# THE IMPACT OF RISK PERCEPTION ON THE PURCHASE INTENTION AMONG GENERATION X ON AUTONOMOUS VEHICLE IN MALAYSIA

BY

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A final year project submitted in partial fulfilment of the requirement for the degree of

BACHELOR OF MARKETING (HONOURS)

FACULTY OF BUSINESS AND FINANCE DEPARTMENT OF MARKETING

SEPTEMBER 2024

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# ABSTRACT

As acceptance of autonomous vehicles is developing in Malaysia, it has been noted that many Generation-Xs have had challenges in attempting the technology when controlling an autonomous vehicle is a hassle to them. As a result, this study is to figure out the factors that affect the Generation X intention in adopting the technology of autonomous vehicle. From the literature review, the Perceived Risk Theory of Bauer (1960) and few other variables that might affect Generation Xs' tendency to purchase autonomous vehicles have been utilised to formulate hypotheses and to gain knowledge of purchase intention to achieve the purpose of the study. The data were gaining from Generation X respondents through researcher assisted electronic questionnaire survey by using PAD. A total of 370 completed data were recorded and they were examined and analysed by using SPSS and SmartPLS software. The analyses found that there were negative relationships between PR and PH with trust whereas PH didn't show any significant relationship with trust. The constructs of SO and FI shown significant negative relationships with PI but PR and PH didn't show any significant value whereas FU shown positive relationship with PI and therefore two relationships were supported and three relationships were not supported. Further, TR shown significant mediation effect on the relationship between PR and PI and between FU and PI but not between PH and PI.

As a conclusion, this study found some significant relationships between perceived risks with PI of autonomous vehicle and there are some perceived risks that do not have such effect. Similarly, same kind of findings also occur on the relationships between three perceived risks and TR. This study would be a key reference for academics, industrial practitioners and government in research, in implementing business strategy and in policy formulation. Limitation and further research suggestions were also provided.

# KEYWORDS

- RISK PERCEPTION
- AUTONOMOUS VEHICLE
- GEN-X
- PURCHASE INTENTION
- TRUST

# SUBJECT AREA

- TL1-484 MOTOR VEHICLES. CYCLES

## LIST OF ABBREVIATIONS

| | |
|---|---|
| **AVs** | **Autonomous Vehicles** |
| **Gen X** | **Generation X** |
| **PR** | **Privacy Risk** |
| **PH** | **Physical Risk** |
| **FU** | **Functional Risk** |
| **SO** | **Social Risk** |
| **FI** | **Financial Risk** |
| **PI** | **Purchase Intention** |
| **TR** | **Trust** |

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# CHAPTER 1: INTRODUCTION

## 1.1 Research Background

Siegfried Marcus developed the first car in 1870. It was actually just an engine-powered waggon without a brake or steering wheel. Rather, the driver's legs did the controlling. It took many steps to transform conventional automobiles into autonomous ones. The first step was taken in 1898, which was 28 years after vehicles were invented. The idea behind this stage was using a remote controller to move a car. Many of the operations of modern automobiles have been made completely automatic, eliminating the need for even remote controlling, since this initial step and as computers have become more powerful and advanced. One of the first functions that a car could perform automatically without the driver's assistance was changing gears, hence the term "automatic cars." Nevertheless, modern cars are capable of fully autonomous operation, even though most of the world still forbids their use on public roads. These automobiles are referred as "autonomous vehicles -Avs" (Wiseman, 2022). As the vehicle technology expanded and developed over time, a vehicle's primary functions expanded to encompass comfort level, safety level, and accessibility in addition to transportation. This prompted a great deal of study into making cars better and integrating new and cutting-edge technologies. Autonomous car technology was shortly imagined and developed. Arguably, the next big disruptive breakthrough is autonomous driving. Autonomous passenger cars being equipped with various technology in attempts to make them driverless. To accomplish autonomous driving with high security, Avs are now equipped with a variety of sensors like cameras, ultrasonic actuators, RADAR, and LiDAR. By utilize these sensors can provide the car needed data like traffic flow, lane occupancy, object identification, and more (Parekh et. al., 2022) for smooth operation. Some examples of autonomous vehicle that exist in market like Tesla, Waymo, Zoox and others. Tesla is the most famous AVs brand in the world (Betz, n.d.). However, perceived risk is the main concern that effect the consuming of autonomous vehicle. Since control authority is given to the vehicles in autonomous driving, people cannot control by themselves, the risk and trust are the crucial concerns for those that wanted to utilise these vehicles. According to some research, perceived risks had a big impact on people's intentions to purchase and use autonomous cars (Ha et. al., 2020).

Generation X is defined as people that born between 1965 and 1976. The characteristic of Gen X are: they grew up in a time when divorce rates were skyrocketing, accepted diversity in culture, and placed a higher priority on personal fulfilment. They dislike being singled out and are individualists. They have an unrivalled spirit of enterprise. They advocate an independent and adaptable way of living. (Ting et. al., 2018). Generation X in Malaysia is in the age range of 48 to 69 years old, thus is the group that has highest disposable income and is most likely to try out something that new and quite expensive (lowest price of autonomous Tesla model is RM 181,000-Model 3 (Tesla Malaysia, 2023.). Therefore, this group was chosen as the subject of study.

## 1.2 Research Problems

Some of the inevitable problems with self-driving vehicles may raise the users risks on using them. Firstly, the leakage of privacy, as the relevant databases for such vehicles include exact rider information, pick-up and drop-off locations, times, and routes (Collingwood, 2017). In other words, leaked confidential information can expose personal or sensitive data, such as social security numbers, personal details, financial records, and others. It leads to the possibility of theft, fraud or other meticulous activities (Shakir, 2023). For instance, two former employees from Tesla had misappropriated the information and shared it with the outlet in violation of Tesla’s IT security and data protection policies. This is not the first time Tesla employees have mishandled internal data, furthermore, the company's reputation was affected since the data privacy issues occurred.

Furthermore, unwillingness of individual to adopt self-driving functions in self-driving cars is a major challenge. According to research, consumers may be worried about the safety and dependability of technology for self-driving cars (Castro, 2013). Autonomous vehicles considered to be the ultimate solution for future automotive engineering; however, safety remains a key concern and critical challenge for the development and commercialization of self-driving vehicles (Wang, Zhang, & Zhao, 2020). According to Wang, Zhang, and Zhao (2020), 128 accidents that occurred from 2014 to 2018 were studied, of which about 63% were caused in autonomous mode. The first fatal accident involving a Tesla Model S operating in autopilot mode occurred on May 7, 2016. The automobile collided with a tractor trailer that was crossing a junction on a highway, killing the Tesla driver (Banks, Plant, & Stanton, 2017). In the above case, it was however unclear whether it was a designer error or driver error. Furthermore, uncertainty and potential dangers posed by vehicle sensor vision are often at the crux of autonomous driving safety issues (Wang et. al., 2022). The notion of higher hazards associated with self-driving cars may prevent Generation X buyers from acquiring them. (McKinsey & Company, 2023). Besides, statistics show the market for self-driving vehicles in Malaysia is weak. According to Wong (2024), the electric vehicle that registered in Malaysia only 13,301 out of 832,340 total number of vehicle, which is only 1.60% (Refer to Appendix A). Moreover, from the 13,301 electric cars only 5011 cars are fully support autonomous driving, such as Tesla Model Y, BYD Atto 3 and Tesla Model 3 the amount of autonomous car not even reach 50% of the total sales in the Malaysia 2023 electric cars market (Refer to Appendix B). Further, as shown in appendix B, the average of the sales per month of three autonomous vehicle model Tesla Model Y, BYD Atto 3 and Tesla Model 3 had increased over a year. In year 2023, the sales of Tesla Model Y per month was 15, BYD Atto 3 was 263 and Tesla Model 3 was 140, but in year 2024, the overall sales per month has increased to 285, 280 and 216 per month respectively. These figures suggests that Malaysian customers are adopting driverless vehicles at a slow pace. Therefore, self-driving vehicles still have the safety issue, which is the most important consideration affecting consumers' desire to consume. If the autonomous vehicles industry fails to make better safety improvements than it does now, consumers will remain hesitant to use autonomous vehicles.

Besides that, one critical problem of autonomous vehicles is the potential for technical failures or malfunctions (Muzir et. al., 2022). AVs required variety of sensors and systems to function, including radar, camera, and lidar. If any of these systems failed to perform or breakdown, it may compromise the safety of the AVs and cause accidents (Abu Bakar et. al., 2022). In Malaysia, this risk is especially significant since the climate and road conditions in Malaysia may be more difficult for AVs to manage. For example, severe rain or fog may affect the sensors' capacity to identify obstacles or other vehicles on the road and then may result in accidents (Tan & Taeihagh, 2021).

Following issue is the social risk that affect the purchasing intention of the autonomous vehicles. Individual will consider the opinion of thirds parties before making purchase or may in a post-purchase dilemma after considering the opinion of others. One of the features of autonomous vehicle is the split-second autonomous decisions by the vehicle in determining potentially life-threatening situations of the passengers. Although the use of advanced algorithms, artificial intelligence, and sensor technologies, autonomous cars are already demonstrating cognitive competence in terms of traversing challenging terrain, making split-second decisions, and interacting with infrastructure or other vehicles (Giannaros et. al., 2023), consumers may still have a second thought of using it. Based on the research that conducted by Bonnefon, Shariff, Rahwan (2016), in spite of the fact that autonomous vehicles (AVs) are supposed to decrease traffic accidents, there are situations in which the vehicle must choose between two bad options, like running over pedestrians or try to risk their own lives along with their passenger to save them. It is very complicated define the algorithms that will support AVs in making these moral judgements. AVs buyers may face these ethical dilemmas after the accident, the possibility of disagreement by their friends or relatives towards them, this affect the purchase intention of the potential buyers.

Apart from that, the financial risk is another crucial factor that affect the purchase intention of autonomous vehicle. According to NEWSROOM, the American Automobile Association (AAA) said that the cost of total crash repair can increase by up to 37.6% when using advanced driver assistance systems (ADAS). The functions that including are lane departure warning, emergency braking by automatic, and blind spot monitoring. This is because the sensors that power these systems are very expensive to replace and calibrate. The cost of further repairs for devices like distance sensors or front radar can reach USD1,540 even in cases of minor damage (Moye, 2023). Besides, one of the related news from DRIVE.com mentioned that from the average repair price that announced by the American Automobile Association (AAA), the cost of replacing the front radar sensors—which are utilised for adaptive cruise control and autonomous emergency braking—ranges from USD900 to USD1300, while replacing the rear radar might cost as much as USD2050. Parking sensors may cost as much as USD1300, while mirrors equipped with lane-keeping hardware can fetch up to USD1100, so the cost to repair an autonomous vehicle will be much more expensive if compare with the traditional cars (Collie, 2018).

One of the main reasons for the lack of trust in self-driving car technology is the fear of accidents and breakdowns. Some perceived risk will affect the trust of consumers to purchase autonomous vehicles. Issues include accident liability, decision-making accountability in ethical quandaries calling into doubt self-driving cars' responsible and ethical behavior, such as the inability to accurately assess the traffic environment. (Martinho, Herber, Kroesen, and Chorus, 2021). Furthermore, system and sensor complexity raise vehicle failure rates, potentially increasing accident rates. For more details, the researchers found that the performance risk affect the trust on autonomous vehicles, due to the risk that the vehicles didn't perform up to their expectation after purchasing (Ho et. al., 2023). In addition, based on the findings from Waung (2021), the leakage of privacy information will affect the trust of consumers on autonomous vehicle. This lack of trust will have a significant impact on Generation X customers' buying intentions, resulting in decreased demand for autonomous vehicles.

## 1.3 Research Objective

The objective for conducting this study is to investigate the impact of risk perceptions that affect purchase intention of Generation X towards autonomous vehicles in Malaysia. Specifically,

I. To determine the relationship between perceived risk (Privacy risk, Physical risk, Functional risk, Social risk and Financial risk) and purchase intention of Generation X on autonomous vehicle in Malaysia.
II. To determine the relationship between trust and purchase intention of Generation X on autonomous vehicle in Malaysia.
III. To determine trust as the mediator on the purchase intention of Generation X on autonomous vehicle in Malaysia.

## 1.4 Research Question

I. What are the risk factors that affect the purchase intention of Autonomous Vehicle by Gen X in Malaysia?
II. What is the effect of trust on purchase intention of autonomous vehicle by Generation X?

III. Does trust acts as a mediator between the three perceived risks and purchase intention of autonomous vehicle by Generation X?

## 1.5 Research Significant

The importance of studying the influence of risk perception on Generation X's purchasing intentions for autonomous vehicles in Malaysia extends to researchers, politicians, and industry players alike. This issue allows investigators to investigate the intricate interplay between risk perceptions, consumer behaviour, and technology adoption in specific demographic and cultural situations. Furthermore, by analysing the elements that impact the decision-making process of Generation X autonomous vehicles, researchers can get useful insights into behavioural economics, transport research, and technology adoption theory. Therefore, this study can shape more focused interventions and educational efforts to increase acceptance and adoption of this developing technology.

Next, this research is crucial for policymakers in Malaysia because it allows them to make educated decisions about regulating and supporting the deployment of autonomous cars. By recognizing adoption constraints including legal ambiguity and privacy issues, policymakers may create suitable regulatory frameworks and incentive programs to encourage the safe and responsible integration of autonomous vehicles into the transportation ecosystem. Furthermore, the findings of this study may be used to guide public policy initiatives targeted at tackling societal challenges and increasing trust in autonomous car technology, resulting in an enabling climate for automotive innovation and economic progress.

Furthermore, knowing the intricacies of customer risk perceptions is crucial for industry players, notably automakers and technology developers, when building and marketing self-driving vehicles. By resolving customer concerns about security, dependability, and privacy, industry participants may boost product adoption and market share. Furthermore, the findings of this study may be used to influence investment decisions and R&D objectives, allowing businesses to develop creative products that address the particular demands and preferences of Generation X customers in Malaysia. Finally, by connecting product development plans with customer expectations and societal ideals, industry stakeholders may achieve long-term growth and a competitive edge in the fast-growing autonomous vehicle sector.

## 1.6 Conclusion

In summary, a study on the impact of risk perception on autonomous vehicle purchase intention among Malaysian Generation X identified important factors driving the adoption of this transformative technology. This study explores the impact of risk on purchase intention and market dynamics to illustrate the complexity of autonomous vehicle adoption and its impact on many stakeholders. The results of this study will be helpful to scholars aiming to design sound theoretical frameworks, politicians aiming to implement effective laws, and target consumer groups to drive decision-making processes. They can guide strategic decisions and stimulate informed discussion. This study opens the door to developing more inclusive and collaborative strategies to integrate autonomous vehicles into Malaysia's transportation ecosystem by addressing concerns about safety, legal ambiguity and privacy issues. Going forward, continued cross-sector research and interaction will be critical to address the growing issues and possibilities presented by autonomous vehicle technology, ensuring its responsible and sustainable adoption for the benefit of society as a whole.

# CHAPTER 2: LITERATURE REVIEW

## 2.0 Introduction

In Chapter 2, a research model has been constructed after thorough literature reviews. the Perceived Risk Model was combined with construct Trust to form a new research conceptual model. The main concern in this study is to examine the relationships between the exogenous constructs of five perceived risks with the endogenous construct of purchase intention towards autonomous vehicle among Generation X in Malaysia with moderation effect of trust.

## 2.1 Review of Past Theory

This study is based on Bauer's (1960) theory of perceived risk. The theory finds that customers' perceptions of the risks associated with a product or service influence their purchasing decisions. These perceived risks may be attributed to product or service uncertainty, lack of control, or possible adverse effects. These influence individuals' subjective assessments of the likelihood and severity of negative outcomes (Bauer, 1960). The main focus is on the statistical and intellectual aspects of perceived risk. In the work of Ashoer and Said (2016), Mitchell (1999), Jacoby & Kaplan (1972), Roselius (1971), and Stone and Gronhaug (1993) stated that some early studies examined only 4 risks for traditional firms over the past four centuries. Perceived risk aspects include social risk, physical risk, functional risk and financial risk (Bhatti et al.,2018). These seminal works laid the foundation for understanding the multifaceted nature of perceived risk in consumer decision-making.

Consumers may perceive of some risks due to inappropriate decisions during the purchasing process because it is an individual's subjective opinion regarding potential adverse consequences (Ashoer & Said, 2016; Bonnin, 2020). As noted by Arrow (1950) and

Humphreys and Kenderdine (1979), perceived risk may affect future earnings that are unclear and risky, such as anticipated hazards or losses. The concept of perceived risk has also evolved over time, particularly with the advent of the Internet, leading to new dimensions of risk. Experts also provided evidence that perceived risks on the internet may include delivery, security and privacy, and after-sales dangers. Scholars such as Jacob & Leon (1972) had studied the dynamic nature of perceived risks, how they fluctuate with time and environment, they have revealed the subtle interaction between risk perception and the decision-making process (Jacob & Leon, 1972).

In consumer behavior research, the theoretical framework of perceived risk has been widely used in consumer behavior research on various product and service categories, including technology, medical choices, and investment choices (Ashoer & Said, 2016; Bonnin, 2020). Researchers examined how different dimensions of perceived risk influence consumer perceptions and behavior, providing insights into the complexity of the purchasing process. This theoretical perspective is particularly valuable for understanding consumer decision-making regarding technology adoption, medical decisions, and investment choices. By reviewing past theories of perceived risk, researchers have gained a comprehensive understanding of the multifaceted nature of risk perception and its impact on consumer behavior. This theoretical foundation serves as a framework for analyzing the factors that influencing Malaysian Generation X’s autonomous vehicle purchase intention, providing valuable insights into the complexity of consumer decision-making in this context.

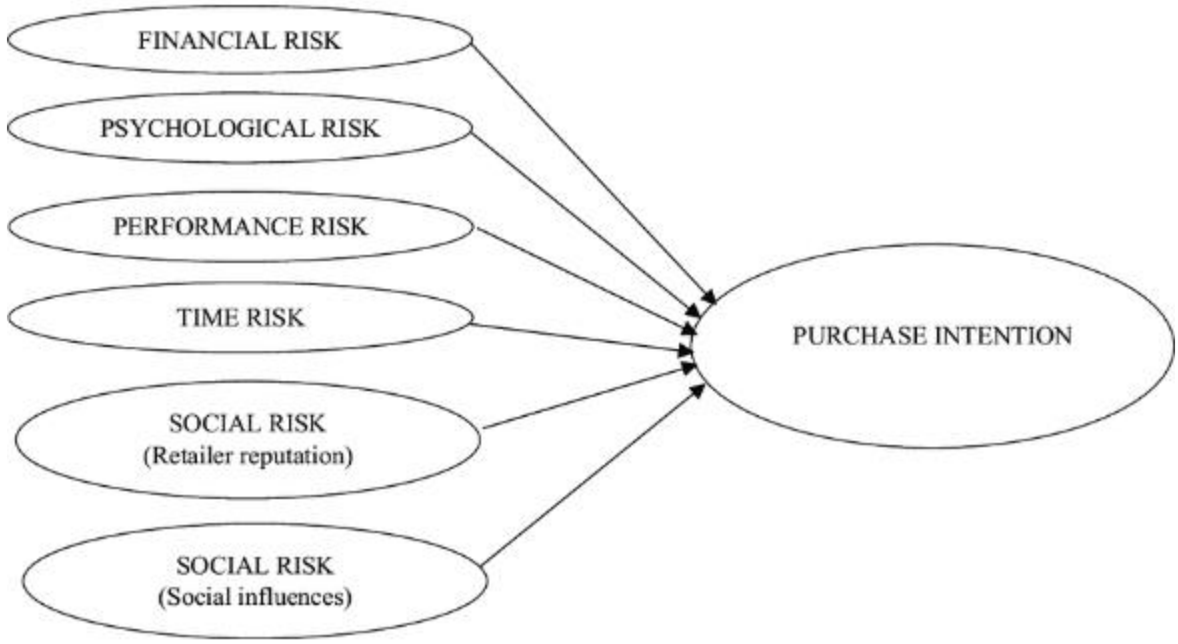


**Figure 2.1: Conceptual framework of the relationship between perceived risk dimensions and purchase intention (Pentz & et al., 2020)**

The conceptual framework from Pentz & et al. (2020), shows that there are six perceived risks that influencing the purchase intention of consumer, the perceived risks are namely financial risk, psychological risk, performance risk, time risk, social risk (retailer reputation) and social risk (social influences). This model is deemed suitable to be used in our research.

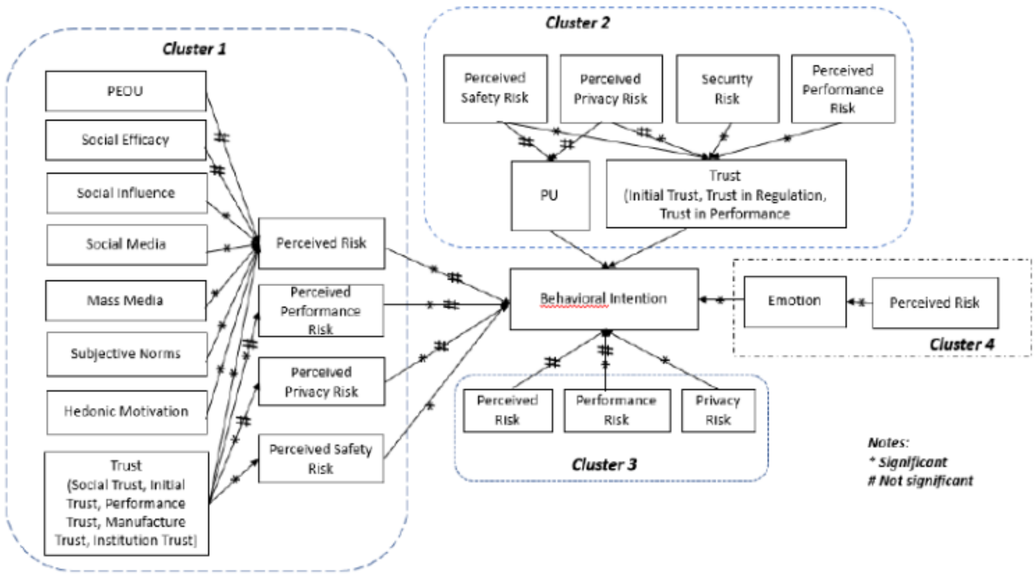


**Figure 2.2: The Knowledge Map of Perceived Risk with Trust (Sim et al., 2023)**

The model from Sim et al. (2023), shows that construct of trust may act as a mediator in some perceived risks situation. The model shows that trust act as mediator between perceived safety risk, perceived privacy risk, security risk, perceived performance risk and behavioral intention. Therefore, these relationships were included into our research model.

## 2.2 Research Conceptual Model

From Bauer theory and above two models, a research conceptual framework has been constructed and it is as shown in figure 2.2. There are three perceived risks, namely privacy risk, product risk and security risk, which affect purchase intention through trust, while social risk and financial risk directly affect purchase intention. These three risks (privacy, functional and physical risks) have a negative relationship with trust. As risk increases, trust will decrease; while trust has a positive relationship with purchase intention. As trust increases, purchase intention will increase; as trust decreases, purchase intention will decrease. This study aims to understand the impact of risk perception on autonomous vehicle purchase intention among Generation X in Malaysia.

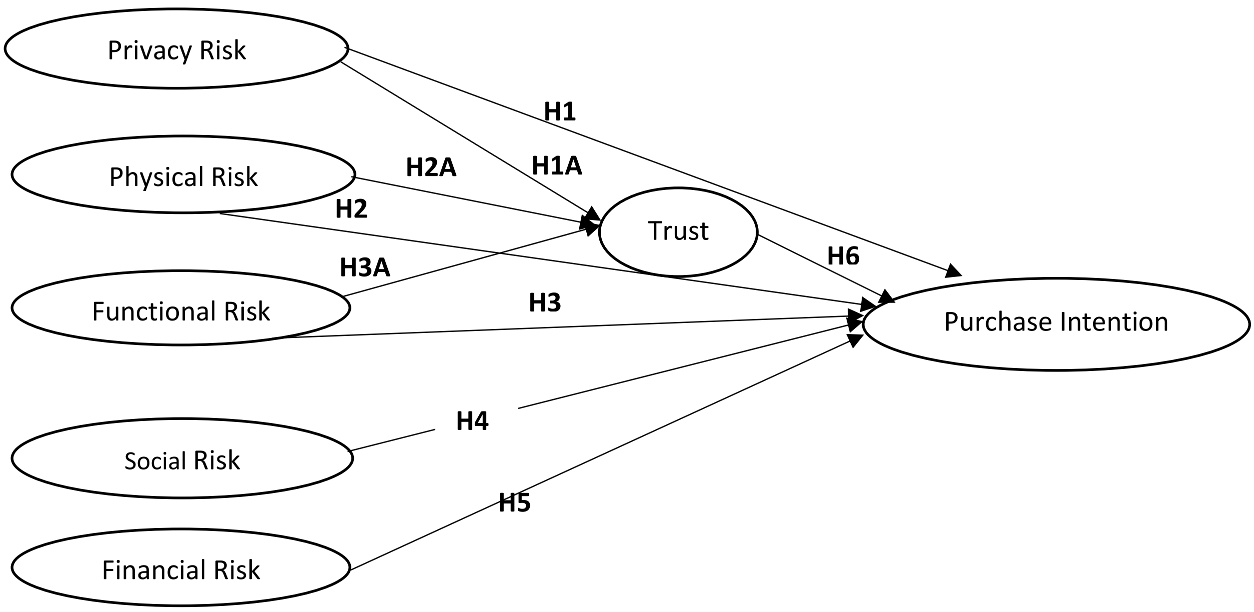


**Figure 2.3 Research Conceptual Model**

## 2.3 Review of Variables

### 2.3.1 Purchase Intention

The endogenous construct in this study is purchase intention, it is the willingness of the consumers to purchase a goods or services in future (Peña-García, Gil-Saura, Rodríguez-Orejuela & Siqueira-Junior, 2020). Based on the finding from Sivaram et al. (2019), when purchase intention increased, the chances that the consumers will buy that product or services will increase. Moreover, purchase intention is a useful metric that researchers can use to estimate consumer behaviour. In another word, purchase intention is a crucial element that evaluates the possible action that a consumer may decide to take. Businesses can better comprehend the market and modify their products or services to increase sales and profit by knowing consumers' purchase intentions. Furthermore, knowing what customers want to buy might help you to predict the customer's intention towards particular brand. (Agmeka, Wathoni, & Santoso, 2019). In this study, the purchase intention is the willingness of consumers to purchase the autonomous vehicle in Malaysia.

### 2.3.2 Privacy Risk

Privacy can be defined as the right to protect their own personal information, right to be alone, the right to control their own's body and right to protect own reputation (Adams & Almahmoud, 2023). For the privacy risk in this study, means that the leakage of personal information, for example the leakage of relevant databases of autonomous vehicles users which recorded the exact rider data, pick-up and drop-off points, times, and routes that been, leakage of this information may lead to the possibility of theft or fraud (Shakir, 2023). Based on the finding of Ho et al. (2023), the autonomous vehicle is still considered new in Asian especially the developing country in Malaysia, it is therefore very important for the related department to handle this risk properly. In relation to this study, the privacy risk may be influencing the purchase intention of Malaysian on AVs.

### 2.3.3 Physical Risk

The possibility that customers may have questions about safety in using the products is related to physical risk. When making a purchase decision, one will frequently take the product or service's safety level into account (Ho, Tan, Lau & Khan, 2023). By relating to this study, the security of driver and passenger will be one of the risks consider when adopting AVs. Based on the research of Wang, Fu, Song & Zhou (2022), the view of the car sensors, which can be confusing and perhaps dangerous, is known as the main issue of the autonomous driving safety issue, for instance the term "potential danger scene" describes the situation in which an autonomous vehicle (AV) is driving in the particular area and other vehicles may enter the area from which the AV's optical sensor's visual field is obscured. This could result in unforeseen conflicts; hence the security risk will occur. The academic community has become more aware of the uncertainty of risk associated with visual field occlusion in recent years.

### 2.3.4 Functional Risk

Functional risk can be known as the risk that related to functioning of the services and product which include the emotion of doubt or fear from consumer that certain product and services may perform under their expectation or fail to perform after purchase (Zhang & Yu, 2020). In term of autonomous vehicles, functional risk is defined as the risk that caused by any potential source of harm such as malfunctioning of electronic system (Lu, 2021). When related to study, some of the consumer who wish to buy AVs hesitate in purchasing one because he/she may face the functional risk after the purchase.

### 2.3.5 Social Risk

According to Lopes et al. (2020), social risk is associated with ethical dilemmas or with the perception of other people, including friends or family, who might believe that the customer has made a poor decision regarding the product they have chosen to buy or their attitude towards making the purchase. The social group may criticise the customer for making such a decision, which is the opposite of what the consumer had hoped for. In this study, social risk is defined as the social dilemmas or the judgement from others people on the consumers that purchase autonomous vehicle. Social Risk can be known as the social acceptance of the people to the pros and cons in adopting AVs (Nishihori et al., 2018).

### 2.3.6 Financial Risk

Financial risk refers to some of the consumers that think they may waste money on buying certain product, for example, when the monetary value that gained is not equal with the product that they had purchase (Lăzăroiu et al., 2020). Financial risk known as the perception of some amount of money that needed or the money that will lost in order to let the certain product or services to function properly. Consequently, the most significant element that influencing consumption among risk perception factors is financial risk perception (Quan, Ansi & Han, 2021). In more details, customers worry that they may suffer financial losses if the product does not live up to expectations, malfunctions, or does not suit their needs (Geetha et al., 2020). In this study, the financial risk is defined as the money that needed to be spend when buying an AV and the maintenance fee needed after purchase.

### 2.3.7 Trust

In addition to perceived risk, trust is a key factor that affects purchase intention, especially in the case of autonomous vehicles. Trust is defined as a consumer's readiness to rely on the competence, dependability, and integrity of a product or service supplier (Mayer et al., 1995). Trust is a person's deliberate consideration or opinion concerning a different party's integrity, warmth, and ability, which results in a behavioural desire to trust. When it comes to autonomous vehicles, trust in self-driving vehicles exists at many levels, including trust in the technology, the manufacturer, authorities, and other road users. Trust is critical in determining customer attitudes and intents to adopt this revolutionary technology.

Consumers' trust in autonomous driving systems is linked to their confidence in its efficacy and safety. This includes beliefs of technology's capacity to effectively perceive and understand its surroundings, make intelligent judgements, and navigate securely without human assistance (Van Brummelen, O'Brien, Gruyer, and Najjaran, 2018). Besides, trust in manufacturers relates to customers' impressions of the trustworthiness, dependability, and ethical behaviour of firms creating and producing self-driving vehicles. Positive impressions of a manufacturer's dedication to safety, openness, and responsibility can boost trust and confidence in technology (Morgan & Hunt, 1994). Finally, confidence in regulators refers to customers' opinions about the efficacy and appropriateness of government rules and supervision systems controlling the deployment and operation of self-driving vehicles. Rules and regulations that prioritise safety, privacy, and consumer rights can help to build confidence and ease worries (Bekmamedova et al., 2020). Previous studies of this sort have also looked at the effect of trust in affecting purchasing intentions for autonomous vehicles. For example, Choi et al. (2015) investigated the effect of trust in manufacturers on customers' readiness to embrace autonomous vehicles. According to the findings of the study, the more participants trust the technology and the company, the greater their buying intention. This outcome emphasises the significance of trust as a significant driver of purchase intention in autonomous vehicles, emphasising the need for more study to understand its underlying processes and influence on customer behaviour.

## 2.4 Development of Hypotheses

### 2.4.1 The Relationship between Privacy Risk and Purchase Intention

### 2.4.2 The relationship between Privacy Risk and Trust

Privacy risks have a big impact on autonomous vehicle purchase intentions. Research has demonstrated that perceived privacy risk has negative effects on consumers' early trust in autonomous vehicles, lowering their willingness to adopt and rely on these autonomous vehicles (Yu & Cai, 2022). According to Liao, Guo & Liu (2023), the consumers who have more privacy conscious will afraid of the leakages of data or the tracking issue that incur in the autonomous vehicle. Moreover, based on the research from Lee & Hess (2022), the studies shown that privacy concerns can greatly affect public perception and adoption of AVs. In addition, the issue of data privacy can negatively affect the trust of AVs, people that wish to avoid privacy issue will prefer purchase other vehicles (Iranmanesh et al., 2023). According to Giannaros et al. (2023), if without appropriated privacy protection for the consumers, the consumer will be losing the trust on the autonomous vehicle technology due to the risk of privacy data leakage. Besides, autonomous vehicle needs a great volume of data such as personal information, the data of location and the sensor reading. This huge amount of data collection will raise the concern about the misuse by others people which will affect the trust on the vehicle (Kargl et al., n.d.). Therefore, the following hypotheses are formulated.

**H1A: Privacy Risk has a negative influence on purchase intention of autonomous vehicle (AVs)**

**H1B: Privacy Risk has a negative influence on Trust**

### 2.4.3 The Relationship between Physical Risk and Purchase Intention

### 2.4.4 The relationship between Physical Risk and Trust

Physical risk in this study mentioned the possibility that customers may have questions about how safely to use the products (Ho, Tan, Lau & Khan, 2023). According to research from Yu & Cai (2022), perceived physical risk reduces consumers' early trust in autonomous vehicles. This indicates that if consumers perceive a significant level of physical risk connected with self-driving vehicles, they are less tending to trust them, which influences their purchasing decision. As example, the view of the autonomous vehicle sensors, which can be confusing and perhaps dangerous, is known as the main issue of the autonomous driving safety issue, if consumer want to avoid this issue, they won't purchase it (Wang et al., 2022). From the research of Naiseh et al. (2024), if there is perceived physical risk on the autonomous vehicle, individuals will have significant negative trust then affect their purchasing intention. Based on the finding from Walker et al. (2023), the physical risk problem such as the unexpected driving situation that may harmful to passenger will affect the trust level of consumer, consumer will take it in to account when deciding to purchase the autonomous vehicle. Therefore, the following hypotheses are formulated.

**H2A: Physical Risk has a negative influence on purchase intention of autonomous vehicle (AVs)**

**H2B: Physical Risk has a negative influence on Trust**

### 2.4.5 The Relationship between Functional Risk and Purchase Intention

### 2.4.6 The relationship between Functional Risk and Trust

Based on the research from Zhang & Yu (2020), functional risk can be recognised as the risk that is related to the functioning of the services and products, or after the purchasing, the product will perform below initial expectations or fail to perform. Besides, functional risk, which refers to the technology's performance and reliability, might raise worries about safety and trust in autonomous vehicles as an example the auto emergency brake, affecting people's willingness to buy and use them (Kenesei et al., 2022). A software fault causes an autonomous disengagement or crash. This was the situation in a low-speed accident involving an autonomous vehicle and the fundamental reason was located in the system design of each vehicle's software (Betz et al., 2019). Functional risk has a major influence on autonomous vehicle purchase intentions. Perceived risk, especially functional risk, has a significant impact on people's trust towards autonomous vehicles (Zheng & Gao, 2021). Based on the finding from Topolsek et al. (2020), some of the consumer that relying on the function in autonomous vehicle like auto brake system and others might face accident. In March 2018, an Uber self-driving vehicle killed a person who was walking, Elaine Herzberg, in Tempe, Arizona. However, there were no software errors or sensor problems in the vehicle. Instead, the object-detection algorithm misidentified Herzberg, resulting in inaccurate projections of her speed and direction, as well as the vehicle's speed and direction, hence the planning software didn't make an emergency brake 1.3 second before knock down the person who was walking (Madrigal, 2018). Therefore, the following hypotheses are formulated.

**H3A: Functional Risk has a negative influence on purchase intention of autonomous vehicle (AVs)**

**H3B: Functional Risk has a negative influence on trust**

### 2.4.7 The Relationship between Social Risk and Purchase Intention

Social risk can associate with ethical dilemmas or with the perception of other people, including friends or family (Lopes et al., 2020). Based on the research from Topolsek et al. (2020), they found that factor like social influence and anxiety have a substantial impact on the purchase intention of autonomous vehicles. For instance, why do you buy this autonomous vehicle cars or some of them will think that you are fool if buy AVs. The findings from Nasiseh et al. (2024), stated that the perceived risk of autonomous vehicles is frequently influenced by the social amplification of risk, wherein the perception becomes emotive rather than rational. People who afraid to the social dilemmas or judgement from third party, will not buying AVs. Therefore, the following hypothesis is formulated.

**H4: Social Risk has a negative influence on purchase intention of autonomous vehicle (AVs)**

### 2.4.8 The Relationship between Financial Risk and Purchase Intention

Financial risk is a crucial element that can influence autonomous vehicles (AVs) purchasing decisions. Consumers' concerns about the safety of autonomous vehicles might contribute to a perception of financial risk, because they may worry about the potential expenses connected with accidents, repairing issue, or other unforeseen incidents (Topolsek et al., 2020). The price or repairing cost will make the consumer purchase intention decrease if compare with normal vehicle, the cost of repairing autonomous vehicle is more expensive (Russell, 2023). The lack of standardisation and regulation in the autonomous vehicle industry can also compound this sense of financial risk. Consumers may be concerned about the legal and monetary costs of owning and running an autonomous vehicle, so if consumer wish to avoid all of these expenses, they will not be willing to purchase AVs (Topolsek et al., 2020). Therefore, the following hypothesis is formulated.

**H5: Financial Risk has a negative influence on purchase intention of autonomous vehicle (AVs)**

### 2.4.9 The Relationship between Trust and Purchase Intention

Based on the research from Hurst & Sintov (2022), the researcher had demonstrated that when trust in autonomous vehicle technology grows, it favourably impacts adoption intentions, regardless of other influencing factors. Trust is an important component that influences consumer purchasing intention of Avs (Zhang et al., 2019). The relationship between trust and the intention to buy AVs is complicated and influenced by several aspects, such as the perceived risk of the vehicle, convenience of use, technology, and the level of trust in the autonomous system (Wang et al., 2023). So, in a simple word, when the trust on autonomous vehicle increases, it will increase the purchase intention of consumer and vice versa, means that it is a positive relationship between trust and purchase intention. Hence, the following hypothesis is been formulated.

**H6: Trust has a positive influence on purchase intention of autonomous vehicle (AVs)**

### 2.4.10 The mediation of trust between privacy risk and purchase intention

The feeling of privacy risks plays a crucial part in determining AV acceptance. Consumers frequently worry about how their information might be collected, saved, and used by companies and other third parties (Naiseh et al., 2024). Thus, due to some of the consumers worries about privacy issue, they will have trust problem with autonomous vehicle. Moreover, the leaking data situation may lead to scepticism regarding the safety and reliability of AV technology in protecting consumer data, ultimately diminishing their trust (Anastasopoulou et al., 2018). In addition, trust is critical for the acceptance of AVs. According to studies, higher degrees of trust correspond with higher willingness to use automated driving systems. When consumers perceive large privacy problems, their trust decreases, and it will negatively be influencing their willingness to adopt Avs (Zhang et al., 2019). Therefore, the following hypothesis is formulated.

**H6a: Trust mediates the relationships between privacy risk and Generation X purchase intention on autonomous vehicle (AVs)**

### 2.4.11 The mediation of trust between functional risk and purchase intention

Functional risk means the potential of a product or service may fail to perform as intended. In the case of autonomous vehicles, this includes dependability and the capacity of the technology to operate in a variety of environments. According to research, perceived functional hazards have a substantial influence on consumer trust in autonomous vehicles (Kenesei et al., 2022). Besides, when the functional risk is high, consumers will have less trust on the technology, in the end it will negatively affect the purchase intention of the consumers (Topolsek et al., 2020). The combination between functional risk and the trust has a direct impact on the decision of individuals to buy an autonomous vehicle. Consumers are more likely to invest in technology when they believe it will work as promised. If consumers have reservations regarding to the vehicle's functionality or security functions, their purchasing intention decreases (Ho et al., 2023). Therefore, the following hypothesis is formulated.

**H6b: Trust mediates the relationships between functional risks and Generation X purchase intention on autonomous vehicle (AVs)**

### 2.4.12 The mediation of trust between physical risk and purchase intention

Physical risk in regard to autonomous vehicles refers to the possible dangers associated with their use, such as accidents or breakdowns. According to research, perceived physical risk can have a negative impact on trust in autonomous vehicle. When consumer estimate a high level of danger, it will affect the trust level, and leading to low purchase intentions (Naiseh et al., 2024). Autonomous vehicles introduce fresh technologies that consumers may not completely trust or understand. They variety of challenging driving conditions may reduce the trust level of consumer. For example, if consumers are concerned that an AV may fail to detect and react to an emergency scenario, the trust of consumer will decrease (Jing et al., 2020). The new technology that may cause perceived physical risk, has a significant impact on trust. If there are uncertainties regarding the autonomous vehicle high technology sensors or software that causing physical risk, potential purchasers may be afraid to trust Avs to perform correctly under any conditions to make sure the passenger safety (Adnan et al., 2018). Therefore, the following hypothesis is formulated.

**H6c: Trust mediates the relationships between physical risks and Generation X purchase intention on autonomous vehicle (AVs)**

# CHAPTER 3: METHODOLOGY

## 3.1 Research Design

This study employed a quantitative technique by collecting data through questionnaire survey. Quantitative research is a well-established research method allowing researchers to gain insight into the nature of the specific group under study and draw conclusions about the larger group. (Holton and Burnett, 2005). Questionnaires used in quantitative approaches should be as devoid of individual bias as feasible to provide statistically trustworthy and precise findings. Furthermore, casual effect design is a way to examine a cause-and-effect relationships between the variables (Dovetail Editorial Team, 2023). As a result, the casual effect design was applied to investigate the effect of risk perception on Malaysian Generation X purchase intention towards autonomous vehicle.

## 3.2 Sampling Design

### 3.2.1 Target Population and Sample Frame

This study's intended audience is Generation X Malaysian citizens born between 1965 and 1980, age ranging from 44 to 55 years. McKenna and Gopnik (2022) define Generation X as resourceful and self-governing, with a desire to preserve a work-life balance. This group is chosen based on their purchasing power and technological shift (from conventional to autonomous automobiles). As a result, we ought to be possible to collect data from respondents to identify which perceived risk are essential in affecting the purchase intention of autonomous vehicles. No sample frame could be identified for this investigation since it is not possible to get the list of Generation X in Malaysia and the cost and time taken to contact the sample will be far too much for this project even if it is available.

### 3.2.2 Sampling Techniques

Considering there was no sample frame, and our targeted respondents are Malaysian Generation X, we have adopted the judgmental sampling approach in our study. A judgmental approach is suitable to collect data since we have a specific targeted respondent group, i.e., Malaysian Generation X, thus a screening question was used to screen out non-respondents whom are not Generation X.

### 3.2.3 Sample size

According to Hair et al. (2019), by utilizing Sample-to-Variable ration, an initial observation-to-variable ratio of 5:1 is recommended, with ratios of 15:1 or 20:1 being desirable. In simple words, a minimum of 5 respondents is needed in one variable, but the most recommended is 15 or 20 respondents to one variable. There are in total 7 of constructs in this study, and with the largest ratio of 20:1, 140 respondents are needed in our study. However, we have decided to collect around 350 responses to increase research reliability.

## 3.3. Data Collection Methods

In this study, the primary data was collected through researcher assisted questionnaires survey. It is a more efficient to collect data due to it is easy and can assist target respondents on the spot. The data was collected by providing a total of 370 sets of survey questionnaires to Generation X respondents. A QR code and link of questionnaire had been created. The QR code has been save in gallery and show to the target respondents when they are ready to fill in the survey. The respondents filled in the questionnaire by using either their mobile phone or tab or pad that can scan the QR code, additionally we also have a pad for them to fill in if their devise/s is/are unable to scan the QR code or has no internet connection. Before scanning, researcher will explain clearly in regards to the objective of this survey to make sure that target respondents understand about it. Besides when they are doing the survey, researcher/s was/were standing beside of them to clear their doubts if there is any. The surveys were conducted in public area, for e.g. malls, bus stations, train stations, schools and universities.

### 3.3.1 Questionnaire Design

The research instrument is questionnaire survey and the questions are either adopted or adapted from the past studies. The questionnaire survey consists of Section A and Section B. In Section A, the information collected are respondents' demographic profile. This action is to understand our target respondents' background. The questions in Section A consists of 7 questions on gender, age, race, marital status, education level, employment status and income level, the data were measured using nominal scale. While in Section B, the questions were separated into 7 parts with each construct in a separate part. In total, there are 32 questions in Section B. The data were measured by using Likert five scale, respondents chose their answer from 1-5, which are strongly disagree to strongly agree, by this, the researchers can know the opinion of respondents. The questionnaire is as shown in appendix C.

### 3.3.2 Pre-test

Pretesting is a phase of research in which the questionnaires are evaluated on members of the study population to determine the validity as well as reliability of the instruments used for survey before final distribution (Hu, 2014). In the study, three lecturers from University Tunku Abdul Rahman (UTAR) were involved in reviewing and approving the questionnaire as shown in Appendix D, therefore the requirement of face validity of the measurement was achieved.

### 3.3.3 Pilot Study

Basically, a pilot study is the first phase in the full research process for researcher/s, and it is typically undertaken prior to the major study. Pilot study also can be known as modification of the major study and smaller sized study in planning, in order to achieve better quality of outcomes for the study (In, 2017). In addition, the primary goal of a pilot study is not to investigate specific research questions, but rather to prevent scientists from embarking on a large research endeavour without adequate knowledge of the processes available (Nancy, 2019). Based on the finding from Sekaran et al. (2016), the minimum number of respondents in the pilot study must be 10% from the whole sample size or at least 30 respondents. We have chosen 30 respondents to participate in our pilot study. Main purpose for choosing them is that they can assist researchers in identifying errors in the questions and giving us the opportunity to make modifications as well as to evaluate the reliability of the instruments before gathering data from the public. As shown in Table 3.2, all the constructs have achieved Cronbach's Alpha values above 0.70 with the highest being 0.826, these figures shown that the measurements are reliable and good for further collection of data.

Table 3.2 Reliability Analysis for Pilot Study

| **Variables** | **Number of Item** | **Cronbach's alpha** | **Result of Reliability** |
|---|---|---|---|
| **PR** | 4 | 0.808 | Very Good |
| **PH** | 3 | 0.729 | Good |
| **FU** | 5 | 0.756 | Good |
| **SO** | 5 | 0.772 | Good |
| **FI** | 4 | 0.765 | Good |
| **PR** | 4 | 0.808 | Very Good |
| **TR** | 5 | 0.826 | Very Good |

# 3.4 Proposed Data Analysis Tool

Since this is quantitative research, we used the Statistical Package for Social Science (SPSS) and SmartPLS software to be our analysis tools in order to complete the necessary data analyses and regression computations (O'connor, 2000).

## 3.4.1 Descriptive Analysis

Based on the research from Kerr et al. (2002), this is the initial step of analysis that help in characterizing and condensing data by using the descriptive analysis, we used it to describe or summarise the demographic profile of respondents from the dataset. Descriptive analysis does not need researchers to test a large number of hypotheses, but it can provide useful descriptive information that we may report in the research. This enables us to provide a summary of the sample as a whole rather than analysing each respondent's score. In summary, descriptive analysis seeks to provide a simple description of enormous volumes of data.

### 3.4.2 Structure Equation Modelling (SEM)

Multivariate data analysis technology enables researchers to model and evaluate the complex relationship between several IVs and DV simultaneously. It provides a statistically meaningful method for organising, visualising, and understanding connections between various data points (Sartorious, n.d.).

### 3.4.3 Partial Least Squares Structural Equation Modelling

Partial Least Squares Structural Equation Modelling is a "causal-predicting" technique for SEM. This method has good performance in both complicated model and small sample size. Moreover, it has high efficiency in parameter estimation. There are two components which include in Partial Least Squares Structural Equation Modelling which is Measurement Model (4 steps) & Structural Model (Hari et al., 2022).

### 3.4.4 Measurement Model Assessment

The first stage in evaluating a measurement model is to analyse the degree to which each indicator's variance is explained by the constructs, which indicates **indicator reliability**. Indicator loadings that greater than 0.708 are suggested since they imply that the construct explains more than half of the indicator's variance, resulting in satisfactory indicator reliability. Researchers may get lower indicator loadings (<0.708), instead of automatically removing indicators when their loading is less than 0.70, researchers ought to carefully analyse the impact of indicator removal on other validity and reliability measurements (Hair et al., 2021).

The second stage will be **assessed internal consistency reliability**. Internal consistency reliability known as the degree to which indicators measuring the same construct that related to one another. Cronbach's alpha and composite reliability will be used to measure of internal consistency and reliability. For example, reliability levels between 0.60 and 0.70 are deemed "acceptable in exploratory research. When the result gets values between 0.70 and 0.90 range from "satisfactory to good." Values greater than 0.90 (and especially more than 0.95) are troublesome since they show that the results are ineffective lowering construct validity (Lance et al., 2006).

The third stage will be **convergence validity**. The ultimate stage is to determine the convergent validity of each construct. Convergent validity is defined as how well the construct merges in explaining the variation of its indicators. The average variation extracted (AVE) for every indicator on a construct is used to assess its convergent validity.  The AVE is defined as the grand mean of the squared loadings of the construct's indicators. As a result, the AVE represents a construct's communality. The lowest acceptable AVE is 0.50, indicating that the concept explains at least fifty percent of the variance in the indicators (Hair et al., 2021).

The last stage will be **discriminant validity**. This step is to measure the extent the distinction between a construct and another in the structure model. Fornell-Larcker criterion was adopted to test discriminant validity, it states that a construct should have greater variance with its own indicators than with any other construct in the model.  (Henseler et al., 2015).

### 3.4.5 Structural Model Assessment

According to Hair et al., (2021), Structural Model Assessment is to analysed the association between constructs and variables. Three tests were included in our study. For **Collinearity Test**, Variance Inflation Factors (VIF) was used to indicate the level of collinearity. The VIF should be no higher or equal to 5, and no lower or equivalent to three. Then the Path **Coefficient Test (p - value, t - value, R square value, F square)** were used to test the hypothesis link between constructs. Path coefficients typically range from -1 to 1 (significant at 5% if value does not fall outside the 95% confidence interval). Last will be **t-test**, the P-value should be less than 0.05 or the t-value should be more than 1.96, and the R-square value should be between 0 and 1 with higher values indicating more influence or greater explanatory power. The F square value is used to evaluate the effect of removing a specific construct on an endogenous construct. These analyses were utilised in this study to investigate the relationship between endogenous construct of Purchase Intention (PI), and the exogenous constructs of Privacy Risk (PR), Functional Risk (FU), Physical Risk (PH), Social Risk (SO), Financial Risk (FI) and mediator Trust (TR) (Hair et al., 2021).

## 3.5 Conclusion

Overall, in our study will used the Statistical Package for Social Sciences (SPSS) software and SmartPLS 4.0 to examine and quantify the data results through Partial Least Squares Structural Equation Modelling. The approaches utilised in this study are described and explained the causal relationships between the constructs. The findings will be examined and analysed in the chapter that follows.

# CHAPTER 4: DATA ANALYSIS

## 4.0 Introduction

Chapter 4 contains the analysis of the primary data that had been collected from target respondents, 370 valid respondents were collected through Google questionnaire. Descriptive Analysis was completed by using SPSS and inferential analysis by SmartPLS 4.0.

## 4.1 Survey Response

The survey responses recorded through electronic form of questionnaires were directly recorded into worksheet format and was then uploaded into SPSS format when running descriptive analysis. The data was transformed into CSV format when analyze by using SmartPLS 4.0.

## 4.2 Data Coding

First step before analysis the data is data coding, this step involved of transforming the data from the worksheet into SPSS and CSV format before analyses since all the data were received in electronic form, no manual recoding is needed. Since all the questions are set to compulsory answer, there is no missing data in the responses and no spurious answer received, therefore, no data was deleted or cleaned.

## 4.3 Demographical Analysis

As shown in table 4.1, the total respondents that collected were 370 respondents. 185 of them are female and 185 of them are male, the percentage of male and female are 50% each.

**Table 4.1 Gender**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Female | 185 | 50.0 | 50.0 | 50.0 |
| | Male | 185 | 50.0 | 50.0 | 100.0 |
| | Total | 370 | 100.0 | 100.0 | |

While for the age, due to our target respondents are Generation X, so the age range are 44-55 years old. From the 370 responses that collected, 175 of them are 44-50 years old and 195 of them are 50-55 years old, the percentage are 47.3% and 52.7% as shown in table 4.2.

**Table 4.2 Age**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | 44-50 | 175 | 47.3 | 47.3 | 47.3 |
| | 50-55 | 195 | 52.7 | 52.7 | 100.0 |
| | Total | 370 | 100.0 | 100.0 | |

For the races of respondents, 215 of them are Chinese, 70 of them are Indian, 66 are Malay and 19 of them are other races. Which mean 58.1% of respondents are Chinese, 18.9% are Indian, 17.8% are Malay and 5.1% are from others races as shown in table 4.3.

**Table 4.3 Race**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Chinese | 215 | 58.1 | 58.1 | 58.1 |
| | Indian | 70 | 18.9 | 18.9 | 77.0 |
| | Malay | 66 | 17.8 | 17.8 | 94.9 |
| | Others | 19 | 5.1 | 5.1 | 100.0 |
| | Total | 370 | 100.0 | 100.0 | |

Next will be the marital status of our target respondents. 56 out of 370 are divorced, 254 of them are married and 60 are currently single. The percentage of married is the highest which is 68.6% and 16.2% are single lastly 15.1% are divorced as shown in table 4.4.

**Table 4.4 Marital Status**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Divorced | 56 | 15.1 | 15.1 | 15.1 |
| | Married | 254 | 68.6 | 68.6 | 83.8 |
| | Single | 60 | 16.2 | 16.2 | 100.0 |
| | Total | 370 | 100.0 | 100.0 | |

For the education level, 166 of them graduated from secondary school, 111 of them graduated from primary school, 91 of them study until tertiary level and 2 of them direct working since they are child. The percentage for secondary school is 44.9% and 30% for primary school, while for tertiary education is 24.6% and 0.5% is for the respondents who direct working, refer to table 4.5.

**Table 4.5 Education Level**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Primary School | 111 | 30.0 | 30.0 | 30.0 |
| | Secondary School | 166 | 44.9 | 44.9 | 74.9 |
| | Tertiary | 91 | 24.6 | 24.6 | 99.5 |
| | Working | 2 | .5 | .5 | 100.0 |
| | Total | 370 | 100.0 | 100.0 | |

There are 189 of our respondents work as full timer, and 112 of them work as part timer and 69 of them are unemployed. The percentage of full-time workers is the highest which is 51.1% and 30.3% for part time worker and 18.6% are unemployed as shown in table 4.6.

**Table 4.6 Work Status**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Full-time | 189 | 51.1 | 51.1 | 51.1 |
| | Part-time | 112 | 30.3 | 30.3 | 81.4 |
| | Unemployed | 69 | 18.6 | 18.6 | 100.0 |
| | Total | 370 | 100.0 | 100.0 | |

For the salary range, 174 of them earned RM1500-3000 per month, 108 of respondents earned RM3000-4500 per month and 88 of them earned RM4500 and above per month. The percentage of getting RM1500-300 is the highest which is 47% and the lowest is RM4500 and above-23.8% as shown in table 4.7.

**Table 4.7 Salary Range**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | RM1500-3000 | 174 | 47.0 | 47.0 | 47.0 |
| | RM3000-4500 | 108 | 29.2 | 29.2 | 76.2 |
| | RM4500 and above | 88 | 23.8 | 23.8 | 100.0 |
| | Total | 370 | 100.0 | 100.0 | |

The data above generally adhere to the Generation X profile of Malaysian, except the race profile.

## 4.4 Descriptive Data

As shown in table 4.8, the minimum statistic is 1 and maximum is 5. While for the Std error is low, the best will be 0 or close with zero. When implementing analysis procedure, it is critical to consider the kurtosis and skewness of both the reported and latent variable scores. Strong skewness and kurtosis suggest that the data does not fulfil the prerequisites required for particular statistical studies, which may have an impact on the model's validity. The central limit theorem states that as the number of indicators rises, the latent variable scores tend to shift towards more normally distributed, which might reduce concerns associated to skewness and kurtosis (Ma et al., 2023). In addition, maintaining Skewness value 3 and Kurtosis value 10 is a recommended practice. According to this advice, all of the findings were within the acceptable range, meaning within +3 and -3 for Skewness and between +10 and -10 for Kurtosis (Ma et al., 2023). As shown in table 4.8, the values of all items are acceptable.

**Table 4.8 Descriptive table**

| | N Statistic | Range Statistic | Minimum Statistic | Maximum Statistic | Sum Statistic | Mean Statistic | Std. Error |
|---|---|---|---|---|---|---|---|
| PR1 | 370 | 4.00 | 1.00 | 5.00 | 675.00 | 1.8243 | 0.04715 |
| PR2 | 370 | 4.00 | 1.00 | 5.00 | 702.00 | 1.8973 | 0.04781 |
| PR3 | 370 | 4.00 | 1.00 | 5.00 | 754.00 | 2.0378 | 0.04524 |
| PR4 | 370 | 4.00 | 1.00 | 5.00 | 756.00 | 2.0432 | 0.04635 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| PH1 | 370 | 4.00 | 1.00 | 5.00 | 679.00 | 1.8351 | 0.04818 |
| PH2 | 370 | 4.00 | 1.00 | 5.00 | 760.00 | 2.0541 | 0.05070 |
| PH3 | 370 | 4.00 | 1.00 | 5.00 | 811.00 | 2.1919 | 0.04714 |
| FU1 | 370 | 4.00 | 1.00 | 5.00 | 683.00 | 1.8459 | 0.04689 |
| FU2 | 370 | 4.00 | 1.00 | 5.00 | 705.00 | 1.9054 | 0.04542 |
| FU3 | 370 | 4.00 | 1.00 | 5.00 | 743.00 | 2.0081 | 0.04894 |
| FU4 | 370 | 3.00 | 1.00 | 4.00 | 724.00 | 1.9568 | 0.04341 |
| FU5 | 370 | 4.00 | 1.00 | 5.00 | 701.00 | 1.8946 | 0.04520 |
| SO1 | 370 | 4.00 | 1.00 | 5.00 | 807.00 | 2.1811 | 0.05526 |
| SO2 | 370 | 4.00 | 1.00 | 5.00 | 839.00 | 2.2676 | 0.05589 |
| SO3 | 370 | 4.00 | 1.00 | 5.00 | 867.00 | 2.3432 | 0.06084 |
| SO4 | 370 | 4.00 | 1.00 | 5.00 | 888.00 | 2.4000 | 0.05721 |
| SO5 | 370 | 4.00 | 1.00 | 5.00 | 843.00 | 2.2784 | 0.05601 |
| FI1 | 370 | 4.00 | 1.00 | 5.00 | 744.00 | 2.0108 | 0.04871 |
| FI2 | 370 | 4.00 | 1.00 | 5.00 | 753.00 | 2.0351 | 0.04533 |
| FI3 | 370 | 4.00 | 1.00 | 5.00 | 797.00 | 2.1541 | 0.04482 |
| FI4 | 370 | 4.00 | 1.00 | 5.00 | 743.00 | 2.0081 | 0.04894 |
| TR1 | 370 | 4.00 | 1.00 | 5.00 | 1358.00 | 3.6703 | 0.05505 |
| TR2 | 370 | 4.00 | 1.00 | 5.00 | 1390.00 | 3.7568 | 0.05440 |
| TR3 | 370 | 4.00 | 1.00 | 5.00 | 1343.00 | 3.6297 | 0.05919 |
| TR4 | 370 | 4.00 | 1.00 | 5.00 | 1282.00 | 3.4649 | 0.06243 |
| TR5 | 370 | 4.00 | 1.00 | 5.00 | 1308.00 | 3.5351 | 0.05892 |
| PI1 | 370 | 4.00 | 1.00 | 5.00 | 1412.00 | 3.8162 | 0.05272 |
| PI2 | 370 | 4.00 | 1.00 | 5.00 | 1393.00 | 3.7649 | 0.05576 |
| PI3 | 370 | 4.00 | 1.00 | 5.00 | 1358.00 | 3.6703 | 0.05518 |
| PI4 | 370 | 4.00 | 1.00 | 5.00 | 1349.00 | 3.6459 | 0.05758 |
| PI5 | 370 | 4.00 | 1.00 | 5.00 | 1323.00 | 3.5757 | 0.05919 |
| Valid N (listwise) | 370 | | | | | | |

| | Std. Deviation | Variance | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|
| | Statistic | Statistic | Statistic | Std. Error | Statistic | Std. Error |
| PR1 | 0.90704 | 0.823 | 1.077 | 0.127 | 1.068 | 0.253 |
| PR2 | 0.91967 | 0.846 | 0.857 | 0.127 | 0.212 | 0.253 |
| PR3 | 0.87027 | 0.757 | 0.770 | 0.127 | 0.593 | 0.253 |
| PR4 | 0.89156 | 0.795 | 0.653 | 0.127 | 0.103 | 0.253 |
| PH1 | 0.92678 | 0.859 | 0.991 | 0.127 | 0.507 | 0.253 |
| PH2 | 0.97519 | 0.951 | 0.931 | 0.127 | 0.707 | 0.253 |
| PH3 | 0.90673 | 0.822 | 0.489 | 0.127 | -0.177 | 0.253 |
| FU1 | 0.90200 | 0.814 | 0.776 | 0.127 | -0.133 | 0.253 |

| | | | | | | |
|---|---|---|---|---|---|---|
| FU2 | 0.87372 | 0.763 | 0.700 | 0.127 | -0.138 | 0.253 |
| FU3 | 0.94134 | 0.886 | 0.925 | 0.127 | 0.616 | 0.253 |
| FU4 | 0.83505 | 0.697 | 0.587 | 0.127 | -0.233 | 0.253 |
| FU5 | 0.86937 | 0.756 | 0.927 | 0.127 | 0.962 | 0.253 |
| SO1 | 1.06288 | 1.130 | 0.491 | 0.127 | -0.621 | 0.253 |
| SO2 | 1.07511 | 1.156 | 0.595 | 0.127 | -0.424 | 0.253 |
| SO3 | 1.17033 | 1.370 | 0.662 | 0.127 | -0.417 | 0.253 |
| SO4 | 1.10038 | 1.211 | 0.532 | 0.127 | -0.433 | 0.253 |
| SO5 | 1.07739 | 1.161 | 0.591 | 0.127 | -0.397 | 0.253 |
| FI1 | 0.93698 | 0.878 | 0.932 | 0.127 | 0.662 | 0.253 |
| FI2 | 0.87194 | 0.760 | 0.770 | 0.127 | 0.581 | 0.253 |
| FI3 | 0.86206 | 0.743 | 0.412 | 0.127 | -0.191 | 0.253 |
| FI4 | 0.94134 | 0.886 | 0.925 | 0.127 | 0.616 | 0.253 |
| TR1 | 1.05893 | 1.121 | -0.260 | 0.127 | -0.777 | 0.253 |
| TR2 | 1.04649 | 1.095 | -0.470 | 0.127 | -0.671 | 0.253 |
| TR3 | 1.13848 | 1.296 | -0.467 | 0.127 | -0.614 | 0.253 |
| TR4 | 1.20077 | 1.442 | -0.398 | 0.127 | -0.857 | 0.253 |
| TR5 | 1.13343 | 1.285 | -0.329 | 0.127 | -0.836 | 0.253 |
| PI1 | 1.01413 | 1.028 | -0.440 | 0.127 | -0.590 | 0.253 |
| PI2 | 1.07262 | 1.151 | -0.607 | 0.127 | -0.385 | 0.253 |
| PI3 | 1.06149 | 1.127 | -0.500 | 0.127 | -0.475 | 0.253 |
| PI4 | 1.10752 | 1.227 | -0.421 | 0.127 | -0.784 | 0.253 |
| PI5 | 1.13861 | 1.296 | -0.254 | 0.127 | -0.962 | 0.253 |

## 4.5 Reliability

Based on the table 4.9, the value range of Cronbach's Alpha are in between of 0.655 to 0.894. Although there are two value falls under 0.7 (FU & PH) they are still in the acceptable range (Hair et. al, 2019). Therefore, the data is ready for next step of analysis.

**Table 4.9 Reliability Analysis**

| Variable | Cronbach α | Result |
|---|---|---|
| PR | 0.700 | Good |
| PH | 0.685 | Acceptable |
| FU | 0.655 | Acceptable |
| SO | 0.858 | Very Good |
| FI | 0.734 | Good |
| PI | 0.831 | Very Good |
| TR | 0.894 | Very Good |

*Note*. Source: “Developed for research”. Financial Risk-FI. Functional Risk-FU. Physical Risk-PH. Purchase Intention-PI. Privacy Risk-PR. Social Risk-SO. Trust-TR

## 4.6 Multicollinearity Issues - Variance Inflation Factors (VIF)

In multiple regression analysis, multicollinearity denotes a considerable correlation among predictor variables (Paul, 2006). The goal of regression modelling is to predict the dependent variable based on independent variables, and the presence of multicollinearity can complicate this process (Paul, 2006). Paul (2006) notes that when predictor variables are closely related, it becomes challenging to ascertain the unique impact of each predictor on the dependent variable. This situation can lead to unreliable estimates of regression coefficients, inflated standard errors, and reduced statistical power, ultimately undermining the validity and interpretability of the regression model (Paul, 2006). As shown as table 4.10, eight VIF value of the constructs are below 3.3, only one value exceeded 3.3. According to Kock (2017), a VIF number above 3.3 is generally regarded high and points to a possible collinearity difficulty. Further analysis on the relationship was conducted by using Fornell-Larcker criterion test.

**Table 4.10 Collinearity Assessment**

**Collinearity Statistics - VIF inner model**

| | **FI** | **FU** | **PH** | **PI** | **PR** | **SO** | **TR** |
|---|---|---|---|---|---|---|---|
| **FI** | | | | 3.437 | | | |
| **FU** | | | | 2.721 | | | 1.280 |
| **PH** | | | | 1.541 | | | 1.536 |
| **PI** | | | | | | | |
| **PR** | | | | 1.954 | | | 1.437 |
| **SO** | | | | 1.519 | | | |
| **TR** | | | | 1.485 | | | |

## 4.7 Inferential Analysis

SmartPLS 4.0 PLS-SEM model has been used by analysing relationships between the constructs. The PLS-SEM algorithm uses a series of regression analyses to calculate latent factor scores, which are then used to compute path coefficients and other model parameters (Hair et al., 2024).

### 4.7.1 Measurement Model Analysis

Convergent and discriminant validity of the measurement models were used to ensure construct validity in this study. Convergent validity determines co-relationships of numerous indicators of a construct, as shown by an Average Variance Extracted (AVE), when AVE is greater than 0.50 the co-relationship of indicators is considered strong. Discriminant validity investigates the extent to which a construct differs from other constructs in the model, and is often assessed using the Fornell-Larcker criterion, and cross-loading. These validity tests are critical for establishing precise and unique construct measurements, which improves the reliability and validity of SEM study findings (Amora, 2021).

### 4.7.2 Factor Loading

Factor loading is an important term in Structural Equation Modelling (SEM) since it represents the link across observed variables (indicators) and their underlying latent components. It is essentially the relationship between an indicator and the factor it represents, demonstrating how well the indicator measures the construct. A factor loading greater than 0.70 is generally deemed satisfactory, indicating that the indicator explains a considerable percentage of the variance in the latent variable. However, loadings below this number but close to it may not require removal, only indicators that have much lower value need to be removed (Rick, 2023). In the study, FU1 (0.370) and FI3(0.437) have been removed due to the low loadings. Average Variance Extracted (AVE) and Composite Reliability (CR) in the research are all above the requirement of above 0.5 and 0.7, as shown in table 4.11. These results shown that the constructs have achieved convergent validity.

Table 4.11 Construct Validity Test

| | Cronbach's alpha | Composite reliability (CR) | Average variance extracted (AVE) |
|---|---|---|---|
| **PR** | 0.700 | 0.805 | 0.511 |
| **PH** | 0.685 | 0.819 | 0.605 |
| **FU** | 0.655 | 0.803 | 0.579 |
| **SO** | 0.858 | 0.898 | 0.639 |
| **FI** | 0.734 | 0.850 | 0.657 |
| **PI** | 0.831 | 0.881 | 0.598 |
| **TR** | 0.894 | 0.922 | 0.704 |

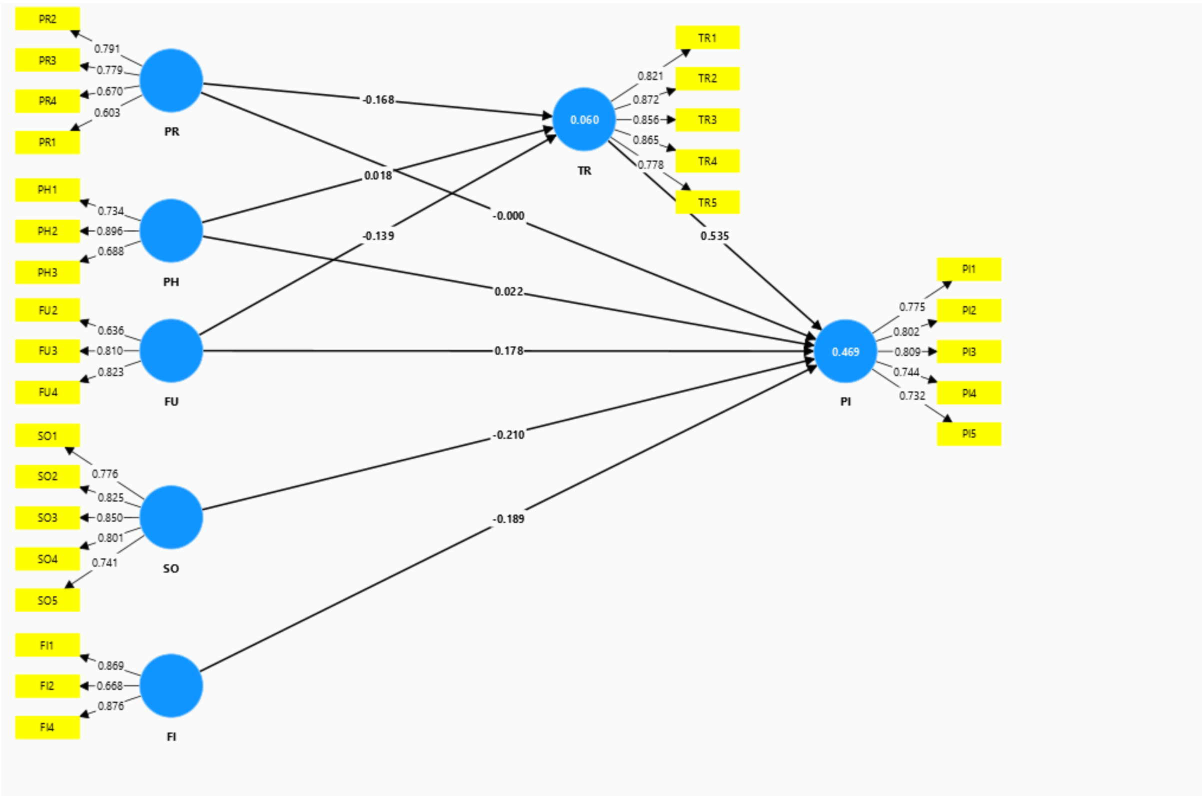


**Figure4.1 Measurement Model**

Figure 4.1 above shown the factor loadings of the items and the coefficient values of the relationships between the constructs.

## 4.7.3 Discriminant Validity

The Fornell-Larcker criterion is a common method for determining discriminant validity in SEM. It states that a construct should have greater variance with its own indicators than with any other construct in the model. To use it, compute the average variance extracted (AVE) for each construct and make sure that the square root of each construct's AVE exceeds its maximum correlation with any other construct. Table 4.12 shown the Fornell-Larcker criterion of the constructs of study. The results shown that AVE of all constructs are higher than the correlation with other constructs and therefore achieved the required discriminant validity.

**Table 4.12 Fornell-Larcker Criterion**

| | FI | FU | PH | PI | PR | SO | TR |
|---|---|---|---|---|---|---|---|
| **FI** | **0.810** | | | | | | |
| **FU** | 0.770 | **0.761** | | | | | |
| **PH** | 0.465 | 0.439 | **0.778** | | | | |
| **PI** | -0.187 | -0.108 | -0.099 | **0.773** | | | |
| **PR** | 0.601 | 0.370 | 0.530 | -0.198 | **0.715** | | |
| **SO** | 0.209 | 0.225 | 0.196 | -0.507 | 0.237 | **0.800** | |
| **TR** | -0.190 | -0.193 | -0.132 | 0.652 | -0.210 | -0.563 | **0.839** |

## 4.7.4 Structural Model Analysis

Hair et al. (2021) suggested a resample of 5,000 to analyse beta coefficients, t and p-values, $R^2$ values, effect sizes ($f^2$), and predictive relevance ($Q^2$). This method is effective for evaluating the predictive capacity of a model and determining the importance and degree of variable correlations. The similar methodology was used in this study. Table 4.7 displays the path coefficients, standard deviation, t-values, p-values for each hypothesis evaluated in the study. The t-values show the significance and direction of the correlations between variables under examination. The study employed p-values <0.05 to identify significant connections.

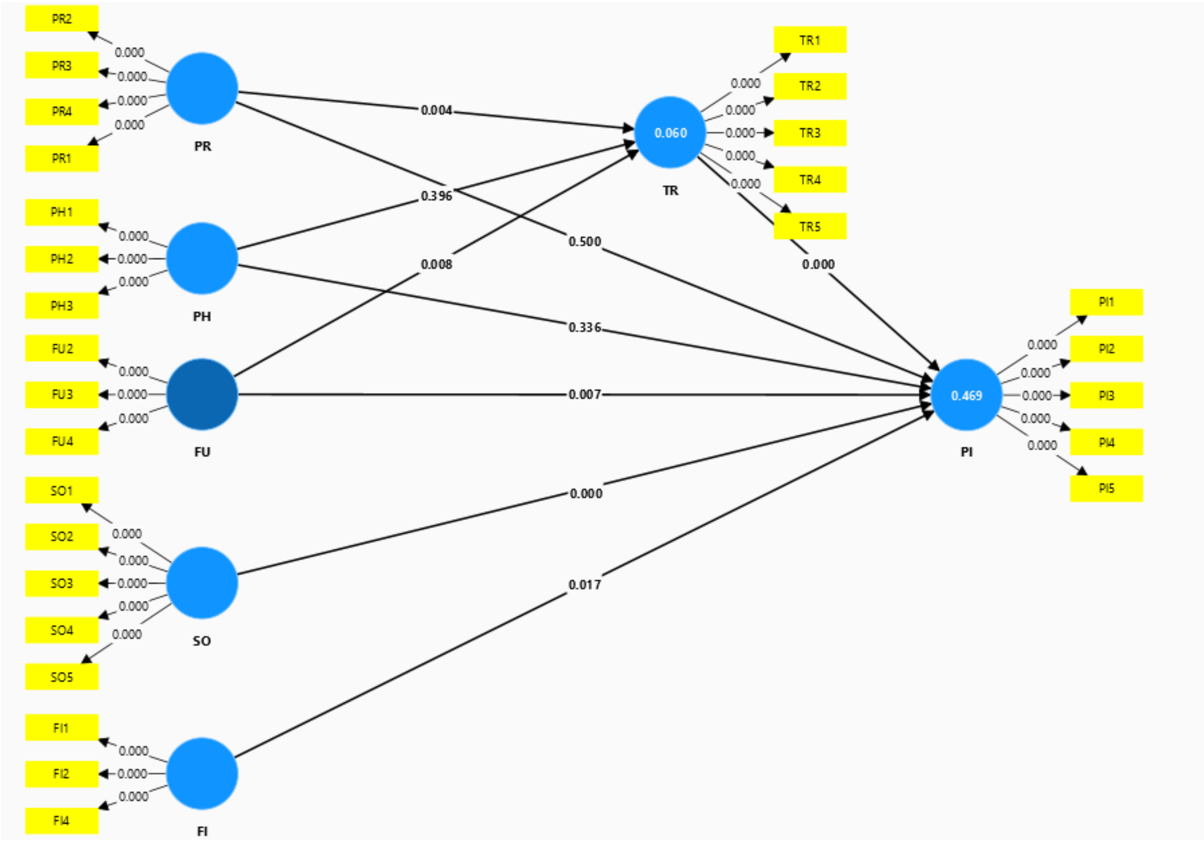


**Figure 4.2 The Structural Model and the Respective Path Coefficients**

## 4.8 Direct Effect (Hypothesis Testing)

In structural equation modelling, direct effect refers to the direct relationship between two variables under examination. It reflects the link between predictors (IVs) and outcomes (DVs) in the absence of any mediating factors. In structural modelling, route coefficients (β) predict direct influence. Bootstrapping is used to determine whether a direct effect is significant or not. Since our hypotheses are directional, so one-tail test has been applied in this study.

The interpretation of hypotheses' result is important in helping researchers to understand the significance of relationship. The present significance level for the p-value is set at 0.05. If the P-value exceeds 0.05, the relationship between constructs is considered insignificant by statistics. If the P-value is less than 0.05, the relationship or effect is considered statistically significant. The study tested hypotheses using a p-value ($P < 0.05$).

**Hypothesis 1A: PR have negative impact on PI**

The result of test showing that it is a non-significant relationship and negative impact of PR on PI as the p value (0.500) is more than 0.05. In conclusion, the hypothesis is not supported.

**Hypothesis 1B: PR have negative impact on TR**

The result of test showing that there is a significant and negative impact of PR on TR as the p value (0.004) is lesser than 0.05. In conclusion, the hypothesis is supported.

**Hypothesis 2A: PH have negative impact on PI**

The result of test showing that there is a non-significant and negative impact of PH on PI as the p value (0.336) is more than 0.05. In conclusion, the hypothesis is not supported.

**Hypothesis 2B: PH have negative impact on TR**

The result of test showing that there is a non-significant and negative impact of PH on TR as the p value (0.396) is more than 0.05. In conclusion, the hypothesis is not supported.

**Hypothesis 3A: FU have negative impact on PI**

The result of test showing that there is a significant impact of FU on PI as the p value (0.007) is lesser than 0.05. However, the relationship was positive when the $\beta$ value is +0.178, therefore this hypothesis is not supported.

**Hypothesis 3B: FU have negative impact on TR**

The result of test showing that there is a significant and negative impact of FU on TR as the p value (0.008) is lesser than 0.05. In conclusion, the hypothesis is supported.

**Hypothesis 4: SO have negative impact on PI**

The result of test showing that there is a significant and negative impact of SO on PI as the p value (0.000) is lesser than 0.05. In conclusion, the hypothesis is supported.

**Hypothesis 5: FI have negative impact on PI**

The result of test showing that there is a significant and negative impact of FI on PI as the p value (0.017) is lesser than 0.05. In conclusion, the hypothesis is supported.

**Hypothesis 6: TR have positive impact on PI**

The result of test showing that there is a significant and positive impact of TR on PI as the p value (0.000) is lesser than 0.05. In conclusion, the hypothesis is supported.

**Table 4.13 Direct Effect Hypothesis Testing**

| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values | Decision |
|---|---|---|---|---|---|---|
| **H1 PR -> PI** | -0.000 | -0.007 | 0.061 | 0.001 | 0.500 | Not Supported |
| **H2 PH -> PI** | 0.022 | 0.020 | 0.053 | 0.424 | 0.336 | Not Supported |
| **H3 FU -> PI** | 0.178 | 0.170 | 0.072 | 2.469 | **0.007** | Not Supported Due to positive relationship |
| **H3 SO -> PI** | -0.210 | -0.210 | 0.056 | 3.748 | **0.000** | Supported |
| **H5 FI -> PI** | -0.189 | -0.179 | 0.089 | 2.115 | **0.017** | Supported |
| **H6 TR -> PI** | 0.535 | 0.539 | 0.058 | 9.293 | **0.000** | Supported |
| **H1A PR ->TR** | -0.168 | -0.173 | 0.064 | 2.643 | **0.004** | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | | | Supported |
| **H2A PH ->TR** | 0.018 | 0.004 | 0.067 | 0.263 | 0.396 | Not Supported |
| **H3A FU ->TR** | -0.139 | -0.144 | 0.058 | 2.405 | **0.008** | Supported |

## 4.9 Indirect Effect /Mediation Analysis

Bootstrapping in SmartPLS is applied to assess the significance of indirect effects. The confidence intervals for the path coefficients and standard errors are computed by resampling the data using SmartPLS bootstrapping. Bootstrapping calculates t-values, and a t-value greater than 1.96 (at 95% confidence level) indicates a statistically significant indirect impact. For one-tail, the t-value must be greater than 1.645, while for two-tail, it should be greater than 1.96. The P-value is also included when calculating the indirect effect. An indirect impact is considered significant if $p > 0.05$ and if $p < 0.05$ is insignificant. The study's hypotheses were directional; hence a one-tail test was chosen during bootstrapping.

**Hypothesis 6A: TR mediates the relationship between PR and PI.**

The result shows that TR mediates the relationship between PR and PI, with a p-value of less than 0.05 and a $\beta$ value of -0.090. This shows that the relationship is negative and is statistically significant. Thus, the hypothesis is supported.

**Hypothesis 6B: TR mediates the relationship between FU and PI.**

The result shows that TR mediates the relationship between FU and PI, with a p-value of less than 0.05 a $\beta$ value of -0.074. This shows that the relationship is negative and is statistically significant. Thus, the hypothesis is supported.

**Hypothesis 6C: TR mediates the relationship between PH and PI.**

The result shows that TR did not mediates the relationship between PH and PI, with a p-value of more than 0.05. This shows that the outcome is non- significant. Thus, the hypothesis is not supported.

**Table 4.14 Indirect Effect/Mediation Analysis**

| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values | Decision |
|---|---|---|---|---|---|---|
| **PR >TR> PI** | -0.090 | -0.093 | 0.036 | 2.466 | 0.007 | Supported |
| **FU >TR> PI** | -0.074 | -0.078 | 0.033 | 2.268 | 0.012 | Supported |
| **PH >TR> PI** | 0.009 | 0.003 | 0.037 | 0.259 | 0.398 | Not Supported |

## 4.10 R-Square ($R^2$)

The R-Square ($R^2$) value is an important metric in PLS-SEM, indicating how much of the variance in the endogenous construct can be explained by the exogenous constructs. $R^2$ values vary from 0 to 1, and higher values indicate more explanatory power. $R^2$ values can be interpreted differently depending on the study environment. For example, values of 0.75, 0.50, and 0.25 are typically considered significant, moderate, and weak, respectively. According to Falk and Miller (1992), a $R^2$ value of at least 0.10 is considered appropriate for explaining the variation of an endogenous construct. Table 4.15 shown that $R^2$ for PI is 0.469 and TR is 0.060. Which means that PI was 46.9% predicted by the exogenous constructs but TR was only 6% predicted.

**Table 4.15 $R^2$ and $R^2$ Adjusted Value**

| | R-square | R-square adjusted |
|---|---|---|
| **PI** | 0.469 | 0.460 |
| **TR** | 0.060 | 0.052 |

## 4.11 Effect Size ($f^2$)

F-Square ($f^2$) is a key statistic in PLS-SEM that evaluates the impact of an exogenous variable on an endogenous variable. It measures the change in R-Square ($R^2$) after removing an exogenous variable from the model. This enables researchers to assess the impact of individual predictors on the entire model. Cohen's recommendations are followed when interpreting $f^2$ values: 0.02 indicates a tiny effect size, 0.15 represents a medium effect size, and 0.35 indicates a big impact size. As shown in table 4.16, TR have the largest effect size on PI, while So, FI and FU have minimum effect on PI. Lastly PR have minimum effect on TR too.

**Table 4.16 $F^2$ -Effect Size**

| | FI | FU | PH | PI | PR | SO | TR |
|---|---|---|---|---|---|---|---|
| **FI** | | | | 0.020 | | | |
| **FU** | | | | 0.022 | | | 0.016 |
| **PH** | | | | 0.001 | | | 0.000 |
| **PI** | | | | | | | |
| **PR** | | | | 0.000 | | | 0.021 |
| **SO** | | | | 0.055 | | | |
| **TR** | | | | 0.363 | | | |

## 4.12 Conclusion

In a nutshell, Average Variance Extracted (AVE) and Composite Reliability (CR) in the research are reaching the requirement of above 0.5 and 0.7, as shown at table 4.4. The relationship of FU, SO, FI and TR with PI is significant and result show that TR could mediate the relationship between PR to PI and FU to PI. While for PH to PI, TR does not show mediating effect.

# CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATIONS

## 5.0. Introduction

This chapter provides the key findings in connection to the research goals. The final section looks at theoretical and managerial implications to evaluate the findings complement existing theories and may be implemented in real-world management scenarios. In addition, the study's limitations were addressed, including any constraints that may have influenced the results and their generalisability. Finally, the chapter includes recommendations for future research, highlighting areas where future research might build on present work to improve knowledge and address any unanswered concerns.

## 5.1. Discussions of Major Finding

**H1A: Privacy Risk has a negative influence on purchase intention of autonomous vehicle (AVs)**

According to table 4.14, the p-value of privacy risk (PR) on purchase intention (PI) is 0.5 and it is more than 0.05, therefore, the hypothesis is not supported. This result indicates that privacy risk does not has any effects on purchase intention of Gen X on autonomous vehicles (AVs). Although Lee & Hess (2022), mentioned that privacy risk has negative effects on consumer purchase intention and Liao, Guo & Liu (2023) said that consumer have more privacy concern, such as on data leakages. But after analysis, Gen X in Malaysia might not care much about privacy risk as now all cookies' trackers are tracking our activities online.

**H1B: Privacy Risk has a negative influence on Trust**

As shown at table 4.14, the p-value of privacy risk to trust (TR) is less than 0.05, therefore the hypothesis has been accepted. It shows that PR have effect on TR with a negative relationship being supported. Similar with the research from YU & Cai (2022), researchers have demonstrated that perceived privacy risk has negative effects on consumers' trust in autonomous vehicles. In addition, based on the finding from Iranmanesh et al. (2023), if privacy problem occurs, it will affect the trust of consumers towards autonomous vehicle.

**H2A: Physical Risk has a negative influence on purchase intention of autonomous vehicle (AVs)**

The p-value of physical risk on PI is 0.336 and it is exceeding value 0.05, therefore there it has no effect on purchase intention of autonomous vehicle. Even though the past studies from Ho et al. (2023) mentioned that customers may have questions about how safely to use Avs. Besides, researchers mentioned that autonomous vehicle sensors, which can be confusing and perhaps dangerous, is known as the main issue of the autonomous driving safety issue, if consumer want to avoid this issue that can cause physical risk, they won’t purchase it (Wang et al., 2022). PH didn’t show significant effect on PI mainly due to there is not much physical risk different between conventional vehicle and autonomous vehicle, therefore it didn’t show any effect on PI.

**H2B: Physical Risk has a negative influence on Trust**

Based on the analysis from table 4.14, the p-value of physical risk on trust is 0.396, this shown that physical risk does not has effect on trust. Although it was shown that physical risk reduces consumers' trust in autonomous vehicles (Yu & Cai, 2022). Moreover, based on the finding of Naiseh et al. (2024), if the perceived physical risk occur it will affect the trust of consumer, the result in this study is inconsistent with the finding of the researchers. PH didn’t show significant effect on TR mainly due to there is not much physical different between conventional vehicle and autonomous vehicle, therefore there won’t be any effect on TR. Further, Chancey et al. (2016), mentioned that mediation analysis depends on the level of physical risk, if the risk level is high, it will affect the trust, but if the consumers assume that the risk level is low, it won’t affect the trust. In short, the level of risk is different for each respondent, some of them will take PH into account but some of them will not, it depends on the level of risk that they feel and evaluated by themselves.

**H3A: Functional Risk has a negative influence on purchase intention of autonomous vehicle (AVs)**

With the p-value of functional risk lower than 0.05 but β value is +0.178, this shows FU has a significant positive influence on purchase intention of autonomous vehicle, this result is not supported. This result is inconsistent with the finding of Topolsek et al. (2020), who said that consumers that relying on the function in autonomous vehicle like auto brake system and others might worry about functional risk. Besides, software fault causes an autonomous disengagement or crash had effect the PI of consumer towards Avs (Betz et al., 2019). Based on the finding from Yang et al. (2017), safety case on road vehicle functional security criteria is necessary to prove that the automobile has low malfunctioning and dependable for driving. As an instance, the LUTZ pathfinder automated vehicle established a feasible safety case utilising the FEMA technique in the vehicle, moreover, they also include a modified application of the ISO26262 automotive functional safety requirement, this action is to make sure that their consumers no need to worry about the risk of malfunction towards the AVs and avoid the AVs fail to perform or perform under the consumers' expectation. The possible explanation for this positive finding against the hypothesized negative relationship may be due to the AV now has good functioning features and is no longer a concern for the respondents.

**H3B: Functional Risk has a negative influence on trust**

The relationship of functional risk negatively impacts on trust been accepted due to the p-value is 0.008. This is same with the result of Kenesei et al. (2022), functional risk, which refers to the technology's performance and reliability, may generate concerns about trust in autonomous vehicles, such as the reliability of auto emergency brake. Furthermore, based on the research of Zheng & Gao (2021), consumer scare about the perceived risk especially functional risk, they will lose their trust on autonomous vehicle if functional risk occurs.

**H4: Social Risk has a negative influence on purchase intention of autonomous vehicle (AVs)**

The result of p-value in table 4.14 shown that social risk has a value of 0.000 which is significant. This result shown that SO has negative influence on purchase intention. As parallel with the findings of Topolsek et al. (2020), people might scare about the substantial impact from the family members or friends around them who feel that buying Avs is a bad decision. Not only that, the perceived risk of autonomous vehicles is commonly influenced by social amplification of risk, resulting in an emotive rather than rational impression. People who are terrified of social dilemmas or judgement from third parties will not purchase Avs (Nasiseh et al., 2024).

**H5: Financial Risk has a negative influence on purchase intention of autonomous vehicle (AVs)**

As shown in table 4.14, p-value of financial risk is 0.017, this indicates that financial risk has significant impact on purchase intention. Same as the study from Topolsek et al. (2020), consumer worry about the potential expenses connected with accidents, repairing issue, or other unforeseen incidents that incur by autonomous vehicle. Apart from this, Russell (2023) shows that the cost of repairing autonomous vehicles are more expensive compared with conventional vehicles. So, consumer who wish to avoid extra expenses will choose to buy conventional vehicle rather than autonomous vehicle.

**H6: Trust has a positive influence on purchase intention of autonomous vehicle (AVs)**

In table 4.14, the p-value of trust is 0.000, hence it has positive impact on purchase intention, in simple words, when the trust is higher the purchase intention will be higher too. The result is parallel with the finding of Hurst & Sintov (2022), increased trust in autonomous vehicle technology has a positive impact on adoption intentions, regardless of other influencing factors. Besides, Zhang et al. (2019), mentioned that trust is the most crucial component that influences consumer purchasing intention of Avs. The researchers also found that the high level of trust will make consumer to try new things such as the autonomous vehicle (Wang et al., 2023)

**H6a: Trust mediates the relationships between privacy risk and Generation X purchase intention on autonomous vehicle (AVs)**

Trust shows a mediation effect in the relationship between privacy risk and Generation X purchase intention on autonomous vehicle (AVs), the p-value of privacy risk to purchase intention is 0.007, which is significant. As mentioned before by Anastasopoulou et al. (2018), some consumers will be sceptical of autonomous vehicles because they are concerned about privacy. Furthermore, the leaking data problem may lead to cynicism about the safety and reliability of AV technology in preserving consumer data, eventually reducing their trust. In addition, when the consumers faced privacy problem, their trust will decrease thus they will not purchase the Avs (Zhang et al., 2019). Lastly, based on the finding of Naiseh et al. (2024), people nowadays worry about how their data been collected, saved or used, if the privacy problem exist, it will affect the trust and thus the purchase intention.

**H6b: Trust mediates the relationships between functional risks and Generation X purchase intention on autonomous vehicle (AVs)**

As shown in table 4.15, the p-value of functional risk on purchase intention mediates by trust is 0.012. Referring to the research, consumer trust in autonomous vehicles is strongly influenced by perceived functional threats (Kenesei et al., 2022). Furthermore, when the functional risk is large, consumers will lose trust in the technology, which will have a negative impact on their purchase intention (Topolsek et al., 2020). The combination of functional risk and trust has a direct impact on individuals' decisions to purchase an autonomous vehicle. Consumers are more likely to invest in technology when they believe it will perform as advertised. When consumers have reservations about the vehicle's functionality or security features, their purchasing intention diminishes (Ho et al., 2023). The result is parallel with the studies.

**H6c: Trust mediates the relationships between physical risks and Generation X purchase intention on autonomous vehicle (AVs)**

The p-value of physical risk on purchase intention mediates by trust is 0.398. The value is greater than the value 0.05 and therefore this hypothesis is not supported. Although according to Naiseh et al. (2024), when consumers assume a high amount of danger, it affects their trust level, resulting in poor purchase intentions. Apart from this, user concerns about the vehicle's ability to keep the user safe in a variety of demanding driving conditions may undermine trust. For example, if customers apprehensive that an AV will fail to detect and respond to an emergency scenario, consumer trust will decline (Jing et al., 2020). Not only that, if there are ambiguities about the autonomous vehicle's advanced sensors or software that pose a physical risk, potential buyers may be hesitant to believe that Avs would work appropriately under any conditions to ensure passenger safety (Adnan et al., 2018). Next, according to the researchers, they observed that the error-proneness of automation that might cause physical integrity had an impact on people's trust level, but in term of subjective trust, it did not show mediation effect (Hoesterey et al., 2022).  As summarize, the mediation of trust to physical risk and purchase is not significant due to the subjective trust is different for every single individual.

## 5.2 Implications of the Study

### 5.2.1 Theoretical Implications

This study adopts Bauer's (1960) perceived risk theory framework to explore the impact of risk perception on the purchase intention of autonomous vehicles among Malaysian Generation X by studying six exogenous constructs (privacy risk, physical risk, functional risk, social risk, financial risk, and trust). These six constructs can predict personal purchase intention and influence the purchase intention of Malaysian Generation X for autonomous vehicles. Among the six constructs, privacy risk, functional risk, and physical risk are negatively correlated with trust. As risk increases, trust will decrease; while trust has a positive relationship with purchase intention. However, social risk and financial risk have a direct impact on PI.

The framework proposed in this study can provide a reference for other researchers who intend to explore related research in the future. In addition, the data analysis revealed the main characteristics that activate PI, allowing industry players, notably automakers and technology developers to further study the industry development.

### 5.2.2 Managerial Implications

From a managerial standpoint, this study is useful for automotive manufacturers, marketers, and politicians who want to encourage the use of autonomous vehicles among Malaysia's Generation X population. Privacy risks has a negative impact on trust. Especially for personal data, Malaysian Generation X consumers may be particularly sensitive to data privacy issues, and they may worry that their driving habits or personal information may be misused or not adequately protected. For example, some autonomous vehicle users may accidentally leak their personal privacy data, causing disruption and impact on their lives. In this case, consumers may ask for a refund or any other compensation, which is more likely to erode trust and have a negative impact on purchase intention. Therefore, in order to address privacy issues, manufacturers must implement and clearly communicate strong data protection measures and adopt advanced encryption technology to protect users' personal data. Consumers may ensure that they recognise how their data is processed by implementing transparent privacy rules that describe how data is collected, utilised, kept, and shared. This can increase consumer trust in businesses and alleviate fears about privacy breaches. In addition, sellers can increase consumers' understanding and awareness of privacy protection in autonomous vehicles by holding consumer education activities. By explaining data protection measures and privacy management functions, consumers' misunderstandings and concerns can be eliminated, which will help build trust.

Functional risk identified as the main obstacle, it shows the relationship between functional risk and the willingness of Malaysian Generation X to purchase autonomous vehicles. This type of consumers has great concerns about the reliability and actual performance of new technologies. For example, in sudden bad weather conditions (such as heavy rain or dense fog), can the self-driving system correctly identify road signs and surrounding environment to avoid accidents. For Generation X, they are accustomed to traditional driving methods, when faced with brand-new self-driving technology, they often question whether it can operate stably under various road conditions and emergencies. In the face of these situations, sellers can show consumers the performance of self-driving vehicles in various environments by organizing actual operation demonstrations and test drives. This includes bad weather conditions, congested traffic environments, etc., to help consumers experience the functionality and reliability of the vehicle with their own eyes and enhance their confidence. In addition, sellers should provide detailed technical information and functional descriptions to explain to the potential buyers the working principle, core technology, and response mechanism of the self-driving system in different scenarios. By providing transparent information, consumers' fear of unknown technologies can be reduced. Sellers can also obtain reliable functional safety certifications by working with independent third-party safety certification agencies. These certifications can help consumers confirm the performance of self-driving vehicles has been rigorously tested and verified and is a trustworthy product.

In addition to functional risks, social risks negatively impact autonomous vehicle (AV) purchase intentions. Social risk, or fear of social judgment or negative perception by others, may deter consumers from purchasing AVs. Gen Xers may worry that adopting this advanced technology may be viewed as risky or eccentric by their peers, leading to social alienation. For example, consumers may worry about being perceived as overly dependent on technology or unable to control the vehicle in an emergency, which may exacerbate this risk. To address social risk, marketing strategies should focus on normalizing AV by using and leveraging social proof by highlighting testimonials from early adopters. This may also involve campaigns featuring testimonials from respected figures or influencers within the community that have adopted the technology. Marketing campaigns should focus on the positive impacts of AVs on society, such as fewer traffic accidents and lower carbon emissions, to align the product with socially desired outcomes. Additionally, promoting AV ownership as a forward-thinking and environmentally responsible choice can help shift social perceptions in a positive way. Creating community events where AV owners and potential buyers can interact and share experiences can also reduce social risk by fostering a sense of belonging among early adopters.

Understandably, financial risk is one of the main barriers of Generation X in Malaysia regarding their willingness to purchase autonomous vehicles. Autonomous vehicles are typically more expensive than ordinary vehicles, particularly during the introduction of new technologies. Generation X is in the middle to late phases of their professions, and they may confront financial challenges in education of their children, retirement, and health care. The high purchase price makes people more cautious when evaluating the purchase, as they are concerned about a low return on investment or a car that depreciates too rapidly. In addition, consumers may also understand that the price of this car is much higher than that of traditional cars, and they are worried about the subsequent maintenance costs, software update fees, and even the repair costs caused by possible unexpected failures or accidents, which will increase additional expenses. For Generation X, they often need to balance family expenses and retirement planning, so they are particularly sensitive to financial risks. To alleviate clients' financial burdens, vendors might provide a number of flexible financing and lending choices, such as minimal down payments, instalment payments, or zero-interest loan programs. This allows consumers to more easily fit the purchase of self-driving automobiles into their budgets. Sellers can also offer extended warranties or maintenance packages included in the price. These measures can protect consumers from high repair costs when problems arise with their vehicles, thereby reducing financial risks and increasing their willingness to purchase autonomous vehicles.

Beyond that, trust has a positive impact on purchase intention. Trust in autonomous car technology and companies is critical for influencing purchasing intentions. Consumers are more inclined to contemplate a purchase if they feel the vehicle is safe, dependable, and supported by a reputable firm. For example, if Gen X customers feel a company has a strong track record of car safety and innovation, they are more inclined to trust its autonomous vehicle options. As a result, gaining client trust necessitates continual communication and demonstration of autonomous vehicles' safety and reliability. Companies should prioritise openness, particularly in terms of data protection, car safety regulations, and consumer feedback. In addition, autonomous car makers may boost their reputation by forming alliances with reputable third-party safety certification organisations. Continuously teaching customers about the benefits and safety aspects of self-driving cars through seminars, workshops, and digital information may assist to create trust and confidence.

Furthermore, trust mediates the link between privacy risks and purchase intention, implying that even when privacy risk exists, high levels of trust might minimise its detrimental influence on purchase intention. However, if confidence is low, privacy concerns become a big obstacle. Corporations should take a proactive approach on privacy management in order to boost customer trust and reduce the effect of privacy breaches. This strategy includes explicitly disclosing data policies, providing customers control over their data, and responding rapidly to privacy concerns. These measures can help build a solid foundation of trust between customers, salespeople and autonomous vehicle manufacturers, which can reduce the negative impact of privacy risk on purchase intention.

Besides, research indicate that functional risk erodes consumer confidence in autonomous vehicles in addition to having a direct impact on purchase intention. Customers' desire to buy autonomous vehicles may decline if they think the technology and manufacturers may fail, which will erode their faith in the system. Manufacturers must exhibit the dependability and robustness of their technology through certification, impartial evaluations, and open performance metric reporting in order to address this problem. Educating customers on the redundancy and fault protection included in the system may also contribute to a sense of trust. Offering longer warranties and post-purchase assistance can further comfort customers about the vehicle's functional dependability.

Lastly, a mediating component between functional risk, privacy risk, and purchase intention is trust. This implies that even in cases when customers view risk as high, they may still be inclined to buy an AV provided they have a high degree of faith in both the maker and the technology. Building and sustaining trust should be a top priority for manufacturers at every point of the customer experience, given the mediating role that trust plays. This might entail providing trial periods or satisfaction guarantees, keeping up a high standard of client service, and aggressively disclosing risk mitigation strategies. Furthermore, using independent certifications and ratings, like safety scores or data privacy certifications, can boost confidence and lessen the adverse effects of perceived risk.

## 5.3 Limitations of the Study

While this study sheds light on factors that influence AV purchase intention among Generation X in Malaysia, several limitations must be recognized. First, this study focused only on Generation X (44 to 55 years old), ignoring other age groups such as Millennials (28 to 43 years old) and Generation Z (12 to 27 years old), who may have different risk perceptions and circumstances that influence their purchase intentions. Future research may examine these changes to gain a more complete understanding of consumer behaviour across generations.

Second, self-reported data were used in this investigation. This method is widely used in behavioural research, however bias is always existed. In addition to recall bias—where participants have partial recollections of prior events or attitudes that may lead to inaccuracies—respondents may answer questions in ways that they believe to be more socially acceptable. Social desirability bias falls under this category.

Additionally, if autonomous vehicle technology develops fast, customer perceptions and market dynamics will very certainly change as well. Because of this changing context, the study's conclusions might become out of date when new legal frameworks, technical advancements, and societal perspectives arise. As a result, the insights offered in this work could only be useful for a short time, and further research is required to stay up to date with these advancements.

Lastly, although perceived risk is highlighted in this study, this might mask other significant variables that affect purchase intention. This study may not adequately reflect the potential advantages of AVs, such as increased safety, convenience, and environmental sustainability, because it largely focusses on the drawbacks of AV adoption, such as functional, social, financial, and privacy issues. A more thorough knowledge of consumers' decision-making processes may be obtained by a more balanced examination of risks and rewards.

## 5.4 Recommendations for Future Research

A number of recommendations for further study are made in light of the findings and limitations. First and foremost, it is imperative to broaden the study's reach in order to include a more varied sample. Other generational groups, including millennials and Generation Z, may view risks differently and accept technology differently, so future studies should take that into account. Furthermore, cross-cultural comparisons can offer insightful information on how cultural variations impact risk perception and purchase intention, offering a more global viewpoint on the adoption of autonomous vehicles.

To supplement self-reported data, future research could employ experimental or observational methods. These methods would provide more objective measures of consumer behavior, potentially reducing the impact of bias associated with self-reporting. For example, experiments could simulate the driving experience of an AV to observe consumers’ real-time reactions, while observational studies could track actual purchasing behavior across different market segments.

Additionally, as AV technology develops, it is crucial to do continuing research to comprehend new discoveries and how they affect customer perceptions of danger and trust. The elements influencing the attitudes and actions of consumers will change along with technology. To guarantee that findings stay pertinent and useful, future research should proactively anticipate new trends, such as modifications to regulatory laws, advancements in technology, and shifts in public opinion.

Researchers and business stakeholders may also learn a lot by looking at how new risks—like cybersecurity threats—affect consumer trust and buying intentions. Additional investigation may also look at how different management strategies affect people's perceptions of risk and their level of trust in AV technology, leading to useful suggestions for regulators and manufacturers.

## 5.5 Conclusion

In conclusion, this study highlights the intricate relationships between various hazards and trust, offering significant insights into the variables influencing Malaysian Generation X's desire to purchase autonomous vehicles. The results imply that social and financial risks are just as important as privacy, physical, and functional hazards in influencing trust and purchase intention. A crucial mediating component that appears to be important is trust, and higher levels of trust may lessen the negative impacts of perceived risk. The study's conclusions imply that in order to build trust and promote adoption, automakers and marketers should concentrate on enhancing functional dependability, resolving problems with social cognition, and guaranteeing financial accessibility.

## References

Abu Bakar, A. I., Abas, M. A., Muhamad Said, M. F., & Tengku Azhar, T. A. (2022). Synthesis of Autonomous Vehicle Guideline for Public Road-Testing Sustainability. *Sustainability*, *14*(3), 1456. https://doi.org/10.3390/su14031456

Adam Aubrey. (2022). *PDRM Bans Hands-free Autopilot Systems In Malaysia - Auto News | Carlist.my*. Carlist.my - Malaysia's No.1 Car Site; Carlist.my. https://www.carlist.my/news/pdrm-bans-hands-free-autopilot-systems-in-malaysia-89195/89195

Adams, J., & Almahmoud, H. (2023). The Meaning of Privacy in the Digital Era. *International Journal of Security and Privacy in Pervasive Computing*, *15*(1), 1–15. https://doi.org/10.4018/ijsppc.318675

Adnan, N., Md Nordin, S., bin Bahruddin, M. A., & Ali, M. (2018). How trust can drive forward the user acceptance to the technology? In-vehicle technology for autonomous vehicle. *Transportation Research Part A: Policy and Practice*, *118*, 819–836. https://doi.org/10.1016/j.tra.2018.10.019

Agmeka, F., Wathoni, R. N., & Santoso, A. S. (2019). The Influence of Discount Framing towards Brand Reputation and Brand Image on Purchase Intention and Actual Behaviour in e-commerce. *Procedia Computer Science*, *161*, 851–858. https://doi.org/10.1016/j.procs.2019.11.192

Ahmad, H. b, & Halim, H. b. (2017). *Determining Sample Size for Research Activities: The Case of Organizational Research. Selangor Business Review, 2(1), 20-34.*

Akhtar, I. (2016, February 1). *AkhtarResearch Design. Research in Social Science: Interdisciplinary Perspectives, 68-84.*

Ali, M. N., & Ahmad, A. (2020). *Mobilizing workforce management for Gen-X: The challenges of new baby boomers in Malaysia. Home Health Care Services Quarterly. 10. 67-73.*

Amora, J. T. (2021). *Convergent validity assessment in PLS-SEM: A loadings-driven approach*. https://www.researchgate.net/publication/351984581_Convergent_validity_assessment_in_PLS-SEM_A_loadings-driven_approach

Anastasopoulou, K., Williams, E., Whitnall, C., Tryfonas, T., Oswald, E., Morgan, P., Voinescu, A., Piechocki, R., & Tassi, A. (2018). Effects of privacy risk perception and cultural bias on intention of connected autonomous vehicle use. *Proceedings of the 8th Workshop on Socio-Technical Aspects in Security and Trust*. https://doi.org/10.1145/3361331.3361336

Arrow, K. (1950). *A DIFFICULTY IN THE CONCEPT OF SOCIAL WELFARE. Journal of Political Economy, 58(4), 328.*

Ashoer, M., & Said, S. (2016). *The Impact of Perceived Risk on Consumer Purchase Intention in Indonesia; A Social Commerce Study. Proceedings of the International Conference on Accounting, Management, Economics and Social Sciences (ICAMESS), 1-13.*

Banks, V. A., Plant, K. L., & Stanton, N. A. (2018). Driver error or designer error: Using the Perceptual Cycle Model to explore the circumstances surrounding the fatal Tesla crash on 7th May 2016. *Safety Science*, *108*, 278–285. https://doi.org/10.1016/j.ssci.2017.12.023

Bartlett, J., Kotrlik, J., & Higgins, C. (2001). Organizational research: Determining organizational research: Determining appropriate sample size in survey research appropriate sample size in survey research. *Information Technology, Learning, and Performance Journal*, *19*(1), 43. https://www.opalco.com/wp-content/uploads/2014/10/Reading-Sample-Size1.pdf

Bekmamedova, N., Thiel, C., & Urbaczka, T. (2020). *The role of trust in autonomous vehicles: A systematic literature review. Procedia Computer Science, 175, 527-535.*

Benleulmi, A. Z., & Ramdani, B. (2022). Behavioural intention to use fully autonomous vehicles: Instrumental, symbolic, and affective motives. *Transportation Research Part F: Traffic Psychology and Behaviour*, *86*, 226–237. https://doi.org/10.1016/j.trf.2022.02.013

Betz, Heilmeier, Wischnewski, Stahl, & Lienkamp. (2019). Autonomous Driving—A Crash Explained in Detail. *Applied Sciences*, *9*(23), 5126. https://doi.org/10.3390/app9235126

Betz, S. (2024, March 11). *28 Top Self-Driving Car Companies to Know | Built In*. Builtin.com. https://builtin.com/articles/self-driving-car-companies

Bhatti, A., Saad, S., & Gbadebo, S. (2018). Science Arena Publications International journal of Business Management Convenience Risk, Product Risk, and Perceived Risk Influence on Online Shopping: Moderating Effect of Attitude. *Convenience Risk, Product Risk, and Perceived Risk Influence on Online Shopping: Moderating Effect of Attitude*, *3*(2), 1–11. https://sciarena.com/storage/models/article/8xpUQ6k77Kn7ff9bdbTxWSsx1sE1TPHudDPKU3Z3Gkg4DAvRDcwHC1vRRfc6/convenience-risk-product-risk-and-perceived-risk-influence-on-online-shopping-moderating-effect-of.pdf

Bonnefon, J.-F. ., Shariff, A., & Rahwan, I. (2016). The social dilemma of autonomous vehicles. *Science*, *352*(6293), 1573–1576. https://doi.org/10.1126/science.aaf2654

Bonnin, G. (2019). *The roles of perceived risk, attractiveness of the online store and familiarity with AR in the influence of AR on patronage intention*.

Castro, D. (2013). *The Road Ahead: The Emerging Policy Debates for IT in Vehicles*. https://www2.itif.org/2013-road-ahead.pdf

Chancey, E. T., Bliss, J. P., Yamani, Y., & Handley, H. A. H. (2016). Trust and the Compliance–Reliance Paradigm: The Effects of Risk, Error Bias, and Reliability on Trust and Dependence. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *59*(3), 333–345. https://doi.org/10.1177/0018720816682648

Chen, Y. (2022). *马来西亚新能源政策 电动车渗透率 2040 增至 38%-icspec*. Icspec.com. https://www.icspec.com/news/article-details/2089908

Chikaraishi, M., Khan, D., Yasuda, B., & Fujiwara, A. (2020). Risk perception and social acceptability of autonomous vehicles: A case study in Hiroshima, Japan. *Transport Policy*, *98*, 105–115. https://doi.org/10.1016/j.tranpol.2020.05.014

Choi, J. K., & Ji, Y. G. (2015). Investigating the Importance of Trust on Adopting an Autonomous Vehicle. *International Journal of Human-Computer Interaction*, *31*(10), 692–702. https://doi.org/10.1080/10447318.2015.1070549

Collie, S. (2018, October 29). *Semi-autonomous Systems Significantly Increase Repair Costs - Study*. Drive. https://www.drive.com.au/news/semi-autonomous-systems-repair-costs/

Collingwood, L. (2017). Privacy implications and liability issues of autonomous vehicles. *Information & Communications Technology Law*, *26*(1), 32–45. https://doi.org/10.1080/13600834.2017.1269871

Dovetail Editorial Team. (2023, May 15). *Causal Research Design: Definition, Benefits, Examples*. Dovetail.com. https://dovetail.com/research/causal-research/

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). *Comparison of convenience sampling and purposive sampling. American journal of theoretical and applied statistics, 5(1), 1-4.*

Fagnant, D. J., & Kockelman, K. (n.d.). *Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. Transportation Research Part A: Policy and Practice, 77, 167-181.*

Falk, R. F., & Miller, N. B. (1992, January). *(PDF) A Primer for Soft Modeling*. ResearchGate. https://www.researchgate.net/publication/232590534_A_Primer_for_Soft_Modeling

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: a perceived risk facets perspective. *International Journal of Human-Computer Studies*, *59*(4), 451–474. https://doi.org/10.1016/s1071-5819(03)00111-3

Featherman, M., Jia, S. (Jasper), Califf, C. B., & Hajli, N. (2021). The impact of new technologies on consumers beliefs: Reducing the perceived risks of electric vehicle adoption. *Technological Forecasting and Social Change*, *169*, 120847. https://doi.org/10.1016/j.techfore.2021.120847

Geetha, C., Chin, K., Iswarnie, F., Bachok, B., Kong, W., Liew, H., & Lim, M. (2020). THE PERCEIVED RISKS THAT INFLUENCE THE INTENTION OF CONSUMERS TO DO ONLINE PURCHASES IN EAST MALAYSIA BACKGROUND OF STUDY. *MJBE*, *8*(1), 2289–8018. https://jurcon.ums.edu.my/ojums/index.php/mjbe/article/download/3327/2330/13157

Giannaros, A., Karras, A., Theodorakopoulos, L., Karras, C., Kranias, P., Schizas, N., Kalogeratos, G., & Tsolis, D. (2023). Autonomous Vehicles: Sophisticated Attacks, Safety Issues, Challenges, Open Topics, Blockchain, and Future Directions. *Journal of Cybersecurity and Privacy*, *3*(3), 493–543. MDPI. https://doi.org/10.3390/jcp3030025

Guilford, J. P. (1954). *GuilfordPsychometric methods.*

Ha, T., Kim, S., Seo, D., & Lee, S. (2020). Effects of explanation types and perceived risk on trust in autonomous vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *73*, 271–280. https://doi.org/10.1016/j.trf.2020.06.021

Hair, J. F., Black, W. C., & Babin, B. J. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning Emea.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R. In *Classroom Companion: Business*. Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7

Hair, J. F., Tomas, G., & Ringle, C. M. (2022). *Modèles d'équations structurelles Partial Least Squares PLS-SEM | Presses Universitaires*. Presses-Universitaires.univ-Amu.fr. https://presses-universitaires.univ-amu.fr/modeles-dequations-structurelles-partial-least-squares-pls-sem

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in Second Language and Education research: Guidelines Using an Applied Example. *Research Methods in Applied Linguistics*, *1*(3). https://doi.org/10.1016/j.rmal.2022.100027

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hoesterey, S., & Onnasch, L. (2022). The effect of risk on trust attitude and trust behavior in interaction with information and decision automation. *Cognition, Technology & Work*. https://doi.org/10.1007/s10111-022-00718-y

Holton, E. F., & Burnett, M. F. (2005). *The basics of quantitative research. Research in organizations: Foundations and methods of inquiry, 29-44.*

Hu, S. (2014). Pretesting. *Encyclopedia of Quality of Life and Well-Being Research*, 5048–5052. https://doi.org/10.1007/978-94-007-0753-5_2256

Humphreys, M. A., & Kenderdine, J. M. (1979). *Perceived risk and consumer decision making: An alternative view of uncertainty. Chicago: American Marketing Association.*

Hurst, K. F., & Sintov, N. D. (2022). Trusting autonomous vehicles as moral agents improves related policy support. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.976023

Hussain, Q., Alhajyaseen, W. K. M., Adnan, M., Almallah, M., Almukdad, A., & Alqaradawi, M. (2021). Autonomous vehicles between anticipation and apprehension: Investigations through safety and security perceptions. *Transport Policy*, *110*, 440–451. https://doi.org/10.1016/j.tranpol.2021.07.001

In, J. (2017). Introduction of a Pilot Study. *Korean Journal of Anesthesiology*, *70*(6), 601–605. https://doi.org/10.4097/kjae.2017.70.6.601

Iranmanesh, M., Morteza Ghobakhloo, Foroughi, B., Mehrbakhsh Nilashi, & Elaheh Yadegaridehkordi. (2023). Factors influencing attitude and intention to use autonomous vehicles in Vietnam: findings from PLS-SEM and ANFIS. *Information Technology & People*. https://doi.org/10.1108/itp-11-2022-0825

Jacoby, J., & Kaplan, L. B. (1972). *The components of perceived risk. In Venkatesan, M. (Ed.), Proceedings of the Third Annual Conference of the Association for Consumer Research (pp. 382-393).*

Jing, P., Xu, G., Chen, Y., Shi, Y., & Zhan, F. (2020). The Determinants behind the Acceptance of Autonomous Vehicles: A Systematic Review. *Sustainability*, *12*(5), 1719. https://doi.org/10.3390/su12051719

Kargl, F., Krontiris, I., Weimerskirch, A., Williams, I., Trkulja, N., & Reports, D. (n.d.). Privacy Protection of Automated and Self-Driving Vehicles. *Dagstuhl Reports*, *12*(1), 83–100. https://doi.org/10.4230/DagRep.12.1.83

Kenesei, Z., Ásványi, K., Kökény, L., Jászberényi, M., Miskolczi, M., Gyulavári, T., & Syahrivar, J. (2022). Trust and perceived risk: How different manifestations affect the adoption of autonomous vehicles. *Transportation Research Part A: Policy and Practice*, *164*, 379–393. https://doi.org/10.1016/j.tra.2022.08.022

Kock, N. (2017). Common Method Bias: A Full Collinearity Assessment Method for PLS-SEM. *Partial Least Squares Path Modeling*, 245–257. https://doi.org/10.1007/978-3-319-64069-3_11

Lance, C. E., Butts, M. M., & Michels, L. C. (2006). The Sources of Four Commonly Reported Cutoff Criteria. *Organizational Research Methods*, *9*(2), 202–220. https://doi.org/10.1177/1094428105284919

Lăzăroiu, G., Neguriţă, O., Grecu, I., Grecu, G., & Mitran, P. C. (2020). Consumers' Decision-Making Process on Social Commerce Platforms: Online Trust, Perceived Risk, and Purchase Intentions. *Frontiers in Psychology*, *11*(1). Frontiersin. https://doi.org/10.3389/fpsyg.2020.00890

Liao, Y., Guo, H., & Liu, X. (2023). A Study of Young People's Intention to Use Shared Autonomous Vehicles: A Quantitative Analysis Model Based on the Extended TPB-TAM. *Sustainability*, *15*(15), 11825. https://doi.org/10.3390/su151511825

Ljubi, K., & Groznik, A. (2023). Role played by social factors and privacy concerns in autonomous vehicle adoption. *Transport Policy*, *132*, 1–15. https://doi.org/10.1016/j.tranpol.2022.12.013

Lu, W. (2021). *AUTONOMOUS VEHICLE AND RISK ASSESSMENT*. https://lup.lub.lu.se/luur/download?fileOId=9066296&func=downloadFile&recordOId=9066295

Ma, K., & Zhang, W. (2023). Assessing univariate and multivariate normality in PLS- SEM. *Analysis Perspectives Journal*, *4*(1), 1–7. https://scriptwarp.com/dapj/2023_DAPJ_4_1/Ma_Zhang_2023_DAPJ_4_1_AssessingNormality.pdf

Madrigal, A. C. (2018, May 24). *Uber's Self-Driving Car Didn't Malfunction, It Was Just Bad*. The Atlantic; The Atlantic. https://www.theatlantic.com/technology/archive/2018/05/ubers-self-driving-car-didnt-malfunction-it-was-just-bad/561185/

Martinho, A., Herber, N., Kroesen, M., & Chorus, C. (2021). Ethical issues in focus by the autonomous vehicles industry. *Transport Reviews*, *41*(5), 556–577. https://doi.org/10.1080/01441647.2020.1862355

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). *An integrative model of organizational trust. Academy of Management Review, 20(3), 709-734.*

McKenna, A., & Gopnik, A. (2021, June 7). *Generation X | Origin, Years, Characteristics, & Facts*. Encyclopedia Britannica. https://www.britannica.com/topic/Generation-X

McKinsey & Company. (2023, January 6). *Autonomous driving's future: Convenient and connected*.

Mitchell, V.-M. (1992). *Understanding Consumers' Behaviour: Can Perceived Risk Theory Help? Management Decision, 30(2), 26-31.*

Morgan, R. M., & Hunt, S. D. (1994). *The commitment-trust theory of relationship marketing. Journal of Marketing, 58(3), 20-38.*

Moye, B. (2023, December 14). *Fixing Advanced Vehicle Systems Makes Up Over One -Third of Repair Costs Following a Crash*. AAA Newsroom. https://newsroom.aaa.com/2023/12/fixing-advanced-vehicle-systems-makes-up-over-one-third-of-repair-costs-following-a-crash/

Muzir, N. A. Q., Mojumder, Md. R. H., Hasanuzzaman, Md., & Selvaraj, J. (2022). Challenges of Electric Vehicles and Their Prospects in Malaysia: A Comprehensive Review. *Sustainability*, *14*(14), 8320. https://doi.org/10.3390/su14148320

Naiseh, M., Clark, J., Akarsu, T., Hanoch, Y., Brito, M., Wald, M., Webster, T., & Shukla, P. (2024). Trust, risk perception, and intention to use autonomous vehicles: an interdisciplinary bibliometric review. *AI & Society*. https://doi.org/10.1007/s00146-024-01895-2

Nancy K, L. (2019). *What Is a Pilot Study?* AWHONN. https://www.jognn.org/article/S0884-2175(19)30006-1/pdf

Nishihori, Y., Kimura, K., Taniguchi, A., & Morikawa, T. (2018). What Affects Social Acceptance and Use Intention for Autonomous Vehicles --Benefits, Risk Perception, or Experience? -Meta-Analysis in Japan-. *International Journal of Intelligent Transportation Systems Research*, *18*(1), 22–34. https://doi.org/10.1007/s13177-018-0170-x

Parekh, D., Poddar, N., Rajpurkar, A., Chahal, M., Kumar, N., Joshi, G. P., & Cho, W. (2022). A Review on Autonomous Vehicles: Progress, Methods and Challenges. *Electronics*, *11*(14). https://mdpi-res.com/d_attachment/electronics/electronics-11-02162/article_deploy/electronics-11-02162.pdf?version=1657531632

Paul, R. K. (2006). *MULTICOLLINEARITY: CAUSES, EFFECTS AND REMEDIES*. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=300f806f39ea84cfbe999cb52903726a2e8f0458

Peña-García, N., Gil-Saura, I., Rodríguez-Orejuela, A., & Siqueira-Junior, J. R. (2020). Purchase intention and purchase behavior online: A cross-cultural approach. *Heliyon*, *6*(6).

Pentz, C. D., du Preez, R., & Swiegers, L. (2020). To bu(Y) or not to bu(Y): Perceived risk barriers to online shopping among South African generation Y consumers. *Cogent Business & Management*, *7*(1). https://doi.org/10.1080/23311975.2020.1827813

PeoplePulse. (n.d.). *Survey Response Rates*. PeoplePulse™ - Online Survey Software | Australian Survey Software. https://peoplepulse.com/resources/useful-articles/survey-response-rates/

Qu, W., Xu, J., Ge, Y., Sun, X., & Zhang, K. (2019). Development and validation of a questionnaire to assess public receptivity toward autonomous vehicles and its relation with the traffic safety climate in China. *Accident Analysis & Prevention*, *128*, 78–86. https://doi.org/10.1016/j.aap.2019.04.006

Quan, L., Al-Ansi, A., & Han, H. (2022). Assessing customer financial risk perception and attitude in the hotel industry: Exploring the role of protective measures against COVID-19. *International Journal of Hospitality Management*, *101*, 103123. https://doi.org/10.1016/j.ijhm.2021.103123

Rick H. Hoyle. (2023). Review of *Handbook of Structural Equation Modeling* Review of *Handbook of Structural Equation Modeling* (2nd ed.), Edited by Rick H. Hoyle, The Guilford Press (2023), 785 pp. $125.00 (Hardcover), ISBN: 978-1462544646. *Structural Equation Modeling a Multidisciplinary Journal*, *30*(6), 1022–1024. https://doi.org/10.1080/10705511.2023.2235083

Roselius, T. (1971). *Consumer rankings of risk reduction methods. Journal of Marketing, 35, 56-61.*

Russell, M. (2022). What Factors Influence The Consumer Use of Fully Autonomous Vehicles within the U.S.? *FIU Electronic Theses and Dissertations*. https://digitalcommons.fiu.edu/etd/5120/

Sekaran, U., & Bougie, R. (2016, June). *Research Methods For Business: A Skill Building Approach, 7th Edition | Wiley*. Wiley.com. https://www.wiley.com/en-us/Research+Methods+For+Business%3A+A+Skill+Building+Approach%2C+7th+Edition-p-9781119266846

Shakir, U. (2023, August 21). *Tesla points to "insider wrongdoing" as cause of massive employee data leak*. The Verge. https://www.theverge.com/2023/8/21/23839940/tesla-data-leak-inside-job-handelsblatt

Silvestri, F., De Fabiis, F., & Coppola, P. (2024). Consumers' expectations and attitudes towards owning, sharing, and riding autonomous vehicles. *Case Studies on Transport Policy*, *15*, 101112. https://doi.org/10.1016/j.cstp.2023.101112

Sim, H. J., Chen, T. B., Chai, L. T., & Khan, N. (2023). A Review of Perceived Risk Role in Autonomous Vehicles Acceptance. *International Journal of Management, Finance and Accounting*, *4*(1), 22–36. https://doi.org/10.33093/ijomfa.2023.4.1.2

Sivaram, M., Niknik, A., Munawar, & Ali, H. (2019). DETERMINATION OF PURCHASE INTENTION THROUGH BRAND AWARENESS AND PERCEIVED QUALITY (Case Study: For consumers PT. Sentosa Santosa Finance Tangerang area). *DETERMINATION of PURCHASE INTENTION through BRAND AWARENESS and PERCEIVED QUALITY*, *1*(2). https://doi.org/10.31933/DIJMS

Staton, A. D. (2012, October 22). *PPT - Descriptive Research PowerPoint Presentation, free download - ID:880794*. SlideServe. https://www.slideserve.com/nat/descriptive-research/

Stone, E., F., & Gronhaug, K. (1993). *Perceived risk: Further considerations for the marketing discipline. European Journal of Marketing, 27(3), 39-50.*

Tan, H., Chen, C., & Hao, Y. (2020). How People Perceive and Expect Safety in Autonomous Vehicles: An Empirical Study for Risk Sensitivity and Risk-related Feelings. *International*

*Journal of Human–Computer Interaction*, *37*(4), 340–351. https://doi.org/10.1080/10447318.2020.1860515

Tan, S. Y., & Taeihagh, A. (2021). Adaptive Governance of Autonomous Vehicles: Accelerating the Adoption of Disruptive Technologies in Singapore. *Government Information Quarterly*, *38*(2), 101546. https://doi.org/10.1016/j.giq.2020.101546

Tesla Malaysia. (2023). *Design Your Model 3 | Tesla*. Design Your Model 3 | Tesla. https://www.tesla.com/en_my/model3/design#overview

Ting, H., Lim, T.-Y., de Run, E. C., Koh, H., & Sahdan, M. (2018). Are We Baby Boomers, Gen X and Gen Y? a Qualitative Inquiry into Generation Cohorts in Malaysia. *Kasetsart Journal of Social Sciences*, *39*(1), 109–115. https://doi.org/10.1016/j.kjss.2017.06.004

Topolšek, D., Babić, D., Babić, D., & Cvahte Ojsteršek, T. (2020). Factors Influencing the Purchase Intention of Autonomous Cars. *Sustainability*, *12*(24), 10303. https://doi.org/10.3390/su122410303

Twenge, J. M. (2023). *Generations*. Google Books. https://books.google.com.my/books?hl=en&lr=&id=zsV0EAAAQBAJ&oi=fnd&pg=PA1&dq=characteristic+of+gen+x&ots=7pKU16oruC&sig=YHB3kbqDyjlHcaaWHVGNhWkNqG4&redir_esc=y#v=onepage&q=characteristic%20of%20gen%20x&f=false

Van Brummelen, J., O'Brien, M., Gruyer, D., & Najjaran, H. (2018). Autonomous vehicle perception: The technology of today and tomorrow. *Transportation Research Part C: Emerging Technologies*, *89*, 384–406. https://doi.org/10.1016/j.trc.2018.02.012

Vimal Rau Aparow, Cheok Jun Hong, Lee Kah Onn, Hishamuddin Jamaluddin, Anwar, K., & Zulhaidi Mohd Jawi. (2022). Challenges and Approach: Scenario-Based Safety Assessment of Autonomous Vehicle for Malaysian Environment and Driving Conditions. *2022 17th International Conference on Control, Automation, Robotics and Vision (ICARCV)*. https://doi.org/10.1109/icarcv57592.2022.10004224

Walker, F., Forster, Y., Hergeth, S., Kraus, J., Payre, W., Philipp Wintersberger, & Martens, M. (2023). Trust in automated vehicles: constructs, psychological processes, and assessment. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1279271

Wang, D., Fu, W., Song, Q., & Zhou, J. (2022). Potential risk assessment for safe driving of autonomous vehicles under occluded vision. *Scientific Reports*, *12*(1). https://doi.org/10.1038/s41598-022-08810-z

Wang, J., Zhang, L., Huang, Y., & Zhao, J. (2020, October 6). *Safety of Autonomous Vehicles*. Journal of Advanced Transportation. https://www.hindawi.com/journals/jat/2020/8867757/

Wang, Y., Chiu, W., Wei, C., Wang, H., Yang, J., & Wang, Y. (2024). What drives consumers' intention to purchase self-driving cars. *Managerial and Decision Economics*. https://doi.org/10.1002/mde.4090

Waung, M., McAuslan, P., & Lakshmanan, S. (2021). Trust and intention to use autonomous vehicles: Manufacturer focus and passenger control. *Transportation Research Part F: Traffic Psychology and Behaviour*, *80*, 328–340. https://doi.org/10.1016/j.trf.2021.05.004

Wiseman, Y. (2022). *Autonomous Vehicles*. Research Anthology on Cross-Disciplinary Designs and Applications of Automation. https://www.igi-global.com/chapter/autonomous-vehicles/291671

Wong, A. (2024, May 27). *Are EV sales increasing in Malaysia? Here's the data from JPJ*. Malay Mail ; Malay Mail. https://www.malaymail.com/news/malaysia/2024/05/27/are-ev-sales-increasing-in-malaysia-heres-the-data-from-jpj/136772

Yang, J., Ward, M., & Akhtar, J. (2017). The Development of Safety Cases for an Autonomous Vehicle: A Comparative Study on Different Methods. *SAE Technical Papers on CD-ROM/SAE Technical Paper Series*. https://doi.org/10.4271/2017-01-2010

Yu, Z., & Cai, K. (2022). Perceived Risks toward In-Vehicle Infotainment Data Services on Intelligent Connected Vehicles. *Systems*, *10*(5), 162. https://doi.org/10.3390/systems10050162

Zhang, T., Tao, D., Qu, X., Zhang, X., Lin, R., & Zhang, W. (2019). The roles of initial trust and perceived risk in public's acceptance of automated vehicles. *Transportation Research Part C: Emerging Technologies*, *98*, 207–220. https://doi.org/10.1016/j.trc.2018.11.018

Zhang, X., & Yu, X. (2020). The Impact of Perceived Risk on Consumers' Cross-Platform Buying Behavior. *Frontiers in Psychology*, *11*(1). https://doi.org/10.3389/fpsyg.2020.592246

Zheng, H., & Gao, H. (2021). The Research on Influencing Factors of Autonomous Vehicle Usage Behavior: Root Analysis Based on UTAUT2 Model. *Journal of Physics: Conference Series*, *1910*(1), 012057. https://doi.org/10.1088/1742-6596/1910/1/012057

# APPENDICES

Appendix A: Vehicle Registration Type in Malaysia

**Vehicles Registered by Fuel type**

| | 2022 | | 2023 | | (until 30 April) 2024 | |
|---|---|---|---|---|---|---|
| **Electric** | **3,129** | **0.42%** | **13,301** | **1.60%** | **6,298** | **2.28%** |
| Hybrid Petrol | 15,368 | 2.06% | 22,210 | 2.67% | **7,953** | 2.88% |
| Hybrid Diesel | 9 | 0.00% | 5 | 0.00% | | 0.00% |
| Green Diesel | 59,768 | 8.03% | 60,958 | 7.32% | **16,775** | 6.08% |
| Diesel | 4,147 | 0.56% | 5,230 | 0.63% | **1,453** | 0.53% |
| Petrol | 662,331 | 88.93% | 730,630 | 87.78% | **243,232** | 88.22% |
| Others | 5 | 0.00% | 6 | 0.00% | **1** | 0.00% |
| Total | **744,757** | | **832,340** | | **275,711** | |

**Source:** data.gov.my

Appendix B: Total Sales of Electric Cars in 2023

| | 2022 | 2023 | (until 30 April) 2024 | Total (Past 5 years) |
|---|---|---|---|---|
| Tesla Model Y | 88 | 178 | **1,138** | 1,404 |
| BYD Atto 3 | 0 | 3,157 | **1,118** | 4,308 |
| Tesla Model 3 | 186 | 1,676 | **862** | 2,740 |
| BYD Seal | 0 | 0 | **840** | 840 |
| BYD Dolphin | 0 | 1,313 | **605** | 1,918 |
| Chery Omoda E5 | 0 | 2 | **244** | 246 |
| Smart #1 | 0 | 198 | **202** | 400 |
| GWM Ora | 14 | 463 | **145** | 623 |
| BMW i7 | 0 | 634 | **121** | 763 |
| Porsche Taycan | 185 | 470 | **112** | 951 |
| BMW i5 | 0 | 98 | **106** | 204 |
| BMW iX | 976 | 1,467 | **100** | 2,543 |
| Lotus Eletre | 0 | 9 | **80** | 90 |
| Volvo XC40 | 328 | 210 | **74** | 612 |
| Mercedes-Benz EQE | 7 | 167 | **68** | 242 |
| Volvo C40 | 35 | 286 | **68** | 389 |
| BMW i4 | 40 | 289 | **57** | 386 |
| Mercedes-Benz EQA | 61 | 250 | **48** | 359 |
| Neta V | 0 | 27 | **46** | 73 |
| MG4 | 0 | 0 | **39** | 39 |
| Mercedes-Benz EQS | 70 | 173 | **28** | 271 |
| BMW iX1 | 0 | 617 | **24** | 641 |
| Audi Q8 E-Tron | 0 | 136 | **23** | 159 |
| Hyundai Ioniq 6 | 0 | 58 | **23** | 81 |
| Mini Cooper | 274 | 477 | **18** | 845 |
| Jaguar I-Pace | 3 | 29 | **7** | 39 |
| BMW iX3 | 273 | 130 | **6** | 409 |
| Mercedes-Benz EQB | 39 | 180 | **6** | 225 |
| Mercedes-Benz EQC | 35 | 128 | **5** | 168 |
| Nissan Leaf | 35 | 24 | **5** | 87 |
| Hyundai Ioniq 5 | 118 | 138 | **4** | 260 |
| Audi RS E-tron GT | 0 | 15 | **3** | 18 |
| Renault Zoe | 2 | 4 | **3** | 61 |
| Audi SQ8 E-tron | 0 | 0 | **2** | 2 |
| Maxus Mifa 9 | 0 | 2 | **2** | 4 |
| MG ZS | 8 | 5 | **1** | 14 |
| Rolls Royce Spectre | 0 | 0 | **1** | 1 |
| Hyundai Kona | 160 | 54 | **0** | 218 |
| Kia EV6 | 76 | 39 | **0** | 115 |
| Kia EV9 | 0 | 1 | **0** | 1 |
| Kia Niro | 0 | 10 | **0** | 10 |
| Mazda MX-30 | 4 | 30 | **0** | 34 |

Appendix C: Sources of Questionnaire Constructs

| **Variables** | **Author** | **Original Question** | **Question Used** | **Adopt/Adapt** |
|---|---|---|---|---|
| Privacy Risk | Kenesei et al., (2022) | 1. I am worried that if I use autonomous vehicles, I will lose control over my personal data. | 1. I am worried that if I use autonomous vehicles, I will lose control over my personal data. | Adopt |
| | | 2. I am concerned that autonomous vehicles will use my personal information for other purposes without my authorization. | 2. I am concerned that autonomous vehicles will use my personal information for other purposes without my authorization. | Adopt |
| | | 3. I am concerned that autonomous vehicles would not be able to guarantee the security of my personal information. | 3. I am concerned that autonomous vehicles would not be able to guarantee the security of my personal information. | Adopt |
| | Zhang et al., (2019) | 4. I am concerned that autonomous vehicles will collect too much personal information from me. | 4. I am concerned that autonomous vehicles will collect too much personal information from me. | Adopt |

| | | | | |
|---|---|---|---|---|
| Physical Risk | Zhang et al., (2019) | 1. I'm worried about the general safety of such technology | 1. I'm worried about the general safety of such technology | Adopt |
| | | 2. I'm worried that the failure or malfunctions of autonomous vehicles may cause accidents | 2. I'm worried that the failure or malfunctions of autonomous vehicles may cause accidents | Adopt |
| | Hussain et al., (2021) | 3. I have concerns about securing the autonomous driving system from computer hackers | 3. I have concerns about securing the autonomous driving system from computer hackers | Adopt |
| Functional Risk | Kenesei et al., (2022) | 1. Chances are high that something will go wrong when using autonomous vehicles. | 1. Chances are high that something will go wrong when using autonomous vehicles. | Adopt |
| | | 2. Autonomous vehicles may not perform well, and problems may occur when using them. | 2. Autonomous vehicles may not perform well, and problems may occur when using them. | Adopt |
| | | 3. Considering the potential future service performance of | 3. Considering the potential future service performance of | Adopt |

| | | | | |
|---|---|---|---|---|
| | | autonomous vehicles, their use could be risky for me. | autonomous vehicles, their use could be risky for me. | |
| | | 4. I'm worried that the failure or malfunctions of autonomous vehicles may cause accidents. | 4. I'm worried that the failure or malfunctions of autonomous vehicles may cause accidents. | Adopt |
| | Hussain et al., (2021) | 5. I have concerns about the performance of AV in harsh environmental conditions (such as during raining weather condition) | 5. I have concerns about the performance of AV in harsh environmental conditions (such as during raining weather condition) | Adopt |
| Social Risk | Ljubi & Groznik (2023) | 1. Possessing an AV would give me social recognition | 1. Possessing an AV would not give me social recognition | Adapt |
| | | 2. I would be more eager to use an AV if my friends and family were using one | 2. I would not be more eager to use an AV if my friends and family were using one | Adapt |
| | | 3. I would feel more confident in using an AV if they were | 3. I would not feel more confident in using an AV if they were | Adapt |

| | | | | |
|---|---|---|---|---|
| | | commonly used by others. | commonly used by others. | |
| | Benleulmi & Ramdani (2022) | 4. People who are important to me think that I should use autonomous cars. | 4. People who are important to me think that I should not use autonomous cars. | Adapt |
| | | 5. People who influence my behaviour would think that I should use autonomous cars. | 5. People who influence my behaviour would think that I should not use autonomous cars. | Adapt |
| Financial Risk | Hussain et al., (2021) | 1. I have concerns about increase in maintenance cost | 1. I have concerns about increase in maintenance cost | Adopt |
| | | | | |

| | | | | |
|---|---|---|---|---|
| | Qu et al., (2019) | 2. A self-driving car would lower insurance rates. | 2. A self-driving car would increase insurance rates. | Adopt |
| | Silvestri et al., (2024) | 3. Vehicles will be too expensive to be purchased | 3. Autonomous vehicles will be too expensive to be purchased | Adopt |
| | | 4. Taxi services will be more expensive than now | 4. Cost of using autonomous vehicle will be more expensive | Adapt |

| | | | | |
|---|---|---|---|---|
| | | | than using non autonomous vehicle. | |
| Trust | Zhang et al., (2019) | 1. Autonomous vehicles are dependable. | 1. Autonomous vehicles are dependable. | Adopt |
| | | 2. Autonomous vehicles are reliable. | 2. Autonomous vehicles are reliable. | Adopt |
| | | 3. Overall, I can trust autonomous vehicles | 3. Overall, I can trust autonomous vehicles | Adopt |
| | Kenesei et al., (2022) | 4. AV manufacturers and distributors will keep their promises | 4. AV manufacturers and distributors will keep their promises | Adopt |
| | | **5.** AV manufacturers and distributors will be reliable and dependable. | **5.** AV manufacturers and distributors will be reliable and dependable. | Adopt |
| Purchase Intention | Kenesei et al., (2022) | 1. I predict I would use autonomous vehicles in the future | 1. I predict I would use autonomous vehicles in the future | Adopt |
| | | 2. I plan to use autonomous | 2. I plan to buy autonomous | Adapt |

| | | | | |
|---|---|---|---|---|
| | | vehicles in the future. | vehicles in the future. | |
| | | 3. I will purchase an autonomous vehicle as my next car | 3. I will purchase an autonomous vehicle as my next car | Adopt |
| | | 4. If the opportunity arises, I will use a self-driving car in the future | 4. If the opportunity arises, I will use a self-driving car in the future | Adopt |
| | Hussain et al., (2021) | 5. AV can make my travel more comfortable. | 5. AV can make my travel more comfortable. | Adopt |

Appendix D: Pre-test for Questionnaire for Main Study

**The Impact of Risk Perception on the Purchase Intention among Generation Xon Autonomous Vehicle in Malaysia**

Dear Respondents,

We are final year undergraduate students of Bachelor of Marketing (Hons), from Faculty of Business and Finance in University Tunku Abdul Rahman (UTAR) Kampar campus. As part of our research, we are conducting a research project on " The Impact of Risk Perception on the Purchase Intention among Generation X on Autonomous Vehicle in Malaysia. " This research aims to investigate about the risk perception that affect the purchase intention of autonomous vehicle of Gen X in Malaysia.

This survey will only take you approximately 10 minutes, and all participation towards this survey are voluntary. Rest assured that all the responses collected will be used solely for academic purposes, and will be kept private and confidential. Thank you in advance for your time and cooperation in answering our questionnaire.

Your participation is highly appreciated.

For further inquiries, please contact us:

TENG WEN HAO/ wenhao010410@1utar.my/ 011-16951681

ANG JIA HUI/ bellajh0510@1utar.my/ 011-12404926

Screening Question

1. Do you know about autonomous vehicles (AVs)?
Eg: Tesla

- Yes
- No

Section A Demographic Question

1. What is your gender?

- Male
- Female

2. What is your age

- 44-50
- 50-55

3. What is your race

- Malay
- Chinese
- Indian
- Others

4. Your marital status

- Single
- Married
- Divorced

5. Highest education level

- Primary School
- Secondary School
- Tertiary

6. Employment status

- Unemployed
- Part-time
- Full-time

7. Average income level

- RM 1500-3000
- RM 3000-4500
- RM 4500 and above

Section B: These questions are to investigate about the risk perception that affect the purchase intention of autonomous vehicle of Gen X in Malaysia.

Please select the answer that suitable for you, thanks

| 1. Privacy Risk | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
|---|---|---|---|---|---|
| I feel worried if I use autonomous vehicles, my personal data cannot control by myself. | | | | | |
| I scare that autonomous vehicle will using my personal data without my permission | | | | | |
| I scare that autonomous vehicle cannot guarantee my personal data safety | | | | | |
| I am concerned that autonomous vehicles will collect too much personal information from me. | | | | | |
| 2. Physical Risk | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
| I'm concerned about the overall security of such technology. | | | | | |
| I'm concerned that the failures or breakdowns of autonomous vehicles may result in accidents. | | | | | |
| I'm worried about the safety level of autonomous vehicle | | | | | |
| 3. Functional Risk | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
| Chances are high that something will go wrong when using autonomous vehicles. | | | | | |
| Autonomous vehicles may not perform well, and problems may occur when using them. | | | | | |
| Considering the potential future service performance of autonomous vehicles, their use could be risky for me. | | | | | |
| I'm worried that the failure or malfunctions of autonomous vehicles may cause accidents | | | | | |
| I have concerns about the performance of AV in harsh environmental conditions (such as during raining weather condition) | | | | | |
| 4. Social Risk | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
| Possessing an AV would not give me social recognition | | | | | |
| I would not be more eager to use an AV if my friends and family were using one | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| I would not feel more confident in using an AV if they were commonly used by others. | | | | | |
| People who are important to me think that I should not use autonomous cars. | | | | | |
| People who influence my behaviour would think that I should not use autonomous cars. | | | | | |
| 5. Financial Risk | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
| I have concerns about increase in maintenance cost | | | | | |
| A self-driving car would increase insurance rates. | | | | | |
| Autonomous vehicles will be too expensive to be purchased | | | | | |
| Cost of using autonomous vehicle will be more expensive than using non autonomous vehicle. | | | | | |
| 6. Trust | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
| Autonomous vehicles are dependable. | | | | | |
| Autonomous vehicles are reliable. | | | | | |
| Overall, I can trust autonomous vehicles | | | | | |
| AV manufacturers and distributors will keep their promises | | | | | |
| AV manufacturers and distributors will be reliable and dependable. | | | | | |
| Purchase Intention | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
| I predict I would use autonomous vehicles in the future | | | | | |
| I plan to buy autonomous vehicles in the future. | | | | | |
| I will purchase an autonomous vehicle as my next car | | | | | |
| If the opportunity arises, I will use a self-driving car in the future | | | | | |
| AV can make my travel more comfortable. | | | | | |

Below is the signature from three lectures in University Tunku Abdul Rahman who had viewed the questionnaire.

| Name | Signature |
|---|---|
| 1. Mr Thiagarajan a/l Viran | |
| 2. Mr Peramjit Singh | |
| 3. Mr Raja Kumar | |