FACTORS INFLUENCING THE CUSTOMER INTENTION IN ADOPTING AUTONOMOUS VEHICLES (AVS)

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FACTORS INFLUENCING THE CUSTOMER INTENTION IN ADOPTING AUTONOMOUS VEHICLES (AVS)

BY

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DECLARATION

I hereby declare that:

(1) This undergraduate FYP is the end result of my own work, and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Sole contribution has been made by me in completing the FYP.

(4) The word count of this research report is 10,250 words.

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LIST OF ABBREVIATIONS

AV	Autonomous Vehicles
TAM	Technology Acceptance Model
CTAM	Car Technology Acceptance Model
IDT	Innovation Diffusion Theory
TRA	Theory of Reasoned Action
TPB	Theory of Planned Behavioral
PU	Perceived Usefulness
PEU	Perceived Ease of Use
PS	Perceived Safety
T	Trialability
P	Price
ATU	Attitudes
BI	Behavioral Intention
SPSS	Statistical Package for Social Science

PREFACE

This research project unit, UKMZ 3016 Research Project is completed by one Bachelor of International Business student as the partial requirement for the academic study. The tittle of the final year project is “Factors influencing the Customer Intention in adopting Autonomous Vehicles”.

The global surge in autonomous vehicles (AVs) marks a profound transformation in transportation dynamics, driven by technological breakthroughs, shifting consumer inclinations, and evolving regulatory frameworks. Worldwide, corporations are channelling resources into state-of-the-art sensor technology, machine learning algorithms, and real-time mapping capabilities to augment the sophistication and safety of AVs. Collaborative efforts among traditional automotive manufacturers, tech titans, and burgeoning startups are propelling innovation at a rapid pace, while pilot programs and testing initiatives yield invaluable insights into practical feasibility and user experiences. As the promise of AVs to reshape transportation looms large, grasping the determinants shaping consumer acceptance and adoption of this innovation is of utmost importance. This research delves into factors such as perceived usefulness, ease of use, safety perceptions, trialability, and pricing to elucidate their influence on attitudes and behavioral intentions toward AV usage.

ABSTRACT

The research is developed to investigate the factors influencing the customer intention in adopting the autonomous vehicles. The main concern of this research will be around the determine factors includes perceived usefulness, ease of use, safety perceptions, trialability, and price influencing attitudes and behavioral intention to use the autonomous vehicles. There are six hypotheses constructed in order to study and generate comprehensive result.

The target respondents in the study are Malaysians who are aged at least 18 years old and possess driving license and drive. In addition, 274-sets of valid questionnaires were collected and being analysed by using Statistical Package for Social Science (SPSS) version 29. The researcher adopted Pearson Correlation Analysis and Multiple Linear Regression. Besides, the results of internal reliability test (Cronbach's Alpha) indicated that the measurement scales were consistent and reliable in measuring the proposed constructs. According to results, there are five hypotheses are supported and only one hypothesis is not supported. The justification will be explained in the following chapters.

Lastly, few limitations that hinder the research to be conducted effectively were identified and recommendations are presented to propose beneficial suggestions for further studies to be conducted.

CHAPTER 1: RESEARH OVERVIEW

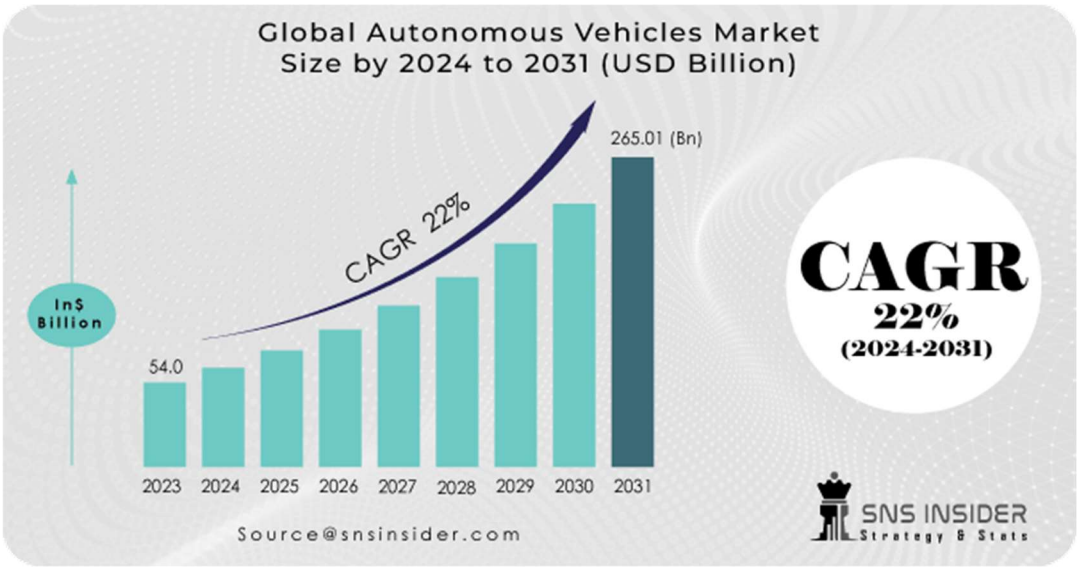
1.0 Introduction

This research aims to examine the factors influencing customer intention in adopting AVs. A research background will be presented in this chapter followed by an explanation of the rationale and objectives of the research, along the importance of the research.

1.1 Research Background

In recent years, AVs have gained significant attention globally, prompting intense competition among various stakeholders to develop this cutting-edge technology. There are some key players in AVs development. For example, the well-known automakers like Ford, Audi, and Volvo. Additionally, tech giants such as Google, Huawei, and Intel have also entered the scene to refine AVs technology. Ride-sharing services such as Uber, Lyft, and DiDi Chuxing are also gearing up to integrate AVs into their fleets (Kassim, Jawi et al., 2021). The involvement of these industry players is driving substantial growth in the AVs market. According to the SNS Insight Research (Figure 1.1), the AVs Market Size in 2023 was valued at USD 54 billion. By 2031, it is expected to reach USD 265.01 billion, with a remarkable compound annual growth rate (CAGR) of 22% over the forecast period 2023-2031 (SNS insider, Strategy and Stats, 2022). As a result, the future of AVs holds great promise, with the potential to transform the way people commute and travel.

Figure 1.1 : Global Autonomous Vehicles Market Size by 2023 to 2031

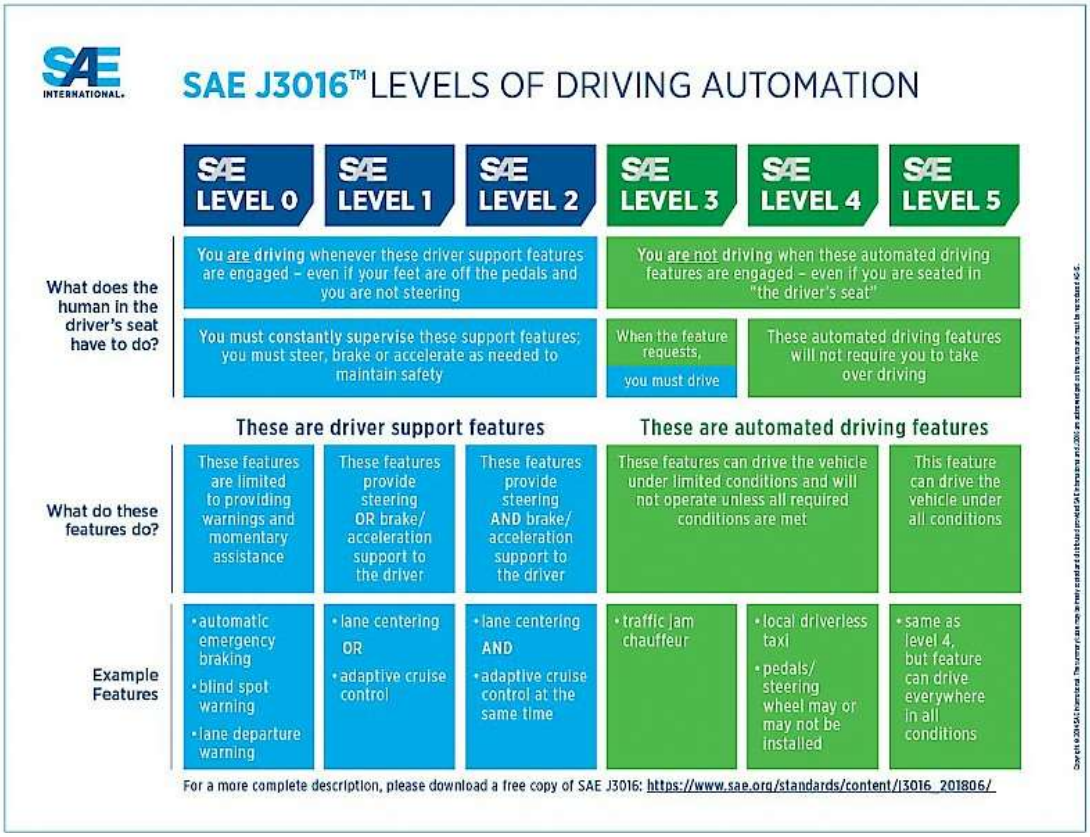


Source: SNS insider, Strategy and Stats (2022).

With AVs interest growing, Malaysia is preparing for the future of transportation with a significant increase in self-driving cars expected over the next decade. Developing Malaysia's automotive industry has contributed significantly to the nation's industrialization, improved living standards, and creation of higher-paying jobs (MITI Malaysia, 2020). While AVs are in introductory stage in Malaysia, the Malaysian government is actively promoting their adoption to address congestion, enhance safety, and mitigate pollution (Razak, 2023). Additionally, the government of Malaysia has updated the National Automotive Policy (NAP) aimed at enhancing competitiveness and embracing emerging technologies (Shahril, 2020). Furthermore, the Ministry of Transport (MOT) and Futurise are also working on establishing guidelines and regulations for AVs. The Cyberjaya Malaysia Autonomous Vehicle (MyAV) Testing Route initiative has been cleared for use in future AVs development projects, it has been announced. The designated routes for testing AVs are located at Cyberjaya, Putrajaya, Selangor, and Johor (Team, 2020).

Figure 1.2 below shows that AVs can be categorized into six levels (Level 0- Level 5). Only level 3 AVs will be focused on this research. Level 3 AVs possess the ability to perceive their surroundings and have the capacity to make self-informed decisions, including passing a slowly moving car by accelerating. However, they still require a human override. In Malaysia, the Honda Sensing Elite, a Level 3 system, is available in the TC-P variants of the Honda Civic, Honda CR-V and Honda Accord (Weng, 2021).

Figure 1.2 : Levels of Driving Automation



Source: Warrendale (2018).

1.2 Research Problem

Prior research has mostly focused on understanding the public opinion, issues, and opportunities of AVs rather than the factors influencing consumer intentions to adopt AVs. For example, Kassim et al. (2021) pointed out the Malaysian populace and assessed their opinions on AVs. Therefore, the research is not focused on the needs of consumers consequently nobody will try to comprehend the AVs. Consequently, the slow adoption rate of AVs indicates potential gaps in consumer understanding or acceptance, which can hinder the progress and potential benefits of this technology.

Besides, there is a gap in existing research is less research about the use of AVs in the Malaysian context. Malaysia's neighboring country Thailand, like us, is a developing country that has done many of relevant research (Ramjan & Sangkaew, 2022), and the influence on the factors affecting AV adoption is comparatively limited in Malaysia. Although there have been many empirical studies on AVs in other nearby nations, there is still a lack of research and attention to this specialized sector in the Malaysian context.

Moreover, the Technology Acceptance Model (TAM), which highlights perceived usefulness (PU) and perceived ease of use (PEU) as primary factors of technology acceptance, provides a robust framework for understanding these challenges. However, the application of TAM has not been explored enough in examining factors influencing the customer intention in adopting AVs. This research seeks to fill this gap by adapting TAM to expand specific factors such as perceived safety, trialability and price, which are crucial in the Malaysian context.

1.3 Research Objectives

1.3.1 Main Objective

In this research, the general goal is to assess the factors influencing Malaysian consumers' intentions to use AVs.

1.3.2 Specific Objectives

Specifically, there are several objectives to investigate the relationship between factors and attitudes, as well as the behavioral intention to use AVs in Malaysia.

1. To determine the relationship between the PU and the ATU toward AVs.
2. To determine the relationship between the PEU and the ATU toward AVs.
3. To determine the relationship between the PS and the ATU toward AVs.
4. To determine the relationship between the T and the ATU toward AVs.
5. To determine the relationship between the P and the ATU toward AVs.
6. To determine the relationship between the ATU toward AVs and the BI to use AVs.

1.4 Research Questions

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

1. What is the relationship between PU and ATU toward AVs?
2. What is the relationship between PEU and ATU toward AVs?
3. What is the relationship between PS and ATU toward AVs?
4. What is the relationship between T and ATU toward AVs?
5. What is the relationship between P and ATU toward AVs?
6. What is the relationship between ATU toward AVs and BI to use AVs?

1.5 Research Significance

The automotive industry might benefit from this research since it addresses some of the needs that consumers seek with this technology. In the past ten years ago, producers have concentrated on creating more affordable and effective transportation to replace conventional vehicles due to the growing interest in environmental issues, particularly carbon emissions (Park et al., 2018). However, there is a lack of consensus among manufacturers like Tesla and Uber regarding the specific preferences and needs of consumers for AVs. As a result, the technology development lacks unified norms (Hewitt et al., 2019). Hence, comprehending the needs of users regarding the technology could aid producers in making decisions and planning the creation of AVs in the future (Chan & Lee, 2021).

Furthermore, this research aims to helps in informing industry strategy and guiding policy development. The engineers will know how design technology in a way that will promote greater public acceptability, and it would also help policymakers comprehend public opinion now and encourage the adoption of new mobility options (Zhang & Kamargianni, 2022). Automotive manufacturers and related stakeholders are unsure of how to tailor their strategies to increase consumer acceptance and adoption of AVs (Chan & Lee, 2021). Ideally, this research will also meet the demand of related stakeholders and especially the marketing team in the automotive industry to gain a deeper comprehension of the primary determinants that influence Malaysian consumers' intention and actions regarding an AV. Accordingly, the marketers will be able to create more tailored marketing plans that will quicken the rate of these services' acceptance to a bearable level.

From a theoretical standpoint, this research could provide additional knowledge to the literature and for academics interested in the associated topic, especially since AVs are a new theme in the automotive industry that requires further investigation and analyzes. Not only that, but this research also offers a more profound insight into

customer factors concerning various aspects of AVs technology by extending the Technology Acceptance Model (TAM). While the TAM model has been frequently used in prior studies to promote public acceptance and utilization of new technology, its scope has proven insufficient. With evolving times, customers consider a broader array of factors when embracing new technology. Thus, this research supplements the TAM model with perceived safety, trialability, and price. This enhancement aims to furnish a more exhaustive and thorough elucidation of the factors shaping customer intentions toward adopting AVs.

1.6 Conclusion

This chapter gave readers a clear overview of the problem statement, research background, and importance of this research. The review of the literature will be covered in more detail in the upcoming chapter.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

Chapter 2 details the theoretical framework guiding the research. It also includes operational definitions, the relationship between variables, and hypothesis development for the investigation.

2.1 Underlying Theories

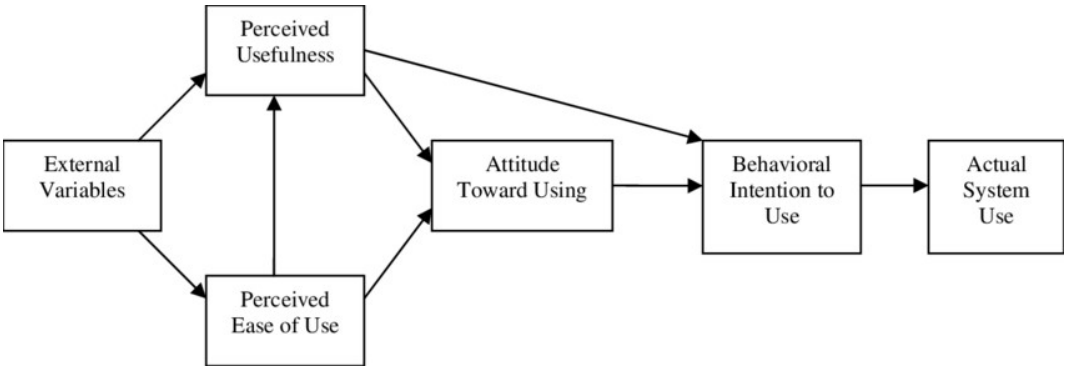
There are three theoretical lenses applied in this research, which are the Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), and Marketing Mix.

2.1.1 Technology Acceptance Model (TAM)

TAM was established by Fred Davis and originated from the Theory of Planned Behavioral (TPB) and Theory of Reasoned Action (TRA) as a framework to explain how people accept and adopt technology (Davis et al., 1989). This concept is founded on the idea that technology adoption is influenced by individual user motives as well as solid innovation, and that such incentives impact attitudes about new technology, which leads to behavioral intention to use the technology (Ramjan & Sangkaew, 2022). TAM consists of four fundamental characteristics that determine an individual's willingness to utilize new technology: perceived usefulness (PU), perceived ease of use (PEU), attitude (ATU), and behavioral intention (BI) (Marangunić & Granić, 2015). Besides, actual usage is influenced by both ATU and BI.

However, AVs are currently in the initial stages of technological development, so this research concentrated on AT and BI rather than actual usage. Consequently, this research utilized BI as the dependent variable. This is because BI is reliable indicator of future conduct (Ajzen, 1991). This allows for insights into individuals' readiness to adopt AVs, crucial in a context where actual usage data is scarce.

Figure 2.1: Technology of Acceptance Model (TAM)



Source: Miller & Khera (2010).

Prior research studies have used TAM to examine the adoption of AVs in other countries. Chen et al. (2023) examined the behavioral intention of individuals to use Level 5 AVs in Australia by expanding the TAM model that included the perceived trust and data privacy. Furthermore, research by Ramjan & Sangkaew (2022) proposed and employed an extended TAM by combining ethical principles, legal considerations, and trust to forecast Thai residents' planned usage of AVs. Moreover, Panagiotopoulos & Dimitrakopoulos (2018) propose a technology acceptance modeling technique that builds on the original TAM to explain and anticipate customer attitudes about AVs. Therefore, TAM is suitable to adopt in this research for determining the factors in adopting AVs.

Besides, prior research studies frequently involve extra elements that improve the TAM framework, considering different features of different technologies. Therefore, the Car Technology Acceptance Model (CTAM) framework added factors to these TAM to analyzes an user's willingness to adopt car-related technologies in this research. CTAM demonstrated to be a useful model for investigating AV adoption determinants since it considers both car-specific elements such as anxiety, perceived safety and self-efficacy (Zhang & Kamargianni, 2022).

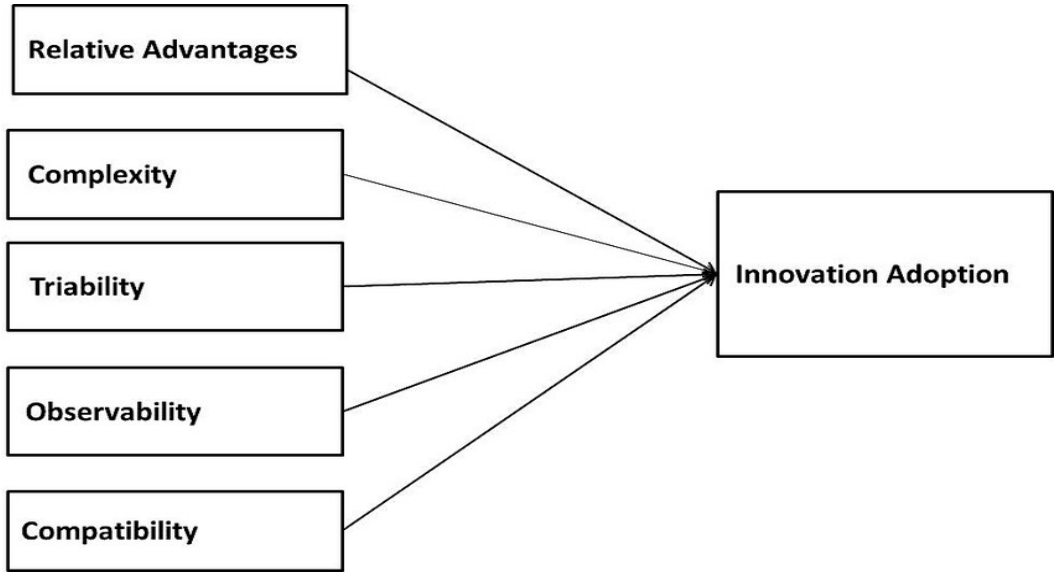
In this research, only perceived safety has been selected as independent variable. Vehicle safety systems have undergone steady innovation over the last several decades, which has contributed to a considerable reduction in the incidence of road deaths and injuries in many nations (Montoro et al., 2019). Although several agencies on road safety have been set up and many road safety campaigns have been launched by government departments, private agencies, and voluntary organizations, road traffic accidents still occur anytime and anywhere, both during weekdays and festive seasons (Kamarudin et al., 2018). Therefore, perceived safety is very important for individuals to consider before adopting AVs.

2.1.2 Innovation Diffusion Theory (IDT)

Another common concept that explains why people decide to embrace or reject an invention based on their beliefs is IDT. According to Figure 2.2 below, the spread of innovations depends on the following characteristics: compatibility, relative advantage, observability, complexity, and trialability (Rogers et al., 2003). This research will choose trialability only because trialability allows potential users to experience AVs directly, such as through test drive, a final step often taken to finalizing the decision to adopt a car.

Following some researchers, the IDT can be used to measure applications or adoption of various new technologies. For instance, Pinho et al. (2020) used IDT to examine the E-learning process within a higher education context. Besides, Marzouqi et al. (2022) have successfully applied IDT to determine the prediction of users' intention to use metaverse systems in medical education. For the autonomous field, Yuen et al. (2020) studied the factors of user acceptance of AVs with IDT.

Figure 2.2: Innovation Diffusion Theory (IDT)



Source: Rogers et al. (2003).

2.1.3 Marketing Mix

According to Singh (2012), a marketing mix comprises controllable elements utilized by a company to cater to its target customers' needs. It includes different marketing choices that the company uses to advertise its products and services, commonly grouped into the "Four Ps of Marketing": product, price, place, and promotion.

In this research, only price is selected as independent variable. Price refers to the amount consumers must pay to obtain the offering (Singh, 2012). The reason behind selecting only price as the independent variable, rather than others, stems from the fact that AVs are high-priced products, particularly during the introductory stage, as the technologies required to develop such vehicles are costly. The price of AVs will pose the biggest challenge to their adoption. Besides, price often holds paramount importance in consumers' decision-making processes (Patrice, 2021).

Based on some previous research, marketing mix often used in the automotive industry research (Catană,2021; Leng & Chin, 2017). Price also considered in previous studies. For example, Kapser & Abdelrahman (2020) has integrated price into the UTAUT2 constructs to study how people in Germany accept autonomous delivery vehicles for last-mile delivery. Besides, Iranmanesh et al. (2023) examined how three personal factors - personal innovativeness, concerns about data privacy, and sensitivity to price - affect attitudes and intentions to use autonomous vehicles in Vietnam. Patrice (2021) includes costs variable to understanding the factors influencing consumers' behavior towards AVs adoption. Therefore, price is an important determinant for consumers when deciding to adopt AVs.

2.2 Review of Variables

2.2.1 Behavioral Intention (BI)

Based on the definition proposed by the TRA, BI is to measure the strength of one's intention to perform a specified action (Davis et al., 1989). According to TPB, the BI to do an activity is the most significant factor in an individual's conduct (Hafeez et al., 2022). In TAM, BI refers to the desire of users to utilize an innovative technology as opposed to the previous way of determining consumers' willingness to embrace an innovative technology (Samsudeen & Mohamed, 2019). Overall, BI is often a strong predictor of actual behavior. The TRA and TPB, both suggest that a person's intention to pertake in an action is a significant predictor of whether they will do it. Given Malaysia's early stage of AVs development, relying on BI as a dependent variable proves reliable in predicting future behavior.

In the view of research, BI has been extensively studied by researchers in the adoption of new technology. For example, BI is used as the dependent variable in much research that is affected by different factors to determine the intention to adopt AVs (Ramjan & Sangkaew, 2022; Foroughi et al., 2023; Chen et al., 2023; Yang et al., 2023; Kenesei et al., 2022; Koul & Eydgahi, 2019; Jing et al., 2019). Overall, BI in this research is appropriate to determine the extent of intention to use AVs.

2.2.2 Attitude (ATU)

Another concept stemming from the TRA involves individuals' evaluative affect towards performing the target behavior, which can manifest as either positive or negative feelings (Davis et al., 1989). In TAM, ATU reflects the willingness or acceptance of individual to accept new technologies. The amount to which individuals have good or bad attitudes about the innovation, which is AVs, is characterized by their attitude toward adopting the innovation (Chen et al., 2023).

There are some researchers have successfully used ATU to examine the public intention to adopt AVs. The study of Chen et al. (2023) stated that ATU is the most significant variable that strongly associated with BI, which leads to acceptance of AVs. Besides, ATU also includes in framework to know user acceptance of fully AVs (Sutarto et al., 2023). Furthermore, the research of Acheampong & Cugurullo (2019) use ATU as independent variable that affect adoption intention on AVs. In summary, the role of ATU as an independent variable is pivotal because it determines the direction of BI regarding AVs.

2.2.3 Perceived Usefulness (PU)

Davis (1989) proposed the PU in the original TAM model as a subjective possibility of employing a certain system to improve job quality within an organizational environment. In this research, PU refers to how individuals perceive the utility or benefits of using AVs. It can also be explained whether individuals believe that AVs offer advantages in terms of some factors such as convenience, time savings, improved accessibility, and productivity.

Panagiotopoulos & Dimitrakopoulos (2018) showed that PU was the primary motivator for the deployment of AVs with the strongest impact. PU also had a substantial indirect beneficial impact on the intention to use shared AVs according to Yang et al. (2023). Apart from that, Ramjan and Sangkaew (2022) assessed the PU is a significant predictor of adoption behavior.

2.2.4 Perceived Ease of Use (PEU)

Davis (1989) defines PEU as the extent to which a person perceives using a technology to be uncomplicated. Additionally, PEU may also relate to an individual's evaluation of the effort necessary to use technology. To be more specific, PEU indicates the simplicity of use of AVs as well as the resolution of any difficulties (Ramjan & Sangkaew, 2022). In this research, PEU refers to how easy individuals find it is to use AVs. In other words, PEU is the perceived simplicity and user-friendliness of AV technology.

Many of research have found that PEU influences the user's intention to utilize technology. For example, the research of Chen et al. (2023) stated that one of the main factors that could influence individual’s acceptance of AVs is PEU. Besides, PEU has been identified as a dependent variable that impacts ATU and BI according to studies conducted by Sutarto (2023), Ramjan & Sangkaew (2022) and Zhang et al. (2021).

2.2.5 Perceived Safety (PS)

Based on the fundamental structure of TAM, this reearch increased PS as an impacting factor on AT and BI. The extent to which customers perceive the level of safety connected with the technology was characterized as PS of AVs (Koul & Eydgahi, 2019). Yao et al. (2023) stated that people are aware of safety requirements in their surroundings and will take action to seek the concept of safety. The number of people killed in traffic accidents each year has a significant influence on public psychology, and the safety of AVs is seen as a key component in public acceptance and adoption. In this research, PS pertains to the level of concern regarding the safety of AVs.

According to Koul & Eydgahi (2019), the PS of AV technology and the BI had a strong relationship. Montoro et al. (2019) examined the influence of PS and value attributed to the AVs on the drivers' intention to use them in Spanish, revealing that the PS has affect the intention of using AVs. Additionally, the importance of PS was also emphasized in the research of Manfreda et al. (2021). Highlighting PS as an independent factor is crucial because when people trust that AVs can enhance safety, they are more likely to use them, which is vital for widespread adoption.

2.2.6 Trialability (T)

T refers to users' ability to try out new technologies for a limited period before choosing whether to embrace them. Experimenting with creation reduces the perception of risk and uncertainty associated with adopting novel technology by allowing people to learn via trial and error (Su et al., 2023). According to Yuen et al. (2020), the ease with which the public can try or test AVs prior to their acceptance is referred to as trialability. The trialability of new transportation technologies such as AVs is significant because it provides the users or the public to test out with the innovations in a controlled and secure environment. In this research, T refers to the opportunities for test drives, temporary usage, or pilot programs that can let individuals experiment with and try out AVs.

Su et al. (2023) examined the impact of technological, innovational, and attitudinal factors on electric motorcycles (EMs) adoption behavior. The findings revealed that trialability is connected to users' adoption of EMs. Additionally, a study by Yuen et al. (2020) used the innovation diffusion perspective as a foundation to examine the factors of public acceptance of AVs. Trialability for the new technology was found to affect the perceived value of AVs.

2.2.7 Price (P)

In marketing mix, price pertains to the total customers pay for the product and services provided by a company (Singh, 2012). Consumers' attitudes and behavioral intention might be significantly affected by the expenses of these technologies, and the pricing model of their maintenance (Patrice, 2021). In this research, P refers to how consumers react to the price of AVs that affect the adoption of AVs.

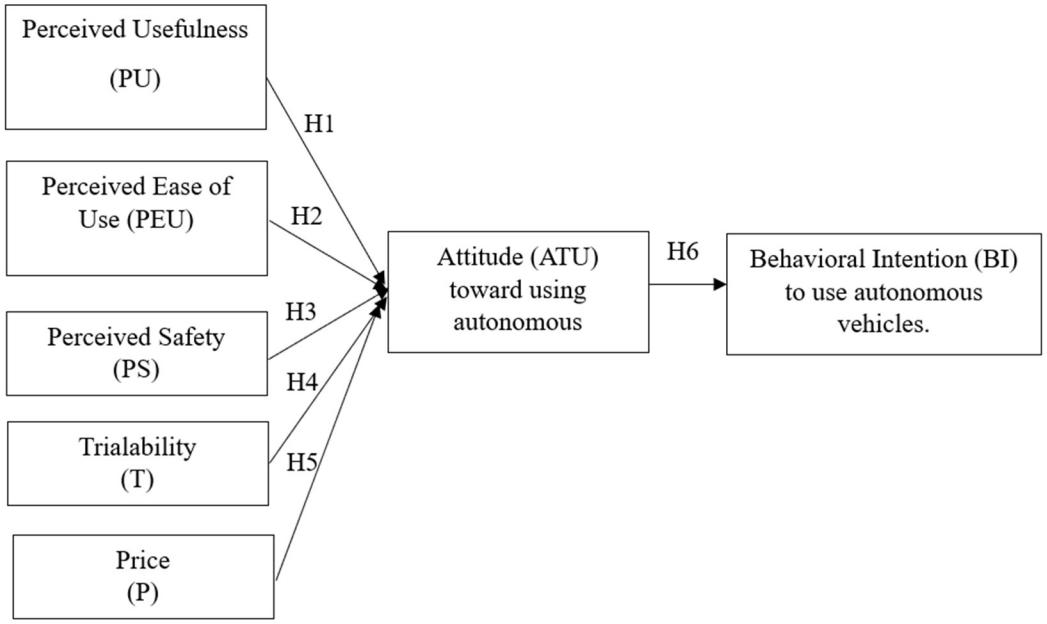
As detailed in Kapser & Abdelrahman (2020), novel or supplementary constructs are identified within the specific realm of acceptance of autonomous delivery vehicles, which is price sensitivity. The article added the price sensitivity as independent variables because it remains an important factor in the fiercely competitive landscape of last-mile delivery. The consideration of price value as independent variable also highlighted in Patrice (2021), encompassing operational, vehicle, maintenance, and network protocol costs. Iranmanesh et al. (2023) focus on the absence of price sensitivity as an independent variable, noting its positive moderation on the influences of PEU and PU on ATU toward using AVs.

Price is used in this research rather than price sensitivity or price value because price emphasize the direct impact of the monetary cost of AV on consumer behavior and attitudes. Since AVs have not sell in Malaysia, it is important to highlight the tangible amount consumers must pay for the AVs rather than broader concept such as sensitivity, which might encompass additional factors beyond the immediate monetary cost. Hence, price has been added as a determinant of attitudes and behavioral intention to use AV.

2.3 Proposed Conceptual Framework

Figure 2.3 depicts the conceptual framework that proposed with the expansion of TAM in this research. Researcher has extended the model by including perceived safety, trialability, and price in the framework. In short, BI is the dependent variable, while PU, PEU, PS, T, P, and ATU are the independent variables.

Figure 2.3: Conceptual Framework for Factors influencing the Customer Intention in adopting Autonomous Vehicles (AVs)



Source: Developed for the research

2.4 Hypotheses Development

2.4.1 The relationship between PU and ATU toward autonomous vehicles.

In this research, PU is main construct in TAM which represents whether AVs can bring any benefits to individuals. Besides, PU is an important factor in describing how beneficial and practical the technology meets customers' expectations (Chen et al., 2023). In short, the higher the PU of AVs, the positive the attitude of individuals toward AVs. Therefore, this research posited that:

H1: There is a significant relationship between the perceived usefulness (PU) and the attitude toward autonomous vehicles (AVs).

2.4.2 The relationship between PEU and the ATU toward autonomous vehicles.

When individuals find that AVs are easy to learn and control, they are more likely have positive attitudes towards AVs. Many studies have shown that PEU has a positive impact on the attitude toward AVs and behavioral intention to adopt AVs (Ramjan & Sangkaew, 2022; Acheampong & Cugurullo, 2019). Thus, the following is proposed:

H2: There is a significant relationship between the perceived ease of use (PEU) and the attitude toward autonomous vehicles (AVs).

2.4.3 The relationship between the PS and the ATU toward autonomous vehicles.

When individuals trust AVs to operate safely with a level 3 of conditional autonomation, they will have positive perceptions on AVs. PS has been noticed in prior research on AV adoption, indicating that PS is likely to have a large and beneficial impact on AV adoption. (Bezai et al., 2021; Manfreda et al., 2021; Koul & Eydgahi, 2019; Montoro et al.,2019). As a result, this research suggested:

H3: There is a significant relationship between the perceived safety and the attitude toward autonomous vehicles (AVs).

2.4.4 The relationship between the T and the ATU toward autonomous vehicles.

With the rise of information and technology, individuals who are increasingly tech-savvy may be more open to AVs. Their willingness to experiment with AVs, facilitated by opportunities like test drives and the use of AVs' mechanisms, fosters learning and awareness about AV benefits. This exposure can lead to better appreciation of AV values over traditional vehicles. Moreover, experimenting with AVs can yield unexpected, good experiences, such as excitement, enhancing the overall appeal of AVs. In short, the more the opportunity to try out the AVs, the more the individuals can think and feel about AVs (Yuen et al., 2020). Thus, below is hypothesized:

H4: There is a significant relationship between trialability and the attitude toward autonomous vehicles (AVs).

2.4.5 The relationship between the P and the ATU toward autonomous vehicles.

Because AVs are pricier than traditional vehicles, price may discourage people attitudes and intentions to buy and use AVs. While AVs may offer the benefit of saving time and labor costs, it is uncertain whether these savings will translate into lower fuel or electricity costs for customers. In addition, the introduction of AVs may result in car suppliers offering them as a premium service, which may result in additional costs to users (Kapser & Abdelrahman, 2020). In short, the higher the price of AVs, the attitude toward AVs becomes more negative. Hence, the following hypothesis is proposed:

H5: There is a significant relationship between the price and the attitude toward autonomous vehicles (AVs).

2.4.6 The relationship between the ATU and the BI to use autonomous vehicles.

In this research, ATU may be a positive attitude or a negative attitude toward AVs. Behavioral intention is the likelihood of individuals using AVs in real future situations. When individuals have a positive attitude towards AVs, it will increase their likelihoods to express an intention to engage in behaviors related to its adoption, purchase, or usage. In TPB, the ATU has strongly affected BI (Hafeez et al., 2022). Therefore, the following is hypothesized:

H6: There is a significant relationship between the attitude and the behavioral intention to use autonomous vehicles (AVs).

2.5 Conclusion

In conclusion, the literature review, suggested conceptual framework, and hypothesis were developed in this chapter. The research methodology will be discussed further in Chapter 3.

CHAPTER 3: METHODOLOGY

3.0 Introduction

The methodology of the research, comprising the research design, sample design, data collection methods, and the proposed data analysis tool, is the main topic of this chapter. Its primary emphasis lies in detailing the methodology used to collect the necessary data for testing the hypotheses outlined in the preceding chapter.

3.1 Research Design

3.1.1 Quantitative Research

Quantitative research is a systematic study of social phenomena using statistical or numerical data. It aims to collect data through measurement, analyze it for trends and relationships (Watson, 2015). In this research, researcher gathered the data from targeted respondents by using surveys to measure on how the ATU and BI towards AVs. Besides, quantitative research will be used in this research to readily evaluate the degree of influence of influence of each factors using Likert scale. Therefore, quantitative research is suitable to help and apply in this research.

3.1.2 Descriptive Research

Descriptive research is a method describing the population or phenomenon characteristics. It focuses more on the “what” rather than ‘why’ of subject (Bhat, 2023). In this research, descriptive study is applied by defining and interpreting the background and factors influencing the customer intention in adopting AVs. Furthermore, justification of independent variables has been included. Descriptive research aids in a better comprehension of the research and highlighting its objectives. Moreover, descriptive research allows researcher to collect and describe the demographic data. Therefore, it was implanted in this research to obtain the respondents ’demographic profile and their driving status to illustrate the accurate profiles.

3.2 Sampling Design

3.2.1 Target Population

The target population defined as the demographic from which researchers conduct the study and gather data (Li & Song, 2020). In this research, the target population comprises individuals who aged 18 years and above and who possess a driving license or drives. The criterion is based on Malaysia regulations, where minimum age for driver’s license is 17 (JPJ Malaysia, n.d.), and the legal age of majority is 18 years old (Yew, 2018). Those with driver's licenses are likely preferring to obtain the private vehicles, making them better equipped to grasp the survey on AVs.

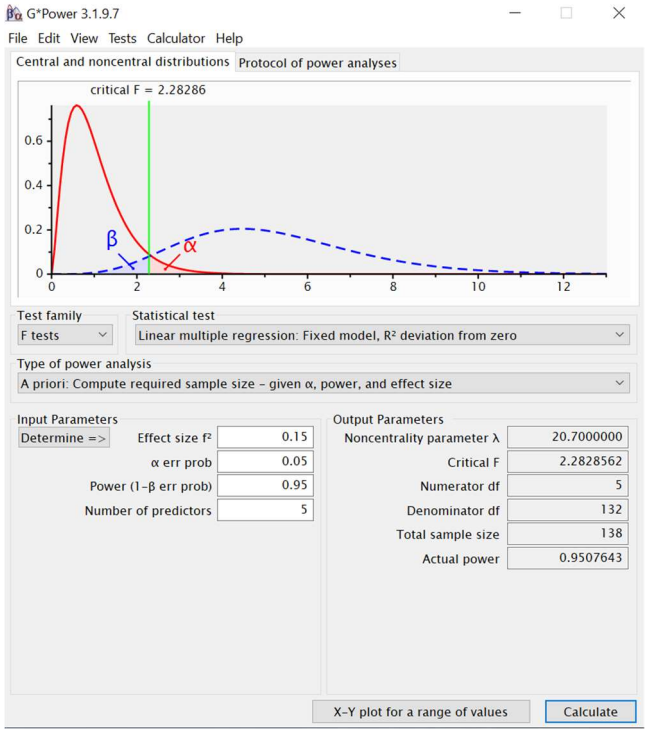
3.2.2 Sampling Techniques

This research applied non-probability sampling. It entails sample selection guided by subjective judgment rather than random selection, allowing for deliberate targeting of specific population groups (Galloway, 2005). In this research, convenience sampling may be appropriate and conducive to achieving the research objectives. Researcher may use convenience sampling to recruit participants from easily accessible locations or settings, such as Malay Peninsula is easier to access than Sabah and Sarawak (Tyrer & Heyman, 2016).

3.2.3 Sample Size

The sample size serves as a representation of the target population to justify its adequacy in providing valuable information aligned with the researcher's goals (Lakens, 2022). In this research, the sample size refers the total of respondents completing questionnaires to enhance the validity and reliability of the findings. Therefore, the G-Power software determined that a minimum sample size of 138 samples is needed for this research, as depicted in Figure 3.1. According to Roscoe (1975) guidelines, most behavioral studies should have sample sizes greater than 30 but not more than 500. Therefore, minimum of 250 surveys were aimed to be distributed among the target respondents for this research.

Figure 3.1: G-Power Test Result



Source: Developed for the research.

3.3 Data Collection Method

3.3.1 Primary Data

Primary data consist of information collected initially and are characterized by their originality and freshness. Common methods for gathering primary data in behavioral sciences include observation, interviews, questionnaires, and database research (Mazhar, 2021). Due to the affordability and simplicity of this method, the collection of data relies on surveys administered by the respondents themselves. A survey using a Google Form questionnaire was shared with the desired participants via social media platforms. Once respondents submit their responses, their firsthand data will be recorded for analysis.

3.4 Research Instrument

3.4.1 Questionnaires Design

The survey presents the questionnaire in English and comprises close-ended questions with multiple-choice answers. The survey consists of three primary parts, namely Part A, Part B, and Part C. There is also a screening question in questionnaire used to determine if the respondent fits the criteria. The screening question pertains to whether the respondent holds a driver's license or not.

In Part A, there are some questions related to demographic information such as gender, age, state that currently reside, highest education level, employment status, and personal income level. Typically, questions are created with various response options, let respondents to choose the one that most accurately represents themselves.

In Part B, there are two general questions. These queries aim to glean further insights into the respondents' characteristics, focusing specifically on their driving experience and the average distance covered in driving on a weekly basis.

Part C encompassed all questions regarding both dependent variable and independent variables. The questionnaire utilized a 5-point Likert Scale Measurement, prompting respondents to express their agreement levels with each statement. Participants' responses were categorized using a scale ranging from 1 for 'strongly disagree' to 5 for 'strongly agree'. Multiple questions were posed under each influence factor to compute an average score, enhancing the precision of measuring respondents' influence levels.

3.4.2 Pilot Test

A pilot test helps researchers find out if there are any confusing questions in the questionnaire by getting feedback from the respondents answering it (Zikmund, 2003). A common rule of thumb is that a sample size of pilot test should be at least 30 to 50 respondents (Nr & Al ,1998). Hence, the pilot test involves a total of 30 respondents.

3.5 Construct Measurement

3.5.1 Nominal Scale

A nominal scale is a type of measurement scale where numbers are assigned as labels to categorize or classify objects. This scale is commonly used in research surveys and questionnaires where only the variable labels are meaningful (Shukla, 2023). In the questionnaire of this research, some questions in Part A and Part B are designed in nominal scale which allowed respondents to tick on the category they belong to and helps in analyzing the responses.

3.5.2 Ordinal Scale

An ordinal scale represents a natural sequence or ranking of items, denoting their relative positions (Shukla, 2023). An example of ordinal scale data in the questionnaire is highest education level question in Part A, with the possible options including classes such as high school, diploma, undergraduate, master's degree, and doctoral degree. The answer options can be arranged in an order, but the order does not indicate any quantitative meaningful numerical measure.

3.5.3 Interval Scale

Interval scale measurements indicate both order and degree of difference, allowing mathematical operations like addition and subtraction to reflect intervals between values. However, they do not imply a true absence, as a "zero" value doesn't signify complete absence (Shukla, 2023). In this research, a 5-point Likert Scale is used in the questionnaire, simplifying respondents' expression of agreement levels across five points: 1 for "Strongly Disagree," 2 for "Disagree," 3 for "Neutral," 4 for "Agree," and 5 for "Strongly Agree." These responses can address the questions in Table 3.1.

Table 3.1: Origin of Construct

Variables	Questionnaires	Modified Questionnaires	Source
Perceived Ease of Use (PEU)	1. I think it is easy to learn how to operate an autonomous vehicle.	1. I think it is uncomplicated to learn how to operate an autonomous vehicle	Ramjan & Sangkaew (2022)
	2. I think I can understand the controls on autonomous vehicles.	2. I think I can understand the controls on autonomous vehicles.	
	3. Overall, I think autonomous vehicles are easy to use.	3. Overall, I think autonomous vehicles are easy to use.	
Perceived Usefulness (PU)	1. Traveling in a shared autonomous vehicle can improve my travel efficiency.	1. Traveling in an autonomous vehicle can improve my travel efficiency.	Yang et al. (2023)
	2. Shared autonomous vehicles can improve my quality of life.	2. Autonomous vehicles can improve my quality of life. (e.g. making the most of travel time, and increased accessibility for OKU)	
	3. Shared autonomous vehicles can reduce traffic congestion.	3. Autonomous vehicles can reduce traffic congestion. (e.g. optimize driving routes and reduced human error)	
	4. Shared autonomous vehicles can reduce the probability of traffic accidents.	4. Autonomous vehicles can reduce the probability of traffic accidents.	

Perceived Safety (PS)	1. I am worried about the general safety of such technology.	1. I am worried about the general safety of such autonomous vehicle technology.	Yang et al. (2023)
	2. I am worried that the failure or malfunctions of shared autonomous vehicles may cause accidents.	2. I am worried that the failure or malfunctions of autonomous vehicles may cause accidents.	
	1. I would trust that a computer in an autonomous vehicle could get me to my destination safely with no assistance from me.	3. I am worried that an autonomous vehicle may not safely reach my destination.	Koul & Eydgahi, (2019)
Trialability (T)	1. Before I decide to buy an autonomous vehicle, I would like to test-drive it.		Yuen et al., (2020)
	2. Before I decide to buy an autonomous vehicle, I would like to borrow it for a day or two.		
	3. Before I decide to buy an autonomous vehicle, I would like to try a friend's autonomous vehicle.		
	4. Before I decide to buy an autonomous vehicle, I would like to view a demonstration of using an autonomous vehicle.		
	5. Before I decide to buy an autonomous vehicle, I would like to receive training or attend a course on using an autonomous vehicle.		
Price (P)	1. I would not mind paying more to use autonomous vehicles.		Iranmanesh et al. (2023)
	2. I would not mind spending a lot of money to use autonomous vehicles.	2. I would not mind investing a lot of money to use autonomous vehicles.	
	3. I would be less willing to pay for autonomous vehicles if I thought it to be high in price.		
	4. If using autonomous vehicles are likely to be more expensive than conventional vehicles, that would not matter to me.		
	5. A really great transportation option would be worth paying a lot of money for.		
Attitude (ATU)	1. I have a positive attitude toward shared autonomous vehicles.	1. I have a positive attitude toward autonomous vehicles.	Yang et al. (2023)
	2. I would be happy if shared autonomous vehicles were available.	2. I would be happy if autonomous vehicles were available.	
	3. I am in favor of using shared autonomous vehicles.	3. I am in favor of using autonomous vehicles.	

Behavioral Intention (BI)	1. Assuming I have access to an autonomous vehicle, I would intend to use it.	Foroughi et al. (2023)
	2. Given I have access to an autonomous vehicle, I predict I would use it.	
	3. In the future, I would not hesitate to use an autonomous vehicle.	

Source: Developed for the research.

3.6 Data Processing

After collected all questionnaire, the data processing is necessary to carry out by researcher. The data processing consists of converting the raw data into valuable information.

3.6.1 Data Checking

The first step is data checking involves examining data collected in questionnaires to identify and correct errors and omissions. In this research, out of the 303 questionnaires collected, 29 invalid ones were excluded during data cleaning due to the absence of income or indicated that the respondents did not drive. As a result, a total of 274 valid surveys was collected.

3.6.2 Data Editing

Data editing refers to the preparation of data for coding and transcription. It consists of a questionnaire screening process designed to ensure data completeness, consistency, and reliability. The purpose of data editing is to prevent incomplete responses as questionnaires with missing values or invalid responses will be considered unacceptable. If missing values are found in the questionnaire or fails the screen question, the researcher exclude unsatisfactory or invalid respondents (Zikmund, 2003). Question 3 (P3) in Price is phrased

negatively, while the rest of the questions are phrased positively. Consequently, reversing the responses for P3 is necessary; for instance, a response of "Strongly Agree" will be adjusted to "Strongly Disagree".

3.6.3 Data Coding

According to Zikmund (2003), the researcher must code the data to identify and categorize each answer with a numeral score or other character symbol. In simple term, data coding is the process of converting the data from word term to numbers. Therefore, it helps the data analysis process easier and smoother.

3.6.4 Data Transcribing

During this stage, researchers will input the coded data into statistical analysis software, such as the Statistical Package for Social Sciences (SPSS), for further analysis. The specific analysis methods employed in SPSS will be elaborated on in subsequent sections.

3.7 Proposed Data Analysis Tool

According to Singh (2015), data analysis involves a set of operations to organize the gathered data so it can address research questions and hypotheses. The IBM Statistical Package and Social Science (SPSS) version 29.0 will be employed to analyses the gathered data.

3.7.1 Descriptive Analysis

Descriptive analysis entails examining a dataset to highlight its key characteristics. It aims to depict the essence of a subject or phenomenon by uncovering patterns within the data to address inquiries regarding who, what, where, when, and to what degree. This analytical approach serves as a crucial step in exploring data, involving the synthesis and depiction of fundamental attributes such as frequency distribution, central tendency, dispersion, and positional identification (Loeb et al., 2017).

3.7.2 Scale Measurement

3.7.2.1 Reliability Test

Reliability pertains to the degree of stability and consistency in the measurement of a phenomenon. Assessing reliability is crucial as it indicates the consistency of the measurement instrument across different dimensions.The Cronbach alpha coefficient is often used as the main indicator of internal consistency, especially when using Likert scales (Taherdoost, 2016). In this research, the Cronbach' Alpha Rule was utilized to examine the reliability of the survey questionnaire. Table 3.2 of the rules of thumb for Cronbach' Alpha was shown in below. As the result, Table 3.3 shows all variables in pilot test

have a value of more than 0.70 indicating that the variables have high internal consistency with P3.

Table 3.2: Cronbach's Alpha Rules

Cronbach's Alpha	Rules
Cronbach's Alpha ≤ 0.5	Unacceptable
0.5 < Cronbach's Alpha ≤ 0.6	Poor
0.6 < Cronbach's Alpha ≤ 0.7	Questionable
0.7 < Cronbach's Alpha ≤ 0.8	Acceptable
0.8 < Cronbach's Alpha ≤ 0.9	Good
Cronbach's Alpha > 0.9	Excellent

Source: George and Mallery (2003).

Table 3.3: Cronbach's Alpha Results for Pilot Test

Variables	Cronbach's Alpha	Rules
Perceived Ease of Use (PEU)	0.927	Excellent
Perceived Usefulness (PU)	0.924	Excellent
Perceived Safey (PS)	0.952	Excellent
Trialability (T)	0.875	Good
Price (P)	0.848	Good
Attitudes (ATU)	0.941	Excellent
Behavioral Intention (BI)	0.833	Good

Source: SPSS Version 29.0

3.7.3 Inferential Analysis

While descriptive analysis helps researcher to summarize the data, the inferential analysis aims to conclude and make forecast based on the data. It combines mathematical techniques and logical reasoning to enable researchers to use data obtained from probability samples to assess hypotheses about a population (Andereck, 2017). In this research, SPSS was utilized to draw overall conclusions by employing the Pearson correlation analysis and multiple regression.

3.7.3.1 Pearson Correlation Coefficient

The Pearson correlation coefficient (r) evaluates the linear correlation between variable pairs, necessitating numerical coding for categories within each variable (Chen & Anderson, 2023). This coefficient efficiently assesses if two changes exhibit a similar trend, facilitating the analysis of their relationship (Liu et al., 2022). In this research, it used to examine the relationship between each independent variable and dependent variable. The r value can interpret the correlation coefficient into descriptors like "weak," "moderate," or "strong" relationship as illustrated in Table 3.4, which provides general guidelines for interpreting the r value:

Table 3.4: Rules of Thumb of Correlation Coefficient

Size of Correlation	Interpretation
± *0.91 to* ± *1.00*	Very Strong
± *0.71 to* ± *0.90*	High
± *0.41 to* ± *0.70*	Moderate
± *0.21 to* ± *0.40*	Small but define relationship
0.00 to ± *0.20*	Small, almost negligible

Source: Hair et al. (2003).

3.7.3.2 Multiple Linear Regression

Multiple regression is used to examine the correlation between a dependent variable and multiple independent variables (Moore et al., 2006). The objective of this method in this research is to use the independent variables which are PU, PEU, PS, T, P to forecast the value of the single dependent value which is ATU. The relationship is described using a variation of the equation of a straight line.

$$Y=a+b1X1+b2X3+\ldots+bnXn$$

Y represents the dependent variable, and X1,…,Xn stand for the n independent variables. Through analysis, the weights, such as a, b1,…,bn, computed to maximize the prediction of BI from independent variables (Moore et al., 2006).

3.8 Conclusion

In summary, this chapter provides a complete explanation of the methodology and data analysis tools employed in this research. Therefore, the next chapter will utilize these tools for data analysis after data collection.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

Upon collecting all the survey questionnaires, researchers need to conduct data analysis. The SPSS will be utilized to analysis the data. Consequently, this chapter will explain the results of each data analysis method employed in this research.

4.1 Descriptive Analysis

4.1.1 Demographic Profile

Table 4.1: Summary of Demographic Profile

Demographic	Frequency	Percentage (%)
Gender		
Male	129	47
Female	145	53
Age		
18-25 years old	119	43
26-35 years old	61	22
36-45 years old	38	14
46-55 years old	41	15
56 years old and above	15	6
States		
Federal Territory of Kuala Lumpur	74	27
Federal Territory of Labuan	5	2
Federal Territory of Putrajaya	24	9
Johor	6	2

Kedah	3	1
Kelantan	1	0
Malacca	7	2
Negeri Sembilan	14	5
Pahang	3	1
Penang	8	3
Perak	10	4
Sarawak	2	1
Selangor	117	43
Highest Education Level		
High School	20	7
Diploma	70	26
Undergraduate	163	59
Master's degree	19	7
Other: Professional Degree	2	1
Employment Status		
Full-time employment	160	58
Part-time employment	76	28
Self-employed	38	14
Personal Income Level (RM)		
Below RM2,000	77	28
RM2,000 - RM5,000	88	32
RM5,001 - RM10,000	72	26
RM10,001 - RM15,000	17	6
RM15,001 - RM20,000	13	5
RM25,001 - RM30,000	2	1
Above RM30,000	5	2
Total	274	100

Source: Developed for the research.

Table 4.1 presents the result of the demographic profile with a total of 274 respondents. The breakdown of respondents by gender, showing that 47% are male and 53% are female. Besides, most of the respondents are between 18 to 25 years old, making up 43% of total sample. Moreover, the geographic representation of respondents across different states and federal territories in Malaysia indicates a concentration in urban areas, notably Selangor (43%) and Kuala Lumpur (27%). Regarding education level, majority of respondents hold undergraduate degrees (59%). In terms of employment status, over half of the respondents are engaged in full-time employment (58%). Furthermore, 32% of respondents had the income level between RM2,000 to RM5,000.

4.1.2 General Information

Table 4.2: Summary of General Questions

General Information	Frequency	Percentage (%)
Driving Experience (Year)		
1-5 years	130	47
6-10 years	36	13
11-15 years	27	10
16-20 years	27	10
21-25 years	26	10
26-30 years	16	6
Above 30 years	12	4
Weekly Average Driving Distance		
Less than 100km	106	39
101km-200km	66	24
201km-300km	52	19
301km-400km	25	9
Above 400km	25	9
Total	274	100

Source: Developed for the research.

Table 4.2 presents the result of Part B general questions. It shows that most respondents (47%) have 1-5 years of driving experience, followed by 6-10 years (13%) and so on. Additionally, the data reveals that the most common range for weekly driving distance is less than 200km, accounting for 39% of respondents.

4.1.3 Central Tendencies Measurement of Constructs

Table 4.3: Descriptive Statistics on Variables

Variables	Mean	Standard Deviation	Items	Mean	Standard Deviation
Perceived Ease of Use (PEU)	3.725	0.940	PEU 1	3.63	0.990
			PEU 2	3.78	0.904
			PEU 3	3.76	0.921
Perceived Usefulness (PU)	3.763	0.944	PU1	3.97	0.853
			PU2	4.04	0.857
			PU3	3.60	0.952
			PU4	3.45	0.979
Perceived Safey (PS)	3.647	1.021	PS1	3.63	0.990
			PS2	3.78	0.979
			PS3	3.53	1.080
Trialability (T)	3.869	1.012	T1	4.34	0.847
			T2	3.60	1.020
			T3	3.59	1.038
			T4	4.09	0.873
			T5	3.73	1.046
Price (P)	3.055	1.084	P1	3.30	1.015
			P2	3.10	0.997
			P3	3.80	0.987
			P4	3.17	1.050
			P5	3.42	0.931
Attitudes (ATU)	3.809	0.794	ATU1	3.85	0.738
			ATU2	3.88	0.785
			ATU3	3.69	0.844
Behavioral Intention (BI)	3.909	0.845	BI1	3.79	0.864
			BI2	3.88	0.820
			BI3	4.06	0.830

Source: SPSS Version 29.0

In Table 4.3, PU2, T1, T4, and BI3 received higher average scores, approximately 4.0, indicating strong agreement from most respondents. All statements scored above 3.0 on average, suggesting many respondents either agreed or were neutral. Statements PS3, T2, T3, T5, P1, and P4 showed higher standard deviations, around 1.0, indicating more varied responses. Conversely, ATU1 and ATU2 had standard deviations around 0.7, suggesting responses were closely grouped around the average score.

Overall, the BI has the highest mean which is 3.909 while the P has the highest standard deviation with 1.084. On the other hand, PS has the lowest mean of 3.055 while ATU has the lowest standard deviation of 0.794. When excluding data from P3, the mean increases from 3.055 to 3.247. Besides, the standard deviation decreases from 1.084 to 1.005.

4.2 Scale Measurement

4.2.1 Reliability Test

Table: 4.4: Cronbach's Alpha Results

Variables	Number of Item	Cronbach's Alpha	Rules
Perceived Ease of Use (PEU)	3	0.887	Good
Perceived Usefulness (PU)	4	0.795	Acceptable
Perceived Safey (PS)	3	0.882	Good
Trialability (T)	5	0.810	Good
Price (P)	4	0.839	Acceptable
Attitudes (ATU)	3	0.830	Good
Behavioral Intention (BI)	3	0.820	Good

Source: SPSS Version 29.0

As mentioned in section 3.7.2.1 (Chapter 3), a minimum coefficient of 0.70 is acceptable (Taherdoost, 2016). Table 4.4 illustrates that each of the seven variables has met or surpassed the minimum alpha coefficient of 0.70. Among them, PEU exhibits the highest alpha value of 0.887, indicating good reliability. On the other hand, PU demonstrates the lowest alpha value of 0.795, barely meeting the acceptable minimum alpha coefficient threshold. Overall, the average Cronbach's Alpha of all variables is about 0.80.

After data collection, an inconsistency was discovered in P3 regarding the independent variable of price. This is because the P3 presents a negative viewpoint unlike the positively framed questions. Besides, the reliability of P increase from 0.677 Cronbach's Alpha to 0.839 Cronbach's Alpha after dropping the P3. Hence, P3 and corresponding responses from the dataset were removed to ensure the integrity of the data analysis.

4.3 Inferential Analysis

4.3.1 Pearson Correlation Coefficient

Table: 4.5: Pearson's Correlation Analysis

		PEU	PU	PS	T	P	ATU	BI
PEU	Pearson Correlation (r)	1						
	Sig. (2-tailed) (p)							
	N	274						
PU	Pearson Correlation (r)	.424**	1					
	Sig. (2-tailed) (p)	<.001						
	N	274	274					
PS	Pearson Correlation (r)	-.015	.195**	1				
	Sig. (2-tailed) (p)	.807	.001					
	N	274	274	274				
T	Pearson Correlation (r)	.293**	.466**	.309**	1			
	Sig. (2-tailed) (p)	<.001	<.001	<.001				
	N	274	274	274	274			
P	Pearson Correlation (r)	.277**	.493**	.158**	.375**	1		
	Sig. (2-tailed) (p)	<.001	<.001	.006	<.001			
	N	274	274	274	274	274		
ATU	Pearson Correlation (r)	.442**	.472**	.017	.406**	.477**	1	
	Sig. (2-tailed) (p)	<.001	<.001	.782	<.001	<.001		
	N	274	274	274	274	274	274	
BI	Pearson Correlation (r)	.395**	.455**	.088	.427**	.442**	.723**	1
	Sig. (2-tailed) (p)	<.001	<.001	.207	<.001	<.001	<.001	
	N	274	274	274	274	274	274	274

**. Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS Version 29.0

Table 4.5 presents the result of Pearson Correlation analysis. The r values are examined according to the rules of thumb of correlation coefficient in Table 3.4. Based on the result, PU, PEU, T, P exhibit r values of approximately 0.4 with respect to ATU. Therefore, the correlation coefficient of 0.4 is between ± 0.41 to ± 0.70, indicating the variables are moderately related to ATU. The highest r value is 0.723 between ATU and BI, suggesting a high correlation. This underscores a strong relationship between ATU and BI. On the other hand, the lowest r value is 0.017 between PS and ATU, which means a negligible correlation. The relationship between PS and ATU is weak.

4.3.2 Multiple Linear Regression Analysis

4.3.2.1 The relationship between PU, PEU, PS, T, P and ATU

Table 4.6: Model Summary for the relationship between factors and ATU

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.630[a]	.396	.385	1.60583	1.980
a. Predictors: (Constant), P, PS, PEU, T, PU					

Source: SPSS Version 29.0

Table 4.6 reports that the result of R is 0.630, indicating a moderate positive relationship between factors and the dependent variable. R^2 is 0.396, which means that the explanatory power of five independent variables to dependent variable (ATU) is 39.6%. Other unidentified factors account for the remaining 60.4% of the variation in ATU.

Table 4.7: ANOVA for the relationship between factors and ATU

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	453.953	5	90.791	35.208	<.001[b]
	Residual	691.087	268	2.579		
	Total	1145.040	273			
a. Dependent Variable: ATU						
b. Predictors: (Constant), P, PS, PEU, T, PU						

Source: SPSS Version 29.0

Table 4.7 shows that p-value is less than 0.001, means that the model is significant. Besides, it also shows a statistically significant outcome with an F value of 35.208, implying that the independent variables (P, PS, PEU, T, PU) have a meaningful impact on dependent variable (ATU).

Table 4.8: Coefficient for the relationship between factors and ATU

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3.920	.695		5.643	<.001		
	PEU	.184	.043	.229	4.278	<.001	0.785	1.275
	PU	.117	.044	.164	2.683	.008	0.602	1.661
	PS	-.069	.038	-.093	-1.838	.067	0.880	1.136
	T	.110	.032	.197	3.475	<.001	0.703	1.423
	P	.178	.034	.285	5.184	<.001	0.746	1.341

Source: SPSS Version 29.0

Based on Table 4.8, the p-value of PEU, PU, T, and P are smaller than 0.05, indicating that they are significant positive relationship with ATU. Therefore, the H1, H2, H4, H5, and H6 are supported. However, only the p-value of PS is 0.067, which is greater than 0.05, so H3 is not supported.

PEU has the highest beta value ($\beta = 0.184$) which indicates PEU has the strongest influence on ATU. Therefore, as PEU increases by 1 unit, ATU increases by 0.184 units, holding other variables constant. Besides, P, PU, and T demonstrate positive influence on ATU, with beta value of 0.178, 0.117, and 0.110 respectively. On the other hand, PS has the lowest beta value with -0.069, which indicating there is a negative relationship between PS and ATU.

The regression equation for predicting ATU is: ATU= 3.920 + 0.184 (PEU) + 0.117 (PU) + (-0.069) (PS) + 0.110 (T) + 0.178 (P).

4.3.2.2 The relationship between ATU and BI

Table 4.9: Model Summary for the relationship between ATU and BI

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics		
					R Square Change	F Change	df1
1	.723[a]	.522	.521	1.49249	.522	297.453	1
a. Predictors: (Constant), ATU							

Source: SPSS Version 29.0

Table 4.9 shows that the output of R is 0.723, indicating a moderately positive correlation between ATU and BI. R^2 is 0.522, which means that the explanatory power of ATU to BI is 52.2%. Other unidentified factors account for the remaining 47.8% of the variation in BI.

Table 4.10: ANOVA for the relationship between ATU and BI

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	662.584	1	662.584	297.453	<.001[b]
	Residual	605.887	272	2.228		
	Total	1268.471	273			
a. Dependent Variable: BI						
b. Predictors: (Constant), ATU						

Source: SPSS Version 29.0

Table 4.10 shows a statistically significant output with an F value of 297.453 and a p-value of smaller than 0.001, implying that overall regression model is significant.

Table 4.11: Coefficients for the relationship between ATU and BI

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3.034	.512		5.925	<.001		
	ATU	.761	.044	.723	17.247	<.001	1.000	1.000

Source: SPSS Version 29.0

Based on Table 4.11, p-value of ATU is smaller than 0.05, indicating that there is a significant and positive relationship with BI. Besides, ATU has the beta value of 0.761 which indicates ATU has the strongest impact on BI. Therefore, as ATU increases by 1-unit, BI increases by 0.761 units.

The regression equation for predicting BI is BI = 3.034 + 0.761 (ATU).

4.5 Conclusion

In conclusion, this chapter has discussed the result of data analysis by using the proposed data analysis tools. Next, the last chapter will explain more about the results and overall research.

CHAPTER 5:
DISCUSSION, CONCLUSION, AND IMPLICATIONS

5.0 Introduction

The last chapter of this research will conclude the analysis results in previous chapter. Besides, the findings and implications of the study are also discussed in this chapter. The recommendations for future research also covered in this chapter based on the limitations of this research.

5.1 Summary of Statistical Analysis

5.1.1 Descriptive Analysis

The research collected questionnaires from 274 respondents across Malaysia, encompassing various demographic and socioeconomic characteristics. Gender distribution shows 47% male and 53% female respondents, while age ranges from 18 to above 56 years, with the majority (43%) falling within the 18-25 age group. State representation reveals a significant presence from Kuala Lumpur (27%) and Selangor (43%), while other states exhibit lower proportions. Educationally, 59% hold undergraduate degrees, and 58% are employed full-time, indicating a relatively educated and employed sample. In terms of income, the majority (32%) earn between RM2,000 to RM5,000 per month before tax. By examining driving experience and weekly average driving distance, the research offers valuable data about the driving habits of the respondents. Driving experience spans various lengths, with 47% reporting 1 to 5 years, and weekly average driving distance is less than 100km (39%).

5.1.2 Inferential Analysis

Table 5.1: Summarized Hypothesized Relationship

Hypothesis	Findings	Decision
H1: There is a significant relationship between the perceived usefulness and the attitude toward autonomous vehicles.	p-value=0.008 β =0.117	Supported
H2: There is a significant relationship between the perceived ease of use and the attitude toward autonomous vehicles.	p-value < 0.001 β =0.184	Supported
H3: There is a significant relationship between the perceived safety and the attitude toward autonomous vehicles.	p-value= 0.067 β = -0.069	Not Supported
H4: There is a significant relationship between trialability and the attitude toward autonomous vehicles.	p-value < 0.001 β = 0.110	Supported
H5: There is a significant relationship between the price and the attitude toward autonomous vehicles.	p-value < 0.001 β = 0.178	Supported
H6: There is a significant relationship between the attitude and the behavioral intention to use autonomous vehicles.	p-value < 0.001 β = 0.761	Supported

Source: Developed for the research.

Based on Table 5.1, only H3 is not supported because of p-value greater than 0.05. Other five hypotheses are supported.

5.2 Discussion of Major Findings

H1: There is a significant relationship between the perceived usefulness (PU) and the attitude toward autonomous vehicles (AVs).

H1 is supported which means PU of AVs is positively affecting ATU towards AVs. PU is the third significant variable is backed by a p-value of <0.001 and a beta value of 0.117. Besides, the result is aligned with previous studies (Panagiotopoulos & Dimitrakopoulos, 2018; Ramjan and Sangkaew, 2022; Yang et al., 2023; Chen et al., 2023; Yang et al., 2023; Man et al., 2020). People who found AVs useful were more likely to have positive attitudes towards using AVs. For example, Level 3 AVs can perform most driving tasks under certain conditions, on motorways or in traffic jams, as well as steer, accelerate, brake, and monitor the environment. Besides, Level 3 AVs can help lessen driver tiredness by doing the driving in certain situations. This means drivers can relax or do other things while the system is controlling (Lehtonen et al., 2022). This functionality influences attitudes and be more willing to adopt the AVs.

H2: There is a significant relationship between the perceived ease of use (PEU) and the attitude toward autonomous vehicles (AVs).

H2 is supported so PEU of AVs is positively affecting ATU towards AVs. PEU emerges as the most critical factor, with a p-value of < 0.001 and a beta value of 0.184. In other words, if individuals find AVs easy to operate, they are more likely to have positive attitudes towards them. The finding is same with previous studies (Hasan et al., 2022; Huang, 2023; Chen et al., 2023). When comparing Level 3 AVs with the lower levels, such as most Malaysian are driving Level 1, the operational differences may not seem overly complex to users. For instance, both levels still require human intervention. Besides, the controls and interface of Level 3 AVs are likely to be designed with user-friendliness in mind. Hence, PEU is important to build the attitudes towards AVs.

H3: There is a significant relationship between the perceived safety and the attitude toward autonomous vehicles (AVs).

H3 is not supported, indicating that PS dis not significantly influence the ATU towards AVs. This is evidenced by a p-value of 0.067 and a beta value of -0.069. In simple terms, whether individuals perceive AVs as safe or not does not significantly change their ATU towards them. One possible reason because trust in technology because among of people can vary widely. The AAA Foundation for Traffic Safety study conducted in 2019 found that people trusted Level 3 AVs more than higher-level ones to prevent crashes. Therefore, most people favored owning vehicles with lower-level automation (Kim et al., 2021). In short, when individuals have high trust on Level 3 AVs, PS is not a priority factor that they need to consider in adopting AVs. Besides, 43% of respondents are aged 18 to 25 years old, which considered young individuals. Younger individuals, being typically more tech-savvy than the elderly, might find the concept of using a vehicle solely reliant on advanced technology more appealing. They are generally more open to new experiences, so they often less safety-conscious than elderly ones (Iranmanesh et al., 2023). As a result, individuals who highly trust and tech-savvy will not consider PS as factor that influence the ATU.

H4: There is a significant relationship between trialability and the attitude toward autonomous vehicles (AVs).

H4 is supported, indicating that the T has significant relationship with ATU. This is evidenced by a p-value below 0.05 and a beta value of 0.110. The study by Yuen et al. (2020) stated that trials create awareness and inform the public about the benefits of AVs. Consequently, the public would have a better attitude of the values that AVs can provide over non-autonomous vehicles. In addition, trying out new things such as AVs can bring unexpected joy and excitement. For instance, letting people test drive or watch the demos of AVs can make them more interested. Especially with the rise of technology such as web and smartphone to provide public transport, people who are used to technology might be more open to AVs. Consequently, they would be more willing to try and experiment with innovations such as AVs, and this testing phrase affects their attitudes towards AVs.

H5: There is a significant relationship between the price and the attitude toward autonomous vehicles (AVs).

H5 is supported, indicating that the P has influence ATU toward AVs. This is substantiated by a p-value less than 0.001 and a beta value of 0.178, making it the second most crucial variable. This finding is supported by prior studies of Patrice (2021) and Kapser & Abdelrahman (2020). When AVs are perceived as affordable and within reach, individuals may view them more favorably. Conversely, if AVs are priced prohibitively high, it may deter potential users and lead to negative attitudes. Additionally, perceptions of value for money play a crucial role; if individuals believe that the benefits offered by autonomous vehicles justify the price, they may be more willing to embrace the technology (Iranmanesh et al., 2023). As a result, if the price change, the attitudes towards AVs may change.

H6: There is a significant relationship between the attitude and the behavioral intention to use autonomous vehicles (AVs).

H6 is supported because it has p-value that smaller than 0.001 and a high beta value of 0.761. The result is supported by the previous research stated that ATU is the most significant variable that correlates with BI (Chen et al., 2023, Ramjan & Sangkaew, 2022; Foroughi et al., 2023). According to the TRA and TPB, a person's attitude toward a behavior positively influences their intention to perform it (Davis et al., 1989). In short, when individuals hold positive perceptions of autonomous vehicles and are more inclined to adopt them, these perceptions significantly influence their decisions and actions when considering adoption.

5.3 Implications of the Research

5.3.1 Theoretical Implications

The first problem statement is lack of studies that about the factors that influencing the customer intentions to adopt AVs. Previous research was more focus on understanding the public opinion, issues, review, impact, and opportunities of AVs (Kassim et al., 2021; Czech, 2018; Bathla et al., 2022). Therefore, this research has assessed the five main factors that influencing the customer intentions. Also, this research also examined the relationship between five independent variables and attitudes towards AVs. Hence, this research has solved the potential gaps in understanding the consumer acceptance that cause slow adoption of AVs.

Next, the second problem statement is the existence of gap of research about AVs in Malaysia. Other countries have done many of relevant research (Ramjan & Sangkaew, 2022; Chen et al., 2023; Sutarto et al., 2023), and the influence on the factors affecting AV adoption is comparatively limited in Malaysia. In this research, it aims to distributes the questionnaires in Malaysia, so all sample respondents are Malaysian. Consequently, this research that focus on Malaysia has solved the gap.

Moreover, the third problem statement is the limited exploration of the application of Technology Acceptance Model (TAM). This research has added Innovation Diffusion Theory (IDT) and Marketing Mix to explain more completely. Not only PU and PEU, but this research has also examined the relationships between PS, T, P with ATU. And found that there is a significant relationship between T, P and ATU. As a result, this result has filled the gap.

5.3.2 Practical Implications

From a practical perspective, this research holds implications for the automotive industry. In the past, the car industry has lack of consensus among the manufacturers regarding the specific preferences and needs of customers (Hewitt et al., 2019). Therefore, this research has founded that the PU, PEU, T, and P have significantly influenced the customer intention in adopting AVs. Due to the introductory stage of AVs now, it is very critical to know the needs and factors of customers to adopt AVs. Therefore, the manufacturers can know the priority concern of consumer about AVs.

After knowing the main concern of customers regarding AVs, the automotive industry can better to design and marketing team can promote the AVs in the future (Zhang & Kamargianni, 2022). What the customer concern about the AVs such as PU, PEU, T, and P, are the success key to promote AVs. Based on the four variables, the industry can tailor more suitable and successful strategies to attract customers. For example, the trialability was significantly affected the attitudes and behavioral intention in adopting AVs. Therefore, the industry can add training or additional services to let customers have more opportunity directly experience the AVs. Besides, the AVs can be designed more easier to understand especially focus on elder people, so may improve the positive attitudes, and increase the behavioral intention in adopting AVs.

5.4 Limitations of the Research

The limitation of this research is respondents have not experienced on AVs and have little understanding of AVs. Although the Level 3 AVs are not common in Malaysia, some companies are work hard in R&D, and the government has not clearly stated the rules and regulation regarding AVs, but it is obviously can be seen AVs in the road in other countries. Therefore, Malaysian who completed the questionnaire might lack a comprehensive understanding of AVs, despite the definition provided within the questionnaire. This could influence participants' perceptions of AVs regarding ease of use, usefulness, trialability, and other factors. Nevertheless, through exposure to media coverage and various sources, people may have gained some understanding of AVs and their advantages.

Additionally, the demographic composition of respondents appears skewed and may not adequately represent the entire Malaysian population. The use of convenience sampling introduces the potential for bias. As depicted in Table 4.1, 45% of respondents fall within the 18 to 25 age range, indicating a lack of representation from older age groups. This imbalance can introduce bias into the findings, reducing their generalizability.

Furthermore, the criteria for selecting respondents lack specificity. Requiring respondents to be at least 18 years old with a driver's license is overly broad, resulting in complex data processing. It may collect the people who meet the criteria but no regular driving or no income, this will not be capable to adopt the AVs.

5.5 Recommendations for Future Research

To solve the lack of understanding of AVs, researcher can simplify the questionnaires to ensure clarity of respondents. Besides, a brief educational materials or explanations about the AVs technology to respondents is needed before filling up the questionnaires. While this research includes a concise explanation of Level 3 AVs in the questionnaire, face-to-face explanations are preferred over self-reading by respondents.

Diverse sampling techniques can solve the imbalance of demographic profile problems. For instance, stratified sampling, a probability method, divides the population into smaller, characteristic-based groups (strata) to ensure representative subject selection. Employing a combination of sampling techniques can effectively address this problem.

Lastly, specific the screening questions is critical to get more accurate responds. For example, refining the criteria to include specific income levels or vehicle ownership requirements could yield more accurate research outcomes. Thinking more about the requirements to adopt AVs.

5.6 Conclusion

In conclusion, all results answered the research question and addressed the problem statement. The hypotheses are tested and only H1, H2, H4, H5, and H6 are supported. H3 was not supported. This last chapter has summarized all descriptive and inferential analysis. Furthermore, the findings of this research have some implications to automotive industry. However, there are some limitations in this research and has given recommendations to improve the quality for future research.

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APPENDICES

Appendix A: SURVEY QUESTIONNAIRES

UNIVERSITI TUNKU ABDUL RAHMAN

FACULTY OF ACCOUNTANCY AND MANAGEMENT (FAM)

BACHELOR OF INTERNATIONAL BUSINESS (HONOURS)

UKMZ3016 RESEARCH PROJECT

A STUDY OF FACTORS INFLUENCING THE CUSTOMER INTENTION IN ADOPTING AUTONOMOUS VEHICLES (AVS).

SURVEY QUESTIONNAIRES

Dear respondents,

I am Chye Chi Ern, a final year undergraduate student currently pursuing Bachelor of International Business (Honours) at Universiti Tunku Abdul Rahman (UTAR). The objective of this research is to identify the factors shaping customer adoption of Autonomous Vehicles (AVs) in Malaysia, offering insights for successful integration into the local automotive landscape.

In this study, we are looking specifically at **Level 3 Autonomous Vehicles**, particularly cars. These **self-driving cars can handle most driving tasks on their own**, including monitoring the environment and navigating through traffic jams. However, they still need a human driver to be ready to take control when needed.

As such, you are invited to take part in this survey. If you have any questions, please feel free to contact me via email at chyechiern@1utar.my.

Your participation is highly appreciated. Thank you.

Yours faithfully,

Name	Student ID	Email
Chye Chi Ern	21UKB01768	chyechiern@1utar.my

SCREENING QUESTIONS

1. Acknowledgment of Notice

In compliance with the Personal Data Protection Act 2010 ("PDPA") , UTAR is dedicated to safeguarding the confidentiality, security, and accuracy of your provided personal information. Your data will only be analyzed for academic purposes, and UTAR pledges to dispose of it in accordance with our retention policy once it is no longer necessary.

- ☐ I have been notified and that I hereby understood, consented and agreed per UTAR above notice.
- ☐ I disagree, my personal data will not be processed.

2. Do you have a driving license?

- ☐ Yes
- ☐ No. Thank you for your participation.

PART A: DEMOGRAPHIC PROFILE

1. Gender

- ☐ Male
- ☐ Female

2. Age

- ☐ 18-25 years old
- ☐ 26-35 years old
- ☐ 36-45 years old
- ☐ 46-55 years old
- ☐ 56 years old and above

3. **In which state do you currently reside?**

- ☐ Federal Territory of Kuala Lumpur
- ☐ Federal Territory of Labuan
- ☐ Federal Territory of Putrajaya
- ☐ Johor
- ☐ Kedah
- ☐ Kelantan
- ☐ Malacca
- ☐ Negeri Sembilan
- ☐ Pahang
- ☐ Penang
- ☐ Perak
- ☐ Perlis
- ☐ Sabah
- ☐ Sarawak
- ☐ Selangor
- ☐ Terengganu

4. Highest Educational Level

- ☐ High School
- ☐ Diploma
- ☐ Undergraduate
- ☐ Master's degree
- ☐ Doctoral Degree
- ☐ Other:

5. Employment Status

- Full-time employment
- Part-time employment
- Self-employed
- Other:

6. Personal Income Level (RM per month before tax)

- Below RM2,000
- RM2,000- RM5,000
- RM5,001- RM10,000
- RM10,001- RM15,000
- RM15,001- RM20,000
- RM20,001- RM25,000
- RM25,001- RM30,000
- Above RM30,000

PART B: GENERAL QUESTIONS

1. How many years of driving experience do you have?

- None
- 1 - 5 years
- 6 - 10 years
- 11 - 15 years
- 16 - 20 years
- 21 - 25 years
- 26 - 30 years
- Above 30 years

2. Please estimate the average distance you usually drive in a week using a car.

- I do not drive.
- Less than100km
- 101km-200km
- 201km-300km
- 301km-400km
- Above 400km

PART C: CONSTRUCT MEASUREMENT

This section is seeking your opinion regarding examining the customer intention to adopt autonomous vehicles (AVs). Please indicate the extent to which you agreed or disagreed with each statement using the Likert scale.

Strongly Disagree (SD)	Disagree (D)	Neutral (N)	Agree (A)	Strongly Agree (SA)
1	2	3	4	5

Perceived Usefulness (PU)

Perceived Usefulness (PU)						
		SD				SA
No.	Description	1	2	3	4	5
1	Traveling in an autonomous vehicle can improve my travel efficiency.					
2	Autonomous vehicles can improve my quality of life.					
3	Autonomous vehicles can reduce traffic congestion.					
4	Autonomous vehicles can reduce the probability of traffic accidents.					

Perceived Ease of Use (PEU)

Perceived Ease of Use (PEU)						
		SD				SA
No.	Description	1	2	3	4	5
1	I think it is easy to learn how to operate an autonomous vehicle.					
2	I think I can understand the controls on autonomous vehicles.					
3	Overall, I think autonomous vehicles are easy to use.					

Perceived Safety

Perceived Safety						
		SD				SA
No.	Description	1	2	3	4	5
1	I am worried about the general safety of such autonomous vehicle technology.					
2	I am worried that the failure or malfunctions of autonomous vehicles may cause accidents.					
3	I am worried that an autonomous vehicle may not safely reach my destination.					

Trialability

Trialability						
		SD				SA
No.	Description	1	2	3	4	5
	Before I decide to buy an autonomous vehicle, I would like to…					
1	test-drive it.					
2	borrow it for a day or two.					
3	try a friend's autonomous vehicle.					
4	view a demonstration of using an autonomous vehicle.					
5	receive training or attend a course on using an autonomous vehicle.					

Price (P)

Price (P)						
		SD				SA
No.	Description	1	2	3	4	5
1	I would not mind paying more to use autonomous vehicles.					
2	I would not mind investing a lot of money to use autonomous vehicles.					
3	I would be less willing to pay for autonomous vehicles if I thought it to be high in price.					
4	If using autonomous vehicles are likely to be more expensive than conventional vehicles, that would not matter to me.					
5	A really great transportation option would be worth paying a lot of money for.					

Attitude (ATU)

Attitude (ATU)						
		SD				SA
No.	Description	1	2	3	4	5
1	I have a positive attitude toward autonomous vehicles.					
2	I would be happy if autonomous vehicles were available.					
3	I am in favor of using autonomous vehicles.					

Behavioral Intention (BI)

Behavioral Intention (BI)						
		SD				**SA**
No.	**Description**	**1**	**2**	**3**	**4**	**5**
1	Assuming I have access to an autonomous vehicle, I would intend to use it.					
2	Given I have access to an autonomous vehicle, I predict I would use it.					
3	In the future, I would not hesitate to use an autonomous vehicle.					

Appendix B: SPSS Output

1. Reliability Test Result for Pilot Test

Perceived Ease of Use (PEU)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.927	.927	3

Perceived Usefulness (PU)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.924	.931	4

Perceived Safety (PS)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.952	.952	3

Trialability (T)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.875	.880	5

Price (P)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.848	.846	5

Attitudes (ATU)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.941	.941	3

Behavioral Intention (BI)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.833	.847	3

2. Output of Central Tendencies Measurement

Perceived Ease of Use (PEU)

Statistics				
		PEU1	PEU2	PEU3
N	Valid	274	274	274
	Missing	0	0	0
Mean		3.63	3.78	3.76
Std. Error of Mean		.060	.055	.056
Median		4.00	4.00	4.00
Mode		4	4	4
Std. Deviation		.990	.904	.921
Variance		.981	.816	.848
Skewness		-.415	-.304	-.418
Std. Error of Skewness		.147	.147	.147
Kurtosis		-.306	-.415	-.224
Std. Error of Kurtosis		.293	.293	.293
Range		4	4	4
Minimum		1	1	1
Maximum		5	5	5
Sum		995	1036	1031

Scale Statistics			
Mean	Variance	Std. Deviation	N of Items
11.18	6.475	2.545	3

Perceived Usefulness (PU)

Statistics					
		PU1	PU2	PU3	PU4
N	Valid	274	274	274	274
	Missing	0	0	0	0
Mean		3.97	4.04	3.60	3.45
Std. Error of Mean		.052	.052	.058	.059
Median		4.00	4.00	4.00	3.00
Mode		4	4	4	3
Std. Deviation		.853	.859	.952	.979
Variance		.728	.739	.907	.959
Skewness		-.650	-.838	-.437	-.140
Std. Error of Skewness		.147	.147	.147	.147
Kurtosis		.298	.793	-.001	-.451
Std. Error of Kurtosis		.293	.293	.293	.293
Range		4	4	4	4
Minimum		1	1	1	1
Maximum		5	5	5	5
Sum		1087	1106	987	944

Perceived Safety (PS)

Statistics				
		PS1	PS2	PS3
N	Valid	274	274	274
	Missing	0	0	0
Mean		3.63	3.78	3.53
Std. Error of Mean		.060	.059	.065
Median		4.00	4.00	4.00
Mode		4	4	3
Std. Deviation		.990	.979	1.080
Variance		.981	.958	1.166
Skewness		-.369	-.698	-.270
Std. Error of Skewness		.147	.147	.147
Kurtosis		-.424	.310	-.640
Std. Error of Kurtosis		.293	.293	.293
Range		4	4	4
Minimum		1	1	1
Maximum		5	5	5
Sum		995	1035	968

Trialability (T)

Statistics						
		T1	T2	T3	T4	T5
N	Valid	274	274	274	274	274
	Missing	0	0	0	0	0
Mean		4.34	3.60	3.59	4.09	3.73
Std. Error of Mean		.051	.062	.063	.053	.063
Median		5.00	4.00	4.00	4.00	4.00
Mode		5	4	4	4	4
Std. Deviation		.847	1.020	1.038	.873	1.046
Variance		.717	1.040	1.078	.762	1.093
Skewness		-1.413	-.343	-.384	-.771	-.498
Std. Error of Skewness		.147	.147	.147	.147	.147
Kurtosis		2.102	-.427	-.432	.279	-.319
Std. Error of Kurtosis		.293	.293	.293	.293	.293
Range		4	4	4	4	4
Minimum		1	1	1	1	1
Maximum		5	5	5	5	5
Sum		1190	986	984	1120	1021

Price (P)

Item Statistics			
	Mean	Std. Deviation	N
Price1	3.30	1.015	274
Price2	3.10	.997	274
Price3	3.80	.987	274
Price4	3.17	1.050	274
Price5	3.42	.931	274

Attitudes (ATU)

Statistics				
		ATT1	ATT2	ATT3
N	Valid	274	274	274
	Missing	0	0	0
Mean		3.85	3.88	3.69
Std. Error of Mean		.045	.047	.051
Median		4.00	4.00	4.00
Mode		4	4	4
Std. Deviation		.738	.785	.844
Variance		.545	.616	.712
Skewness		-.140	-.203	-.144
Std. Error of Skewness		.147	.147	.147
Kurtosis		-.392	-.296	-.228
Std. Error of Kurtosis		.293	.293	.293
Range		3	4	4
Minimum		2	1	1
Maximum		5	5	5
Sum		1055	1064	1012

Behavioral Intention (BI)

Statistics				
		BI1	BI2	BI3
N	Valid	274	274	274
	Missing	0	0	0
Mean		3.79	3.88	4.06
Std. Error of Mean		.052	.050	.050
Median		4.00	4.00	4.00
Mode		4	4	4
Std. Deviation		.864	.820	.830
Variance		.746	.673	.688
Skewness		-.229	-.167	-.620
Std. Error of Skewness		.147	.147	.147
Kurtosis		-.486	-.732	.036
Std. Error of Kurtosis		.293	.293	.293
Range		4	3	4
Minimum		1	2	1
Maximum		5	5	5
Sum		1038	1062	1113

3. Reliability Test Result for Actual Survey

PEU

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.887	.888	3

PU

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.795	.796	4

PS

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.882	.883	3

T

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.810	.812	5

P (After drop P3)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.839	.839	4

P (Before drop P3)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.677	.685	5

ATU

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.830	.831	3

BI

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.820	.820	3

4. Output of Pearson Correlation Analysis

Correlations								
		PEU	PU	PS	T	P	ATU	BI
PEU	Pearson Correlation	1	.424**	-.015	.293**	.295**	.442**	
	Sig. (2-tailed)		<.001	.807	<.001	<.001	<.001	
	N	274	274	274	274	274	274	
PU	Pearson Correlation	.424**	1	.195**	.466**	.479**	.472**	
	Sig. (2-tailed)	<.001		.001	<.001	<.001	<.001	
	N	274	274	274	274	274	274	
PS	Pearson Correlation	-.015	.195**	1	.309**	.072	.017	
	Sig. (2-tailed)	.807	.001		<.001	.235	.782	
	N	274	274	274	274	274	274	
T	Pearson Correlation	.293**	.466**	.309**	1	.332**	.406**	
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001	
	N	274	274	274	274	274	274	
P	Pearson Correlation	.295**	.479**	.072	.332**	1	.490**	
	Sig. (2-tailed)	<.001	<.001	.235	<.001		<.001	
	N	274	274	274	274	274	274	
ATU	Pearson Correlation	.442**	.472**	.017	.406**	.490**	1	
	Sig. (2-tailed)	<.001	<.001	.782	<.001	<.001		
	N	274	274	274	274	274	274	
BI	Pearson Correlation	.395**	.455**	.088	.427**	.452**	.723**	1
	Sig. (2-tailed)	<.001	<.001	.148	<.001	<.001	<.001	
	N	274	274	274	274	274	274	274

5. Output of Multiple Regression

Model Summary[b]							
					Change Statistics		
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1
1	.630[a]	.396	.385	1.60583	.396	35.208	5

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	453.953	5	90.791	35.208	<.001[b]
	Residual	691.087	268	2.579		
	Total	1145.040	273			
a. Dependent Variable: ATU						
b. Predictors: (Constant), P, PS, PEU, T, PU						

Coefficients[a]							
		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B
Model		B	Std. Error	Beta	t	Sig.	Lower Bound
1	(Constant)	3.920	.695		5.643	<.001	2.552
	PEU	.184	.043	.229	4.278	<.001	.100
	PU	.117	.044	.164	2.683	.008	.031
	PS	-.069	.038	-.093	-1.838	.067	-.144
	T	.110	.032	.197	3.475	<.001	.048
	P	.178	.034	.285	5.184	<.001	.110

Coefficients[a]				
		95.0% Confidence Interval for B	Collinearity Statistics	
Model		Upper Bound	Tolerance	VIF
1	(Constant)	5.287		
	PEU	.269	.785	1.275
	PU	.203	.602	1.661
	PS	.005	.880	1.136
	T	.173	.703	1.423
	P	.245	.746	1.341

Model Summary[b]							
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics		
					R Square Change	F Change	df1
1	.723[a]	.522	.521	1.49249	.522	297.453	1

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	662.584	1	662.584	297.453	<.001[b]
	Residual	605.887	272	2.228		
	Total	1268.471	273			
a. Dependent Variable: BI						
b. Predictors: (Constant), ATU						

Coefficients[a]							
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B
		B	Std. Error	Beta			Lower Bound
1	(Constant)	3.034	.512		5.925	<.001	2.026
	ATU	.761	.044	.723	17.247	<.001	.674

Coefficients[a]				
Model		95.0% Confidence Interval for B	Collinearity Statistics	
		Upper Bound	Tolerance	VIF
1	(Constant)	4.042		
	ATU	.848	1.000	1.000