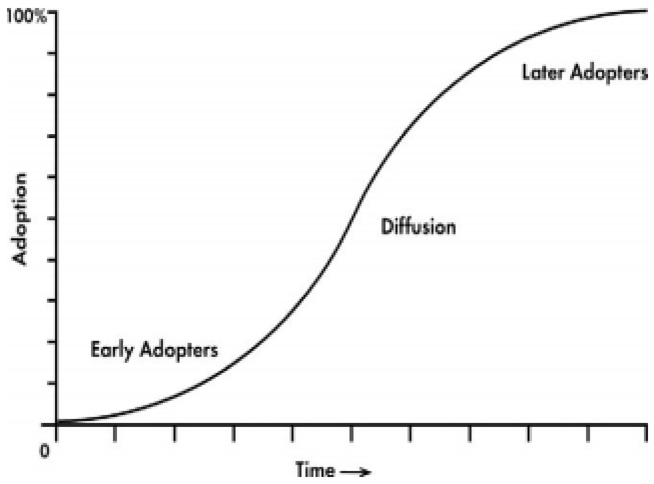


Figure 3.4: Diffusion theory curve (Dearing, 2009)

Innovation and diffusion are inextricably linked into five connecting processes: knowledge, persuasion, decision, implementation, and confirmation (Rogers, 2003). The author categorised adopters on the basis of their inclination to innovativeness; innovators, early adopters, early majority, late majority, and laggards (ibid). In the categorised adopters shown in figure 3.4, the rate of adoption is measured by the relative length of time users require to adopt innovation. The early adopters are the group who willingly experience new ideas – usually young, belonging to high social class, with financial capability, sociable and within reach of scientific research and interaction with innovators (Rogers, 2003). The early adopters are tech-savvy, sharing similar attributes to the innovators, however, they hold leadership roles in the social system. They use their influential position to increase the credibility of innovation in the diffusion process. The early majority possesses above average social status with average exposure or knowledge on technology and its usability. People belonging in the early majority have a high social interaction with other members of the social system. The late majority has below average social status, little financial lucidity, lacks sufficient technical understanding and sceptical about the expectations and usability the system. The laggards are at the lowest spectrum of social status comprising of close family and friends, usually with low financial fluidity, old, resistant to change with traditional views and slow to decide on adoption (Rogers, 2003).

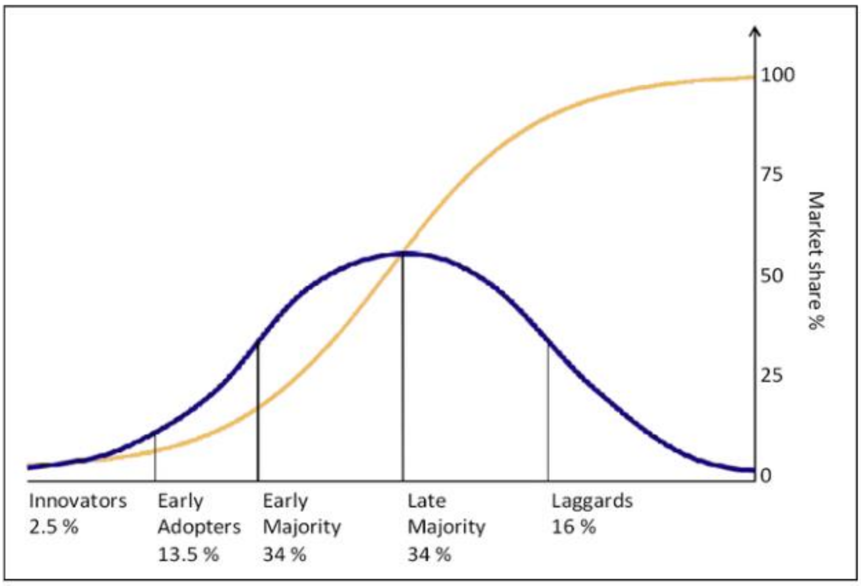


Figure 3.5: Diffusion of innovation – adoption categorization (Roger, 2003)

For example, some innovations have invalidated the DIT model as evidenced from the study conducted on the adoption of mainframe computers where price proved to be statistically insignificant (Stoneman, 1983 cited in Attawell, 1992). In the same manner, Lyytinen and Damsgaard (2001) argue that it is erroneous to assume that the model works in all technology/innovation adoption scenarios. To buttress their point, Lyytinen and Damsgaard (2001) assert that complex technologies do not diffuse in sequential stages according to the adoption categorization presented in figure 3.4. The authors criticised the DIT model by comparing the adoption of Electronic Data Interchange (EDI) technology by large organisations with the claim that different innovation possess different sets of attributes. Eveland and Tornatzky (1990) suggest that if an adopter is an institution, they ignore the principles of DIT by focussing on the business needs and advancement in innovation. According to Lyytinen and Damsgaard (2001) although, the DIT model advocates that the adoption of technology follows a linear pattern as shown in figure 3.5 above, adoption is not likely to be homogeneous where it is compulsory for users.

3.4 CONTINGENT VALUATION METHOD

The measurement of consumer behaviour with respect to making choices and paying or accepting an item of value was developed by economists to assess its economic value. Contingent Valuation Method (CVM) is a concept used to measure the presence or passive use of value, i.e., placing economic value on goods and/or services that are typically not bought or sold in the marketplace (Carson, 2001). CVM was initially developed for use in environmental economics to estimate the financial value of various non-pecuniary items such as natural resources (Carson and Mitchell, 1993). Ciriacy-Wantrup (1947) first developed the CVM which was then aggressively pushed by Davis (1963). Later on, Mitchell and Carson (1989) discovered CVM as a valuable tool in the evaluation of Willingness to Pay (WTP) in environmental goods both theoretically and methodologically. It has been applied to different areas to measure the financial value users place on intangible benefits on goods not exchanged in regular marketplaces such as sports (Johnson et al., 2001; Atkinson et al., 2008); IT adoption evaluation (Kim et al., 2010); forest valuation (Riera, 2012); cultural goods (Willis, 2014); automated road transport systems in cities (McDonald et al., 2018). It is used to analyse the trade-off between the provision of a good and the payment by users. The extensive use of the contingent valuation technique in several areas has resulted in best approaches, procedures and manuals with a focus on practical realities (Cook et al., 2018).

It is usually difficult to set fair market price or cost of purchase for new technologies. Selling a product especially a new technology that had not previously existed in the market is a major challenge for manufacturers of new products. Specifically developed techniques are adopted in setting prices for new goods and services before they arrive the marketplace. One of the strategies adopted to gauge consumers' willingness to pay, how much they will pay and what they have to give up for the new technology is usually through surveys (Kim et al., 2010; Steiner and Hendus, 2012; Aizuddin et al., 2014). Surveys of population could be used as the basis for estimating aggregate willingness to pay or through inferences from observed behaviour of potential users of a technology. Estimating the demand by analysing hypothetical demand for a good reveal how much of the good an individual wishes to purchase as a function of the price, holding all other factors and the person's utility constant. The difference between the willingness to pay for a unit and the amount that the consumer actually pays is defined as consumer surplus (Haveman and Weimer, 2001).

The CVM approach is a ‘hedonic price model,’ which provides a theoretical basis for statistically isolating the independent effects of the various characteristics of a product on the price (Kim et al., 2010). It is dependent on interrogating potential consumers about their Willingness-to-Pay (WTP) and/or Willingness-to-Accept (WTA) a certain hypothetical product or service. WTP is a measure of the maximum inclination to obtain a desired good yet to be possessed whilst WTA is the minimum disposition to voluntarily give up an item or activity of value in possession. Chapman et al. (2017) posited that WTA and WTP are slightly correlated, nonetheless, differ from individual to individual as well as between commodities. What is significantly valuable to one individual, may be worthless to another. But Hanemann (1991) demonstrated empirically that using various types of measurements and procedures has produced some evidence of discrepancies between WTP and WTA. The author suggests that the relationship or difference between WTA and WTP has led to an impasse difficult to reconcile.

In econometric theory, the variations found when valuing a good or service between WTA and WTP is attributable to income effect (Bauer and Schmidt, 2012). The theory speculates that payment capacity is attained before fulfilment of the compensation is perceived. WTA and WTP are affected not only by income, but also on the availability and extent of substitutes (Bizon and Poszewiecki, 2016). However, Hanemann (1991) concluded that the differences between WTA and WTP could be significantly large; sometimes reaching infinity depending on the level of exchangeability amongst non-tangible items and ordinary market commodity. The fewer substitutes available for non-tangible goods, the larger the difference between WTP and WTA. For any individual whose WTP exceeds WTA, that leads to Kaldor-Hicks or potential Pareto criterion (Hoffman and Spitzer, 1993). However, on the other hand, loss is weighted far more profoundly than gain. This phenomenon is known as loss aversion leading to an endowment point where WTA is greater than WTP (ibid).

3.4.1 WILLINGNESS TO PAY FOR AUTONOMOUS VEHICLES

There is no doubt that autonomous vehicles will alter future mobility, however, consumers are still highly circumspect about the technology. Several benefits have been adduced to the adoption of the technology, including high level of safety, congestion-free roads, cleaner environment and democratisation of mobility (Fagnant and Kockelman, 2015; Litman, 2015; Bagloee et al., 2016; Baruch, 2016; Bonneau et al., 2017; Daziano et al., 2017; Bosch, 2018; Zhao et al., 2018). The significance of the impending effect of autonomous vehicles on the society has necessitated the need to investigate the willingness of consumer to pay and accept. Some extent of work has been conducted on the economic measure of consumers and the value they attach to self-driving vehicles to understand how much they will be willing to pay (Schoettle and Sivak, 2014; Fagnant and Kockelman, 2015; Bansal et al., 2016; Daziano et al., 2017; Litman, 2019). These studies were conducted in different locations but what is common to all the studies is that the socio-economic and demographic make-up of the respondents such as gender, age, income, and education is important in assessing willingness to pay. It affirms that consumer preferences are not random, but, differ systematically and are conditioned to some noticeable demographic characteristics.

Pricing will be a major factor that will determine acceptance of autonomous vehicles. In a research finding conducted by Bain & Company, they found that several motorists are willing to adopt AV but unwilling to pay substantial amount for the additional capabilities that comes with self-driving vehicles (Heider et al., 2017). It is estimated that between $22 billion and $26 billion annually is required for the software, hardware and services to make driverless or autonomous vehicles self-assistive (ibid). Automotive manufacturers and technology companies are concerned about committing huge investments without a corresponding pricing advantage. However, in some research, users indicated their willingness to pay an additional price depending on the level of automation; $7253 for full autonomy and $3300 for partial autonomy (Bansal et al., 2016); $2000 – $4000 depending on the impact of the vehicle and utilization (Fagnant and Kockelman, 2015); $3,500 for partial levels of automation and about $4900 for full automation (Daziano et al., 2017). Although, these figures are only hypothetically suggestive, however, until the stated concerns (safety, security, privacy, reliability and ethic) expressed by users are fully addressed, it will be too early to categorically determine what users will pay for autonomous vehicles. Several literatures have indicated substantial concerns about the use of autonomous vehicle; manufacturers must prove the reliability of these vehicles in all conditions. Currently, the extent of reliability of tests carried out on the technologies is approximately 90% operability in all conditions (Wharton, 2017). There appears to be a significant improvement over the years, achieving full automation is distance away from user expectations.

The initial adoption for AV will be niche market in densely congested urban cities like Singapore, London, New York, Tokyo, and Shanghai (Heider et al., 2017). This growth according to the authors will be spurred by incentives and regulations. City planners and administrations are already exploring ways to reduce congestions and the nuisance caused by conventional vehicles in these cities. The rate of adoption may not be as expected in the early years of deployment. The figure 3.6 shown below depicts uptake projections according to different industry experts. It is expected that adoption will be introduced in phases; in low-speed environments like airport shuttles, health and university environments before wider application to major urban roads. Early adopters of technologies are likely to be the first users of AV either for personal mobility, shared taxis, delivery services and other possible uses. Indications from the industry shows that AV appeals to different segments of the society depending on the expected benefits they hope to derive from its use. Millennials and Gen Z leads the user segment for autonomous vehicles in nearly most of the studies conducted (Menon, 2017). This is due to the declining need to drive or own personal cars as a result of the proliferation of ridesharing and cab-hailing services.

According to Roger (1995) theory of innovation diffusion, there are five key factors of adoption of innovation – relative advantage, compatibility, complexity, trial-ability and observability. In addition, the acceptance of new technologies or any other technologies is highly influenced by generational adoption (Sackmann and Winkler, 2013; Lee and Coughlin, 2015; Smith, 2018). As indicated in figure 3.7 below, the younger generations (Gen Y and Gen Z) have been found to adopt easily all technologies including autonomous vehicles when compared to their older counterparts (Gen X and Baby Boomers) due to the influence of digital connectivity (Taylor, 2016). For example, from 2001, the vehicle miles travelled by young people in the US have drastically reduced due amongst others to improvements in technologies that offers alternatives to owning or driving vehicle (Davis and Dutzik, 2012). The willingness to pay for autonomous vehicles will be tremendously impacted by several factors ranging from technology adoption, age, income, lifestyle, and other social and economic dynamics.

Scenario	Description and reference points	CAV uptake (share of new vehicle sales)		
Progressive	Follows global uptake projections from Goldman Sachs, 2015[12] and high global uptake projections from McKinsey 2016[13]	2025	2030	2035
	- Safe and reliable technical solutions fully developed and introduced by mass market leaders before 2025	L3: 11%	L3: 29%	L3: 54%
	- Significant cost reductions to hardware (following similar trends to smartphones) are achievable in the next 10 years - Levels of scepticism can be reduced in a short time frame, supported by the regulatory environment and the rapid solution of remaining technological challenges.	L4/5: 0.4%	L4/5: 8%	L4/5: 30%
Central	Follows global uptake projections set out in BCG, 2015[14]	2025	2030	2035
	- Assumes that uptake is governed predominantly by consumer willingness to pay; possible effects of regulations (e.g. those mandating autonomy) are not accounted for	L3: 11%	L3: 18%	L3: 15%
	- Uptake is based on comparing projections of cost reductions (which are based on extensive industry consultation and cost trends for existing ADAS technology) with consumer willingness to pay (based on survey results)	L4/5: 0.3%	L4/5: 3%	L4/5: 10%
Obstructed	Follows low global uptake projections from McKinsey 2016[15]	2025	2030	2035
	- Technical and cost challenges for L5 are not addressed in the next 10 years - Regulations (excluding those in the UK) do not enable sufficient use of CAVs in varied environments	L3: 0.2%	L3: 3%	L3: 5%
	- Negative publicity following incidents; consumers take longer to trust the technology	L4/5: 0%	L4/5: 0.2%	L4/5: 3%

Figure 3.6: Projected global adoption of AV (Transport Systems Catapult, 2017)

In general, the adoption of autonomous vehicles will depend on several factors not only restrictive to demography and economic power, but also by social and environmental factors and changes to commuting behaviours. It will be systematic and gradual depending on the travel needs of users. Several young people and families prefer to live close to urban areas with transport alternatives, mixed-use developments or working from home has reduced their need for vehicles. (Giffi et al., 2017). Partial autonomy with advanced vehicle technologies will become easily adopted compared to full autonomy. The mandated introduction of features with autonomous capabilities such as anti-lock braking systems (ABS), cruise control, parking sensors, lane-changing and weather control devices as basic features in all cars are expected to help introduce drivers into autonomy before full automation. According to indications from the industry, for companies to become profitable in the autonomous vehicles business, they have to adopt mobility as a product and service models (McKinsey & Company, 2015; Anderson, et al., 2016; Transport Systems Catapult, 2017).

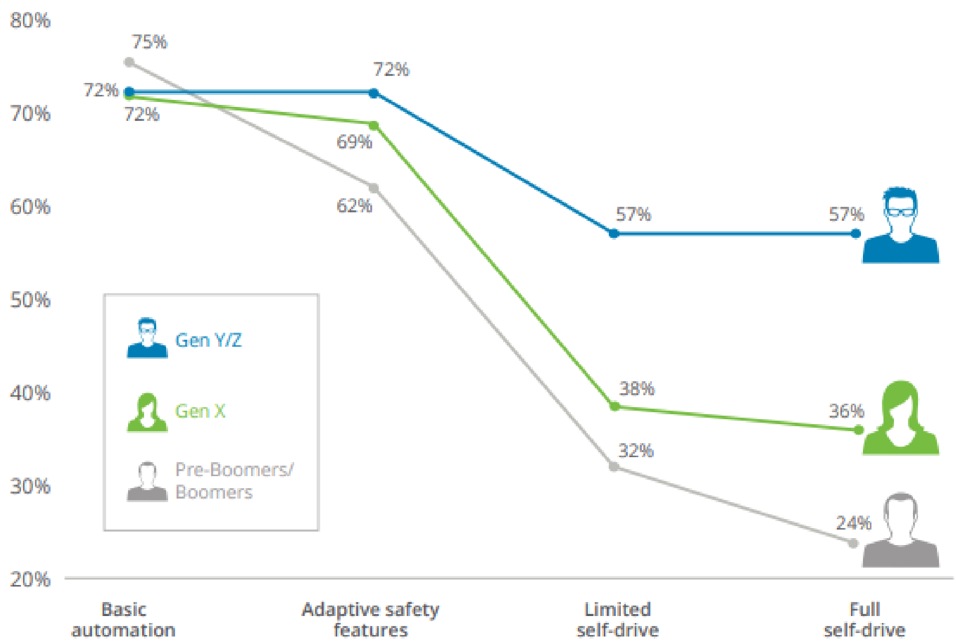


Figure 3.7: Adoption of AV according to level of autonomy (Giffi et al., 2017)

3.5 THEORETICAL ACCEPTANCE OF AUTONOMOUS VEHICLES

As widely mentioned in the previous chapters, autonomous vehicles are expected to be on public roads before 2025 (Fagnant and Kockelman, 2015; Tarpley et al., 2017; EU Commission, 2018; Kiilunen, 2018; Kolirin, 2019; BBC, 2019). According to estimates, CAVs are projected to be around 50 percent of all vehicle sales, 30 percent of all vehicles plying urban roads and 40 percent of all travels by 2040 (EU Commission). In a more ambitious projection, expert members from one of the foremost engineering advancement societies, the IEEE project that one of the most popular form of intelligent transport will be CAVs, making up about 75 percent of all vehicles by 2040 (Read, 2012). It is therefore only a matter of time before we would begin to see driverless cars on the road. Several benefits have been alluded to the advent of CAVs, some of which are safety, environmental sustainability, mobility for all, reduced congestion and many others. However, one of the main potential obstacles that may affect these forecasts regarding AVs is user acceptance. This is a well-known fact that have the potential to delay the introduction of CAV technologies into the markets.

According to Cho and Jung (2018) a comprehensive investigation of the acceptance of autonomous driving from the user perspective is required to help understand the implications for the emerging technologies. There is no doubt that self-driving cars have been peddled to have a generally positive impact on the future of mobility; to accurately evaluate the level of acceptance will provide necessary insights for researchers, governmental institutions and the automotive industry. Ordinarily, technology acceptance is such a complex issue of which AV will no doubt be more complex as it involves relinquishing control of driving to robots especially since it involves human lives. Many vehicle owners find the lack of control disturbing; with the beliefs that technology could sometimes be unreliable particularly when there is a possibility of computer algorithm malfunctioning. These fears are not unfounded; several instances abound where a robot behave contrary to its originally intended function. These and several other reasons stemming from trust, privacy, security, liability, and ethics are some of the recurrent issues commonly ascribed as the potential negative impact likely to affect the acceptance of AV technologies. These constructs will significantly impact the behaviours of users and their interaction with the technology.

The AV literature is replete with studies on the user acceptance of AV technologies, however, some of these studies are either presumptions from consulting firms, industry players or government sponsored studies. There is therefore the need for extensive academic investigation in this field. Among the several studies conducted on user acceptance of AV technologies, surveys and focus groups have been used to understand public opinion and perception of AVs (AAA foundation, 2016; Bansall et al., 2016; Maurer et al., 2016; KPMG, 2018; Nordhoff et al., 2018; Hewitt et al., 2019). In some of these surveys, the user public in Asia, Europe and North America indicated their interest to use AVs when it becomes available. In the study conducted by Begg (2014) in London, over 3500 transport professionals believe that Level 2 automation will be commonplace by 2024 and Level 3 in 2030 or 2040 since many modern vehicles are already being equipped with automated features. A significant percentage of respondents, when asked about the prospects for removing human driver component completely, 30% believe this may never be commonplace. Schoettle and Sivak (2014) surveyed about 618 licenced US drivers, they reported that acceptance of vehicle automation declines as the level of automation grows, 15.5% preferred a completely self-driving car, and 38.7% welcomes a partially automated car, while 45.8% preferring to rely on manual driving. 94.5% of the drivers preferred to have access to a steering wheel or pedals, to allow them to intervene in case of an emergency. Litman’s (2015) proposed that in the 2020s AV will have a hefty price premium and reliability issues, however, will reach a significant market penetration of 40% by 2040s leading up to saturation in the 2060s. The study conducted by Lavasini et al (2016) is slightly different with market penetration of around 1.3 million in the first five years, which is expected to increase to 36 million by the 2040s. They developed a scientific market penetration model using Bass Diffusion Model to estimate prospective diffusion curves for AV technology using historic data based on Hybrid Electric Vehicles, internet as well cell-phone adoption in the USA. They based AVs market saturation on 87 million by 2059 when an estimated 75% of US households would have adopted AVs.

Majority of these studies concludes that the consumers will be the engine pulling the AV industry. In a survey conducted by AAA (2016) it found that 75% of Americans in the population surveyed are unwilling to be passenger in an autonomous vehicle. Amongst the respondents, 81% of females where particularly the most concerned preferring to trust only systems already been in operation such as adaptive cruise control or lane departure warning and assist. Although, it is evidently clear that majority of drivers still consider control as at when required as an important factor of safety. That will negatively impact the adoption of self-driving cars; however, it is indicated that other factors such as cost, social habits, human psychology, infrastructure, legal and others will also affect the entire commercialization and adoption of self-driving cars. Even though there are already automated transport systems in operations such as airplanes, ships, mass-transit trains and military combat vehicles; these systems are still supervised or controlled by humans when the need arises. In addition to the numerous reasons presented by these studies, Litman (2020) contend that two main reasons have also contributed to the delay why autonomous vehicles may not find wider application from the onset despite being a concept which has existed for decades; the technology requires controlled environments and the presence of large-scale infrastructural investments suited purposely for the technology to work. Therefore, until the market is ready for the technology, the investments would not be justified.

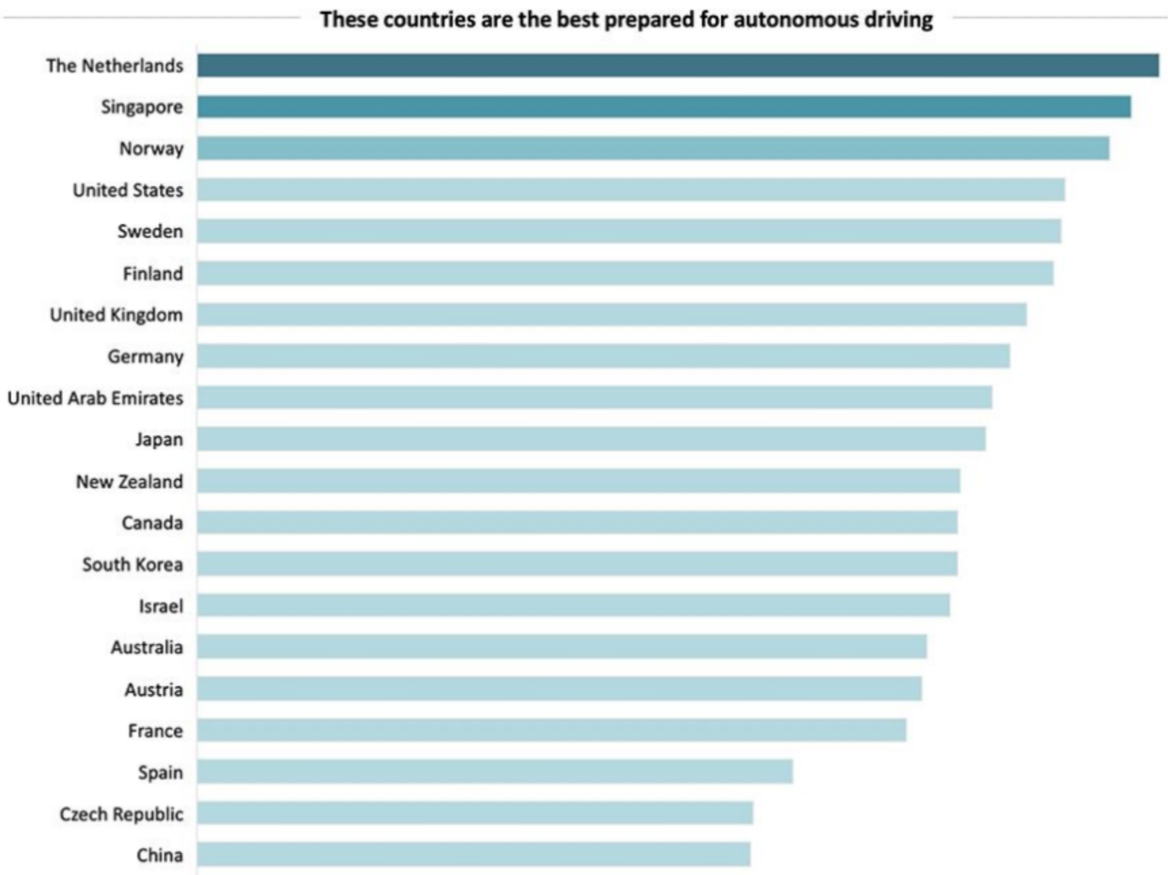


Figure 3.8: Autonomous readiness index by countries (KPMG, 2018)

3.5 OVERVIEW OF REVIEWS OF SELF-DRIVING/AUTONOMOUS VEHICLES ACCEPTANCE

Several studies investigated in our review examined acceptance of driverless vehicles by sampling different segments of road-users and driving public. Those sampled were familiar with self-driving vehicle and associated technologies. A large portion of the studies measured the attitudinal characteristics and latent construct of the general public to understand user preferences. Nearly all the papers reviewed claim that self-driving technology has the potential to increase safety, reduce congestion, democratise mobility and reduce driving stress thereby improving productivity (Bonneau et al., 2017; Brummelen et al., 2018; Cunningham et al., 2019; Yuen et al., 2020; Zhang et al., 2020). However, findings from these papers suggests that drivers and other road users enunciate misgivings about the technology. Kaur and Rampersad (2018) found trust a key factor influencing the decision to use a self-driving car. Similarly, Zhang et al. (2020) found social factor in addition to trust in their study conducted on 647 drivers in China. Yuen et al (2020) found amongst 526 respondents, perceived value was the highest determinant of acceptance. In a real simulation study carried out on participants, Zoellick et al (2019) the positive attitude towards the use of AV was increased after physical drive test over a distance of 20km in Berlin in a realistic driving mixed-use environment with pedestrians, cyclists and intersections. Although, the participants in the studies asserts that the presence of human in the vehicle may have influenced their positive attitudes. Gkartzonikas and Gkritza (2019) performed a review of literature on the stated preference hinged on the behavioural intention to ride a level 4 or fully automated vehicles. They concluded that transport professionals and researchers were more acquiescent to the adoption of AV more than the general user public. In a heterogeneous review published academic and industry articles, Becker and Axhausen (2017) found that urban young men, as well as those who currently own a vehicle with advanced driver assistance systems appear to be most positive with the intent of using the technology either as shared or private ownership. Bansal et al. (2016) conducted online survey of 347 respondents in Austin Texas, the uppermost concerns for majority of the respondents were system failure and the cost of purchase. With older and traditional drivers unwilling to adopt, two-third of the respondents who constantly drive stated that they would prefer to build their usage confidence by a gradual use of each successive level of automation. Pakusch et al (2018) performed an online survey of 302 participants in Germany with respect to travel mode preference with a visual demonstration presentation using AV as Private Autonomous Vehicle (PAV), Shared Autonomous vehicle (SAV), and Public Transport Autonomous Vehicle (PTAV). The results showed PAV as most preferred choice followed by SAV and PTAV but with significant influence from travel distance, population density and other factors such as income, age and education.

Table 3.1: Review of literature on acceptance studies of autonomous/self-driving vehicles

Authors, Year and Title of Publication	Research objectives	Data Collection/Methodology	Findings	Conclusion	Future Research
Yuen et al. (2020). The determinants of public acceptance of AV: An innovation diffusion perspective	To identify the factors influencing public acceptance of AVs and examine their interrelationships.	Questionnaire – online self-completion survey of 526 respondents in Seoul using structural equation modelling for analysing and testing the theoretical model.	Innovation diffusion variables have significant effect on public acceptance of AV	Total effects analysis revealed that perceived value has the largest influence on public acceptance of AVs.	Compatibility of AV innovation in different regions. Longitudinal survey for dynamic preferences. AV driving for diverse groups.
Zhang et al. (2020). Automated vehicle acceptance in China: Social influence and initial trust are key determinants	To identify the impact of social influence on AV adoption in the Chinese society/culture	Self-completion online questionnaire survey administered to 647 drivers in China. Goodness of fit (GoF) structural equation modelling using Technology Acceptance Model (TAM) factors.	Trust, social factors, personal traits and TAM factors are major determinants for adoption of AV.	Social influence and initial trust are a major determinant of AV adoption or rejection.	Investigate the perception of influential individuals such as family seniors, group leaders and key members on AV usage.
Zoellick et al. (2019). Assessing acceptance of electric automated vehicles after exposure in a realistic traffic environment	To standardise procedure to approach AV attitude research through improved instruments To demonstrate how open items, add value to quantitative survey.	Questionnaire – 125 participants in realistic AV ride with 20km/h speed in Berlin. Exploratory factor, and Confirmatory factor analyses performed on survey data while Qualitative content analysis MXQDA applied to qualitative data.	Physical ride in electric AV changed attitude towards acceptance of sampled participants.	The study generated positive attitudes; the inability to drive traditional vehicles positively influenced acceptance of AV.	Future studies on emotion and anxiety using interdisciplinary, mixed methods approaches.

Gkartzonikas and Gkritza (2019). What have we learned? A review of stated preference and choice studies on autonomous vehicles	To provide a comprehensive review of the literature on stated preference/choice studies examining potential user preferences/behaviours regarding AVs.	Literature review survey on stated preference/choice in AV adoption including Econometric analysis (multivariate ordered probit and multinomial logit models for assessing willingness to pay	Factors that affect behavioural intention to ride AV includes consumer innovativeness, level of awareness, safety, trust of strangers, environmental consideration, relative advantage, self-efficacy, compatibility, subjective norm.	Provision of incentives will determine adoption and willingness to pay for AV. Studies on the general public focused on socio-demographic and travel characteristics while studies on transport experts disentangle policy-planning for AV from agency perspective	The potential impact of AV on travel demands and land use. The inter-relationship between behavioural factors or set of factors affecting the intention to ride AV.
Kaur and Rampersad (2018). Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars	What are the key factors influencing trust in driverless cars	Online survey and case using Confirmatory factor analysis	Understanding trust in driverless cars in closed settings such as parks, campuses, airports	Provided preliminary strategies for the promotion of AV uptake	To obtain the views of the aged and disabled on AV use in closed environment. Longitudinal study to monitor changing sentiment over time.
Pakusch et al. (2018). Unintended Effects of Autonomous Driving: A Study on Mobility Preferences in the Future	Empirical study of user research on choice of travel mode using multimodal analysis	Online survey of 302 participants in Germany using paired comparison of n objects	Private AV preferred over shared alternative, however, AV car-sharing rank higher than traditional car-sharing	Germans prefer traditional vehicles to AV; however, gamification may trigger behavioural changes towards AV adoption	Investigate how new automated public transport for last mile will affect adoption for future public AV transport
Becker and Axhausen (2017). Literature review on surveys investigating the acceptance of automated vehicles	To investigate the various methods currently being applied to the adoption of AV	Online database query – forward and backward snowballing. Categorized studies according to type of experiment, response and explanatory variables	AV most popular among young people in cities; men who currently own vehicle with ADAS technology	Increased level of comfort and ability to perform other tasks will impact on acceptance of AV. Passion for driving is expected to be restricted	Cost predictions with diffusion theory on private AV adoption curve. Identify factors responsible family adoption process

				to certain road and traffic conditions	
Rahman et al. (2017). Assessing the utility of TAM, TPB, and UTAUT for advanced driver assistance systems	To assess the utility of TAM, TPB, and UTAUT for modelling driver acceptance of ADAS	Online survey of 400 licensed drivers from Boston in addition to ADAS driving scenario simulation focused on various driving environments.	Most participants were less familiar with ADAS, but upon experience with simulation, acceptance increased significantly	Trial experience increased acceptance of ADAS	Investigate the predictive abilities of human and systems factors and their utilization to augment theoretical acceptance models
Bansal et al. (2016). Assessing public opinions of and interest in new vehicle technologies: An Austin perspective	To explore user preferences for adoption of emerging vehicle and transport technologies	Online survey of 358 respondents in Austin Texas using exploratory variables for model estimation.	Estimation of SAVs adoption rates under three pricing scenarios per mile.	AV acceptance depend on adoption rates of friends and acquaintances. Frequent drivers to adopt without influence from others	Measuring factors affecting acceptance across different regions
Abraham et al. (2016). Autonomous Vehicles, Trust, and Driving Alternatives: A survey of consumer preferences	Are consumers satisfied with technology that is already in their vehicle? How are consumers learning about in-vehicle technologies? Are consumers willing to use various alternatives to drive? Are consumers willing to use automation in vehicles? Are older adults willing to use autonomous vehicles and/or	Online survey on 3034 adult drivers	Younger adults are willing to pay more for the features and technology proposed in AV leading to significant association between attitudes and behavioural intentions to use.	Training improves the ease of use of technology leading to potential adoption of AV	Examine difference in attitudes towards transportation alternatives according to regions (suburban vs rural)

	alternatives to drive in order to increase mobility?				
Fagnant and Kockelman (2015). Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations	To explore the feasible aspects of AVs and discuss their potential impacts on the transportation system	Exploratory method	The US federal government to expand research in AV and created a nationally recognized licensing framework for AVs to determine appropriate standards for liability, security, and data privacy	Huge annual economic benefits of up to $27 billion with 10% penetration and savings up to $450 billion in the US alone.	Near-term distribution prospects. Personal vehicle automation commercialization. AV operational requirements. Road infrastructure needs for CAV
Kyriakidis et al. (2015). Public Opinion on Automated Driving: Results of an International Questionnaire among 5000 Respondents	To measure public opinion on automated driving and its effect on acceptance and purchase highly automated vehicles.	Online survey of 5000 participants in 109 countries basing the correlation coefficient of each country road safety objectives and GDP. Exploration of association with the Big Five Inventory personality test.	Respondents with higher neuroticism were less concerned about software and data hacking. Manual driving was most preferred, but autonomous driving Frequent commuters/drivers more willing to pay more for automated driving.	Substantial section of respondents believe AV will reach 50% market penetration before 2050 despite stated concerns amongst which include privacy and liability.	

3.6 EVALUATION OF FUZZY LOGIC APPLICATION IN TECHNOLOGY ADOPTION

The decision to adopt a technology varies between users as a result of the processes involved in arriving at the conclusion to use or adopt a new technology. The decision to adopt new technology depends on user perception, opinion and attitudes which are usually subjective. Zadeh (1975) the founder of fuzzy logic suggests that making rational decision in the face of incomplete information occur in daily human engagement. The way and manner humans think, and act is replete with high degree of vagueness, inconsistences and uncertainties. Humans think or make decisions in conformity with personal beliefs, perception and judgements; usually rife with imprecise labels known as linguistic hedges such as slightly, fairly, extremely, very, warm, cold, small, large, good, poor, high, moderate, generous, average, low. These words are subjective and imprecise signifying different meanings from one context to another. Fuzzy logic is therefore a concept that model uncertainties and imprecisions inherent in human reasoning (Abraham, 2005).

Fuzzy logic has been applied to technology adoption across different domains; renewable energy (Paim-Neto and Bianchini, 2015; Zhai and Williams, 2012); cloud software (Ali et al., 2020); electric vehicle charging (Fett et al., 2019); mobile digital library services (Al-Faresi and Patel, 2012); smart grid technology (Ponce et al., 2016). The earliest application of fuzzy logic was by Sugeno and Murakami (1984) for automated car parking system and vehicle trajectory handling. Since then, fuzzy logic has found application in domains such as driving environment, ride comfort, vehicle dynamics and electric vehicles (Ivanov, 2015). In some of the studies, it was applied in combination of machine learning algorithms (Godjevac, and Steele, 2001; Dai et al., 2005) and integrated with other software (Etilik et al., 2021).

Although, fuzzy logic has been applied severally in automotive engineering and autonomous vehicle development in the areas of parking assistance, motion stabilization, braking, speed and navigation controls, however, to the author’s knowledge, there are no application in autonomous vehicle user adoption and acceptance.

3.7 CHAPTER SUMMARY

This chapter discussed the concept of technology adoption by users from conceptual frameworks which focused on the subject using inherent perceptions and the benefits of technologies before adoption. The various concepts of user behaviour and adoption of technologies provides theoretical background for this research. The technology adoption models are multi-disciplinary in their approach with applications in different fields of technology. For any new technology to become mainstream, the intention to use by potential users is a major consideration according to several factors which includes performance, contingency, epicurean, motivational, circumstantial, and many others.

Majority of the studies investigated the use and adoption of AV based on statistical relationship between user demography, income and mode of adoption. Most of the studies adopted the adoption models as the basis for their research. The studies performed basic statistical techniques in the analysis of their results. These methods lack the rigours of identifying the exact impact of these factors on levels of adoption. This thesis collected demographic data and opinion data which was modelled using machine learning techniques to determine the level of adoption considering the extent of performance of the measured variables.

The next chapter presents the user study design, survey design and data collection methods adopted in this research. It presents the rationale and justifications for selecting the adopted methods in measuring user attitudes towards the adoption of autonomous vehicles. The measuring instrument and distribution are equally provided in the chapter.

CHAPTER FOUR

4.0 USER STUDY DESIGN

4.1 INTRODUCTION

This chapter presents the design of the user study to accomplish the research objectives and provide answers to the research questions. The processes adopted in obtaining the primary data from users and its justifications are enumerated in this chapter. This study investigated the barriers that are likely to affect the adoption of autonomous vehicles by collecting opinion-based data from diverse potential users to understand how those barriers affect the adoption of AV. Different methodologies have been applied in vehicle automation to explore the adoption and acceptance of automotive technologies especially from the IT/IS domain, in this research, the study in conducted on a diverse road user population to elicit their attitudes and perception towards autonomous vehicles. Consequently, the various stated barriers will help to define adoption categories.

4.2 SURVEY DESIGN

One of the main objectives of this study is to collect relevant data from the public and potential road users to understand their perception and potential acceptance of AV before the arrival of driverless cars on public roads. Surveys are methods used in collecting data from numerous individuals or group of individuals related to emotions, opinions, feelings, perception, knowledge, and behaviour (Fink, 2017). Given that this study is aimed at understanding the research problem from the perspective of users, the research is considered as an evaluation research to measure the latent construct relating to the probable opinion and attitudes of future users of autonomous vehicles. According to Nardi (2018) quantitative method is particularly suited to explore research themes which measures the social construct of respondents pertaining to their attitudes, sentiments, opinions, or perceptions. Creswell and Creswell (2017) contend that knowledge and observations can be quantified and numerically understood when sought from a diverse study population. This research is required to measure a large sample of potential users to understand their perceptions of autonomous vehicle in relation to their personal concerns. Consequently, the need to obtain data from a wide group of respondents is significant to determine if the AV technology will succeed or fail when introduced into the market.

Surveys can be conducted via different means, which includes post, fax, email, telephone, online, face-to-face interviews, panel, experimental and observation (Fink, 2017). Reaching a target population with the probability of belonging to the vehicle user segment requires the design of a survey instrument bearing in mind the importance of capturing the specific attributes identified as potential barriers in the literature. According to Bulmer (2004 cited in Bird, 2009) questionnaire is one of the well-established research tools for obtaining information on behaviour, attitudes, and reasons for action. Generally, questionnaires are relatively easy, cheap, and flexible to deploy. They help to compare respondents and the relationship between variables. Therefore, a questionnaire was considerably suited for gathering data from multi-population respondents of adult age in the UK. The survey was targeted towards different people who were expected to have a basic knowledge of autonomous vehicles.

4.3 QUESTIONNAIRE DESIGN

The survey instrument adopted for this study is a multiple choice close-ended Likert scale questionnaire segmented into sections according to significant areas of concerns identified from the review of literature. The choice of questionnaire was preferred over other methods on the premise that attitudes are concealed constructs which are not openly recognisable (Zikmund et al., 2012). Buttressing this further, Brace (2018) contend that questionnaires are ideal in research for testing the attitudes and opinions of large-scale respondents. People can linguistically express perceptions and experience quantitatively. Moreover, questionnaire offers ease of replication, comparability, and reliability of measurement on account of being quantifiable (Blaxter et al., 2001 cited in Kaur and Rampersad, 2018). The Likert scale was considered as the most suitable instrument to measure the attitudes, behaviours, opinions, and feelings of respondents for the fact that it adds granularity to this research. According to Nemoto and Beglar (2013) Likert scale provides respondents with multiple category options consistent with their actual or inferred option. With respect to this study, eleven-point Likert scale was adopted with 0 = extremely negative and 10 = extremely positive likelihood. The 11-point Likert provided respondents with a full breadth of possible extremes for each item under consideration. This was preferred over the five or seven-point Likert because the wider the two extremes, the better the linearity and minimisation of response biases (Chimi and Russell, 2009). The rationale for selecting an 11-point scale over lesser scales is based on increased inter-rater reliability and validity as demonstrated by Preston and Coleman (2000) and Loken et al. (1987). The use of 11-point Likert scale was found to produce high correlated responses in psychometric studies especially when numerical rating scales were used as evidenced in their review of 54 papers (Hjermstad et al., 2011). In this research, the potential respondents are expected to have knowledge of AV, which means, they are educated and conversant with the innovation in transport and mobility. Therefore, a wider rating scale will provide respondents with options for elaborate expression of attitudes.

To determine the factors that are likely to influence the decision to use or adopt autonomous vehicle, a self-completion online questionnaire with 34 – item Likert scale questions were developed according to similar research (Hewitt et al., 2019; Kaur and Rampersad, 2018). The choice of online survey was to reach numerous respondents without the need to travel and completion of the survey at the convenience of the respondents. The questions were divided into three major sections: demographic, general AV knowledge and personal concerns (safety, trust, accessibility, privacy and ethics):

i. Demography: This section was designed to elicit general information such as age, gender, education, marital status, occupation, income, and ethnicity.
ii. General AV Knowledge: This section was to recognise the current understanding of respondents in AV technologies and trends, travel needs, frequency of commuting, mode of travel, determine their overall familiarity with autonomous vehicles, perception of the technology and propensity to use. Specifically, the first question was marked to indicate the relevance of knowledge in AV before participation.
iii. Perceived Concerns: This section was divided into sub-sections relating to questions focusing on the probable personal concern's drivers or road users may entertain towards driverless cars. The questions in this section bothers on ethic, privacy, accessibility, safety and trust. This section probed the willingness of respondents to own or share a driverless vehicle for meeting their travel purposes.

4.4 POPULATION SAMPLING

Sampling in research is a predetermined part of research which involves identifying a group of people or subset of participants sampled from a target population in a scientific research (Martínez-Mesa et al., 2016). Noordzij et al. (2010) contend that sampling is the experimental aspect of a study; one of the first practical steps designed to answer the research questions. As an integral part of the research process, it must be carefully considered. Researchers must systematically evaluate the significance of sampling for validity and generalisation of results. A target population is usually a part of an entire population with features of interest to the researcher. Research sample is a representation of the overall population from which conclusion may be drawn with a certain level of confidence using statistical inference. It is only from representative samples that findings can be extrapolated to a wider population. Martinez-Mesa et al. (2016) argue that it is unreliable to draw conclusion from a sample that lack representation. However, lack of representativeness may be due to several reasons: inconsistent selection process or low participation in the research.

Over the years, sampling techniques have evolved just as research design and methodical approaches have evolved (Barglowski, 2018). The selection of a population sample depends on the kind of contribution the study intends to add to the body of knowledge (ibid). Accordingly, sampling may be randomized or non-randomized; determined by the research process or intuitively motivated; subjective or objective; however, purposeful selection of participants enables researchers to obtain quality data for comprehensive analysis (Grossarth-Maticek and Ziegler, 2008; Hair et al., 2016). In randomized sampling, which is typically applied in quantitative research, participants are chosen randomly whilst non-randomized sampling is mostly applied to qualitative research depending on the researcher's judgement (Bryman, 2016; Creswell and Creswell, 2017; Hair et al., 2016).

Brewer and Hunter (2006) maintain that every research possess its own exclusive requirement, such that researchers must consciously include participants or group of participants of interest in relations with the study whilst others are considered beyond the scope of the research. The sample size selection is a function of the circumstance at the disposal of the researcher in terms of resources, access, connection, and timing (Reybold, et al., 2012). When the circumstances are altered, there are likelihood of obtaining different results. This difference in results is attributable to random error, which is due to the diversity in participants. Although, sample size is determined by circumstance identified, it could also be determined by mathematical formula. Sue and Ritter (2012) posit that a typical sample size should be 10 times more than the number of constructs using multivariate modelling approach. Following these approaches, the sample size for this study is estimated at 60 – 70 participants. However, Hair et al (2014) recommend caution in adopting this approach due to its effect on validity and reliability. For the purpose of this research, a projected population sample size of 450 was envisioned judging from similar research and thesis in user acceptance of autonomous vehicles. Using the sample size calculation with 95% confidence and 5% margin of error, the projected population sample for this research is 208. Nonetheless, the larger the size, the higher the reliability of the research conclusion (Bryman and Bryman, 2016).

Sampling for this research was conducted using online channels such as emails and social media to reach different respondents. The respondents cover a wide spectrum of the population in terms of age, gender, ethnicity, education, marital and income status.

4.5 FACE VALIDITY

It is generally advisable to pre-test even the most well-developed survey instrument to ensure that the survey items measure the desired concept. Face validity is conducted when an expert or peers review the content and appearance of a survey instrument for ambiguity, grammar, coherence and clarity. Bryman (2016) maintain that an entire research could be affected if the content amongst other things is not easily understandable, poor grammar, sequence of questions and channel of distributions. According to Sekaran and Bougie (2016) face validity could be as simple as a casual examination or rigorous evaluation usually conducted pre-test and post-test by the subject or instrument expert.

In this research, the questionnaire was examined before and after the pilot test by both an instrument and subject expert, as well as colleagues. Few changes were made after examining the items in relation to the construct and harmonised in the Likert-scale items, standardising the questions, and counter-balancing the sub-question categories. Evidence of these measures are shown in the reliability test conducted on the pilot and actual test.

4.6 PRE-TESTING THE SURVEY

Prior to full data collection, a pilot study was required to be conducted to pre-test the questions on a wide group of respondents to help refine the survey instrument for the main data collection process. Also known as pilot test, the pilot study was used to evaluate the survey instrument for problem detection on a group of respondents from the sampled population. Thabane et al. (2010) concludes that pilot testing a survey instrument helps to validate and ensure it is free from errors and ambiguities. The pilot data instrument was a 5-point Likert scale where 1 = strongly disagree and 5 = strongly agree. A web-based multi-population survey tool, Qualitrics was used to design and administer the pilot survey. Piloting the survey instrument allows amongst other advantages for reliability and validity testing. In the pilot test, it was decided that students from Coventry University and some social media users will be approached. Accordingly, the first target population to test the pilot survey are students of driving age in the Faculty of Engineering, Environment and Computing from Coventry University and adult social media users.

Majority of the respondents were contacted via email and direct messages on social media profiles containing the direct link of the self-completion online questionnaire to seek their participation in the pilot study. A total of 200 were emailed in July and August 2019 with a follow-up email sent after one week to remind participants to complete the survey. 159 people responded during the specified period, out of which 135 completed the questionnaire. After removing incomplete samples and cleaning the data, only 73 responses were acceptable for further processing. The reliability of the pilot study was tested according to the Cronbach Alpha formula on SPSS (version 25) for internal consistency.

$$\alpha = \frac{N\bar{c}}{\bar{v}+(N-1)\bar{c}}$$

where: N = No of scale items

$\bar{c}$ = Average of all covariance between items

$\bar{v}$ = Average variance of each item

Cronbach Alpha $\alpha = 0.864$

Although, the Cronbach Alpha is considered to represent good reliability, it was necessary to effect certain modifications identified by the subject and instrument expert. The modifications included increasing the Likert scale point for wider extremes, unifying the response options and standardizing questions per variable.

4.7 ETHICAL APPROVAL

Ethics in research covers different activities in the process of conducting research, but more importantly in data collection. Bryman (2016) conclude that ethical consideration is an integral part of research which includes collecting and reporting data honestly, collecting only the necessary data that pertains to the study, avoid exaggerating the accuracy of data and misuse of data. Generally, ethical consideration in research is to ensure that participants and data are safe without violating the rights and privileges of anyone connected to the study. Cacciattolo (2015) argue that unethical practices in research could make participants and researchers vulnerable or may invalidate the outcome of a research.

Ethical consideration in research is about how research is conducted with respect to the study design, data collection, processing, storage and presentation of findings with moral responsibility. According to the guidelines of Coventry University, ethical approval must be sought prior to data collection. An ethical approval form was completed and submitted along with the survey instruments to the Coventry University FTC Ethics Committee for approval. After a rigorous scrutiny of the application bordering on the impact of the research on the researcher, participants and the university, an ethical approval certificate was issued. The consent of participants was sought, and the participants were informed of their liberty to decline at any stage. Efforts were made to anonymize participation to maintain privacy and confidentiality of respondents' data.

4.8 DATA COLLECTION

After reviewing the pilot study, it was observed that some of the contents were not consistent throughout, missing contents were identified and readjusted to increase validity and reliability. The content and order of the questions was adjusted according to the recommendation of members of author's PhD supervisory team, research colleagues and other with suitable knowledge in designing questionnaire. In addition, a User Experience (UX) expert in automotive design was approached to evaluate the questions before the main study commenced. The questionnaire was updated without actually altering its content and composition. The 34-item questionnaire with 26 measured items was expected to be completed within 8 – 10 minutes, but not less than 7 minutes. Since the mode and channel of distribution was online, a Coventry University Faculty of Engineering survey distribution portal – onlinesurveys.ac.uk former BOS account was created to upload the questions after ethical approval was granted and certificate of compliance issued. Data collection began in May for a duration of 2 months and ended in July 2020. From the pilot study, it became easier to commence data collection from some of the respondents who previously participated and were available and willing to take part in the main study. Additional respondents were reached via email, Facebook, LinkdIn and Amazon MTurk with set conditions on who should and should not participate in the study. To access respondents with knowledge of autonomous vehicles, the researcher joined exclusive and relevant groups on social media to be able to access professionals with knowledge in autonomous vehicles and associated technologies.

Those who received the questionnaire were adults from 18 years and above who were automotive consumers either as passengers, riders or drivers in the UK. Most of the respondents where accessed based on their social media profiles which relates to automotive or transport profession on LinkedIn, Amazon MTurk, Facebook. The rationale for using the online self-administered method is the advantage of accessing individuals who may be impossible to reach using alternative channels as well as providing the opportunity to forward the link to other interested participants and the instant compilation of responses. Huff and Tingley (2015) in their assessment of online survey respondents reinforced the popularity of MTurk surveys in experimental and survey-based research. They contend that MTurk respondents are more often representative of a wider sample in line with the specific requirements relevant to a research sample than physical and offline respondents. On the covering page of the survey, respondents were informed about the survey objectives, the expected time-duration required for completion, contact details and consent agreement for respondents to sign before proceeding with the rest of the questions. This was to increase the rate of response ensuring that respondents understood that they were under no obligation to take part in the study if at any time they decided to withdraw. In accordance with data protection guidelines, participants were assured of anonymity and confidentiality of their responses.

The BOS web application portal is equipped with time-stamp feature for registering the duration spent in completing the survey, the percentage of completion as well as important analytical features such as real-time monitoring of responses and demographics. These features where then deployed for quality assurance in processing the data. Ray (1990) contends that in questionnaire survey, certain responses must be eliminated due to the possibility of response bias, fake respondents, straight-lining or donkey vote effect. To ensure data quality, all incomplete responses and those completed below 240 seconds timeframe where deleted.

4.9 RELIABILITY AND VALIDITY TESTING

A social phenomenon which can be systematically measured and scientifically assessed, should be reliable and validated using proven techniques (Nardi, 2018). One of the main objectives of conducting research is the ability to generalize the outcome or repeat the study (Bryman, 2016).

Reliability and validity are inseparably connected concepts that contributes to the accuracy and consistency of the results. According to Golafshani (2003) reliability and validity are approaches commonly used in quantitative research for observable and measurable quantities. These are standardized approaches supported by scientific paradigm. Reliability is therefore the extent to which a survey instrument produces same or similar results when subjected to multiple trials (Salkind, 1997; Golafshani, 2003; Bashir and Marudhar, 2018). It is a measure of the accuracy of the survey instrument and the quality of research data which implicitly precedes validity, nonetheless, it is not a necessary precondition.

To test the content validity and ensure that the respondents represented a broad range of category, the theoretical construct of interest in a questionnaire design with respect to clarity, comprehensiveness and accuracy was measured. There are several processes of validating survey instruments: face validity, content validity, construct validity and criterion validity. In designing the questionnaire, relevant constructs were included in the content in relation to the research criteria. The questionnaire was sent to research colleagues for content assessment such as errors, repetitions and vagueness. Some of the non-explicit questions where adjusted or rephrased before it was sent to the director of studies for approval.

The internal consistency of the instrument is measured using the Cronbach alpha coefficient by comparing the total variance scores with the variance of the constituent items (Richardson, 2004). Cronbach alpha tends to be higher as a result of homogeneous variance amongst the measured items. The higher the homogeneity of variance among the items, the higher the empirical consistency. As Cronbach alpha coefficient tend towards 1, it signifies a highly shared covariance measuring the same concept. According to Cortina (1993) a high Cronbach alpha does not necessarily mean the scale is unidimensional.

The reliability or internal consistency of the data was measured on 26 items which were aggregated into their respective constructs of 6 items excluding the demographic data using the Cronbach Alpha formula below. In the main research data collection, the alpha coefficient of 0.896 obtained from the data collected which is observed to have improved compared to the pilot study alpha coefficient of 0.864. Although, an alpha coefficient higher than 0.7 is generally acceptable, however, the higher the alpha coefficient the better.

$$\alpha = \frac{N\bar{c}}{\bar{v}+(N-1)\bar{c}}$$

where: N = No of scale items

$\bar{c}$ = Average of all covariance between items

$\bar{v}$ = Average variance of each item

The Cronbach alpha coefficient for each of the variables shown in table 2 indicate that all the factors are above the minimum alpha threshold of 0.6.

Table 4. 1: Cronbach alpha measured variables

Measured Construct	Number of measured respondents	Number of items	Cronbach Alpha
Safety	235	6	0.884
Trust	235	6	0.890
Accessibility	235	6	0.903
Privacy	235	6	0.929
Ethics	235	6	0.872
Level of acceptance	235	6	0.900

The Cronbach alpha for each of the measured items from 0.872 to 0.929 are considered exceptional, an indication that the items are highly inter-related. With an overall Cronbach Alpha α = 0.896, there is high internal consistency between the measured variables.

To validate the data further, the survey results were sent to industry player for evaluation to remove spurious claims and responses that are likely to be outliers in the data.

4.10 LIMITATION

Collecting robust data from a good representative number of respondents could be difficult due to the time expended in filling out surveys. Several respondents either did not attempt or complete the survey and this affected the total number of data size. The size of data obtained for this study may not represent the exact indication of the driving public at this stage of the research. Other segment of the society such as independent individuals such as children, disables or elderly were not specifically captured. As often the case, only limited non-parametric tests are statistically possible. It is expected that for a research of this nature, more data is required to be collected to expand the sample size and representativeness to draw robust conclusions.

4.11 CHAPTER SUMMARY

This chapter discussed the methodology adopted for user data collection and for testing the reliability of the collected data. The quantitative research methodology using survey was considered the most appropriate for collecting opinion-based data with respect to adoption of autonomous vehicles. A pre-test of the survey instrument was conducted to evaluate the strength of the instrument on a small sample. At the end of the pilot study, modifications were implemented before the main data collection was conducted. The main survey employed an 11-point Likert scale for data collection to increase instrument reliability and validity. Responses were obtained from a diverse sample of population to provide their perception and opinion regarding autonomous vehicle use and adoption.

The next chapter includes data analysis and research findings by using relevant software packages such as SPSS and WEKA tools for data processing and mining to identify insights, and for applying machine learning algorithms to test the accuracy of the classification and regression models.

CHAPTER FIVE

5.0 DATA ANALYSIS AND RESEARCH FINDINGS

5.1 INTRODUCTION

The data analysis and research findings are presented in this chapter to answer the research objectives and questions. In this chapter, insights, meaning and association are drawn from the collected data. The completed questionnaire responses were exported into excel for cleaning and preparation before analysis was conducted using statistical tools. The choice for the data analysis software tools are due to availability and frequency of use in scientific researches as such, Coventry University provides full and unrestricted access to students.

The data are presented using tables, charts and graphs to illustrate their distribution and structure. The analysis is implemented using statistical package SPSS 25, and WEKA toolkits. Data analysis is executed in three stages; the first stage is the use of SPSS to prepare the data including descriptive statistics, tests for reliability, factor analysis, relationship between the data features and central tendency of the statistical distribution. The second stage is the use of WEKA to build adoption decision models using different machine learning techniques and the third stage is the implementation of fuzzy logic in MATLAB 2020a to build and validate Fuzzy Logic Adoption Models of Autonomous Vehicles (FLAVAM) according to the concerns which were identified as the major barriers from the literature with the potential to inhibit the adoption.

5.2 DESCRIPTIVE DATA ANALYSIS

The main data collection was conducted over a period of 2 months, May – July and a total of 286 responses were obtained of which only 235 were considered relevant after removal of incomplete responses and missing data. To validate the data, a summary of the data composition and responses were sent to industry expert in the automotive and transport industry. A summary of the data distribution is shown in table 5.1 below. Although, the data is diverse and representative covering a potentially wide driving and/or vehicle user audience, however, the socio-demography is unevenly distributed consisting of Asians, Blacks, Mixed Race and Whites. Of the 235 respondents, 66.4% where males and 33.2% females, signifying that the sample is male dominated. In the age group category, approximately one-third of the sample belongs to the 30 – 39 age group with 37.4% while the next highest age bracket is 20 –

29 with 27.7% followed by 40 – 49 making up 17%. Therefore, the majority of the respondents belong to the active age group 20 – 39 forming a combined total of 65.1%. The data was collected predominantly via online channels. Thus, signifying a high preponderance of educationally qualified people amongst the respondents. The highest number of respondents holds undergraduate degrees at 43.8% followed by 35.7% with postgraduate degrees. Majority of the respondents belong to the marriage segment with 62.1% while 34.0% are single and 0.9% separated. The ethnic/race composition of the respondents are 46.8% Whites, 26% Blacks, 23.4% Asians and 3% mixed race. Majority of the respondents 63.0% are employed, 15.3% are self-employed, and students make up 12.3% while 8.9% are retired.

Table 5.1: Demography of respondents

Demography	**Classification**	**Frequency**	**Percentage**
Gender	Male	156	66.4
	Female	78	33.2
	Undisclosed	1	0.4
Marital status	Single	80	34.0
	Married	146	62.1
	Separated	2	0.9
	Undisclosed	7	3.0
Age	20 - 29	65	27.7
	30 - 39	88	37.4
	40 - 49	40	17.0
	50 - 59	19	8.1
	60+	23	9.8
Ethnicity	Asian	55	23.4
	Black	61	26.0
	Mixed	7	3.0
	White	110	46.8

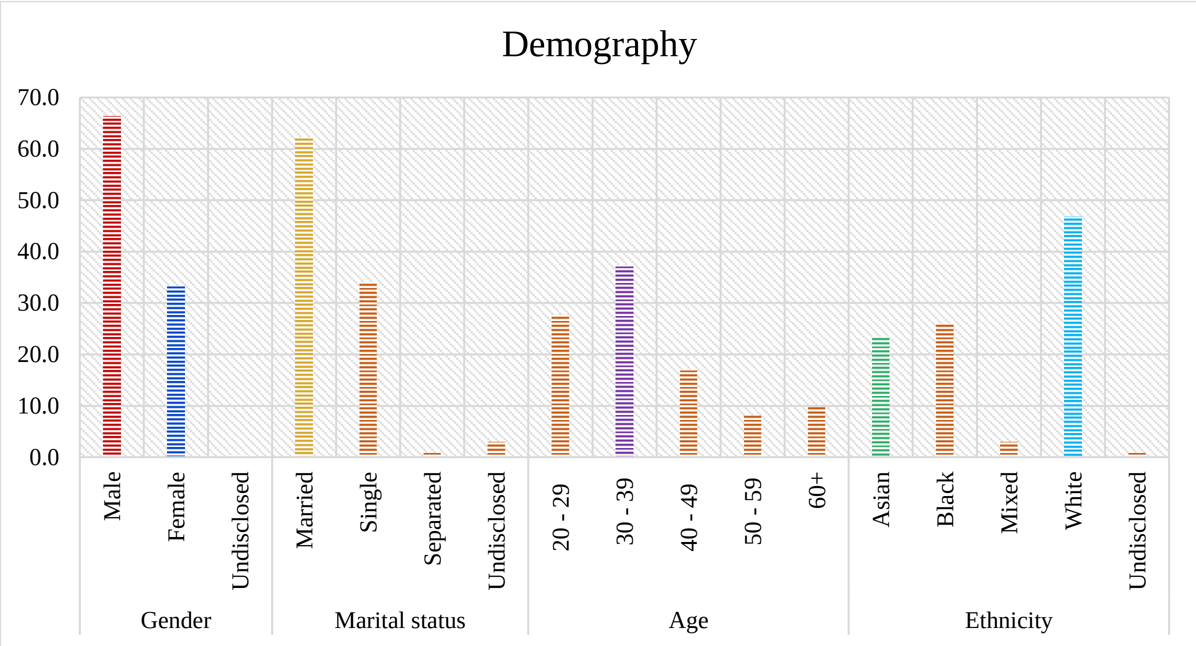


Figure 5.1: Graphical representation of demography

Table 5.2: Status of respondents

Respondents' status	Classification	Frequency	Percentage
Education	Bachelor	103	43.8
	College	29	12.3
	High school	15	6.4
	Postgraduate	84	35.7
	No qualification	4	1.7
Employment	Student	29	12.3
	Employed	148	63.0
	Self employed	36	15.3
	Retired	21	8.9
Annual Income (£)	0 – 19000	72	30.6
	20000 – 39000	63	26.8

	40000 – 59000	37	18.4
	60000 - 79000	29	12.3
	80000+	30	12.8
	Undisclosed	4	1.7

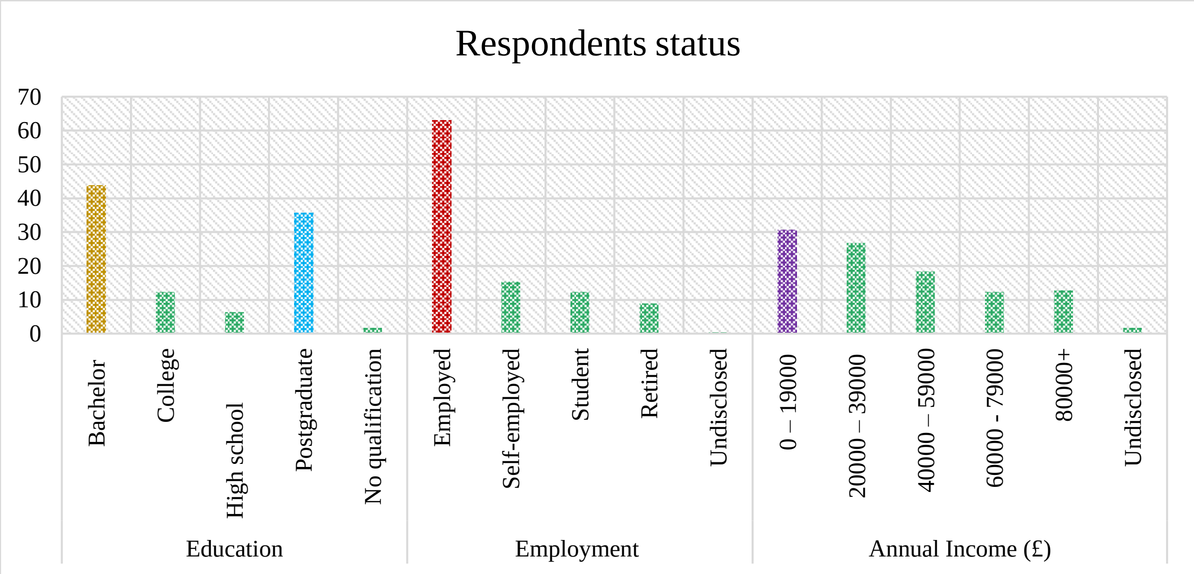


Figure 5.2: Graphical representation of respondents' status

5.3 EXPLORATORY FACTOR ANALYSIS

In questionnaires, numerous variables and subsets are usually applied to classify the research objectives particularly in research testing phenomenon from the mental repository of participants. Exploratory factor analysis is a commonly applied statistical technique to determine the relationships, patterns and interpretation of the variables of interest prior to analysis (Yong and Pearce, 2013). Its origin dates back to the early 1900s when Charles Spearman developed the two-factor theory in human ability using mathematical principles. Occasionally, some of the variables measure different features of the same objective, thus making the study convoluted. To perform exploratory factor analysis, the data must exhibit certain characteristics (Costello and Osborne, 2005; Tabachnick and Fidell, 2007; Hill, 2011):

1. Exploring latent construct in research

2. Ensure appropriate epistemological orientation is exploratory and ontological orientation is reflective
3. Select appropriate variables with few or no missing data
4. Sample size of equivalent to a ratio of the number of respondents to variables not less than 10 to 1

The exploratory factor analysis was tested to determine the most influencing factors that affects the adoption of autonomous vehicles with a view to identifying those factors with the most and least impact. The initial test was to validate the internal consistency of the data using the Cronbach alpha coefficient. The overall output of the internal consistency at 0.896 is an indication of high validity. Secondly, the Kaiser Meyer Olkin (KMO) test was performed to determine the relationship between the variables. A KMO value larger than 0.5 is recommended as the barest minimum value to be considered (Kaiser, 1974; Field, 2000). Whilst 0.6 and 0.7 are considered appropriate (Pallant, 2013) and from 0.8 is a commendable value (Hadi et al., 2016). In the same test, the Bartlett's Test of Sphericity higher than 0.05 indicate the extent of strength of the relationship between the variables.

The sample size of this study is 235 which exceeds the minimum size according to the mathematically permissible size as a requirement for performing EFA. To determine the factor relationship in this study, the KMO, and Bartlett's test of sphericity were plotted. From the results shown in table 5.3 below, the KMO and Bartlett's test of sphericity produce outstanding values, an indication that the data are acceptable for further analysis.

Table 5.3: KMO and Bartlett’s Tests

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.885
Bartlett's Test of Sphericity	Approx. Chi-Square	863.011
	df	15
	Sig.	0.000

Spearman’s correlation coefficient was used to determine the effect and strength of association between the independent variables and the dependent variable, with the results shown in table 5.4 below. The choice for Spearman’s rho (ρ) test is most suited for ordinal data – Likert scale

(Schober et al., 2018). With respect to the ranking, trust has the strongest positive correlation followed by accessibility, privacy, ethics, and safety with the level of adoption of autonomous vehicle respectively shown in 5.4. The spearman's rho is less sensitive to bias due to its ability to reduce the effect of outliers (Rousselet and Pernet, 2012). The p-value <0.001 suggests that the adoption of autonomous vehicles will be slow considering that users' concerns will act as potential barriers. The p-value of this research aligns with other research in vehicle technology adoption such as electric and conventional vehicles which is typically $p < .001$ (Bozorg and Ali, 2016; Haustein and Jensen, 2018). However, the diffusion of AV technology will be faster in combination with other associated enabling technologies as well as demonstrable impact on lifestyles of users.

Table 5.4: Spearman's rho correlation coefficient

Spearman's rho		
Variable	Degree of Adoption	Rank
Trust	.816**	1
Accessibility	.697**	2
Safety	.645**	3
Privacy	.575**	4
Ethics	.544**	5
Correlation is significant at the 0.01 level (2-tailed).		

5.4 ADOPTION BEHAVIOUR: FINDINGS FROM SURVEY

The study provided an insight into the pattern of autonomous vehicles adoption consistent with demographic characteristics of the sampled population. As stated in section 5.2, the dataset consists of diverse respondents from the public including drivers, passengers, pedestrians and cyclists representing different age groups, education, employment, marital, and ethnic backgrounds. The results from the survey shows different adoption behaviours according to the demographic distribution. Previous studies on AV adoption have provided fascinating evidence on adoption behaviour amongst the general population (Kyriakidis et al., 2015; Bansal et al., 2016; Abraham et al., 2016; Becker and Axhausen, 2017).

5.4.1 FACTORS INFLUENCING THE ADOPTION OF AV

It is critical to understand the factors that will affect the adoption of AV to assist stakeholders in planning and executing policies and initiatives to guide the whole gamut of deployment, research, development, testing and launch. Understanding these factors will help to lead the various stakeholders in the AV and associated technologies space towards wider adoption. From the review of several literature, five factors were identified as the predominant concerns expressed by conventional vehicle users including traditional road users who are equally the future users of autonomous vehicle (Fagnant and Kockelman, 2015; Kaur and Rampersad, 2018; Zhang et al., 2020). Respondents were requested to select their major concerns as factors that affects their adoption of autonomous vehicles. They expressed their concerns accordingly as shown in figure 5.3. Majority of 72% considers safety as the most significant concern that would affect their degree of adoption, followed by accessibility at 11% - which also includes cost of ownership; while trust is 10% respectively and the least concerns for respondents are privacy and ethics at 4% and 3%respectively.

The aim of this research is to evaluate how these concerns are likely to act as barriers to AV adoption by predicting their impact on the level of adoption. Since this is the core of the research, these concerns remain significant amongst respondents. These concerns were continuously expressed by users as germane to their participation in the adoption of AV. The concerns cut across the different user groups such that 39.57% of men considers safety as a barrier to their adoption compared to women with 21.70%. Married users are more safety-conscious with 37.87% as against 20.43% of single users. With respect to ethnicity, 28.51% respondents from white ethnicity are concerned about safety whilst blacks and Asians are 15.74% and 15.32% respectively. Majority of the respondents who fall within the ages of 20 – 39; a combined total of 48.30% are more concerned about safety than other potential barriers than other groups within the study.

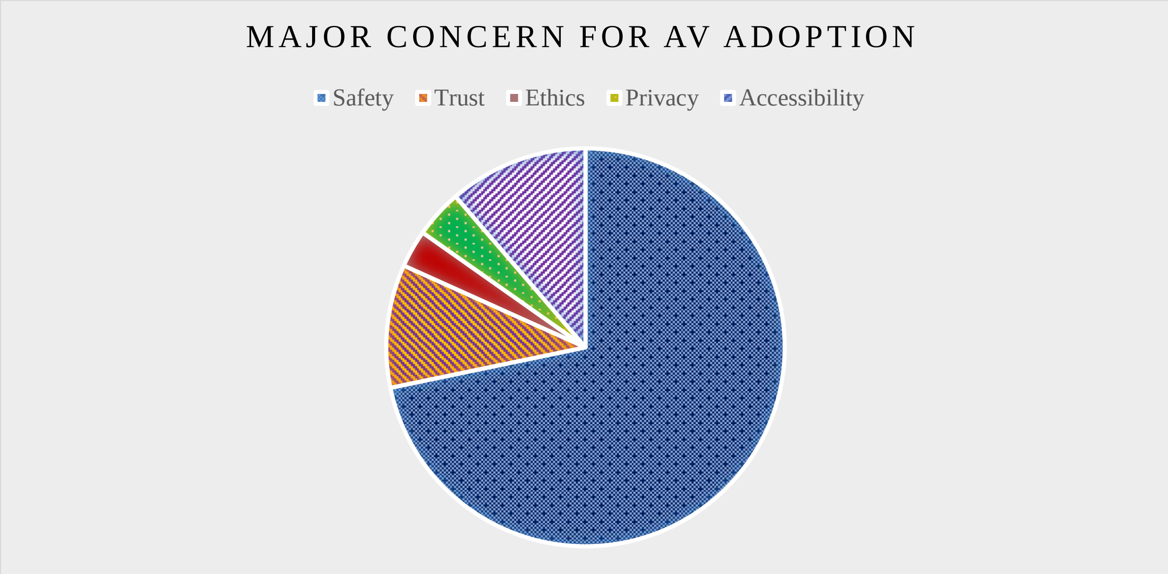


Figure 5.3: Major concerns relating to the adoption of autonomous vehicles

5.4.2 HOW WILL THE FACTORS DETERMINE THE LEVEL ADOPTION OF AV

The factors that have been identified in this research to impact the level of adoption of autonomous vehicles are much the same as those found in several similar research (Kaur and Rampersad, 2018; Abraham et al., 2016; Fagnant and Kockelman, 2015). As shown in figure 5.3 above, respondents to our survey aligned, selected and ranked the factors that will affect their level of adoption. Majority of the survey participants consider safety, trust, and accessibility as the critical determinant that will affect their adoption decision. These are fundamental consideration which are capable of mitigating the use or rejection of the technology. In addition, other demographic considerations such as gender, income, age, education etc. will equally affect adoption, but with no significant effect. However, these indicators are perceived and may be altered when AV becomes reality on city roads.

According to our data, all these considerations are evident choices that will determine the adoption of AV. The promoters of AV are enthusiastically promoting the widespread adoption of driverless vehicles on the account of apparent contribution to a wide aspect of human development more than the current conventional vehicles (Kyriakidis et al., 2015; Bansal et al., 2016; Bagloee et al., 2016; Bonneau et al., 2017; Brummelen et al., 2018). Ordinarily, these apparent possibilities would encourage the adoption of autonomous vehicle, sadly the measure of central tendency from our data, respondents cannot validate the proposed benefits from the proponents of AV. This is gleaned from the responses shown in table 5.5. From a total of 235 participants, on a scale of 0 – 10 where 0 is the lowest and 10 the highest score, the mode values for each of the questions confirm user attitudes towards adopting autonomous vehicles.

Table 5.5: User adoption score based central tendency

Questions	**Mean**	**Median**	**Mode**
How likely are you to ride in a self-driving vehicle?	4.46	4.00	0.00
How much do you agree that autonomous vehicles will be reliable?	4.15	4.00	2.00
How confident are you about riding in a completely self-driven vehicle?	4.58	4.00	3.00
Would you prefer to ride in an autonomous vehicle that allows driver to take control when required?	2.57	2.00	0.00
Do you agree that autonomous vehicles will perform according to their designed functionality?	3.87	4.00	3.00

Generally, the adoption of AV is expected to be two-fold; ownership commonly known as privately-owned (PAV) and shared known as shared autonomous vehicles (SAV). The questions border on use by ownership and/or use by sharing. Similar to (Schoettle and Sivak, 2014) majority of the men, 66.38% of the participants prefers to own an autonomous vehicle compared to women, 57.45% who prefer to share. Overall, female respondents favour adoption less than their male counterpart. Majority of these respondents believe that a human driver should be part of the driving task at any given time. On the question of the importance of human driver taking total control in driving shown in figure 5.4 below: cumulatively, over 50% of respondents agree and expect a human driver to be part of the process of driving in any capacity even if passively. It is therefore important that the aforementioned factors act as assurance and not consternation for future users of autonomous vehicles.

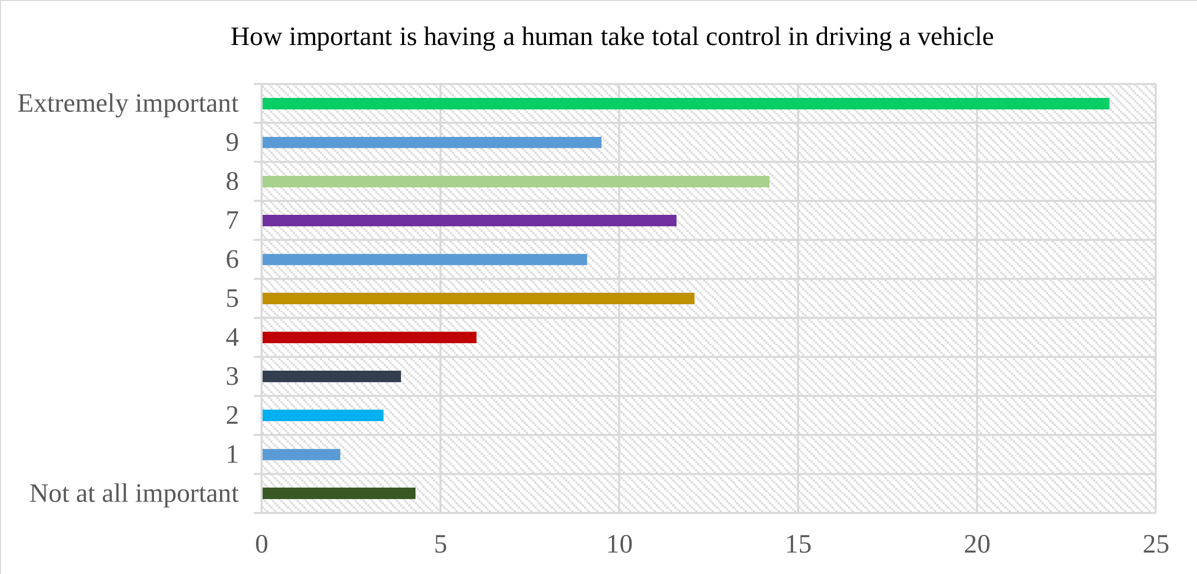


Figure 5.4: Importance of human driver taking control during driving

To reinforce the question, respondents agreed that autonomous vehicles will be reliable when they become mainstream, however, they will prefer models that allows humans to take total control or switch to human driving mode as situation demands. Although, this feature presently exists in L2 vehicles. From our data, 39.57% of male respondents prefers to take control of driving when the need arise compared to 18.30% of female. In total, 57.87% of the respondents both males and females support AV models that provide occupants with the functionality of taking control when required. Locus of control is important across different generations of the surveyed respondents. It was found to be more prominent amongst the 30 – 39 age cohort with 19.57% compared to 15.32% of the 20 – 29 age group and 11.06% in 40 – 49%. To increase adoption, the majority of the respondents agree that autonomous vehicle should have their dedicated driving lanes without sharing with conventional vehicles to reduce the rate of accidents.

The demographic implication for the adoption of AV is significant in the area of age, marital status, income, and ethnicity. It is therefore important that the deployment of autonomous vehicles is guided by the highest level of safety standards in accordance with all known regulations established for the industry. Subsequently, test drives and gradual inclusion of automated features into new model vehicles before the mass introduction of full autonomy into mainstream vehicles will prove to be a welcome option for most of the survey participants. In addition, respondents prefer to experience vehicle autonomy in tasks with less of human participation such as delivery and other logistics services.

5.5 CLASSES OF AV ADOPTION

From our data, a combination of questions was aggregated to determine the level of acceptance of autonomous vehicles. These questions were asked to provide an overview of how respondents would adopt AV. The results were classified into three different classes, low, high, and full adoption. As shown in table 5.6, 0 – 5 represents low adoption and 6 – 9 was classed as high adoption while 10 was classed as full adoption. Respondent however indicated their level of adoption as shown with 46.38% falling into the low adoption category; majority of whom are old, retired and females basing their concerns on safety of the vehicles and privacy of their personal information. A good number of this category are low-income earners, who perhaps consider AV a luxurious technology. The high adopters ascribe their level of adoption synonymous with high level of safety, trust and privacy of autonomous vehicles. They contend for example, the higher the safety, trust, and privacy, the higher their rate of adoption. The high adopters of AV are made up of 53.62% of the 235 respondents out of which half are of white ethnic background, employed, married, and educated above college level.

Although, more than 96% of the respondents are familiar with the technology from the knowledge obtained from media and research institutions; none has experienced a physical ride which may have the potential to influence the decision to adopt autonomous vehicles. Predictably, full adoption is considered to be 10. There was no respondent who fall into the full adoption category. This is not surprising since self-driving vehicle technologies is a concept still undergoing research and development. Its adoption will not occur rapidly as it depends on a total shift from the traditional driving process. It is therefore important that manufacturers, city planners and policy makers will continue to improve the technology as well as provide increased exposures to users to encourage adoption when AV becomes mainstream.

Table 5.6: Classes of AV adoption

Level of Acceptance	No. of Adopters	Percentage Adoption	Class of Adoption
0 – 5	109	46.38	Low
6 – 9	126	53.62	High

5.6 MODELLING LINGUISTIC DATA

There are several statistical modelling approaches available to process linguistic data obtained from survey instruments (Rayson, 2002; Hirschberg and Manning, 2015; Wu et al., 2018). The fundamental objective of this research is to investigate the concerns that are likely to act as barriers to the adoption of autonomous vehicles. These barriers are measures of the perception of potential users to understand their specific concerns towards autonomous driving technology. The questions sought to measure multiple factors; opinions, perceptions and/or judgements in relation to the degree of acceptance of autonomous vehicles based on priori defined variables. These are subjective constructs which are regarded as ordinal scale data; not measurable nor observable, but typically cognitive. Vonglao (2017) contend that these ordinal scale linguistic constructs cannot be analysed using conventional statistical tools. Arithmetic operations such as subtraction, addition, multiplication, and division cannot be performed on linguistic variables due to the unequal intervals between the variables. According to Li (2013), it is difficult to obtain precision from ordinal scale questions due to the obscurity and ambiguity in the responses.

The survey instrument was designed to capture linguistically constructed statements using eleven-point unipolar Likert scale to measure the degree of agreement. The responses were measured using sequential integer scores from extremely agree to extremely disagree with a measuring ranking from 0 – 10; were 10 = extremely agree or likely and 0 = extremely disagree or unlikely.

Table 5.7: Statistical distribution of data

	Safety	Trust	Accessibility	Privacy	Ethics	Level of Acceptance
Mean	4.59	4.08	4.64	4.69	3.28	3.20
Median	5.00	4.00	4.00	4.00	3.00	3.00
Mode	5	4	5	4	3	3
Std. Deviation	1.926	2.201	2.419	2.363	0.901	1.615
Variance	3.709	4.846	5.852	5.586	0.812	2.608

The results below show the average scale ratings respondents awarded each variable within the scale were 0 = negative agreement (extremely unlikely; completely disagree; not at all confident) and 10 = positive agreement (extremely likely; strongly agree; extremely confident).

Table 5.8: Measured variable of respondents' opinion

Scale	**Safety (%)**	**Trust (%)**	**Accessibility (%)**	**Privacy (%)**	**Ethics (%)**	**Level of Acceptance (%)**
0	1.70	2.13	2.55	2.13	0.43	4.26
1	2.98	8.09	5.96	4.68	1.28	12.34
2	8.09	17.02	13.19	8.94	17.45	17.45
3	18.72	17.02	14.89	17.45	42.55	26.81
4	17.87	19.15	14.04	20.00	31.91	18.30
5	20.85	15.74	17.45	14.89	6.38	12.77
6	14.89	5.11	10.64	9.79	0.00	8.09
7	7.66	6.81	9.36	5.53	0.00	0.43

8	5.96	5.53	3.83	11.06	0.00	0.00
9	0.85	1.70	4.26	3.40	0.00	0.00
10	0.43	1.70	3.83	2.13	0.00	0.00

In table 5.8 respondents ranked the measured variables according to their likelihood to adopt or reject autonomous vehicles based on the concerns. The higher the rank on the scale of 0 – 10, the lower the likelihood on rate of adoption.

5.61 ESTIMATING AV ADOPTION USING SUPERVISED MACHINE LEARNING MODELS

Machine learning techniques have begun to find application in the estimation and modelling of adoption-based user stated preference (Golshani et al., 2018; Wang and Ross, 2018; Lee at al., 2019). One of the explanations machine learning has been applied to these studies is their ability to automatically solve nonlinear problems irrespective of data source. Despite the apparent predictive accuracy of machine learning techniques, they generally lack interpretability due to their repetition in algorithmic computation. The data for this research are quantitative with latent constructs which cannot be measured directly based on their subjectivity. Therefore, predicting opinions and attitudes on these subjective constructs is sometimes difficult due to prediction accuracy and interpretability (Lee et al., 2019). Kamargianni et al. (2014) substantiate that empirical analysis to determine individual preference and attributes is challenging.

To determine the degree of acceptance of autonomous vehicle by the surveyed population, different machine learning algorithms were applied to the linguistic data using the Waikato Environment for Knowledge Analysis (WEKA) open-source tool version 3.8. WEKA is a data mining tool with a combination of several machine learning algorithms in Java developer used for classification, regression, visualization, and clustering (Zao, 2017). Originally developed in 1992 by the University of Waikato, New Zealand as an open-source software for research in agriculture, it immediately gained adoption in the wider research community irrespective of discipline (Maimon and Rokach, 2010). WEKA use highly parametric machine learning framework with Bayesian optimization to determine the best objectification model in a given dataset. Weka can be used exclusively as standalone tool or/and integrated with other analytical software tools using API. One of its advantages is the availability of a huge collections of algorithms which are relevant to perform different tasks using simple interface. The data file can be in CSV or the traditional ARFF file format, which includes special tags to indicate different attributes in the data: attribute names, attribute types, attribute values and the data. Different panes on the GUI interface of which the explorer and experimenter are the commonly used to run tasks for learning, training, and testing algorithms.

According to Kotthoff et al. (2017) it uses a learning algorithm A = {A(1), . . . , A(k)} and their associated hyper-parameter spaces Λ(1) , . . . , Λ (k) and aims to identify the combination of algorithm A(j) ∈ A and hyper-parameters λ ∈ Λ (j) that minimizes cross-validation loss:

$$A^{*}\,\lambda^{*} \in \frac{\text{argmin}}{\mathrm{A(j)}\in \mathrm{A},\lambda\in\Lambda(\mathrm{j})}\ \frac{1}{k} = \sum_{i=1}^{k} \mathcal{L}\left(A_{\lambda}^{(j)}, D_{train}^{(i)}, D_{test}^{(i)}\right) \tag{5.1}$$

where $\mathcal{L}\left(A_{\lambda}^{(j)}, D_{train}^{(i)}, D_{test}^{(i)}\right)$ represents the loss achieved by algorithm A with hyper-parameters λ when trained on $D_{train}^{(i)}$ and evaluated on $D_{test}^{(i)}$. This is a combined algorithm selection and hyperparameter optimization also known as the sequential model-based optimization, an iterative method that fits probabilistic models (Brochu et al., 2010). It is focused on Gaussian process model with excellent performance for low-dimensional problems on a given data (Eggensperger et al., 2013).

WEKA perform predictions by automatically predicting the most frequent class in the training data. In our case, we used 80% for training and 20% for testing. For validation, WEKA applies 10-fold cross validation automatically to the model. The supervised machine learning algorithms applied to perform regression, classification and neural network are random forest, multiplayer and logistics regression. The different algorithms performed differently in terms of levels of accuracy. Amongst the classifiers, random forest classifiers performed with better accuracy and lowest error values as shown in table 5.9.

Table 5.9: Machine learning prediction models

Machine Learning Algorithm	**Correctly classified**	**Mean absolute error**	**RMSE**	**Relative absolute error**	**Ranking**

Random Forest	92.77	0.22	0.27	64.70	1
Multilayer Perceptron	85.53	0.09	0.23	26.54	2
Logistic Regression	79.07	0.15	0.20	56.62	3

5.61.1 RANDOM FOREST

The random forest model performs equally high at 92.77% accuracy, a mean absolute error (MAE) of 0.22 and root means square (RMSE) of 0.27. It operates by averaging results of different trees using ensemble of decision trees trained by bagging method to increase overall prediction. The predicted model is actually a combination of different trees/models which is improved by a reduction in variance as well as correlation between the trees. Random forest is peculiar in that it can solve both regression and classification problems efficiently (Genuer et al., 2010). Equation for regression problem according to the model is as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(fi - yi)^2 \qquad (5.2)$$

Where: N = number of data points

fi = value returned by the model

yi = actual value for data point i

This equation calculates the distance of each node from the predicted actual value by deciding which branch contributes to the best decision.

For classification problem, the Gini index equation is applied:

$$Gini = 1 - \sum_{i=1}^{c}(Pi)^2 \qquad (5.3)$$

Where: Pi = relative frequency of the class of observation

C = Number of classes

5.61.2 MULTILAYER PERCEPTRON

Multilayer perceptron (MLP) is a supervised classification neural network that provides nonlinear mapping between input vectors and corresponding output with interconnecting hidden layer based on static modelling in practical problems such as image and speech recognition as well as prediction (Gupta and Sinha, 2000). With respect to the sampled data, the MLP model for AV adoption is feed forward algorithm with a correlation coefficient of 85.53%, mean absolute error (MAE) of 0.09, root means square (RMSE) of 0.23. The MLP is a network that contains several layers where each layer is represented by the equation:

$$y = f(Wx + b) \tag{5.4}$$

Where: f = activation function

W = weights in the layer

x = input vector

b = bias vector

5.61.3 LOGISTICS REGRESSION

Logistics regression classified the prediction model with 79.07% correlation, 0.15 MAE and RMSE 0.20. The logistic regression model applies the logit transformation, a natural logarithm (In) to the dependent variable, level of acceptance. The probability (P) that users will accept autonomous vehicles is given by the equation:

$$\log\left(\frac{P}{1-P}\right) = \text{logit }(P) = \propto + \beta nXn \tag{5.5}$$

$$P = \frac{1}{1+e^{-(\propto + \beta nXn)}} \tag{5.6}$$

Where: $\propto$ is the intercept

β = regression coefficient

X = independent variables

N = variables

Similar to other research where logistic regression model has been applied to technology adoption research in digital innovation (Jahanmir and Cavadas, 2018); agriculture (Conteh et al, 2015; Li et al., 2019), it was found that accessibility and safety negatively affected the level of adoption compared to other variables.

Using the five input variables, the training and testing data was split in 80 and 20 percent respectively. The low value of the RMSE indicates a significantly consistent relationship between the predictors and the target.

The three models from the different machine learning algorithms suggests predictive accuracy considered to be of excellent performance. However, there is the possibility of generalization in the model performance with a likelihood of bias performance estimation (Raschka, 2018).

Typically, machine learning algorithm may memorize the data fed into it and fail to make good prediction on future datasets. Model selection is therefore the process of selecting the best model from potentially available models (Emmert-Streib and Dehmer, 2019). In supervised machine learning, there is the likelihood of pessimistic bias aiming to achieve best performing model selection. According to Raschka (2018) all models contain predictive errors due to different statistical noise in the data; therefore, the concept of the best performing model could be misleading considering several other factors such as data size and model complexity.

5.7 CHAPTER SUMMARY

The chapter presents the analysis of the user data using statistical processing and data mining tools adopted in this research. The results from the data indicate an assortment of performance with respect to user adoption. It was observed that adoption differ from person to person according to demographic and specific peculiarities. An understanding of the socio-demographic characteristics of users is vital to the adoption of AV as shown in our results. The data shows a high validity, strong relationship as well as significant correlation between the variables. Adoption of autonomous vehicles will be slow according to the p-value which is expected of every new technology. The supervised machine learning algorithms applied shows high accuracy and low RMSE values.

The next chapter provides the background to the novel fuzzy logic inference system, which is the major component of the application tool for modelling human reasoning, attitudes and perception which is the area of contribution to the body from this research. The chapter presents the fuzzy logic autonomous vehicle adoption model, where human reasoning is modelled based on linguistic labels. The chapter demonstrates how fuzzy logic is capable of extracting knowledge from human reasoning to capture attitudes and perceptions.

CHAPTER SIX

6.0 FUZZY LOGIC IN LINGUISTIC MODELLING

6.1 INTRODUCTION

The way and manner humans reason differ significantly from scientific reasoning and systems processes. Logic and rationality are an essential part of human reasoning. This informed the numerous works in classical logic by Aristotle, Leibniz, Bolzano, Boole and others in the 19^{th} and 20 centuries (Peckhaus, 2018). However, logic has now become a major component of discrete mathematics using abstract symbolic language to define concepts, propositions, symbols, laws and processes, and the semantic contents of reasoning. Although, logic is necessary in handling human reasoning, however, it is insufficient considering the uncertainties in language and description of an outcome. To complement this deficiency, semantics, cognitive and linguistics are combined to form suitable analytical framework to understand reasoning.

Lofti Zadeh, recognized the limitations of applying probability theory and Boolean logic in handling human reasoning; he developed fuzzy logic and fuzzy set theory which allows human reasoning to be encoded as mathematical functions in order to express a phenomenon (Zadeh, 1975).

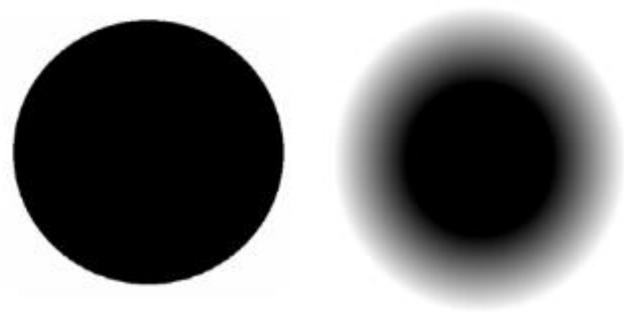


Figure 6.1: Schematic depiction of classical (crisp) set and fuzzy set (Dernoncourt, 2013)

6.2 ORIGIN OF FUZZY LOGIC AND ITS DEVELOPMENT

In a period of five decades, the use of fuzzy logic has grown from a few engineers to a large community of scientists and engineers working and applying the theory of uncertainties in scientific research. Fuzzy logic was developed by Lofti Zadeh in 1965 in his seminal paper, fuzzy sets in information and control. Zadeh proposed the concept of fuzziness which he referred to as the ambiguity of certain concepts and attributes within an intermediate state without clear delineation (Seising, 2015). The concept was to mathematically model vagueness expressed in natural language. In 1971, Zadeh published a paper, quantitative fuzzy semantics where he presented formal concepts, methodology and derivations which other researchers have built upon (Garido, 2011). Zadeh differentiated fuzzy sets from classical sets with the introduction of degree of membership to define the extent of a function belonging to a set.

Over the years, the concept of fuzzy logic and fuzzy mathematics have continuously evolve resulting in several theoretical and application expansion. The impact of fuzzy logic within mathematical and physical sciences continue to increase and has expanded into a wide spectrum of knowledge-based applications. These developments gave rise to soft computing; where decision-making, reasoning and computation exploit the tolerance of imprecision and uncertainty in data to achieve low-cost solutions. Fuzzy logic formed the basis upon which soft computing developed (Zadeh, 1994). According to Zadeh, soft computing has found application in a growing number of consumer electronics, medical diagnostic systems and several machine interface quotients (MIQ) systems (ibid).

Several researchers have contributed to the development of the fuzzy logic field (Mamdani, 1976, 1994; Tagaki and Sugeno, 1985; Dubois and Prade, 1980, 1996). These authors have contributed immensely to the field using computational intelligence which represents knowledge combination and information processing. Hans Jurgen Zimmermann, the editor of Fuzzy Sets and Systems Journal in 1995 decided that works in the field should appear in the International Journal for Soft computing and Intelligence (Seising, 2009). During this early years, congresses, conferences, and seminars were organised in the USA, Europe and Japan where disciples of the new discipline converged to define systems and methodologies which opened the doors for fuzzy thinking.

Although, the fuzzy logic discipline has gathered momentum since 2000, however, in the beginning, Zadeh’s paper received major criticisms from the scientific community. It was regarded as unnecessary extension of classical logic (Hajek, 1998; Gerla, 2017; Gelepithis, 2016). According to Celikyilmaz and Turksen, (2009) fuzzy logic is not easy to understand as any original model should be, it is counter intuitive and a complicated artificial mathematical construct. Wolkenhauer and Edmunds (1997) argue that since the concept is built on human perception, there will barely be any linearity perceived by means of common-sense; it is essentially founded on trial-and-error procedure in designing fuzzy controllers. Zadeh, the founder of fuzzy logic, indicated that, though, there is great potentials in the discipline, however, some of the issues relates to interpolation, knowledge representation, data compression, stability analysis and signal processing (Zadeh, 1994).

6.3 FUZZY LOGIC

Fuzzy logic is defined on a universe of discourse X, characterised by membership function µA that takes on values in the interval of [0, 1] (Musikkasuwan, 2013). A few decades ago, it was considered as an obscure mathematical approach developed from human thinking and natural language. It continues to find application in several engineering and scientific domains for developing intelligent systems for decision-making, pattern recognition, optimization, and control. It has been applied to systems control in air conditioning, washing machine, and vehicular braking systems, unmanned devices in automation and robotics, weather forecast, medical diagnosis, financial and business transactions as well as several other areas. Fuzzy logic is a mathematical concept that applies the extent of a degree of truth in validating a condition (Dernoncourt, 2013). It uses imprecise and uncertainties in linguistic expressions as interval values or fuzzy sets rather than numeric probabilistic or statistical variables (Li and Huang 2010). Every variable has an element of uncertainty under specific conditions. Generally, it is an attempt to formalize human capabilities; to converse, reason and make rational decisions in an environment of imprecision, uncertainty, incomplete information, partial truth and partial possibility (Zadeh, 2008). It is reputed for its ability to model linguistic variables expressed in natural language. Zadeh (1992) proposed fuzzy theory with the following characteristics:

i. Everything is a function of degree
ii. Any system can be fuzzified
iii. Inference is viewed as a process of elastic constraints
iv. Knowledge is interpreted as a collection of variables with fuzzy constraints
v. Exact reasoning is viewed as a limiting case of approximate reasoning

Fuzzy logic operates on the basis of IF – THEN rules where, IF is the antecedent and THEN the consequent. The antecedent, a fuzzy expression is composed of one or more fuzzy sets connected by fuzzy operators; whilst the consequent assigns fuzzy values to the output variables (Liu, 2015). The IF – THEN rule builds inference inputs which acts as the main classification feature in the process. Modelling, data analysis, clustering, prediction, and control are some of the other processes the IF – THEN rule is applied.

The fundamental idea of the fuzzy set theory is that an object may have partial membership of a set, which could possess all possible values between 0 and 1. When the membership of an element is nearer to 1, that element is more likely to belong to that set; likewise, when the membership of an element is nearer to 0, the less likely that the element belongs to that set. The lower values imply lower membership while higher values imply higher membership of the set. The degree of belonging to a set is determined by the membership function μA

Where $\mu A: X \rightarrow [0, 1]$, where $x \varepsilon X$ (6.1)

A finite fuzzy set can be denoted as

$A = \mu A\ (x1)/x1 + \mu A\ (x2)/x2 + ... + \mu A\ (xn)/xn$ (6.2)

$\mu A(x) = \{1$ if and only if $x \in A$, 0 if and only if $x \in A$.

Where x is the collection of variables in X the universe of discourse and A the fuzzy set

Fuzzy logic comprises of four main components shown in figure 6.2: the fuzzifier, inference engine, knowledge base (rules) and defuzzifier:

i. Fuzzifier – translates crisp values/inputs into fuzzy values
ii. Inference engine – applies fuzzy reasoning mechanism to obtain fuzzy output (Mamdani inference)
iii. Knowledge base (rules) – consists of both fuzzy rules and membership function representing the fuzzy sets of linguistic variables
iv. Defuzzifier – translates the fuzzy output into crisp value.

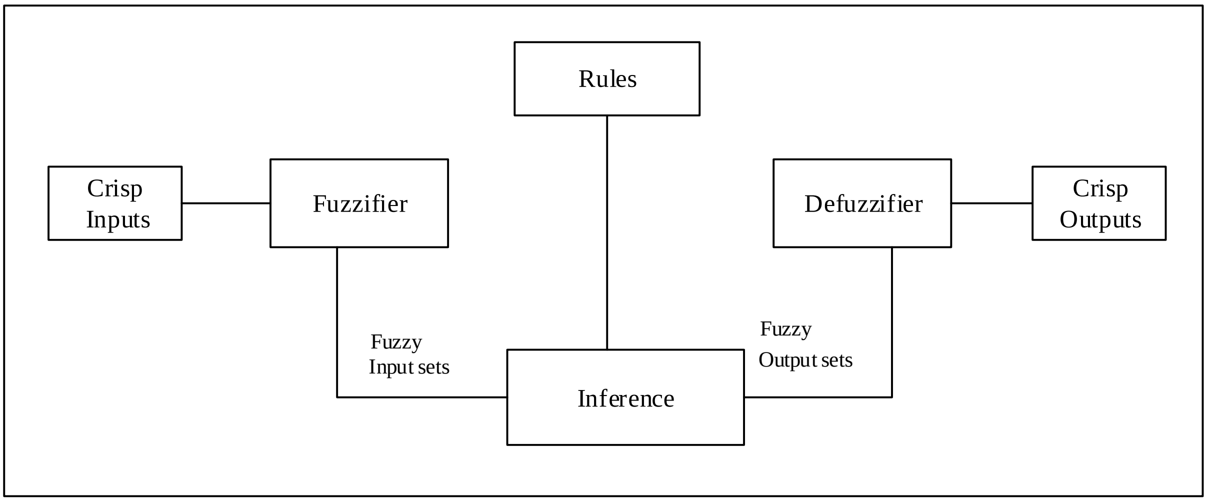


Figure 6.2: Fuzzy Logic System

Fuzzy logic is categorised into two types: type-1 and type-2; Type-1 was developed to simulate human reasoning using uncertainties to generate decision (Zadeh, 1965). Type-2 was developed to complement Type-1 in complex system but requires substantial increase in computational modelling (Musikkasuwan, 2013). There are six most widely used membership functions as indicated in figure 6.3 below; triangular, trapezoidal, gaussian, z-shape, bell and sigmoidal (Pappis and Siettos, 2014). In designing membership functions, fuzzy inference systems (FIS) are implemented. The two most commonly used FIS are Mamdani-type and Sugeno-type which were developed in 1977 and 1985 respectively (Kalogirou, 2014).

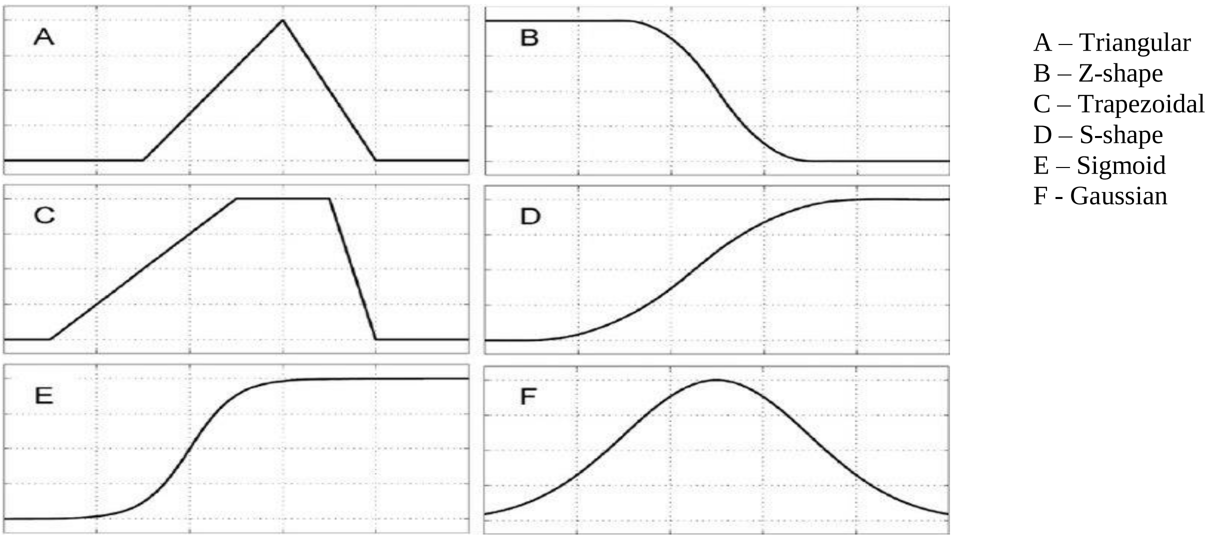


Figure 6.3: Types of membership function (Pappis and Siettos, 2014).

6.31 FUZZY PREASONING

Fuzzy logic is the process of expressing human reasoning with subjective terms for decision-making in knowledge-based systems. Knowledge-based systems sometimes also called expert systems emulate human thinking to arrive at decisions (Siler and Buckley, 2005). These depend on developing theoretical framework for approximate reasoning using if-then-rule (Zadeh, 1975). It has been adopted in decision situations where classical framework is unable to perform due to insufficient inputs. Mathematically, in fuzzy reasoning, the implication function relates the premise or antecedent to consequent or conclusion according to the form:

If x = Ai, then y = Bi (6.3)

In eqn. 4.3, i = 1, 2, 3 …. N, number of rules

X = antecedent linguistic variable

Ai = antecedent linguistic term

Similarly, y = consequent linguistic variable

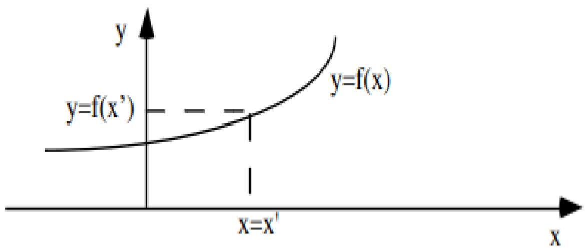
Bi = consequent linguistic term

The fuzzy relation in the rule using the relational calculus for values x and y is denoted as:

Ri = (X *x* Y) (6.4)

That is μRi (XY) = μRi (X) ∧ μRi (Y) (6.5)

The inference rule states that if y = f(x), then y' = f(x')



X is A (or) X is B, then X is A ∪ B (6.6)

X is A (and) X is B, then X is A ∩ B (6.7)

In fuzzy reasoning, the relationship between two statements regarding the variables in a system expressed by a function *f* mapping each value *x* of A into a value *y* of B. The mapping then provides the basis upon which decision is made. According to Shang (2005), fuzzy reasoning entails forward-chaining and backward-chaining reasoning systems. Forward-chaining is when data is placed in the working memory, then the system goes through a sequence of identifying the premises and rules which matches with the facts within the working memory and selects the best output. In backward-chaining reasoning system, the output is placed in the working memory. The system matches rules with the goal, selects the best rule and places the corresponding premises in the working memory. This process through iteration makes the premises to become the new goal which matches against the rule conclusions. In this process, the system works backward from the original goal until all the sub-goals in the working memory are ascertained to be true. For example, expert configuration (XCON) by Digital Equipment Corporation was the first commercial success of a forward-chaining expert system which saved the company about $40 million annually (McDermott, 1982 cited in Shang, 2005).

6.32 MEMBERSHIP FUNCTION

In fuzzy sets, grade of membership is assigned to all elements, such that the transition from membership to non-membership is gradual rather than abrupt. The degree of membership for all elements in a fuzzy set indicate its position in a solution spectrum. The set of elements that have a non-zero membership is called the support of the fuzzy set. The membership function may appear such that values outside the interval are omitted from the associated fuzzy set. Although, several membership functions exist; trapezoidal, Gaussian, bell and sigmoidal, exponential, the triangular membership functions are commonly used due to their simplicity in computational processes (Touil and Attous, 2013).

The membership function is derived from experimental data constructed on the linguistic terms which is associated with a real number between [0, 1] with each element x in X representing the degree of membership of x in A. Membership function is usually shown as a curve – linear, triangular, trapezoidal or bell-shaped. The curve consists of three components; horizontal axis – the domain element of the fuzzy set; vertical axis – degree of membership and surface of the set, which relates the degree of membership to the domain element (Ordoobadi, 2009). The membership function represents the degree of truth, where the peak of the distribution (kernel) depicting the highest degree mean close to 1 and the tail of the distribution (support) showing the lowest degree close to 0.

6.33 DEFUZZIFICATION

The output from the fuzzy inference system remains fuzzy and needs to be processed into crisp (non-fuzzy) value. The process of converting fuzzy to crisp values is known as defuzzification, conversion of linguistic variables into numerical values. This transformation process helps to identify the exact position of the fuzziness in the real world. There are several defuzzification methods; centre of area (CoA) or centre of gravity (CoG) and Mean of Maxima (MoM). The CoA/CoG method takes the output distribution and finds its centre of mass to obtain a single crisp number.

Thus, it uses the following equation to calculate the geometric centre of this area.

$$CoA = \frac{\int f(x).\, xdx\ xmax\ xmin}{\int f(x)dx\ xmax\ xmin} \quad (6.8)$$

Where: CoA = centre of area

x = linguistic variable

xmin and xmax = range of the linguistic variable.

In the case of Mean of Maxima (MoM): The mean of maxima defuzzifier selects the mean value of the points where the membership grade attains its maximum.

$$\text{MoM (u)} = x = \frac{\sum xi \in Mxi}{|\mathrm{M}|} \quad (6.9)$$

Where: M = {x ∈ X|u(x) = height of the fuzzy set.

6.4 DEVELOPING RULE-BASED EXPERT SYSTEMS

Fuzzy logic relies on knowledge and thoughts of individuals usually domain experts in the filed under which a system is being developed. An expert system is a computer system with algorithmic program designed to emulate the decision-making capability of humans (Tan, 2017). For an expert system to perform optimally, it must possess intelligent characteristics based on rules and heuristics to be able to solve complex decision problems. According to Hartono and Simanihuruk (2017) a rule-based expert system, also known as inference engine, typically goes through a simple recognize-assert cycle whose control architecture is for data-driven and goal-driven reasoning. It is an intelligent system that emulates expert ability synonymous with humans in making decisions using encoded knowledge.

The main structure of an expert system consists of knowledge base, memory, reasoning machine, interpreter and human-computer interaction interface (Tan, 2017). The knowledge base acts as the expert system expertise where facts and rules are stored. It should be able to acquire new information, demonstrate and store the information for easy processing for the computer. The memory stores the inputted rules or facts, and the reasoning machine matches the rules with the knowledge and obtain new information. The interpreting unit interprets the outcome from the output of the inference engine.

The structure of the rule-based expert system works on three principal components: conditional rules, database storage and control execution. For example, if a conditional statement such as: the temperature is high; the results will be to reduce the temperature using pre-configured parameters. The database stores the conditions or rule statements; such that when a command is issued, the database processes the command against the stored conditions. The control at the inference engine prompts the system on how to apply the rule to solve the problem of high temperature using the appropriate rules. In instances where there are several rule conditions, the control decides on the best fit to apply in the prevailing situation. The control then operationalises the rule against the database to reduce the temperature to an acceptable pre-determined level.

6.5 CATEGORIES OF FUZZY REASONING SCHEMES

Fuzzy logic is the combination of hypothetical scenarios which necessarily does not fit a specific value to obtain crisp outcomes. According to Koukol et al (2015), a single situation without comparison offers no meaning in fuzzy logic. It combines expertise and a priori qualitative knowledge of dependent or heterogeneous information about an imprecise situation of antecedent to arrive at a precise conclusion; consequent constructed on the combination of rules. In fuzzy reasoning systems, different sources of information may provide inputs for the system make useful decisions. These inputs may be a combination of data and linguistic expressions from sensors and human experts. There are different cases of multiple fuzzy reasoning systems; there are multi-input, multi-output (MIMO) systems and multi-inputs, single-output systems (MISO). Fuller (1999) contend that the technique to accomplish fuzzy output is dependent on three criteria:

a. Find the firing level of each rules
b. Find the output of each rules

c. Combine the individual rule outputs to obtain the overall system output.

6.51 SINGLE INPUT SINGLE OUTPUT (SISO)

The single-input-single-output (SISO) system is a controller that has one variable input on which to produce an output. The single fuzzy rule determines the relationship between the inputs and the out variable.

It has a relationship R: if X is Xi, then Z is Zi

The SISO is a Takagi-Sugeno systems which do not use inference systems like Mamdani and Godel system. In place of the inference system, they use fuzzy rule in computation and conclusion (Bede, 2013). The SISO is a simplified fuzzy logic system with one-dimensional rule table

6.52 MULTIPLE INPUTS SINGLE OUTPUT SYSTEM (MISO)

Typically, in fuzzy logic reasoning system, different inputs, usually two or more forms the variables x and y linguistic values or other values are the antecedents and the output, z, the consequent in a multi-input-single-output (MISO) fuzzy system in the form:

Ri: if x is Ai and y is Bi, then z is Ci

Rn: if xn is An and yn is Bn, then zn is Cn

In the MISO system, there are different possibilities of interactions between the variables. These interactions are determined by the membership function according to degree of freedom of each variable.

6.53 MULTIPLE INPUTS MULTIPLE OUTPUT SYSTEM (MIMO)

The MIMO fuzzy systems are complex system with several interactions between the variables, each with its degree of freedom. The simplest case of a MIMO system is when all input variables are significant for each output variable (Bufardi et al., 2017).

6.6 DETERMINATION OF FUZZY RULES

Fuzzy control systems are designed according to the intrinsic nature of human decision-making ability. Human decisions are either experiential or circumstantial depending on the intended outcome. For fuzzy system to mimic human decisions, rules are established to pair corresponding inputs to execute the IF-THEN commands. Fuzzy rules are developed based on different methods:

a. Expert Knowledge/Experience
b. Data Modelling
c. Self-learning
d. Optimisation

6.7 PREDICTION BASED ON FUZZY LOGIC INFERENCE SYSTEM

The adoption of autonomous vehicles can be modelled using fuzzy logic based on human reasoning. Fuzzy Logic (FL) entails several advantages amongst which are – model vague concepts, exploit small datasets, incorporate known facts, and expert opinion in decision making process. To adequately implement FL, domain knowledge and historical experience of experts are able to contribute relevant inputs to design an effective FL inference system (FIS). Idri et al. (2004) contend that FL can be used to generate accurate estimation models because it offers a superior representation of reality according to insights acquired through knowledge. As a nascent technology with little or no factual experience of use, AV adoption is not a crisp decision, it is a decision that comes with consideration of several factors due to perceived concerns of future users. In this study, the drivers, riders, and other road users provided meaningful data based on their inferred knowledge and anticipated experience of autonomous vehicles. However, before FL is implemented, a degree of expert and domain knowledge is required. To model the data, we applied the Mamdani fuzzy logic algorithm based on linguistic user data using IF-THEN rules. The figure 6.4 shows the steps adopted in building the FLAVAM model.

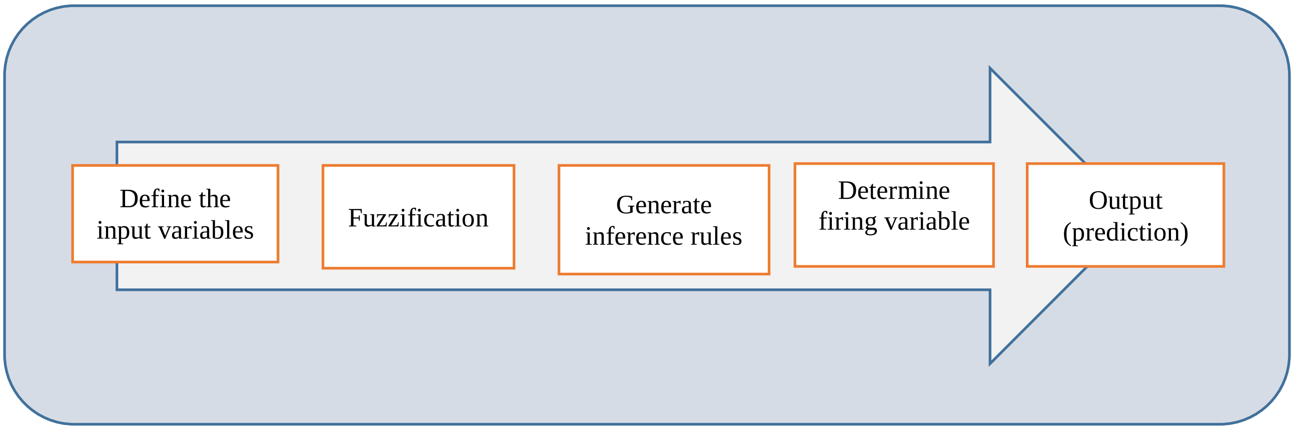


Figure 6.4: Fuzzy logic implementation process

In our survey, 96.2% have heard or seen autonomous vehicles either physically or in the media while 3.8% responded in the negative. The input variables defined for this study are five potential barriers (safety, trust, privacy, accessibility, and ethics) that were identified in the literature which are likely to affect the uptake of autonomous vehicle. The barriers are the vague terms which use linguistic hedges in the 11-point Likert to define the extent of user perception or vagueness. The linguistic hedges are shown in table 6.1 with their associated ranking. The users responded to each question based on their perception using the linguistic hedges to show their level of rating.

Table 6.1: Linguistic hedges ranking

Linguistic Terms	**Likert Scale Rating**	**Linguistic Terms**	**Likert Scale Rating**
Extremely Unlikely (EU)	0	Little Likely (LL)	6
Very Unlikely (VU)	1	Moderately Likely (ML)	7
Highly Unlikely (HU)	2	Highly Likely (HL)	8
Moderately Unlikely (MU)	3	Very Likely (VL)	9
Little Unlikely (LU)	4	Extremely Likely (EL)	10
Moderately (M)	5		

The linguistic data was converted to numerical values according to the Likert scale rating and the average value was obtained for each user in each variable. Due to the requirement of our system, it was required to make all the values for each variable uniform on the same scale. To achieve that, the results were normalized to convert all the values on a scale of 0 and 1 for membership function before fuzzy application. The following equation was used for data normalisation:

$$X(norm) = \frac{(X - Xmin)}{(\mathrm{Xmax} - \mathrm{Xmin})} \qquad (6.10)$$

A sample of the normalised results for fuzzy membership function are shown in table 6.2.

Table 6.2: Normalised numerical values

Participant	Safety	Trust	Access	Privacy	Ethics	Likelihood
R1	0.73	0.60	0.65	0.65	0.80	0.90
R2	0.43	0.50	0.53	0.18	0.30	0.40
R3	0.85	0.90	0.75	0.90	1.00	0.80
R4	0.90	0.88	0.73	0.55	0.70	1.00
R5	0.38	0.20	0.00	0.25	0.30	0.00
R6	0.33	0.58	0.65	0.75	0.40	0.80
R7	0.55	0.70	0.73	0.63	0.60	0.60
R8	0.70	0.53	0.33	0.70	0.60	1.00
R9	0.38	0.35	0.50	0.05	0.80	0.10
R10	0.50	0.80	0.43	0.40	0.50	0.60
R234	0.33	0.88	0.53	0.63	0.00	1.00
R235	0.55	0.48	0.40	0.43	0.30	0.30

6.71 EXTRACTION OF FUZZY RULE LABELS

The linguistic responses from user data were classified according to each barrier-variable based on the defined responses as inputs for the fuzzy inference system in MATLAB Fuzzy toolbox and Simulink. Fuzzy sets were defined for each variable using the triangular membership function. As a multi-input, single output system (MISO), each variable is defined as the antecedent to derive a single output known as the consequent. Consider the fuzzy logic system where X = (X_1 x X_2 x X_3 x X_4 x X_5) as antecedents or inputs and $Y \subset R$ as the consequent or output. The rule extraction is based on Mendel Wang method where rules are generated from data without prior knowledge (Wang, 2003). Wang algorithm is an intuitive data-driven machine learning technique divides the input space into several fuzzy regions and a lookup technique to extract rules from data (ibid). The antecedents are the five barrier-variables, whose fuzzy set are assigned as triangular membership function and trained to identify the predominant rating by each user. To perform the operation, it is recognised that the strength of influence of each variable differ as provided by the user. Therefore, each variable has a different impact on the output. Following Wang (2003) safety ranked top on the list of users; therefore, it presents the most influence on the output. We then chose the fuzzy sets with equally spaced boundaries for all the input variables using boundary range (0.00, 0.30 and 0.55) as low and (0.50, 0.70 and 1.00) as high as shown in figure 6.6.

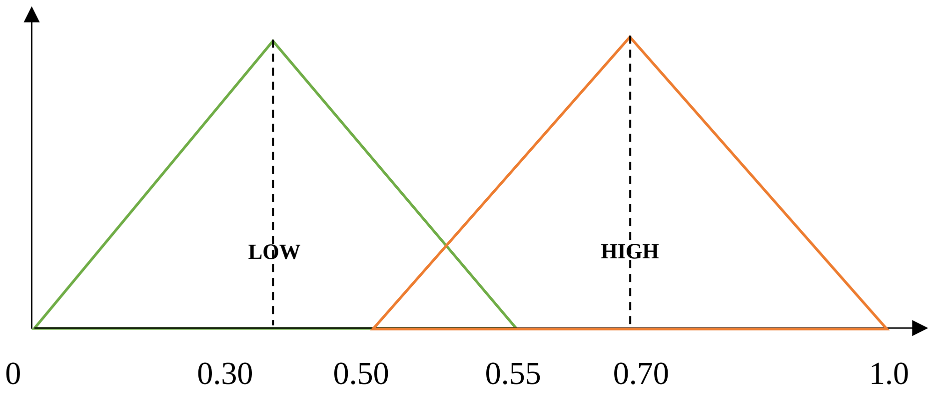
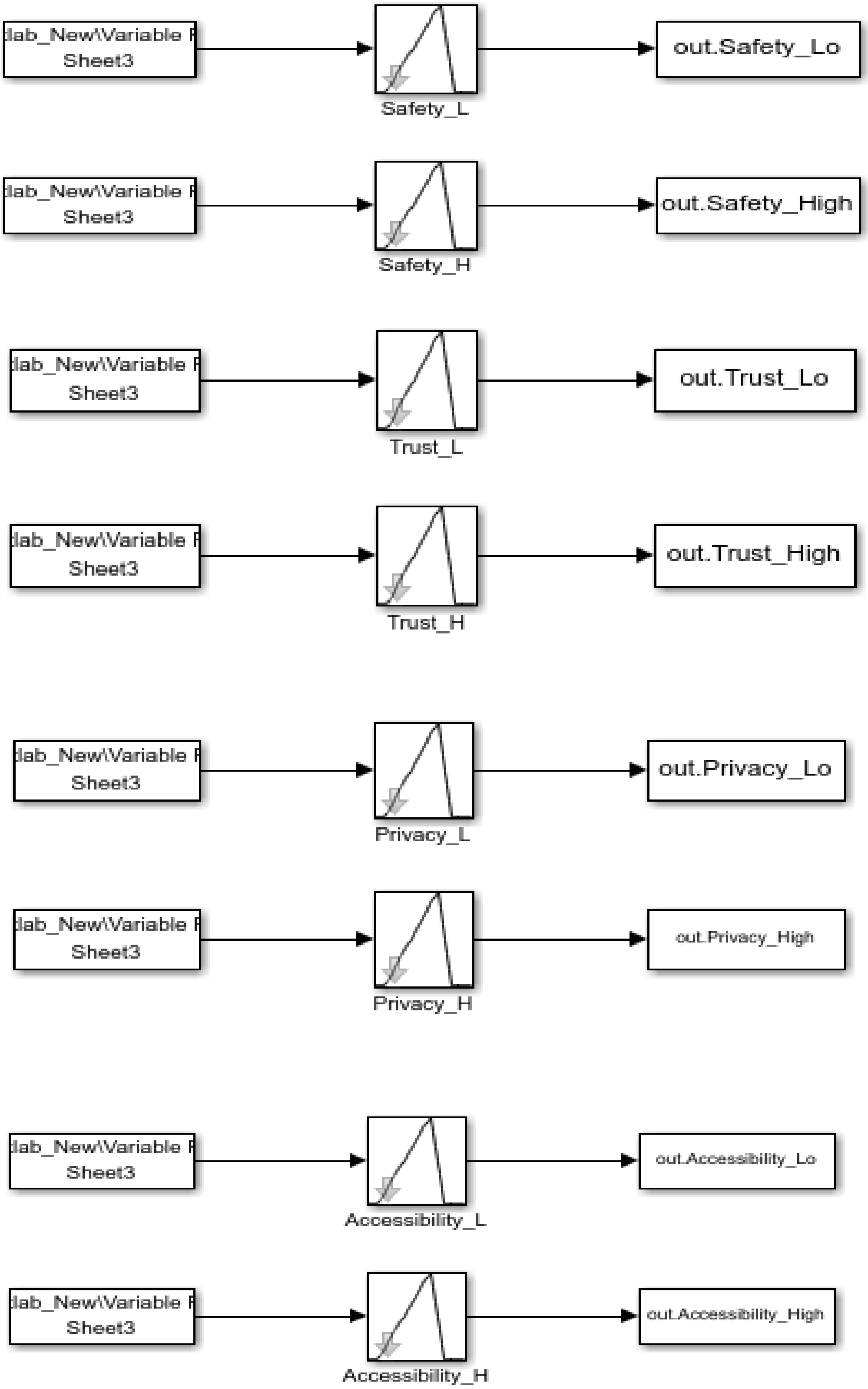


Figure 6.5: Fuzzy input set – triangular membership function

This simulation was performed in MATLAB using the Simulink fuzzy toolbox using the IF – THEN rule where each input is mapped according to the steps shown in figure 6.6. Simultaneously, this process was repeated for each of the variables to determine the dominating state from each user. The target output was set as a single output to either low or high intent to adopt autonomous vehicles shown in figure 6.6.



lab_New\Variable F
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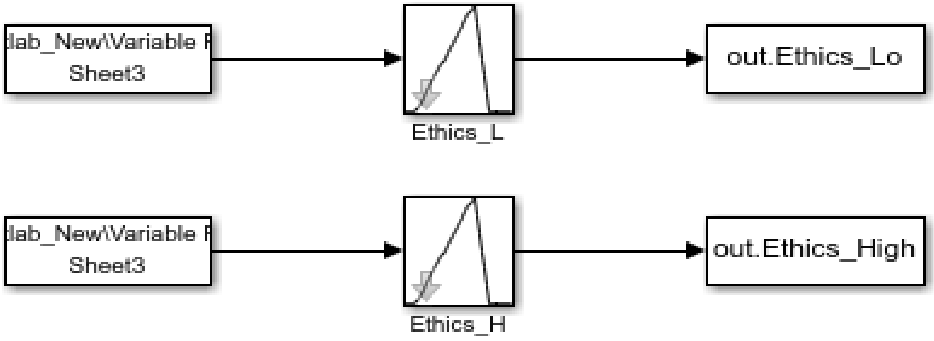

Figure 6.6: Fuzzy label simulation in Simulink

Using the IF x_1 is $A_1^{(l)}$ … and x_n is $A_n^{(l)}$, THEN y is $B_1^{(l)}$ (6. 11)

l = 1, 2, …M, where M is the number of rules and l is the index of the rules. With V_n fuzzy/singleton sets A_s^q, q = 1, ..., V_n, defined for each input x_s where (s = 1, ..., n) and n is the number of inputs, which is 5. With W crisp intervals B^h, h = 1, ..., W defined for the y output.

The process was iterated for each of the variables to obtain the respective linguistic labels from each user data. The output data from the simulation was further processed in Excel using the IF, THEN command to acquire the maximum linguistic output label for each user. The results from the simulation are shown in table 6.3.

Table 6.3: Sample fuzzy extraction rules

User	**Safety**	**Trust**	**Privacy**	**Accessibility**	**Ethics**	**Stated intention to adopt**
1	H	H	H	H	L	H
2	L	L	L	L	L	L
3	H	H	H	H	L	H
4	H	L	L	L	L	L
5	H	L	L	L	L	L
6	L	L	H	H	L	L
7	L	L	L	L	H	L
8	H	H	H	H	H	H
9	H	H	L	H	H	H
10	L	L	L	H	H	L

User perception and ranking of each of the variables is directly proportional to their stated adoption of autonomous vehicles. The derived FL rule base enables us to visualize the relationship between the adoption of AV according to a combination of input variables. It can be observed that users that provide high scores to describe their perceived safety, trust, privacy, accessibility and ethics view on AV are likely to adopt AV in the future. One the other hand, participants with negative views concerning aforementioned variables are more sceptical about AV adoption. The results from the simulation with the output labels shown in table 6.2 illustrates user perception based on the combination of the variables. The results consist of distinct and contradictory outputs.

6.72 PREDICTION APPROACH FOR FUZZY LOGIC AUTONOMOUS VEHICLE ADOPTION MODEL (FLAVAM)

Overall, the FLAVAM model was developed as a model which takes into cognisance the effect of perceived concerns in the adoption of autonomous vehicle technology. To use or adopt a technology is a conditional decision which is predicated upon various inherent criteria. Based on our data, the decision to adopt and use autonomous vehicle varies from person to person according to their perceived importance attached to each of the measured variables as demonstrated in the data. The FLAVAM model is an adaptive FL system that combined our measured variables using the IF – THEN rule to predict adoption decision. Similar to the works of Iqbal et al. (2013) FLAVAM is a Fuzzy Rule-Based Classification System (FRBCS) which has been successfully applied for classification. It is a model that use linguistic labels to predict AV adoption. This model can assist stakeholders effectively predict the intention to adopt AV based on inherent user opinion, while accounting for uncertainties related to the collected data representing their views. The FLAVAM model used the linguistic labels obtained from users to identify how the measured variables will affect their adoption of AV. The linguistic labels were exported to an oracle SQL database to perform the rule-base query where one or more conditional rules are connected. To deduce the adoption tendencies for each user, a structured query was performed on the label output from the fuzzy logic simulation in Oracle database on the 235 data outcomes using the following query:

```
CREATE OR REPLACE FORCE EDITIONABLE VIEW "RULEBASE_TEST" ("SAFETY", "TRUST", "PRIVACY",
"ACCESSIBILITY", "ETHICS", "ACTUAL_INTENTION_TO_USE", "PREDICTED_INTENTION_TO_USE") AS
  select safety, trust, privacy, ACCESSIBILITY, ETHICS, AV_LIKELIHOOD__TARGET__ AS
ACTUAL_INTENTION_TO_USE,
  predicted value (SAFETY, TRUST, PRIVACY, ACCESSIBILITY, ETHICS) as PREDICTED_INTENTION_TO_USE
 FROM MAIN_DATA
/
```

This RULEBASE query automatically generated a set of rules which includes distinct and contradictory targets. The distinct and contradictory target are output where some fields with the same antecedent report expected consequents similar to expert knowledge and contradictory consequent respectively. The output target is a combination of levels with different firing strength. All the rules have their firing strengths which is the degree that a rule matches its input pattern either as distinct or contradictory. Each rule is calculated using fuzzy support and confidence level; the support level is a fraction of the total coverage of data in which an item occurs, and the confidence rule is the likelihood of occurrence (Zou et al., 2021). To extract the distinct patterns, the following query was applied:

```
CREATE OR REPLACE FORCE EDITIONABLE VIEW "DISTINCT_PATTERNS" ("SAFETY", "TRUST", "PRIVACY",
"ACCESSIBILITY", "ETHICS", "AV_LIKELIHOOD__TARGET__") AS
  select distinct safety, trust, privacy, ACCESSIBILITY,                ETHICS, AV_LIKELIHOOD__TARGET__ FROM
MAIN_DATA
```

To extract the contradictory pattern, the following was query applied:

```
CREATE OR REPLACE FORCE EDITIONABLE VIEW "CONTRADICTORY_PATTERNS" ("SAFETY", "TRUST",
"PRIVACY", "ACCESSIBILITY", "ETHICS", "RESULT_1", "RESULT_2") AS
  select A.safety, A.trust, A.privacy, A.ACCESSIBILITY, A.ETHICS, A.AV_LIKELIHOOD__TARGET__ AS RESULT_1,
B.AV_LIKELIHOOD__TARGET__ RESULT_2
 FROM DISTINCT_PATTERNS   A, DISTINCT_PATTERNS B
 WHERE A.safety = B.safety AND  A.trust=B.trust AND A.privacy = B.privacy AND A.ACCESSIBILITY = B.ACCESSIBILITY
AND
  A.    ETHICS= B. ETHICS AND A. AV_LIKELIHOOD__TARGET__ NOT LIKE B. AV_LIKELIHOOD__TARGET__
/
```

To overcome the problem of contradicting patterns, compression rule was executed on the fuzzy sets to extract rules with higher firing strength (Iqbal et al., 2014). The rule compression technique helps to summarise the data and derive scaled fuzzy weight for each data point as proposed by (Wu et al., 2010). The rule compression method measures reliability and generality for each distinct rule pattern, where reliability is the confidence level and generality are the number of instances in the rule pattern (ibid). The reliability and generality were used to calculate the scaled weight of each distinct rule pattern. The scaled fuzzy support helps to identify and eliminate duplicate instances by compressing the rules into M distinct patterns (Alhabashneh et al., 2017). Scaled fuzzy support equation in 6.11 eliminate opposing duplicity by compressing the rule base into a set of inimitable modelling rules (Ishibuchi and Yamamoto, 2005).

$$\text{scFuzzSup (FXi)} = \frac{\text{CoFXi}}{\text{CoFXi+CoFRi}} \qquad (6.11)$$

where scFuzzsup = fuzzy support

i = 1 – M, i is the index of the rule

FXi = unique antecedent combination associated with consequent label B

CoFXi = number of instances supporting rule pattern FXi

FRi = unique antecedent combination associated with consequent label A

CoFRi = number of instances supporting FRi

The confidence in a rule measures the validity representing the strength of a unique rule instance against contradictory rule instance FRi similar to the other rule with the same antecedents but different consequent.

$$\text{scConf (FRi)} = \frac{\text{scFuzzSup (FXi)}}{\text{CoFRi}} \tag{6.12}$$

In the same vein, the scale rule weight is the product of the scaled fuzzy support and confidence of the rule

$$scWi = scFuzzSup\ X\ scConf \tag{6.13}$$

Where the scaled fuzzy weights $scWi$ are assigned to generate a number of rules. The scaled fuzzy weight is used to rank the fuzzy rule to select the rule with the most firing strength. For example, when a user's intention to use AV is at variance with the selected input variables, fuzzy rule generates a corresponding firing strength according to the inputs variable and provide the true output. The resulting output shown in table 6.4 corresponds to either high or low depending on the input of each variable and its combination as well as firing strength.

Table 6.4: Sample of scaled weight fuzzy rule

User	Safety	Trust	Privacy	Access	Ethics	Stated intention to use	Support	Conf.	Firing str
1	H	H	H	H	H	H	0.51304	0.9516129	0.488215
2	H	H	H	H	H	L	0.49167	0.51304348	0.252248
3	H	H	H	H	L	H	0.23478	0.77142857	0.181116
4	H	H	H	H	L	L	0.225	0.58695652	0.132065
5	H	H	H	L	H	H	0.08696	0.76923077	0.066892
6	H	H	H	L	H	L	0.08333	0.58823529	0.049018
7	H	H	H	L	L	H	0.05217	0.75	0.039128
8	H	H	H	L	L	L	0.05	0.6	0.03
9	H	H	L	H	H	H	0.03478	0.66666667	0.023187
10	H	H	L	H	H	L	0.03333	0.66666667	0.022220
11	H	H	L	H	L	H	0.04348	0.625	0.027175

12	H	H	L	H	L	L	0.04167	0.71428571	0.029764
13	H	H	L	L	H	H	0.01739	0.66666667	0.011593
14	H	H	L	L	H	L	0.01667	0.66666667	0.011113
15	H	H	L	L	L	L	0.025	1	0.025
16	H	L	H	H	H	H	0.0087	1	0.0087
17	H	L	H	H	L	H	0.01739	0.66666667	0.011593

The performance accuracy of the FLAVAM model was 86.30%. This accuracy was compared with the actual user intention to use/adopt AV. To objectively evaluate the forecasting accuracy of the FLAVAM, the K-fold cross validation technique was applied.

Table 6.5: Sample of The FLAVAM Prediction model

User	Safety	Trust	Privacy	Accessibility	Ethics	Stated intention to use	Predicted intention to use
1	H	H	H	H	L	**H**	**H**
2	L	H	H	L	L	**H**	**H**
3	H	H	H	H	H	**H**	**H**
4	H	L	L	L	L	**L**	**L**
5	H	L	L	L	L	**L**	**L**
26	H	H	H	H	H	**H**	**H**
57	L	L	L	L	L	**L**	**L**
78	H	H	H	H	L	**H**	**H**
90	L	H	H	H	H	**L**	**H**
110	L	L	L	L	L	**L**	**L**
211	H	H	H	H	L	**L**	**H**
235	H	H	L	H	L	**L**	**H**

6.73 RULE-BASED SUMMARIZATION WITH K-FOLD CROSS-VALIDATION

To validate the model, the k-fold cross validation method was applied to avoid input bias and overfitting. The k-fold cross-validation method is required to enhance generalizability of the predictive model and prevent overfitting by dividing the data into training and testing set (Hastie et al., 2008). In k-fold cross-validation, the dataset D is split into k equal parts of size n folds. The validation is performed with k repetitions and each partition is used as test and the remaining as hold-out set D_h. In the case of our model, 5-folds cross validation was implemented to were performance of overlapping training sets and evaluation on non-overlapping sets.

The accuracy of the model for each fold is calculated using the following equation:

$$\mathrm{acc}_j = \frac{1}{\mathrm{h}} \sum_{(\mathrm{v_i}, \mathrm{y_i}) \in \mathrm{D_h}} \sigma(\mathrm{v_i}, \mathrm{y_i}) \qquad (6.14)$$

Where $\boldsymbol{\sigma}$ ***(v, y) = 1*** if $v=y$ and 0 otherwise. $\boldsymbol{v_i}$ is the predicted value of the instance ***i*** $\boldsymbol{y_i}$ is the actual value of the instance ***i***.

5-fold cross validation					
Partition 1	1	2	3	4	5
Partition 2	1	2	3	4	4
Partition 3	1	2	3	4	5
Partition 4	1	2	3	4	5
Partition 5	1	2	3	4	5

The final accuracy of the model is calculated by taking the average of the 5-folds shown in table 6.6 and it was calculated using the equation:

$$\mathrm{ACC} = \frac{1}{\mathrm{h}} \sum_{j=1}^{k} accj \qquad (6.15)$$

In our study, we used a 5-fold cross-validation technique. This technique uses 20% of the dataset for testing whilst 80% of the dataset was used for training.

Table 6.6: 5-fold cross validation prediction results

Training instant	Training set	Dataset sample	Accuracy (%)
1st	20%	1 – 47	76.10
2nd	20%	48 – 94	93.60
3rd	20%	95 – 141	89.40

4th	20%	142 – 188	78.70
5th	20%	189 - 235	93.80
		Overall accuracy	86.30

Table 6.7 presents the results obtained from the different machine learning models with their performance accuracy. By comparison, random forest is the only algorithm that performed better than the FLAVAM model. It is possible that the performance of the model could be increase if user data were not based on perception.

Table 6.7: Comparing the prediction models

S/No	**Prediction Algorithm**	**Accuracy (%)**
1.	Random Forest	92.77
2.	Fuzzy Logic (FLAVAM) model	86.30
3.	Multiplayer Perceptron	85.53
4.	Logistic regression	79.07

The performance of the FLAVAM model demonstrates that user intention in adopting technology can be modelled despite the inherent uncertainties in the data. Similar to the FLAVAM, Lee et al. (2019) conducted a similar research to measure the adoption choice behaviour of individual user characteristics and system characteristics using a machine learning technique, Gradient Booster Machine (GBM). The authors obtained 80% accuracy performace despite measuring user AV sentiments, technology interest and environmental concerns.

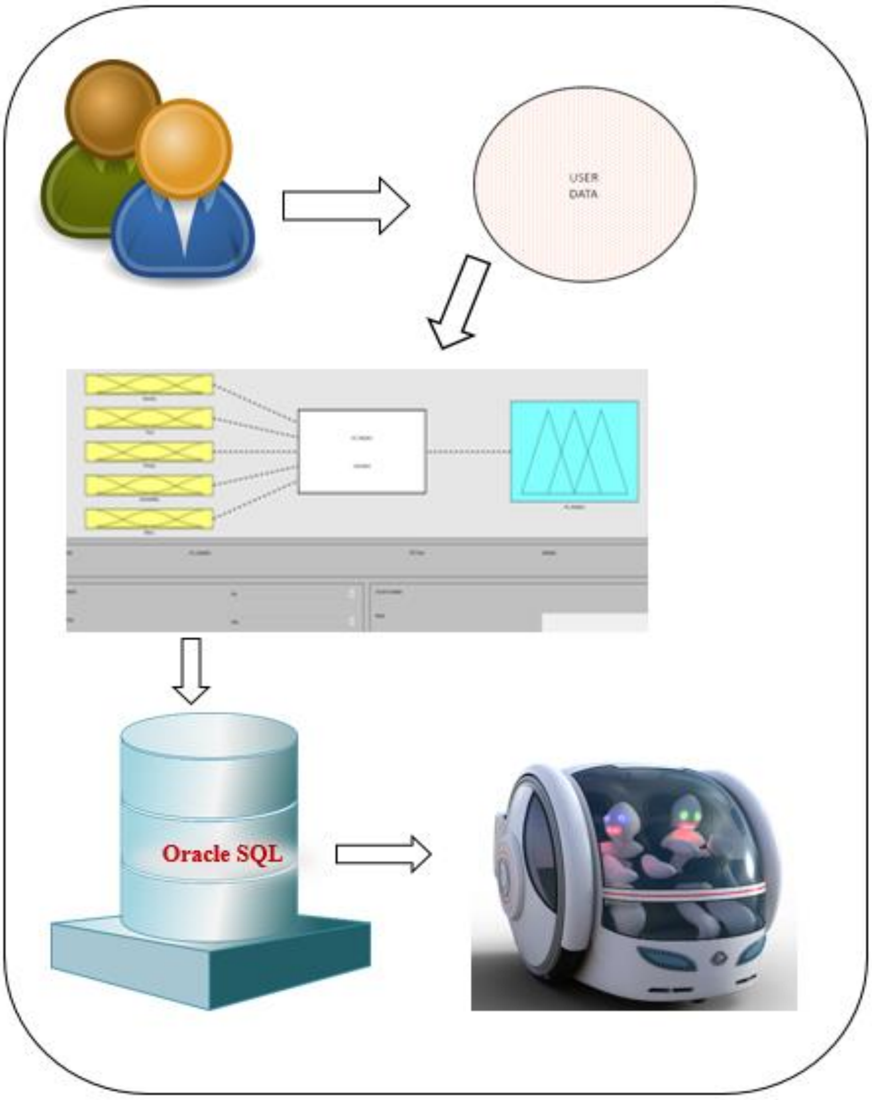

Figure 6.7: Schematic diagram of the FLAVAM process

6.8 CHAPTER SUMMARY

The chapter focused on fuzzy logic as a computational tool capable of processing data that reflect subjective opinions and perceptions with high degree of uncertainties and noise. Inherent user data on attitudes and emotions are uncertain and consist of noise. The use of fuzzy logic as an intelligent tool to handle linguistic uncertain data was presented. Fuzzy logic was used to predict a model of adoption which consists of user stated preferences with an accuracy of 86.30%.

A 5-fold cross validation method was applied to the dataset to test the accuracy of the fuzzy classifier. The cross-validation showed 93.80% and 76.10% as the highest and lowest accuracy results respectively and an overall average of 86.30% which aligns closely with other machine learning algorithms used in this study.

The model was able to account for individual preferences and through its fuzzy rule base, it allows for effective visualization of the knowledge hidden in user data. Since, the adoption of autonomous vehicle differs from one individual to another, fuzzy logic is able to satisfactorily predict adoption given the inherent uncertainties concerning individual user preferences.

The next chapter will present the conclusion and recommendations as well as the limitations of this research.

CHAPTER SEVEN

CONCLUSION AND RECOMMENDATIONS

7.1 INTRODUCTION

The background for this research was presented in chapter one and extensive literature review was provided in the subsequent chapters. The objectives set out to be achieved in this research were to: conduct in-depth critical analysis of autonomous vehicle adoption; investigate the barriers which may affect adoption; conduct user study to examine adoption; and to apply suitable machine learning technique and build an accurate AV adoption forecasting model and evaluate the model using proven evaluation methods. Several road users belonging to different demographic groups provided data to reflect their intention with regards to the use and adoption of AV based on certain barriers identified in the literature. As always, the case with every new technology, the point of adoption diffusion and acceptability is a major component for obvious reasons which is an indication that new technologies are alien to users, as such, they usually face some resistance. In the case of driving, locus of control is a fundamental consideration for many users which AV plans to completely remove. The ability to control a vehicle signifies safety, trust, and security for many drivers, passengers and other road users. Several barriers which are likely to affect the use and adoption of AV abound which may lead to adoption apathy even before the first AV is introduced on urban roads. Therefore, the use and adoption of the technology is as important as the technology itself.

This thesis provided a comprehensive study on the acceptance and adoption of AV by reviewing copious literature on the foregoing discipline from multiple perspectives. This area of research focuses on and utilizes opinions, attitudes, perceptions and behaviours to decipher intention to adopt technology. Therefore, there are several uncertainties and noise involved when measuring user degree of acceptance. Every user has its unique requirements for using, accepting and adopting technologies. Preliminary findings from our results indicates that adoption and use of AV will experience major hurdle. This is because the advent of AV will not only affect transport and mobility, but it will also influence travel behaviours. Although, AVs are touted to be safer than human driving by the promoters. According to the results from this study, perception towards AV will act as a barrier, until those inherent perceptions are transformed with the performance of AV in terms of safety, security, trust, privacy and ethics. From our study and other similar research, these factors are fundamental to the use and adoption of new technologies.

This research measured user acceptance of AV according to selected identified barriers from the literature. Using an 11-point Likert scale, the five barriers identified for this thesis: safety, trust, privacy, accessibility and ethics were measured. 235 user-data were obtained from different demographic categories of roads users including drivers, passengers, cyclists and pedestrians. The collected linguistic data initially processed and analysed using statistical and data mining software, SPSS and WEKA. From the data, mixed results were obtained from the composition of the demography in terms of their intention to use and adopt AV across ethnicity, education, economic status, age and marital status with the greatest influence. From our understanding of potential users, whites, upper-class, male, young and unmarried adults tend to favour the use and adoption of AV more than any other group. However, the majority of these users would prefer hybrid AV models that allows alternation of control, driveability and ease of use when the need arise to switch between humans and autonomy. However, there are road users that will not adopt or use except when it becomes mainstream until its performance has been proven safer that conventional human-driven vehicles. This category falls within old, male and ethnic people (Blacks and Asians).

To predict AV adoption in this study, Likert-scale data were obtained from potential users who belong to different segment of road users. Due to the nature of the question, the data obtained which was required to be normalized. Different machine learning algorithm and simulation techniques were applied to the pre-processed data. Simulink in MATLAB was used to extract rules and linguistic labels from the data. A fuzzy logic and Oracle SQL approach was applied to the linguistic labels to determine the degree of adoption from the FLAVAM adoption model. As demonstrated in this thesis, fuzzy logic is a suitable technique for processing ambiguous and perceptual data of future users of autonomous vehicles. The FLAVAM was able to predict user adoption by combining the measured variables using different labels as contained in the user data.

7.2 SUMMARY OF RESEARCH

This research focused on user intention to adopt and use autonomous vehicles when they become available on the motorway. The acceptance and adoption of new technologies is an important research area which have been investigated across different disciplines in the last decades. AV is a new technology and as such it has begun to generate varying interests amongst researchers who are conducting studies in its acceptance.

This research aimed to investigate the barriers that pose inhibition to the adoption of autonomous vehicles by outlining a general research overview in chapter one including the aim, objectives, research questions, motivation, contributions and scope. In chapter two, a systematic review of literature was conducted covering various concepts and developments in autonomous vehicle technology as a component of intelligent transport. It presented the history of autonomous vehicles in retrospection from a futuristic idea which eventually advanced through the introduction of intelligent features in vehicles and motor ways to improve safety. The chapter equally presented the activities of government and legislation in pursuit of the realization of vehicle autonomy. The review of literature provided the author with the gaps in the research. In chapter three, different theories related to technology acceptance like TAM, UTAUT, TPB, TRA, DIT and their application to multiple technologies were extensively discussed. The chapter discussed different approaches that motivate users to adopt technology including performance, benefits, hedonism and others. In addition, a comprehensive review of autonomous vehicle technology adoption theories contributed by different authors including WTP, WTA, CVM was presented.

In Chapter four, the methodology adopted in collecting user data from targeted road users comprising of drivers, passengers, pedestrians and cyclists was provided. Quantitative methods were employed to collect opinion-based data from 235 users. The reliability and validity of the data was calculated to ascertain the relationship between the data. Chapter five presented the user data analysis by using statistical and data mining tools, SPSS and WEKA respectively. Statistical analysis conducted on the data revealed interesting correlations and also used for standard machine learning techniques to forecast future AV adoption. In chapter six, the fuzzy logic system as an approach to process linguistic user data by modelling human reasoning was discussed and FLAVAM, a new fuzzy logic-based autonomous vehicle adoption model was presented. The model achieved significant accuracy in forecasting user adoption. The model was validated using a 5-fold cross-validation method and an accuracy of 86.30% was recorded similar to the accuracy obtained from other machine learning models.

7.3 RESEARCH CONTRIBUTION

This thesis extensively reviewed previous studies on technology and autonomous vehicles adoption. Most of the previous studies applied statistical techniques in their investigation of this research problem. The contribution of this research is multidimensional; identifying the diverse causal factors on AV adoption, understanding the effect of these causal factors on user degree of adoption, modelling and predicting user adoption of autonomous vehicles by applying custom fuzzy logic technique able to model uncertainties in human reasoning and help visualise the effect of different causal factors on the degree of adoption of AV. These findings contribute to the developing discipline of AV user adoption which is capable of facilitating policy making and revealing market insights to assist stakeholders.

1. One of the practical contributions from this research is identifying multiple causal probable factors that affect the adoption of AV: From the review of literature, multiple inhibiting factors to AV adoption were identified. These factors among others are safety, trust, privacy, accessibility and ethics. These factors were the main component of the user data collected to measure AV adoption. Users expect these factors to be adequately catered to encourage adoption. However, it is important to highlight that our findings demonstrated that the users also favour a hybrid AV system that is capable of switching between autonomy and human controlled driving more than a fully autonomous system.
2. Understanding the effect of perceived causal factors on user degree of adoption: the causal factors which were identified to act as barriers to AV adoption were graded according to their relative effect on their level of adoption. The statistical analysis conducted on the data revealed that future users of AV are more concerned about the safety, trust and privacy rather than accessibility and ethics. By classifying these factors in different combination revealed different levels of AV adoption either as low or high. The level adoption was also prominent along demographic lines; such that ethnicity, marital status, age, gender and education play significantly in how AV will be adopted.
3. A new fuzzy logic-based computational modelling technique for exploiting expert and user opinion concerning user adoption of autonomous vehicles – the proposed technique supports effective visualisation of the underlying relationship between user adoption and the causal factors under investigation. The fuzzy rules were computed to generate an adoption model with an accuracy of 86.30% similar to the machine learning models.

To the best of the author's knowledge, this thesis is the first to apply a fuzzy logic inference system to model and forecast the adoption of autonomous vehicles. As demonstrated by the results, the proposed FLAVAM model is able to forecast the extent of adoption of a user depending on different variables by each user.

7.4 LIMITATATION OF THE RESEARCH

This research like any other research has some limitations; one of which is that the entire research was focused on a technology still undergoing development. The user study is based on the limited and superficial knowledge of autonomous vehicles without actual experience. It is certain that with actual experience in riding in an AV, the outcome of this research is likely to be different. The FLAVAM adoption prediction model despite its level of accuracy, does not take user segments into consideration. It measures adoption across the entire user population. The size of the user data collected for this research was 235, while this is a reasonable size of data for this kind of study, it is possible that a larger data size may reveal different results especially if it takes into account different user segments beyond the coverage of this research into account. The user data collected for this research were mostly obtained from the UK. The UK is quite advanced in AV research and development activities, as such, there is high literacy of AV.

7.5 FUTURE RESEARCH DIRECTIONS

Future research will need to focus on providing users with real life engagement or experience with actual AV or simulated AV driving and measure the influence on AV adoption. The inclusion of demographic variable would reveal a different accuracy results in model. Future researcher may investigate adoption and use of autonomous vehicles by testing the suitability of different fuzzy logic methods such as Type-2 FL to determine if it is able to predict with different level of accuracy as a result of its higher computational requirements. Future research should expand the size of sample data which may be collected over a longer period of time to obtain spatial insights which this research may not have exposed. This study investigated the use and adoption of AV by users as a mobility option either as shared or owned. It will be interesting to investigate if users will prefer AV for other purposes such as logistics. Future studies may explore the adoption of AV for these purpose and amenability of users. According to research in driving psychology cultures play a role in human driving, future research may consider if these equally applies to the use and adoption of AV probably if the user data is obtained from other parts of the developing world in Asia and Africa.

7.6 CHAPTER SUMMARY

This chapter presents the conclusion, research contributions, limitations, and future research directions. The research highlighted some factors that will act as barriers which will affect the adoption of autonomous vehicles according to user stated perceptions. The participants in this study will accept the use AV when they deliver consistently superior performance compared to human driving. The findings reveal that ability to control a vehicle and the manner in which it drives is important, as such, the higher the performance of AV with respect to the factors measured, the higher the adoption and use of AV. Considering that human driving has been in existence since the advent of automobiles, AV adoption will depend on real experience. An important step towards influencing user adoption is to allow users to engage with vehicles with AV features either as standalone or adapted systems. The more users become familiar with these features, the more likely that their uptake decisions will be influenced.

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APPENDICES – QUESTIONNAIRE

Autonomous Vehicle User Survey

Page 1: Consent Form

Dear Respondent,

I am a PhD research student at the Centre for Future Transport and Cities, Coventry University. My research is to evaluate the potential barriers that are likely to affect the adoption of autonomous vehicles as means of mobility in the future. I am seeking your participation in this brief survey to obtain necessary data. Your participation is completely voluntary, you may opt out at any stage. All your responses will be treated as confidential and anonymous, please do not include your name.

The responses are only necessary for statistical purposes and will be presented in aggregated format. If you choose to participate in this study, please answer the questions as honestly as possible. The survey should take about 10 – 15 minutes to complete. Thanking you in anticipation of your participation.

Should you require any further information or specific concerns regarding this survey, please contact:

Content removed on data protection grounds

1. Do you consent to participate in this survey? □ *Required*

Page 2: Demography Information

2. What is your age

- 20 – 29
- 30 – 39
- 40 – 49
- 50 – 59

2.a. Gender

- Female
- Male
- Prefer not to say

2.b. Marital status

- Single
- Married
- Separated
- Prefer not to say

Education

- No education
- High school
- College
- Bachelor
- Postgraduate

2.d. Employment

- Student
- Employed
- Self-employed
- Retired

2.e. Occupation, please specify:

2.f. Annual income

- £0 - 19,000
- £20,000 - 39,000
- £40,000 - 59,000
- £60,000 - 79,000
- 79,000+

2.g. Ethnicity

- Asian
- Black
- Mixed
- White

Page 3: General Questions

3. How many times do you commute in a week?

- Never
- Rarely
- Occasionally
- Frequently

4. What is your mode of transportation?

- ◯ Car
- ◯ Bus
- ◯ Cycle
- ◯ Train
- ◯ Walk

5. Have you heard of Autonomous Vehicle (self-driving car, driverless car)?

Required

 More info

- ◯ No
- ◉ Yes

Autonomous vehicle or driverless vehicle is any vehicle that can operate itself and perform necessary driving functions with little or no human intervention using sensors and actuators. To move from point to point, they create and maintain a map of their surroundings using GPS and video cameras.

6. What is your personal view/opinion regarding autonomous vehicles?

7. How likely are you to ride in a self-driving vehicle? *Required*

8. What are your major concerns regarding the use of Autonomous Vehicles?

○ Safety ○ Security ○ Privacy
○ Trust ○ Ethics ○ Cost

Page 4: Safety

9. Do you agree that autonomous vehicles will be safer than human drivers?

10. Do you think autonomous vehicle will reduce the rate of road accidents in the future?

11. Do you think autonomous vehicles should share driving lanes with other conventional vehicles?

12. How important is having a human driver take total control in driving a vehicle?

Page 5: Trust

13. How much do you agree that autonomous vehicles will be reliable?

14. How confident are you about riding in a completely self-driven vehicle?

15. How likely would you be willing to be a passenger in a completely self-driving vehicle?

16. Would you prefer to ride in an autonomous vehicle that allows driver to take control when required?

Page 6: Accessibility

17. Do you agree that autonomous vehicle is the solution to mobility in the future?

18. Do you agree that autonomous vehicle will improve access to mobility?

19. How much do you agree that the availability of autonomous vehicles in cities will increase the motivation to travel?

20. How much do you agree that autonomous vehicles will reduce the cost of transportation?

Page 7: Privacy

21. How interested would you be willing to own a self-driving vehicle?

22. How interested would you be willing to share a self-driving vehicle?

23. How concerned are you about your personal data stored in a self-driving vehicle?

24. How interested would you be willing for personalised services based on your personal data?

Page 8: Ethics

25. Do you agree that autonomous vehicles will perform according to their designed functionality?

26. In an accident scenario, whose safety should be prioritised?

- Passenger
- Pedestrian
- Cyclist
- Buildings/infrastructures
- Other vehicles

27. In an accident involving autonomous vehicles, who should be liable?

- Passenger
- Manufacturer
- Service provider
- Government

28. Who do you think should promote autonomous vehicle technology?

- Government
- Auto manufacturers
- Tech companies
- Consulting organisations
- Research institutions
- Academia

Page 9: Thank you

Key for selection options

1 - Do you consent to participate in this survey?

Yes

No

- What is your personal view/opinion regarding autonomous vehicles?

0 Extremely negative

1 2 3 4 5 6 7 8 9

10 Extremely Positive

- How likely are you to ride in a self-driving vehicle?

0 Extremely unlikely

1 2 3 4 5 6 7 8 9

10 Extremely likely

- Do you agree that autonomous vehicles will be safer than human drivers?

0 Completely disagree

1 2 3 4 5 6 7 8 9

10 Strongly agree

- Do you think autonomous vehicle will reduce the rate of road accidents in the future?

0 Completely disagree

1 2 3 4 5 6 7 8 9

10 Strongly agree

- Do you think autonomous vehicles should share driving lanes with other conventional vehicles?

0 Completely disagree

1 2 3 4 5 6 7 8 9

10 Strongly agree

- How important is having a human driver take total control in driving a vehicle?

0 Not at all important

1 2 3 4 5 6 7 8 9

10 Extremely important

- How much do you agree that autonomous vehicles will be reliable?

0 Completely disagree

1 2 3 4 5 6 7 8 9

10 Strongly agree

- How confident are you about riding in a completely self-driven vehicle?

0 Not at all confident

1 2 3 4 5 6 7 8 9

10 Extremely confident

- How likely would you be willing to be a passenger in a completely self-driving vehicle?

0 Not at all likely

1 2 3 4 5 6 7 8 9

10 Extremely likely

- Would you prefer to ride in an autonomous vehicle that allows driver to take control when required?

0 Not at all prefer

1 2 3 4 5 6 7 8 9

10 Extremely prefer

- Do you agree that autonomous vehicle is the solution to mobility in the future?

0 Completely disagree

1 2 3 4 5 6 7 8 9

10 Strongly disagree

- Do you agree that autonomous vehicle will improve access to mobility?

0 Completely disagree

1 2 3 4 5 6 7 8 9

10 Strongly agree

- How much do you agree that the availability of autonomous vehicles in cities will increase the motivation to travel?

0 Completely disagree

1 2 3 4 5 6 7 8 9

10 Strongly agree

- How much do you agree that autonomous vehicles will reduce the cost of transportation?

0 Completely disagree

1 2 3 4 5 6 7 8 9

10 Strongly agree

- How interested would you be willing to own a self-driving vehicle?

0 Not at all interested

1 2 3 4 5 6 7 8 9

10 Extremely interested

- How interested would you be willing to share a self-driving vehicle?

0 Not at all interested

1 2 3 4 5 6 7 8 9

10 Extremely interested

- How concerned are you about your personal data stored in a self-driving vehicle?

0 Not at all concerned

1 2 3 4 5 6 7 8 9

10 Extremely concerned

- How interested would you be willing for personalised services based on your personal data?

0 Not at all interested

1 2 3 4 5 6 7 8 9

10 Extremely interested

- Do you agree that autonomous vehicles will perform according to their designed functionality?

0 Completely disagree

1 2 3 4 5 6 7 8 9

10 Strongly agree