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The Determinants of Acceptance and Intention to use Autonomous Vehicles and its Implication on the Auto Insurance Industry

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The Determinants of Acceptance and Intention to use Autonomous Vehicles and its Implication on the Auto Insurance Industry

A Thesis

By

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The thesis entitled **'The Determinants of Acceptance and Intention to use Autonomous Vehicles and its Implication on the Auto Insurance Industry'** presented by **Cal Thomay**, a candidate for the degree of **Master of Science in Mathematics**, has been approved and is worthy of acceptance.

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ABSTRACT

Autonomous vehicles are an emerging new technology that have sparked the interest of the general public in recent years. Their arrival impacts a wide range of groups, the auto insurance industry being one example. However, many challenges exist that may prevent autonomous vehicles from becoming a part of everyday life. This study aimed to determine factors that influence the acceptance and intention to use autonomous vehicles, as well as provide a discussion on various implications in the auto insurance industry. Participants were recruited to participate in completing a short questionnaire to express their attitudes and opinions about autonomous vehicles. By using factor analysis and regression techniques to perform statistical analyses, results indicated many non-statistically significant results to determine influential factors within the theoretical model presented. These results, however, are only a single data point in time and should not be considered as fact. Many other studies indicated that the factors used in this study showed statistically significant results in determining the acceptance and intention to use autonomous vehicles. Further research can build upon the framework presented in this study to develop a more predictive model in determining factors that influence acceptance and intention to use autonomous vehicles.

ACKNOWLEDGMENTS

I'd like to thank my wife, Mia, for her constant encouragement over the last two years since starting this graduate program. I am thankful for the sacrifices that she made for me and our family when it would have been a lot easier for her to ask me to stop when times were tough. She spent many evenings on her own while I worked on this project, time that I will enjoy spending with her again in the near future. I'd also like to thank my advisor, Dr. Darbro, for his willingness to advise a project like this that was outside of his comfort zone. He could have directed me in a different path, but I'm thankful that he was accepting of this research topic.

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CHAPTER I: Introduction

Chapter I will give an introduction to autonomous vehicles as a new technology, provide some advantages and disadvantages to using them, and convey that there are many different thoughts and opinions about them in society today. This chapter will also state the research problem being investigated, the purpose of the study, hypotheses, research design, and theoretical framework, while also providing some context on the assumptions made and limitations surfacing from the formation of this study. Chapter I will conclude by providing an overview of the organization of the thesis.

In this technology age in which we live with smartphones, social networking, and live-streamed TV and movies, the day where we have autonomous vehicles on our roads is not too far in the distant future. Auto manufacturers such as GM, Ford, and Tesla and tech companies like Uber and Google have been testing autonomous vehicles in recent years and are quickly reaching a point where the deployment of autonomous vehicles will be more evident on public roads (Muoio, 2018). There currently exist many advantages to autonomous vehicles, specifically their ability to enhance vehicle safety, reduce traffic congestion, and improve users' transportation experience, to name a few (Yuen et al., 2020b).

However, public acceptance of autonomous vehicles is vital for a society to enjoy the benefits of them. Presently, many challenges exist with its adoption and deployment into society today. Tragically, in 2018 a self-driving Uber car struck and killed a woman in Tempe, Arizona, which was believed to be the first pedestrian death associated with autonomous vehicles (Wakabayashi, 2018). This incident, as well as other psychological and behavioral obstacles, have held back the development and deployment of autonomous vehicles in the automobile industry. This accident aside, research has shown societal concern with autonomous vehicles, such as coping with safety issues, dealing with giving up control, adapting to their steep learning curve, and understanding legal and ethical issues regarding the protection of users and pedestrians (Nastjuk et al., 2020; Yuen et al., 2020b).

In order for autonomous vehicles to become a reality in our current transportation systems and their benefits to be fully realized, the big hurdle of public acceptance needs to be tackled. This study aims to determine factors that influence acceptance and intention to use autonomous vehicles.

Background of the Problem

Every year it seems like new technologies become a part of mainstream society and we look back and wonder how we ever lived life without them. For example, smartphones are now a part of almost everyone's life. Whether you own one yourself or not, you almost certainly know someone who does. As another example, consider something as common as GPS. Years ago, this technology was nonexistent, and people needed maps to get from one place to another. However, GPS is now so common that we forget what life was like without it. The reason that these new technologies have become a part of everyday life is the simple fact that people have come to accept and use them themselves.

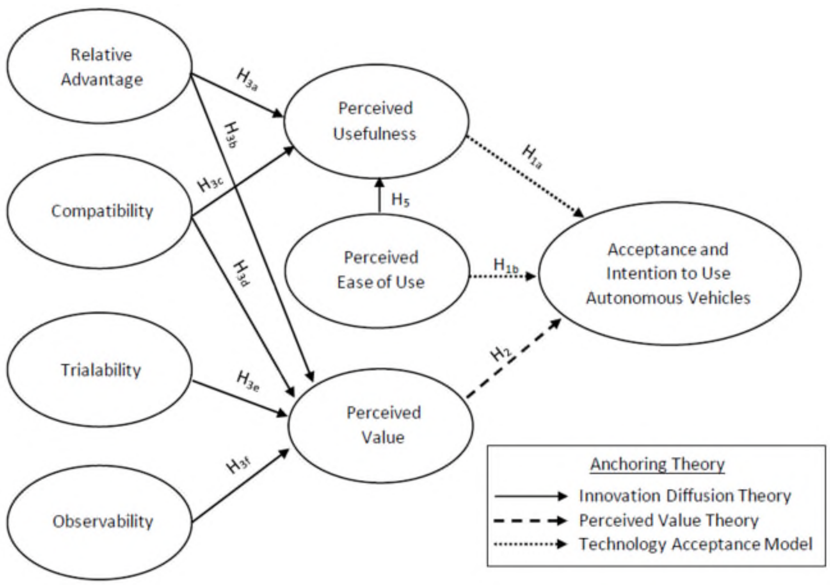
When considering the acceptance and intention to use autonomous vehicles, the research in this space is still relatively new given that testing and initial deployment of this technology has only started in the recent past. The most common theoretical model employed in these studies is the Technology Acceptance Model (TAM) (Koul & Eydgahi, 2018; Nastjuk et al., 2020). There are many branches of the TAM, but the basic theory behind this model is that there exist two main factors in determining acceptance of a new technology, namely perceived usefulness and perceived ease of use of the new technology. Both Koul and Eydgahi (2018) and Nastjuk et al. (2020) found perceived usefulness and perceived ease of use to be statistically significant predictors in a user's acceptance and intention to use autonomous vehicles.

Other recent studies have utilized a theory from the social sciences called Innovation Diffusion Theory. In this theoretical model, there are five main factors that influence adoption of an innovation, which are Relative Advantage, Compatibility, Complexity, Trialability, and Observability ("Diffusion of Innovation Theory", 2019). Studies have found statistically significant relationships among these five constructs to predict intention to use a new technology (Yuen et al., 2020b; Al-Rahmi et al., 2019). Yuen et al. (2020b) proposed a model combining three different theories to predict public acceptance of autonomous vehicles by using Innovation Diffusion Theory, Perceived Value Theory, and Trust Theory. The study hypothesized that a society would accept autonomous vehicles if they (1) have positive feelings toward the relative advantage, compatibility, reduced complexity, trialability, and observability, which would translate to (2) value to the society, and finally, (3) lead to the formation of trust (Yuen et al., 2020b).

Not many studies have combined the TAM, Innovation Diffusion Theory, and Perceived Value Theory, and so the theoretical model of this study aims to fill this gap in research by combining aspects of both the model presented in Yuen et al. (2020b) and the model presented in Nastjuk et al. (2020). Figure 1 below outlines the constructs of the proposed theoretical model of this study and the hypotheses connecting each of the constructs. Note that

Complexity was removed from the five Innovation Diffusion Theory constructs, but since Perceived Ease of Use is incorporated from the Technology Acceptance Model, the Complexity construct was removed for redundancy.

Figure 1. The Theoretical Model



The design of this study was descriptive in nature and tested hypotheses about constructs of the theoretical models presented to determine acceptance and intention to use autonomous vehicles. A survey consisting of 7 demographic questions and 25 model questions crafted from the studies conducted by Yuen et al. (2020b) and Nastjuk et al. (2020) was used to collect the data for this study. Responses were given on a 7-point Likert scale ranging from Strongly Disagree to Strongly Agree. Google Forms served as the platform for which the survey was administered, and where data was collected and exported for further analysis.

A call for participation in the study was sent out via Facebook containing brief details about the study and the time commitment in completing the survey. There were no limitations in who was eligible to participate in the study, other than residing in America, being of legal driving age, and possessing a valid driver's license. Invalid survey submissions (i.e., low-quality responses, selecting the same answer repeatedly, etc.) were discarded after data collection was completed.

Following data collection, results were exported to Microsoft Excel and further analysis was conducted in the statistical software package R, a free and open-source tool to easily conduct statistical tests and which was utilized in this study for such purposes (R Core Team, 2018). Factor analysis and regression techniques were conducted to determine statistical significance of predictor variables on acceptance and intention to use autonomous vehicles.

Statement of the Problem

The Technology Acceptance Model (TAM) has not only been used in studies to evaluate acceptance of autonomous vehicles (Koul & Eydgahi, 2018; Nastjuk et al., 2020), but it has also been applied to fields such as healthcare (Gagnon et al., 2012), education (Zheng et al., 2020), and business (Park et al., 2014). In an attempt to deviate from the widely used TAM, Yuen et al. (2020b) developed a study to predict public acceptance of autonomous vehicles by incorporating aspects of three theoretical models: Innovation Diffusion Theory, Perceived Value Theory, and Trust Theory.

Not many studies have been conducted using a combination of the TAM and the theoretical models in Yuen et al. (2020b), so the aim of this study is to fill this gap in research in pursuit of developing a more predictive model. Additionally, prior studies have discussed implications of autonomous vehicle acceptance on many areas, such as government, auto manufacturing, and fleet operators (Nastjuk et al., 2020), but not many have discussed the implications of autonomous vehicles on the auto insurance industry. This study also aims to fill the gap in implications of this research area.

Purpose of the Study

This research study was a quantitative study to find predictive factors in determining public acceptance and intention to use autonomous vehicles. The independent variables used in the analysis were constructs of Innovation Diffusion Theory, Perceived Value Theory, and Technology Acceptance Model, namely Relative Advantage, Compatibility, Trialability, Observability, Perceived Usefulness, Perceived Ease of Use, Perceived Value, and demographic variables of age, gender, approximate annual miles driven, accident experience, and experience with driver assistance systems (e.g., blind spot warning indicator and automatic emergency braking). The dependent variable in this study was acceptance and intention to use autonomous vehicles. These variables have already been established as reliable variables to use in prior studies, so it made sense to repeat their usage in this study.

The population of interest for this study was anyone in the American general public that was of legal driving age and possessed a valid driver's license. A request to complete a survey questionnaire created on Google Forms was sent out via Facebook. Participants of the study consisted of those that accepted the request and completed the survey, provided that their responses were not invalid (low quality responses, selecting the same answer for nearly every question, etc.).

Significance of the Study

There currently exist many theories relating to technology acceptance, the most commonly used one being the Technology Acceptance Model (TAM). Its applications have been widespread in studies not only related to autonomous vehicles, but also in areas such as healthcare, education, and business. One such recent study conducted by Yuen et al. (2020b) employed some innovative improvements to the typical study about autonomous vehicle perception. Their study aimed to the fill the gap in research by attempting to explain public acceptance of autonomous vehicles through constructs of three theoretical lenses: Innovation Diffusion Theory, Perceived Value Theory, and Trust Theory.

This study aimed to build upon the groundwork laid in the study conducted by Yuen et al. (2020b) while also still incorporating constructs of the Technology Acceptance Model (TAM). Since Yuen et al. (2020b) did not incorporate aspects of the TAM in their study, and their study was unique in this research field, building off of their study while incorporating aspects of the TAM filled a gap in this research field. Combining portions of the study conducted by Nastjuk et al. (2020) with the new theories presented by Yuen et al. (2020b), the intention of this study was to build a more predictive model than others offered by taking the most relevant pieces from each study.

An additional piece that was added to this study is a discussion around the implications of autonomous vehicle perception on the auto insurance industry. Recent studies have described the implications of autonomous vehicle acceptance in areas such as government, auto manufacturing, and fleet operators (Nastjuk et al., 2020), but none have laid out the implications on the auto insurance industry. For insurance companies, the emergence of autonomous vehicles on roads is something that they are preparing for. Autonomous vehicles provide a completely different risk that must be priced accurately for. Since autonomous vehicles are generally thought to be safer than conventional vehicles, many aspects of an insurance policy may become obsolete if accidents are reduced significantly. Knowing the public's acceptance and intention to use autonomous vehicles can help assist insurance companies in determining how best to adjust policies for customers looking to add an autonomous vehicle onto their insurance plan.

Research Questions

There were three primary research questions that this study aimed to answer:

1. What is the relationship between the constructs of the Technology Acceptance Model and acceptance and intention to use autonomous vehicles?
2. What is the relationship between the constructs of Perceived Value Theory and acceptance and intention to use autonomous vehicles?
3. What is the relationship between the constructs of Innovation Diffusion Theory and the constructs of the Technology Acceptance Model and Perceived Value Theory?

There were three secondary research questions that this study aimed to answer as well:

4. What is the effect of accident experience on the acceptance and intention to use autonomous vehicles?
5. What is the effect of experience with driver assisted systems on the acceptance and intention to use autonomous vehicles?
6. Does there exist a difference in acceptance and intention to use autonomous vehicles across gender?

Hypotheses

Hypotheses to these research questions were as follows:

1. There exist positive relationships between the constructs of the Technology

Acceptance Model and Acceptance and Intention to Use Autonomous Vehicles.

2. There exists a positive relationship between the constructs of Perceived Value Theory and Acceptance and Intention to Use Autonomous Vehicles.
3. There exist positive relationships between the constructs of Innovation Diffusion Theory and the constructs of the Technology Acceptance Model and Perceived Value Theory.
4. There exists a difference in Acceptance and Intention to Use Autonomous Vehicles for those that have experienced a car accident in the past compared to those that have not.
5. There exists a difference in Acceptance and Intention to Use Autonomous Vehicles for those that have experience with driver assisted systems compared to those that do not.
6. There does not exist a difference in Acceptance and Intention to Use Autonomous Vehicles across gender.

Research Design

This study employed the use of a survey questionnaire to gather the thoughts and opinions of participants toward autonomous vehicles. Participants consisted of anyone accepting the request to complete the survey through a Facebook posting, where the goal was to reach participants all across the United States.

An online survey through Google Forms was created and distributed to willing participants in the study. Participants' identities were kept confidential throughout the entire process. Data was collected in Microsoft Excel and analyzed in the statistical software package

R. Through means of factor analysis and regression techniques, the goal was to determining factors that influence acceptance and intention to use autonomous vehicles.

Theoretical Framework

The Technology Acceptance Model (TAM) is the core theory behind many of the studies in this field surrounding acceptance of autonomous vehicles. But the TAM is not limited to autonomous vehicles, nor is it a newly developed theory, relatively speaking. Developed in 1985, Fred Davis proposed that a user's motivation to use a new technology is driven by three factors: Perceived Ease of Use, Perceived Usefulness, and Attitude toward using the technology. He argued that Perceived Ease of Use had a direct influence on Perceived Usefulness, and both had direct influences on a user's Attitude toward using the technology (Chutter, 2009).

The TAM is considered to be an extension of the earliest known technology acceptance theory called the Theory of Reasoned Action (TRA). Developed by Arjen and Fishbein in 1967, this theory is recognized as one of the most fundamental theories of human behavior. Considered more of a general model for broader use, Arjen and Fishbein sought to develop a theory that could predict, explain, and influence human behavior, resulting in the Theory of Reasoned Action (Momani, 2017).

Numerous extensions to the groundbreaking work by Arjen and Fishbein were made, including the TAM developed by Davis. The TAM has been used successfully in studies across a wide range of disciplines, including healthcare, education, and business, and results indicate strong relationships among the main constructs of the theory (Gagnon et al., 2012; Zheng et al., 2020; Park et al., 2014). In an attempt to deviate from the norm, Yuen et al. (2020b) developed a study to predict acceptance of autonomous vehicles utilizing the theories of diffusion of innovations, perceived value, and trust. The authors applied the main constructs of these theories to develop a model that would be used to predict acceptance of autonomous vehicles in such a way that had not been widely used before in prior studies.

The second theoretical model used in Yuen et al.'s study was the Innovation Diffusion Theory. It is one of the oldest developed theories in the social sciences, consisting of 5 main constructs: Relative Advantage, Compatibility, Complexity, Trialability, and Observability. Developed by E.M. Rogers in 1962, it theorizes that adoption of a new idea, behavior, or product (i.e., innovation) spreads through a social system (i.e., diffuses) by means of these 5 main constructs ("Diffusion of Innovation Theory", 2019). Yuen et al. (2020b) proposed that these 5 constructs have a direct influence on the perceived value of autonomous vehicles, here applying components of Perceived Value Theory. The acceptance of autonomous vehicles can be improved in a population of people if autonomous vehicles offer the best utility to their users amongst all available alternatives. That is, if people find "value" in autonomous vehicles, they are more likely to accept and use them. The final theoretical component in their study comprises aspects of Trust Theory, in which the authors argue that increasing trust in autonomous vehicles will in turn increase the likelihood of acceptance and intention to use autonomous vehicles (Yuen et al., 2020b).

This study served as an extension to the study conducted by Yuen et al. (2020b), incorporating the aspects of Perceived Ease of Use and Perceived Usefulness from the TAM into the theoretical framework as well. The aim was to model the study conducted by Yuen et al. (2020b), but also create a more predictive model by incorporating aspects of the classic theory of the TAM.

Assumptions, Limitations, and Scope

In this study, survey responses were assumed to have been given from participants who answered truthfully and accurately to the questions asked in the survey. Without this assumption, a study of this nature cannot be performed. Also, an assumption was made that each participant responded to the survey only once. Another assumption made in this study was that autonomous vehicles considered were fully autonomous. In theory, this is the ultimate goal of producing and distributing autonomous vehicles into the public. In practice, it may take many years until autonomous vehicles become fully autonomous. The first mass appearance of autonomous vehicles on the public roads will likely be semi-autonomous with opportunities for user intervention. However, it made sense to assume that autonomous vehicles in this study were fully autonomous since that is the eventual end goal of what manufacturers are looking to produce, and what will likely be the safest and most efficient way to commute in a vehicle.

There were also some limitations in this study that must be presented. First, the manner of data collection through a link to a Google Forms survey on Facebook was not ideal. Lack of a true random sample and generalization of findings were challenging to make, if not impossible. Given the global pandemic that exists currently, distribution of the survey in this way provided the easiest and safest way to collect quality data for analysis and attempt to draw some high-level conclusions.

Another limitation to this survey design was in the theoretical model factors chosen to predict acceptance and intention to use autonomous vehicles. There could exist more and better factors than the ones chosen for this study, but given that current studies have used similar factors, it made sense to design a study with the factors chosen.

Finally, autonomous vehicles are still relatively new, so there likely existed a knowledge gap for people in making informed decisions about attitudes and opinions toward them. Without a background on things about autonomous vehicles, such as knowing some of the advantages and disadvantages, how difficult they may or may not be to operate, and how safe they are compared to conventional vehicles, participants may not have been able to fully express their opinions toward autonomous vehicles in this study.

The scope of this study was to draw some high-level conclusions about the attitudes and opinions of Americans toward autonomous vehicles. Generalizations and hard conclusions were difficult to claim from the findings of this study, but some interesting findings resulted from the study providing opportunities for further research in this field.

Definition of Terms

The following terms are defined below for the benefit of the reader:

A. Acceptance - An individual's willingness to use autonomous vehicles for the tasks they are designed to support (Nastjuk et al., 2020)

B. Autonomous Vehicle - Driverless vehicles that can sense their environment without human involvement (Yuen et al., 2020b)

C. Compatibility - How consistent autonomous vehicles are with the values, experiences, and needs of the potential adopters ("Diffusion of Innovation Theory", 2019).

D. Complexity - How difficult autonomous vehicles are to understand and/or use ("Diffusion of Innovation Theory", 2019).

E. Observability - The extent to which autonomous vehicles provide tangible results ("Diffusion of Innovation Theory", 2019).

F. Perceived Ease of Use - The degree to which an individual expects autonomous vehicles to be free of effort (Nastjuk et al., 2020)

G. Perceived Value - An individual's evaluation of the merits of autonomous vehicles (Yuen et al., 2020b)

H. Perceived Usefulness - The degree to which an individual sees autonomous vehicles as enhancing their productivity (Nastjuk et al., 2020)

I. Relative Advantage - The degree to which autonomous vehicles are seen as better than non-autonomous vehicles ("Diffusion of Innovation Theory", 2019).

J. Trialability - The extent to which autonomous vehicles can be tested or experimented with before a commitment to adopt is made ("Diffusion of Innovation Theory", 2019).

Summary

Through means of a survey questionnaire, this study gathered the opinions of participants on theorized factors that have shown to influence and have a relationship with public acceptance and intention to use autonomous vehicles. Acceptance of autonomous vehicles has been researched quite a bit in the recent past, but given that this technology is still relatively new, furthering the research and attempting to develop better models was a worthwhile endeavor. Combining theories such as the Technology Acceptance Model, Innovation Diffusion Theory, and Perceived Value Theory, this study aimed to create a more predictive model in determining the public's acceptance and intention to use autonomous vehicles than those done in recent studies.

This chapter introduced the research study by providing a background and statement of the research problem, the purpose and significance of the study, research questions and hypotheses, the theoretical framework that was used, the study's assumptions, limitations, and scope, followed lastly by a list of defined terms used throughout the study. The remainder of this thesis is organized as follows. Firstly, a thorough review of the applicable literature in this space will be provided. It will cover recent studies, gaps in the literature, and present the theoretical framework in more detail. Implications on the auto insurance industry are also presented following the literature review. Next, the methodology of this study will be presented, which will include the design and administration of the survey questionnaire for data collection. Thereafter, results of the study will be presented, including findings resulting from the factor analysis and regression techniques conducted on the data to draw conclusions. Finally, a summary discussion as well as limitations and recommendations for future research are given.

CHAPTER II: Background and Literature Review

Chapter II focuses on the research that has been conducted in recent years in the field of autonomous vehicle acceptance and adoption. First, the speed of technology advancement is discussed, followed by presenting some of the factors that influence technology advancement and how autonomous vehicles fit into this discussion. Then, the widely used Technology Acceptance Model is presented, along with a discussion and analysis of applicable studies that have employed this model. Following this section, Innovation Diffusion Theory is presented by investigating some recent studies that have used this as a different spin on predicting autonomous vehicle acceptance. Some barriers in the way of full adoption of autonomous vehicles are also presented to give some context on hurdles that still need to be cleared before manufacturers start producing them in mass quantities. The chapter closes by providing a discussion on the implications of autonomous vehicles on the auto insurance industry and some of the challenges and opportunities they provide.

Advancement of Technology

Technology has advanced so quickly over the last half century that it seems to be growing at an exponential pace (Winarsky, 2019). Whether it be the diffusion of smartphones into everyday life or the reliance on GPS to get to a destination, the rapid advancement of technology has become a reality in today's society. The evolution of vehicular transportation is not an exception to this phenomenon either. For example, some risks in operating a vehicle have been mitigated with the onset of new technologies like blind spot warning indicators and automatic emergency braking mechanisms, which were first rolled out by Volvo in 2003 as one of the earliest adopters of such technology (*Volvo Car Corporation presents world-first systems* *for improved safety,* 2004). Given how quickly such technology has developed, it is important to understand some of the reasons why it is advancing so quickly.

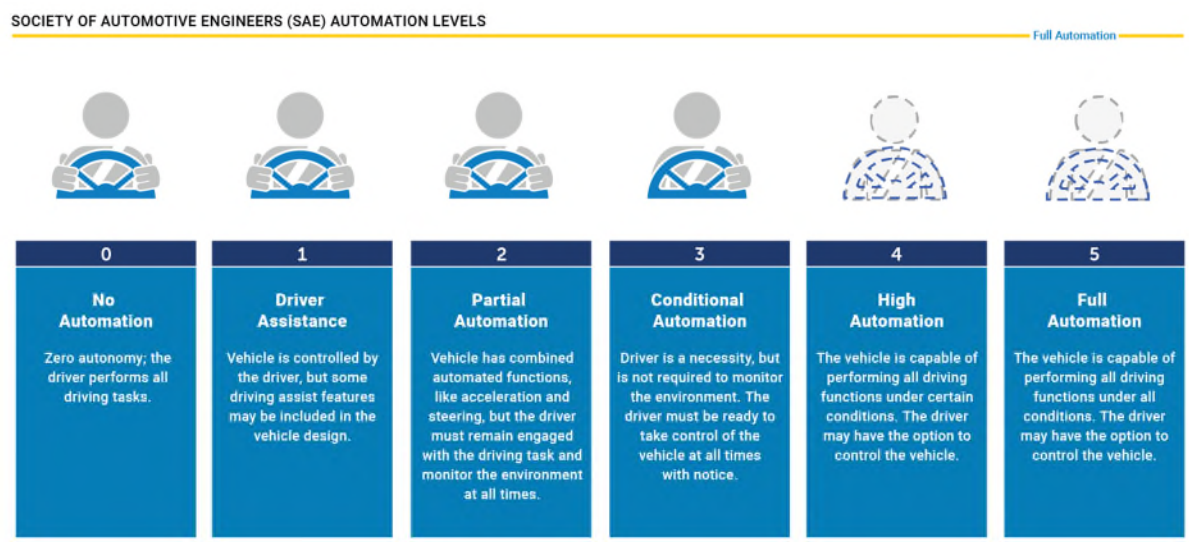
In a study conducted to explain the reasons behind the accelerated speed of technology advancement, Wang et al. (2017) discovered that the further manufacturers lag behind their competition, the quicker they develop advancements in a technology. Grounded on the principles of the Behavioral Theory of the Firm (BTOF), the researchers argued that firms adjust their risk preferences after assessing their performance in the market relative to their appetite towards new technology development. The advancement of technology involves two types of risks: 1) The financial cost of producing a new technology and 2) The opportunity cost of falling behind the competition. When firms fall behind the competition too much, they are much more apt to devote the resources necessary to "catch-up" with the rest of the industry. This constant back-and-forth race among competitors is what continues to drive technology in a particular industry forward. In terms of a newer technology like autonomous vehicles, this theory may not hold as true since there are only a limited number of companies that are currently manufacturing autonomous vehicles (GreyB, 2020). But on the flipside, this means that the opportunity for advancement is ripe since everything is still so new and many of these companies desire to be one of the first to deploy safe autonomous vehicles in the market (GreyB, 2020).

With such a quick advancement in a new technology like autonomous vehicles, expanded and distributed knowledge about them is necessary to continue the advancement. In a study in which researchers observed the advancement of technology in developing countries, results showed that the capability and availability of technology were key factors in determining the advancement of technology, of which developing countries were lacking (Miah, 2012). Deficient infrastructure and funding in these poorer countries were hindering the advancement of technology, whereas in larger and more developed countries these were not issues, and thus technology advanced much quicker (Miah, 2012).

Knowledge about new technology is key to this advancement, but just as important in technological innovation is the sharing of knowledge. In a Rapid Evidence Assessment (REA) conducted by Jones (2017), results indicated that trust, training, and good communication were critical to effective knowledge sharing. Using aspects from theories such as the Absorptive Capacity Theory, Participative Leadership Theory, and Social Exchange Theory, the author stated that: 1) In order for knowledge sharing to take place, one must first collect knowledge, 2) Knowledge sharing is at its best when knowledge is gained by all participants involved, and 3) Knowledge sharing cannot take place without social exchanges between participants (Jones, 2017). The author enacted the use of an REA in his study, in which a systematic review of literature was conducted to develop research questions followed by an analysis of the literature to gain new insights stemming from answering the research questions. In carrying out the REA, the author found that trust among participants, training of the new technology, and good communication were the most common themes among the literature on knowledge sharing and technological innovation (Jones, 2017). Trust and training have also been seen as factors in studies influencing the acceptance of autonomous vehicles (Nastjuk et al., 2020; Yuen et al., 2020b).

Vehicular technology such as blind spot warning and automatic emergency braking continues to be improved upon and has led to the development of some of the first types of autonomous vehicles. In fact, many of the vehicles on roads today have some level of automation incorporated into them, since blind spot warning indicators are considered to be in Level 1-2 of autonomous driving, as seen in Figure 2 below (*Automated Vehicles for Safety, 2020*). Companies such as Tesla claim that they are "very close" to developing vehicles with Level 5 automation (Goh, 2020), so it can be reasonably assumed that this advanced technology is likely not far off into the future. However, what remains as a barrier to deployment of fully autonomous vehicles is acceptance of them by the general public.

Figure 2. Levels of Driving Automation



Technology Acceptance Model

User acceptance and confidence from the general public are vital for further development of new technologies (Taherdoost, 2018). As such, many theoretical models have been developed in recent years in an attempt to predict acceptance of a new technology, many of them stemming from one of the earliest established technology acceptance theories known as the Theory of Reasoned Action (TRA). Developed in the field of social psychology by Ajzen and Fishbein in 1967, the TRA was designed to explain almost any human behavior. Ajzen and Fishbein wanted to develop a theory that would essentially predict, explain, and influence human behavior (Momani, 2018). While their theory was simplistic, it naturally led to many extensions of the model to craft better models to predict and explain human behavior.

One such extension, known as the Technology Acceptance Model (TAM), is considered one of the most widely used models in research studies to predict acceptance of a new technology (Taherdoost, 2018). Originally developed in the information technology field, the model uses two constructs to determine acceptance of a new technology: Perceived Ease of Use and Perceived Usefulness (Momani, 2017). According to Davis et al. (1989), Perceived Usefulness has a direct effect on attitude towards a new technology because when a new technology provides use to an individual, that individual is more likely to have a positive attitude about the new technology. Likewise, when a new technology is deemed easy to use, it enhances an individual's sense of personal control in being able to successfully operate the new technology. Davis et al. (1989) also argued that Perceived Ease of Use has a direct effect on Perceived Usefulness, something that will be tested in this study as well. When a technology is easier to use, less effort is needed to operate the technology, thus in turn giving the individual a positive perception on the usefulness of the technology.

The Technology Acceptance Model (TAM) is a very powerful model that has been used to predict a variety of technologies and has been successfully been applied to new technologies in fields such as healthcare, education, and business (Gagnon et al., 2012; Zheng et al., 2020; Park et al., 2014). Aspects of the TAM have been used to predict the acceptance of autonomous vehicles in many recent studies (Koul & Eydgahi, 2018; Müller, 2019; Yuen et al., 2020a; Nastjuk, 2020).

In a study utilizing the TAM to predict driverless car technology adoption, Koul and Eydgahi (2018) sought to build a model that would more closely examine the relational aspects between the constructs of the TAM by incorporating external variables such as age, gender, and level of education. Koul and Eydgahi referenced relevant studies that have successfully incorporated the TAM to predict technology adoption and applied the theoretical constructs from the model in a different setting compared to other related studies. They employed a survey drawing on the TAM constructs of Perceived Usefulness and Perceived Ease of Use, as well as additional variables noted earlier, and attempted to find relationships between them and intention to use driverless cars. In their research of the available literature, Koul and Eydgahi noted that one study found acceptance of autonomous vehicles was lower in older participants and those with more driving experience, and their study aimed to confirm these results (Koul & Eydgahi, 2018). The quantity of literature evaluated, at least cited in the paper, frankly, is rather lacking for a literature review. However, Koul and Eydgahi do give enough evidence to validate the implementation of this study in the context of furthering the available knowledge of autonomous vehicle adoption. An analysis of reliability on the survey instruments was also conducted, and all measurements achieved a Cronbach's Alpha greater than 0.7, which is the standard in academic research. Therefore, this study can be viewed as valid based on these measures.

Results from this study indicated that the TAM constructs of Perceived Usefulness and Perceived Ease of Use were significant factors in predicting future use of driverless car technologies, with Perceived Usefulness showing a stronger relationship than Perceived Ease of Use. Koul and Eydgahi (2018) note that the finding of both Perceived Usefulness and Perceived Ease of Use showing positive relationships with intention to use driverless cars was consistent with prior research studies. Also, Koul and Eydgahi confirmed their hypothesis that acceptance of driverless car technology was lower in older participants and in those with more driving experience.

One limitation, however, does exist with Koul and Eydgahi's study, and it lies in its inability to fill a significant gap in the literature on this topic. The researchers merely applied established theories in a different setting. This study was similar to Koul and Eydgahi's study by attempting to corroborate the findings that the TAM constructs of Perceived Usefulness and Perceived Ease of Use significantly influence autonomous vehicle acceptance and usage, as well as evaluating the relationship of external variables such as age and driving experience on autonomous vehicle acceptance. But it will further the research by incorporating variables from other behavioral models to gain a better understanding of the factors that may determine autonomous vehicle acceptance.

Müller (2019) enriches the scope of applying the TAM towards not only autonomous vehicles but also battery electric vehicles and car sharing and extends the participant base to a more global scale. In the study, Müller surveyed 1,177 participants across three different continents - Europe, China, and North America. Using such a geographically diverse participant base, as well as combining three technologies into one study to determine their acceptance factors, filled a gap in the research on acceptance of autonomous vehicles.

Employing partial least squares structural equation modeling techniques in his quantitative study, Müller discovered many interesting results. Similar to Koul and Eydgahi (2018), Müller confirmed the basic assumptions of the TAM in his study, noting that positive relationships were found among all three technologies between the constructs of the TAM and attitude towards and behavioral intention to use the technology. Unlike Koul and Eydgahi, however, the control variable age was proved not to be a significant factor in any of the hypotheses provided in the study. The findings from his study furthered the research knowledge on what types of technologies the TAM can be applied to and what variables may or may not be influential in the attitudes towards and behavioral intention to use the three technologies studied.

Tests of internal consistency reliability and validity were conducted on the measurement items, and all tests passed the generally accepted research standards. However, there are some limitations found in Müller's study. First, the literature review provided was adequate for the scope of the study, but not comprehensive. He made a strong case for the appropriateness of conducting the study but failed to go beyond simply reporting what studies have been employed in the recent past in determining adoption of autonomous vehicles, battery electric vehicles, and car sharing. Secondly, since the participant base was so geographically diverse, it was difficult to make many broad generalizations about the population sampled. Even though the sample size from each continent was fairly large, the size of the area that each encompasses is even larger and more difficult to make generalizations about. If the author desired to make general statements about North American attitudes toward autonomous vehicles with a sample size of only 116 participants, these statements would likely prove to be problematic to claim. Similarly, while combining three different technologies to determine possible acceptance factors is original and extends the available research in this field, it is difficult to differentiate the strengths of the relationships for each technology individually. The constructs and measurements of the researcher's study were needed to be made comparable to each other, thus preventing him from exploring one of the three technologies in very much detail (Müller, 2018). This study also aimed to confirm the relationships between the constructs of the TAM and acceptance and intention to use autonomous vehicles, but it tested whether age and other external variables showed significant relationships among the model constructs as well.

Using a unique method to develop initial factors driving autonomous vehicle acceptance, Nastjuk et al. (2020) interviewed 20 participants prior to developing their study in order to form acceptance criteria from an end-user's perspective. Based on their findings from the interviews, the researchers then developed a quantitative study to determine the strength of the relationship of the factors that emerged on the constructs of the TAM, and eventually on the acceptance of autonomous vehicles. The literature review presented from the study appeared to be very thorough and comprehensive, especially in validating the reasoning behind developing factors through qualitative means. There has been some criticism in the recent past in using a simple TAM methodology since it could lead researchers to overlook predictive factors by making assumptions instead, which is why the researchers decided to incorporate qualitative methods into their study as well (Nastjuk et al., 2020).

Nastjuk et al. (2020) conducted quantitative tests of variance-based partial least structural equation modeling on hypotheses developed using the acceptance criteria formed from the pre-study interviews. Tests of common method bias and various tests of validity revealed little concern on the results of the study (Nastjuk et al., 2020). Their study revealed many interesting findings, but a common theme that is present in studies utilizing the TAM is the difficulty in determining only a few central factors that most influence the constructs of the TAM. The factors Perceived Usefulness and Perceived Ease of Use have been well-established as showing strong relationships with acceptance and intention to use autonomous vehicles (Koul & Eydgahi, 2018; Müller, 2019; Yuen et al., 2020a; Nastjuk, 2020). However, determining the factors that have a strong relationship with Perceived Usefulness and Perceived Ease of Use across multiple studies has proved to be more difficult. Nastjuk et al. (2020) noted their findings were both affirmatory and contradictory regarding predictive factors in autonomous vehicle acceptance compared to other similar studies. Like in Nastjuk et al.'s study, this was a limitation in this study as well, and perhaps the only way to change this narrative is to continue with further research as autonomous vehicle technology develops alongside as well.

Innovation Diffusion Theory

Many studies have found influential relationships between Perceived Usefulness and Perceived Ease of Use and the adoption of autonomous vehicles but determining the factors that influence Perceived Usefulness and Perceived Ease of Use has not been sufficiently studied (Yuen et al, 2020a). In their study to determine factors influencing autonomous vehicle adoption, Yuen et al. (2020a) incorporated aspects of Innovation Diffusion Theory (IDT) in order to address these gaps. The researchers tested the strength of the relationships of six constructs of IDT on Perceived Usefulness and Perceived Ease of Use, as well as the relationships of Perceived Usefulness and Perceived Ease of Use on the behavioral intention to use autonomous vehicles. A unique theoretical framework among the available research on autonomous vehicle acceptance, the researchers' combination of the TAM and IDT to predict the adoption of autonomous vehicles is something this study attempted to do as well.

The researchers' literature review presented was adequate, but the discussion does not go much beyond a brief background on the TAM and IDT and how they planned to integrate them together in their study. They did, however, address some of the gaps in the literature and how the multi-model incorporation of their study filled those gaps, which are similar to the gaps presented in this study. Employing structural equation modeling on data collected from a questionnaire in order to determine relationships among the various theoretical constructs presented, Yuen et al. (2020a) first validated their measurement items appropriately using industry standards for model fit and reliability, thus validating their research methods.

Findings of their study showed influential relationships between the constructs of IDT and those of the TAM, supporting the proposition of integrating the two models together to explain behavioral intention to use autonomous vehicles (Yuen et al., 2020a). However, some limitations of this study exist. First, the participant base may be slightly biased since respondents of the study were recruited in high traffic areas of Beijing, China. Generalization of findings may prove to be difficult and may not be applicable to other cultural and geographical areas. Secondly, Yuen et al.'s study failed to use many demographic variables to determine their influence on the acceptance of autonomous vehicles, something this study looked to address. Even so, Yuen et al.'s study showed that IDT fits well with the TAM in the acceptance of autonomous vehicles, and this study aimed to add to the knowledge discovered from their study.

Talebian and Mishra (2018) also extended Innovation Diffusion Theory to predict factors influencing the adoption of autonomous vehicles, with a focus more on predicting the future demand for autonomous vehicle ownership and how long their adoption may take. Drawing on different aspects of IDT than Yuen et al. (2020a), Talebian and Mishra discuss the role of consumer resistance on adoption of autonomous vehicles. Innovation Diffusion Theory classifies consumers as falling into one of five categories: innovators, early adopters, early majority, late majority, and laggards (Talebian & Mishra, 2018). The researchers argued that all consumers are resistant to innovations, at least in some capacity, and that each category contains a certain level of resistance to the innovations, which ultimately influences the timing of adoption (Talebian & Mishra, 2018).

The researchers used theoretical components to develop a simulation model to help predict the adoption of autonomous vehicles. Data was collected through a survey sent to full-time employees at the University of Memphis, gathering 327 complete responses, which was a 13.3% response rate. The researchers, however, appeared to take some interesting methodological liberties in their study. First, they employed Iterative Proportional Updating procedures to "inflate the sample data to the full population of UofM employees" (Talebian & Mishra, 2018). While this methodology has been used in the past, as in Beckman et al. (1996) for U.S. census data, there is also some skepticism towards its appropriateness of use in research studies (Choupani & Mamdoohi, 2016). Having responses from 327 participants should be an adequate amount of data for conducting analysis and drawing conclusions, therefore their use of Iterative Proportional Updating procedures seemed unwarranted. Secondly, the researchers implemented multivariate normal imputation, which is a method used to fill in missing entries in data collected (Choupani & Mamdoohi, 2016). Lee and Carlin (2010) point out many issues with its use, such as assuming the data is normally distributed when this assumption cannot be presumed. Similar to their use of Iterative Proportional Updating, while not theoretically incorrect, its use simply seemed unnecessary. Their missing data rate was only 0.65%, but if missed data was a concern to the researchers, the cleaner method would have been to simply eliminate those responses from the data. In handling missing entries, this study differs from Talebian & Mishra (2018) by eliminating those responses from the data.

Yuen et al. (2020b) conducted a study that was a theory-driven approach to explain autonomous vehicle acceptance, utilizing IDT as well as Perceived Value Theory and Trust Theory. Their main focus was to develop a model to identify some previously unknown factors influencing public acceptance of autonomous vehicles and examine their interrelationships (Yuen et al., 2020b). Kum Fai Yuen was a researcher in another study utilizing IDT (Yuen et al., 2020a), but here he and his fellow researchers chose to use a few different variables within IDT for their study, namely the constructs of Relative Advantage, Compatibility, Reduced Complexity, Trialability, and Observability. Along with Perceived Value and Trust, the researchers developed a model to predict public acceptance of autonomous vehicles. A fairly thorough review of literature was presented, strengthening the argument to include aspects of three different theories in one study.

Adopting structural equation modeling to perform analysis on a set of data collected through a survey, Yuen et al. (2020b) found that all of the factors presented from each of the three theories showed significant relationships in their model. However, the researchers found weak relationships between acceptance of autonomous vehicles and sociodemographic variables such as age and gender (Yuen et al., 2020b), which corroborated other findings that the researchers presented in their literature review as well as some of those presented here in this study (Müller, 2019; Yuen at al., 2020a). Much of Yuen et al.'s study was adapted to fit in this study, along with the incorporation of constructs of the TAM, aiming to determine if similar findings held true with a different participant base and slightly different variables used in the theoretical framework. However, there are some limitations of the researchers' study that need to be pointed out. First, the respondents of the survey reside entirely in Seoul, Republic of Korea. Using participants from a different country with perhaps a different cultural background may yield different results from what were discovered. Also, the researchers recruited participants along five subway stations in predominantly urban parts of Seoul, Republic of Korea. Seoul is a densely populated city with many working professionals who favor the use of autonomous vehicles, creating potential bias in the sample of participants towards those who would accept autonomous vehicles (Yuen et al., 2020b). To differentiate from Yuen et al.'s study, this study aimed to receive as wide of a participant base as possible so as to alleviate concerns of bias either for or against autonomous vehicles.

Potential Barriers to Adoption

In order for autonomous vehicles to become fully adopted into mainstream society, a number of barriers must be tackled. Many studies discuss potential barriers that exist to full adoption and some have crafted their theoretical framework to fit them in, such as Yuen et al. (2020b) incorporating trust in autonomous vehicles as a central factor, and Talebian and Mishra (2018) suggesting that consumers are typically resistant to innovations since new technologies tend to change people's routines. To better understand what the available literature says about barriers that exist to full adoption of autonomous vehicles, Bezai et al. (2021) conducted a study to analyze what has already been presented in applicable research studies on autonomous vehicle acceptance. Their four-step process led to six types of barriers that exist in the full adoption of autonomous vehicles: safety, users' acceptance and behavior, legislation, computer software and hardware/sensors, communication systems, and accurate positioning and mapping. The main focus of this study was on users' acceptance and behavior on autonomous vehicles, and Bezai et al. (2021) found that a lack of trust and determining liability in the case of an accident are the biggest barriers affecting user's acceptance of autonomous vehicles. Other findings indicated that safety, either when as an occupant in an autonomous vehicle or when a pedestrian with autonomous vehicles on the road, along with privacy were the primary concerns of the general public (Bezai et al. 2021). Besides liability concerns, Benzai et al. (2021) pointed out some unanswered questions about autonomous vehicle legislation. What will eligible operators of autonomous vehicles be given instead of a driver's license? Will a new type of license be required? Who is responsible in the case of accidents involving rideshare services such as Uber and Lyft? These questions must be addressed by government officials and policymakers in order for the full adoption of autonomous vehicles to be realized.

Fagnant and Kockelman authored a similar article in which they discussed the benefits of autonomous vehicles, barriers that exist, and recommendations for policymakers (Fagnant & Kockelman, 2015). Through their review of literature, discussions of barriers that exist revolved around many of the same topics as in Bezai et al. (2021), such as concerns with licensing, privacy, security, and litigation and liability. One of the main differences in their study involved a discussion around the high market cost of autonomous vehicles, due mostly to their high-tech sensors, communication, and guidance software included in most autonomous vehicles (Fagnant & Kockelman, 2015). Sources indicated that the cost of autonomous vehicles was over $100,000 in 2015, which is unaffordable for most Americans (Fagnant & Kockelman, 2015). However, as technology progresses and autonomous vehicles become more prevalent, over time the cost of autonomous vehicles has been estimated to decrease between a total of $25,000 and $50,000 (Fagnant & Kockelman, 2015). Even so, basic economics indicate that the benefits of autonomous vehicles still must outweigh the total cost of them in order for consumers to ultimately purchase an autonomous vehicle at whatever price the market dictates (*How Cost-Benefit Analysis Process Is Performed*, 2021). The realization of those benefits will play a key factor in the full adoption of autonomous vehicles as the technology progressively improves.

Implications on the Auto Insurance Industry

When analyzing the available literature on acceptance and intention to use autonomous vehicles, there appeared to be a gap in the research in providing a discussion on their implications in the auto insurance industry. This study aimed to fill that gap. Two primary concerns that auto insurance companies have with autonomous vehicles are determining how much premium to charge insurers for adding these vehicles to their policy and determining liability in the case of an accident (Anderson et al., 2018). In terms of autonomous vehicle liability, Eastman (2016) states, "No longer will human error (driver negligence) be the cause of most automobile accidents". Insurance companies currently do not use the manufacturer of the car to determine fault in an accident (Anderson et al., 2018), but that may need to change with the advent of autonomous vehicles. It is arguable that the manufacturer of an autonomous vehicle can be an influencing factor in determining liability in the case of an accident involving one or more autonomous vehicles and should thus be held accountable for its product. But autonomous vehicle manufacturers have differing opinions on this subject. For example, Volvo claims 100 percent responsibility for its autonomous vehicles whereas Tesla claims 0 percent responsibility (Anderson et al., 2018). Involving the auto manufacturers into the equation of determining fault would lead to legal challenges for auto insurance companies. For many of the reasons listed above and throughout this chapter, determining fault and liability in auto accidents will prove to be difficult for insurance companies when autonomous vehicles are involved.

One potential benefit that insurance companies can take advantage of when underwriting autonomous vehicles is in the data that it provides from each of its trips taken. With all of its sensors to perceive their driving environment, autonomous vehicles collect a massive amount of data (*The importance of data analysis in autonomous vehicle development*, n.d.). Insurance companies already utilize usage-based data to underwrite vehicles which helps determine how much to charge for each vehicle (Pérez-Marín & Guillen, 2019), so it makes sense that they could tap into this data to learn more about the vehicle and its driving history to accurately price how much premium to charge. Anderson et al. (2018) even found that stakeholders in the insurance industry believe that the technology and data collected from autonomous vehicles could aid in determining fault in accidents. Algorithms could be built from this data and the emerging technology to assist in making these challenging decisions (Anderson et al., 2018). Insurance companies face challenges ahead with autonomous vehicles regarding pricing and legal and liability issues, but some of this could be mitigated with the advancement of technology and the amount of data collected directly from the autonomous vehicle.

In this chapter, numerous studies were analyzed and presented on the acceptance and intention to use autonomous vehicles. This new technology, like many innovations, is the product of the technology age in which advancements are made very quickly. Reasons for this speed of advancement were discussed and put into the context of autonomous vehicles. Next, the theories of the Technology Acceptance Model and Innovation Diffusion Theory were presented and discussed using recently conducted studies. These two models will serve as the basis for the theoretical framework of this study. Also, some of the barriers that exist to adoption and acceptance of autonomous vehicles were presented to give the reader some context on the challenges that lie ahead for policymakers, manufacturers, and users alike. The chapter finished by giving a brief discussion on the implications of autonomous vehicles on the auto insurance industry and how some companies may respond to its emergence in the marketplace.

CHAPTER III: METHODOLOGY

Chapter III gives an overview of the methodology used to conduct the research for this study. The setting and participant base is laid out in more detail, as well as the instrumentation used to collect data. Further, procedures conducted and arguments for cleaning the data are presented. Lastly, analysis techniques for the statistical tests of factor analysis, linear regression, and non-parametric t-tests are presented in the following sections.

Setting and Participants

Data collection for this study was conducted through a survey created on Google Forms to gather opinions of participants on autonomous vehicles. Participants were recruited through a public posting on Facebook by providing a link to a survey on Google Forms. The only inclusion criteria for this study were that a participant must be a resident of the United States or a U.S. territory, must be of legal driving age in the United States, and must possess a valid driver's license. Therefore, no restrictions to geographical areas within the United States existed, but generalizations of findings were difficult to make. Given the manner of data collection through an online survey distributed through Facebook, the collection of a true random sample was nearly unattainable and generalizations to the legal driving age public were difficult to make. However, some interesting findings still resulted from conducting this study, providing opportunities for further research in this field. A total of 216 participants completed the survey prior to any data cleaning of invalid responses.

A priori statistical power test was conducted using G*Power (a software used to conduct statistical power tests) on the three primary research questions in this study. Using an alpha level of 0.05 and estimating a moderate effect size of 0.15 for the linear multiple regression test that was conducted, with two predictor variables for the first research question, resulted in a required sample size of 107 participants. For the second primary research question, using the same alpha level and effect size estimation, one predictor variable required a sample size of 89 participants. Finally, for the third primary research question with the same parameters as above but with four predictor variables, the required sample size is 129 participants. Results of the priori power tests can be found in Appendix D.

Instrumentation

The primary source of data collection for this study was through a survey created on Google Forms, which incorporated questions that revealed the central constructs of Innovation Diffusion Theory, The Technology Acceptance Model, and Perceived Value Theory, as outlined in Figure 1 in Chapter I. These seven constructs are Relative Advantage, Compatibility, Trialability, Observability, Perceived Usefulness, Perceived Ease of Use, and Perceived Value. Measurement items used in this study were taken from Yuen et al. (2020b) and Nastjuk et al. (2020), both of which sufficiently referenced sources to validate the development of the various survey questions. A subset of the total questions asked in each survey was used in this study in order to keep the length of the survey to a minimum and reduce the amount of time needed to complete the survey.

In Yuen et al. (2020b), a measurement model analysis was conducted on their data, in particular it was used to assess reliability and validity measurements. The authors reported Cronbach's Alpha measurements for each construct as being greater than the standard values of 0.70 and 0.80. Convergent validity was established by determining the average variances as resulting in values above the standard of 0.50. Further, discriminant validity was attained as the average variances showed to be larger than the squared correlations between the constructs of the model (Yuen et al., 2020b). In the study conducted by Nastjuk et al. (2020), similar tests of reliability and validity were conducted on the measurement items of their survey. Reliability measurements all resulted in values between 0.89 and 0.99, exceeding the standard minimum thresholds. Similarly, tests on average variances and squared correlations met the standards for ascertaining validity in the measurement items (Nastjuk et al, 2020).

Procedure

Data for this study was collected using a survey created in Google Forms consisting of seven demographic questions followed by 25 model questions crafted from studies conducted by Yuen et al. (2020b) and Nastjuk et al. (2020). Google Forms has a setting to allow only one response per user, but this setting required a Gmail account to sign in and complete the survey. To avoid losing participants who did not have a Gmail account and did not want to create one, the decision was made to keep this setting off and not require a Gmail account to take the survey. However, this could allow participants to potentially take the survey more than once. In order to prevent potential gaming of the data in this manner, participants were first presented with a disclosure statement stating that participants were only to complete the survey once to maintain the integrity of the survey and its results. Also, on the first page was a short paragraph explaining more about the study being conducted and what participants could expect when completing the survey. Following the first page of the survey, an image detailing the 6 levels of autonomous vehicles was presented to participants in an effort to provide further information about autonomous vehicles (*Automated Vehicles for Safety*, 2020). There also included an explanation that participants should assume that the autonomous vehicles considered in the survey are Level 5 Full Autonomation vehicles. Copies of the disclosure statement, paragraph about the study, and image explaining the 6 levels of autonomous vehicles can be found in Appendix A.

IRB approval was granted to conduct this study through an Exempt Review Application. A copy of the approved form can be found in Appendix B. Participants' identities were also kept confidential through the entirety of the study. Google Forms provided an option when creating the survey to not collect email addresses, and no other forms of identification were collected (such as name, address, etc.).

Data Processing and Analysis

The statistical software package R was used for various analyses in this study, which is a free and open-source tool to easily conduct statistical tests (R Core Team, 2018). However, prior to conducting any statistical analyses, cleaning of the data was performed to allow for more accurate analysis and results in R. First, reverse-coded question responses were included in the questionnaire specifically for the purpose of determining low quality responses. In other words, responses on the reverse-coded questions that are in line numerically on the Likert scale with other questions not reverse-coded would indicate a potential for low quality survey responses. To clean the data, an average of the original Likert scale responses was taken for each participant and the data was sorted from highest average response to lowest average response. Those with an average response above 6.00 were removed from the data since a noticeable pattern of high scores were given in these responses, a sign of potential gaming and manipulation of the data. From this data scrubbing, six responses were removed from the data. Further, since Question 12 was reverse-coded and states "I don't believe I can benefit from using autonomous vehicles", any responses of 7 for this question as well as a response of 7 for Question 25 which states "I intend to use an autonomous vehicle in the future" were removed due to inconsistency in the participant's attitudes toward autonomous vehicles. It does not seem logical for a participant to answer Strongly Agree that they cannot benefit from using autonomous vehicles while also answering Strongly Agree to intending to use an autonomous vehicle in the future. Question 12 was reverse-coded specifically for this purpose since it appeared to have a strong tie to Question 25. Four responses met this criterion of illogical participant behavior. Additionally, two responses included blank entries and were thus removed from the data, giving a total of 12 responses that were removed for the reasons given above and leaving 204 total responses to perform statistical analyses on.

Following the removal of invalid, low quality responses, the four reverse-coded questions were reversed back again on the 7-point Likert scale (i.e., 1 changed to 7, 2 changed to 6, etc.). The questions that were reverse-coded were Question 2, Question 5, Question 12, and Question 20. A list of all of the questions asked in the survey can be found in Appendix C. Finally, dummy variables were created for all demographic categorical variables used in the study with more than two outcomes (which included Age, Geographical Region, and Approximate Annual Mileage).

Once the data was cleaned up, it was then imported in the statistical software package R for further analyses. The main focus of the statistical tests was on the three Primary Research Questions as well as the three Secondary Research Questions, which are restated below:

Primary Research Questions

1. What is the relationship between the constructs of the Technology Acceptance Model and acceptance and intention to use autonomous vehicles?
2. What is the relationship between the constructs of Perceived Value Theory and acceptance and intention to use autonomous vehicles?
3. What is the relationship between the constructs of Innovation Diffusion Theory and the constructs of the Technology Acceptance Model and Perceived Value Theory?

Secondary Research Questions

4. What is the effect of accident experience on the acceptance and intention to use autonomous vehicles?
5. What is the effect of experience with driver assisted systems on the acceptance and intention to use autonomous vehicles?
6. Does there exist a difference in acceptance and intention to use autonomous vehicles across gender?

The three Primary Research Questions were analyzed using Factor Analysis and Linear Regression techniques to determine relationships between the constructs of the theoretical models as outlined in Figure 1 in Chapter I. The goal was to determine if statistically significant relationships existed between these constructs and acceptance and intention to use autonomous vehicles. In conducting Factor Analysis and Linear Regression statistical techniques, the preliminary checks of low and high correlations, outliers, normality, potential sample size issues, and various residual plots were completed prior to performing any statistical analyses. Factor Analysis inference procedures were used, and principal component analysis was conducted on various measurement items with orthogonal rotation, depending on the research question. The study was designed so that the following components from the theoretical framework would emerge from the principal component analysis: Relative Advantage, Compatibility, Trialability, Observability, Perceived Usefulness, Perceived Ease of Use, Perceived Value, and Acceptance and Intention to Use Autonomous Vehicles. The variables Relative Advantage (Yuen et al., 2020a; Yuen et al., 2020b; Nastjuk, 2020), Compatibility (Yuen et al., 2020a; Yuen et al., 2020b; Nastjuk, 2020), Trialability (Yuen et al., 2020a; Yuen et al., 2020b), and Observability (Yuen et al., 2020b) have been shown to be significant predictors of either the constructs of the Technology Acceptance Model or Perceived Value, while Perceived Usefulness (Yuen et al., 2020a; Nastjuk, 2020), Perceived Ease of Use (Yuen et al., 2020a; Nastjuk, 2020), and Perceived Value (Yuen et al., 2020b) have all shown to be significant predictors of Acceptance and Intention to Use Autonomous Vehicles.

For the three Secondary Research Questions, non-parametric t-tests were conducted to determine the effect that various demographics or experiences have on acceptance and intention to use autonomous vehicles. A non-parametric t-test, such as the Wilcoxon test, was performed due to the lack of an underlying distribution present, given that the data was collected from a survey using a Likert scale. The assumptions of homogeneity of variance and normality were violated due to this method of collecting data. Therefore, the Wilcoxon Rank-Sum Test was conducted to determine statistically significant relationships of acceptance and intention to use autonomous vehicles across the three categorical variables listed in the Secondary Research Questions. All three variables of accident experience, driver assisted systems experience, and gender were collected in Nastjuk et al. (2020) but were never analyzed to determine statistical significance with acceptance and intention to use autonomous vehicles. Further, gender was collected in Yuen et al. (2020a), Yuen et al. (2020b), and Koul and Eydgahi (2018) but was never analyzed for statistical significance. This study aimed to fill this gap by providing results on the statistical relationships seen between these variables and acceptance and intention to use autonomous vehicles.

In this chapter, the methodology carried out for this study on finding determinants of acceptance and intention to use autonomous vehicles is laid out in detail. A description of the eligibility criteria for acceptance into the participant base were included, as well as some initial results of power tests to determine adequate sample size were presented. Then, the survey questionnaire was described in more detail and procedures used to create the survey in Google Forms. After that, methods to clean the data were outlined as well as the reasons for removing certain responses were given. Finally, the statistical methods used to analyze the research questions in this study were presented, as well as a high-level view of the inference procedures conducted while performing the statistical tests.

CHAPTER IV: RESULTS

Chapter IV presents the results of the statistical tests described in Chapter III to answer the Primary and Secondary Research Questions of this study. First, the setup of the survey questionnaire is presented again to get a context of the data that was collected for this study. Next, the steps taken to clean the data are presented in order to properly conduct the various statistical tests. Then, descriptives of the participants included in the study are presented. Lastly, the hypotheses and analyses findings are given based on the Primary and Secondary Research Questions, followed by some conclusions from the tests performed.

Questionnaire Setup

The 25-item questionnaire, along with seven additional demographic questions, was analyzed using the statistical software package R (R Core Team, 2018). The seven demographic questions asked each participant to provide their gender, age, region of the country that they live in, approximate annual miles driven each year, and whether they have been in a car accident before, have experience with driver assisted systems, and if they possess a valid driver's license. Actual questions asked with choices given to the respondents can be seen in Appendix C. Questionnaire responses following the demographic questions were given on a 7-point Likert scale ranging from 1 - Strongly Disagree, 2- Disagree, 3 - Somewhat Disagree, 4 - Neither Agree nor Disagree, 5 - Somewhat Agree, 6 - Agree, and 7 - Strongly Agree.

Data Cleaning

Prior to conducting analysis using R, a series of data cleaning steps were conducted to provide as accurate results as possible. Firstly, two respondents included blank entries to questions asked in the survey and were thus removed from the analysis. Secondly, an average of responses to the survey questions on the Likert scale from 1-7 were analyzed. Six respondents had an average in their responses higher than 6 and were removed from the data, as this was seen as a potential sign for gaming and manipulation of the data. Lastly, four respondents were removed from the data for having illogical responses of 7 to both the reverse-coded Question 12 and normally-coded Question 25 (as explained in Chapter III). This totaled 12 respondents that were removed from the data, leaving 204 responses to perform statistical analyses on. After removing these 12 responses, the four reverse-coded questions (Q2, Q5, Q12, and Q20) were reversed back to normally-coded responses on the 7-point Likert scale.

Descriptives

Table 1 shows the demographic profile of the 204 respondents of the questionnaire survey. Of the respondents, 133 were Females (65.2%) and 71 were Males (34.8%), skewing the distribution of respondents more toward females. However, a more even distribution was seen among the age range of respondents (excluding the under 16 age range), with the highest percentage group lying in the 16–30-year-old range (28.4%). Overwhelmingly, the majority of respondents resided in the Midwest region (states being IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, and WI), with 83.3% of respondents living in this defined region. These results made it difficult to generalize about the entire population of the United States. For approximate miles driven in a year, a seemingly even distribution was discovered, with the highest percentage falling in the 10,000 - 11,999 miles range (25.0%). Finally, more than 75% of the respondents have been in a car accident before, as well as 70% have had experience with driver assisted systems before (e.g., blind spot warning indicator or automatic emergency braking), with all respondents possessing a valid driver's license.

Table 1. Respondents' profile

Characteristics	Items	Frequency (n = 204)	Percentage (%)
Gender	Female	133	65.2
	Male	71	34.8
Age	< 16	0	0.0
	16 - 30	58	28.4
	31 - 40	40	19.6
	41 - 50	19	9.3
	51 - 60	45	22.1
	> 60	42	20.6
Region	Midwest	170	83.3
	Northeast	7	3.4
	Southeast	12	5.9
	Southwest	7	3.4
	West	7	3.4
	Not in the USA	1	0.4
Miles Driven	< 6,000	19	9.3
	6,000 - 7,999	22	10.8
	8,000 - 9,999	32	15.7
	10,000 - 11,999	51	25.0
	12,000 - 13,999	43	21.1
	> 14,000	37	18.1
Accident Experience	Yes	155	76.0
	No	49	24.0
Driver Assisted Experience	Yes	143	70.1
	No	61	29.9
Valid Driver's License	Yes	204	100.0
	No	0	0

Table 2 below shows the means and standard deviations of each question presented in the questionnaire. Interestingly, Questions 7 and 8 related to the Trialability construct in Innovation Diffusion Theory showed fairly high mean Likert scale scores of above 6, while many of the other questions showed means around 4 (equating to responses of Neither Agree nor

Disagree, on average). This indicates a fairly strong desire among the sample participants to test an autonomous vehicle first before committing to buying one.

Table 2. Means and standard deviations of the questionnaire items

	mean	sd		mean	sd
Q1	4.14	1.51	*Q14*	4.39	1.63
Q2	4.29	1.58	*Q15*	4.61	1.52
Q3	4.01	1.56	*Q16*	4.18	1.78
Q4	3.70	1.83	*Q17*	3.93	1.77
Q5	3.72	1.96	*Q18*	4.93	1.71
Q6	3.77	1.75	*Q19*	4.91	1.50
Q7	6.67	0.96	*Q20*	3.88	1.53
Q8	6.20	1.39	*Q21*	3.78	1.84
Q9	5.92	1.59	*Q22*	3.58	1.66
Q10	6.15	1.19	*Q23*	3.92	1.46
Q11	4.71	1.84	*Q24*	4.20	1.83
Q12	4.49	1.71	*Q25*	3.81	1.82
Q13	4.72	1.42			

Prior to conducting factor analysis on the data, various necessary sample size requirements were considered. One method considers the number of cases per variable, with the desire to reach 15 at the minimum. The largest number of items that will be considered in one of the factor analyses presented later is nine, and with 204 survey responses, the number of cases per variable results in a value of 22.67. So, the minimum number of 15 is reached in all three factor analyses performed. Additionally, priori power tests were conducted in G*Power (a software used to conduct statistical power tests) on the three primary research questions, and all three tests indicated a sufficient amount of sample size in the data collected. An F-test of Linear Multiple Regression: Fixed model, R-squared deviation from zero with a moderate effect size of 0.15 was used for all three primary research questions. Primary Research Question #1 has two predictor variables and, when placing all of these inputs into the software, G*Power indicated that a sample size of 107 would be sufficient. For Primary Research Question #2, using the same methodology as in #1 but with one predictor variable, the total sample size needed is 89. Similarly, for Primary Research Question #3 and with four predictor variables, the total sample size needed is 129. In all cases, the sample size in this study was 204 participants, well above the largest sample size needed of 129 according to G*Power. Outputs of the priori power tests conducted can be found in Appendix D.

Hypotheses and Analyses

In this section, hypotheses for the three Primary Research Questions and two Secondary Research Questions are presented, as well as analyses conducted to determine statistical significance for each. The tests conducted for the three Primary Research Questions were Factor Analysis and Simple Linear Regression, and the tests for the two Secondary Research Questions were performed using the Wilcoxon Rank-Sum Test. Assumptions and pre- and post-hoc tests are presented as well, where appropriate.

Hypothesis 1. *There exist positive relationships between the constructs of the Technology Acceptance Model and Acceptance and Intention to Use Autonomous Vehicles.*

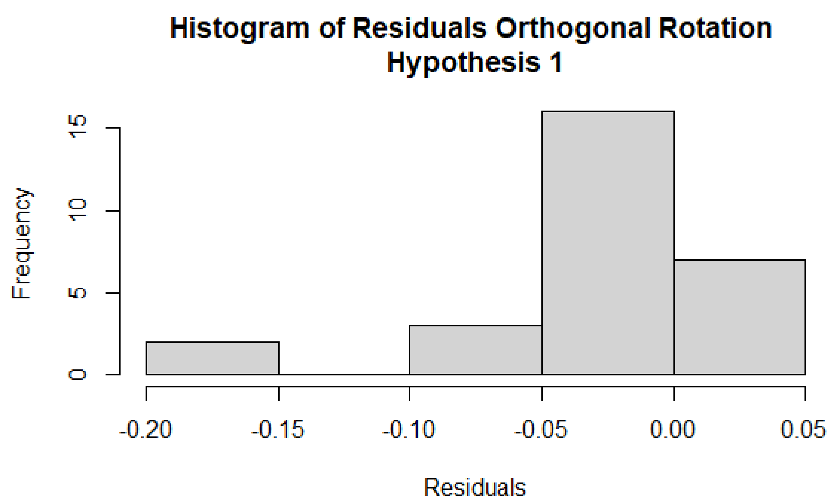
In the survey questionnaire, there were five questions geared towards the constructs of the Technology Acceptance Model and five questions based on the Acceptance and Intention to Use Autonomous Vehicles. So, a principal component analysis (PCA) was conducted on the ten items of the survey questionnaire for these constructs. Bartlett's test of minimum correlations, $\chi^2(45) = 2073.13$, $p < .001$, indicated that the correlations between the items were sufficiently large for PCA. The determinant of the correlation matrix was greater than 0.00001 (2.96×10^{-5}), indicating no concern of multicollinearity in the data for these constructs. Normality of the data was not attained due to the nature of Likert scale data assuming not to be normally distributed.

In starting the factor analysis, an initial model with orthogonal rotation was created to obtain eigenvalues for each of the 10 items in the data for this research question. There are two constructs in the Technology Acceptance Model and one factor for Acceptance and Intention to Use Autonomous Vehicles, so the test design was to examine whether three components should be kept for further analysis. However, Questions 16 and 17 unexpectedly did not load onto their own factor based on the test design setup, as these were questions geared towards the Perceived Usefulness construct in the Technology Acceptance Model. Therefore, Questions 16 and 17 were removed from the analysis and a principal component analysis was conducted with only two factors.

In the two-factor model, Bartlett's test of minimum correlations, $\chi^2(28) = 1604.95$, $p < .001$, indicated that the correlations between the items were sufficiently large for PCA. The determinant of the correlation matrix was greater than 0.00001 (3.21×10^{-4}), indicating no concern of multicollinearity in the data for these constructs. Again, normality of the data was not attained due to the nature of Likert scale data assuming not to be normally distributed.

Upon examining the results with a two-factor model, all questions loaded onto their expected factors and both components exhibited eigenvalues greater than 1. Together, the two components explained 83% of the variance. The screen plot was also examined and showed inflection points that would support retaining two components. Investigating the residuals of the two-component model revealed that 18% of the residuals were above the threshold of 0.05, which is satisfactory since less than 50% of the residuals fall above this threshold. The root-mean-square of the residuals was equal to 0.05, below the standard threshold of 0.08. A histogram of the residuals is shown below in Figure 3, indicating that they appear to come from a normal distribution. Also, the fit based upon off diagonal values was equal to 0.99, another indicator that two components were appropriate here. Finally, the mean h2 values from this model with orthogonal rotation was greater than 0.6, further showing that sample size was not a concern.

Figure 3. Histogram of the residuals for Hypothesis 1



Given the nature of this questionnaire, there was a potential for overlap and higher than normal correlations among the factors. Therefore, an oblique rotation was also investigated. Factor correlations are shown below in Table 3. The two factors show a relatively high correlation between each other (0.55), indicating some appropriateness for using the oblique rotation model.

Table 3. Factor Correlations for Hypothesis 1

	FA1	FA2
FA1	1.00	0.55
FA2		1.00

However, upon examining a histogram of the residuals for this model with oblique rotation, there were serious concerns that the residuals had come from a normal distribution, as seen in Figure 4 below. An analysis of the residuals showed that 75% of them were greater than 0.05, indicating a very poor fit with the data. Therefore, a PCA with oblique rotation was not considered for further analysis and the model using orthogonal rotation was used going forward instead.

Figure 4. Histogram of Residuals with Oblique Rotation for Hypothesis 1

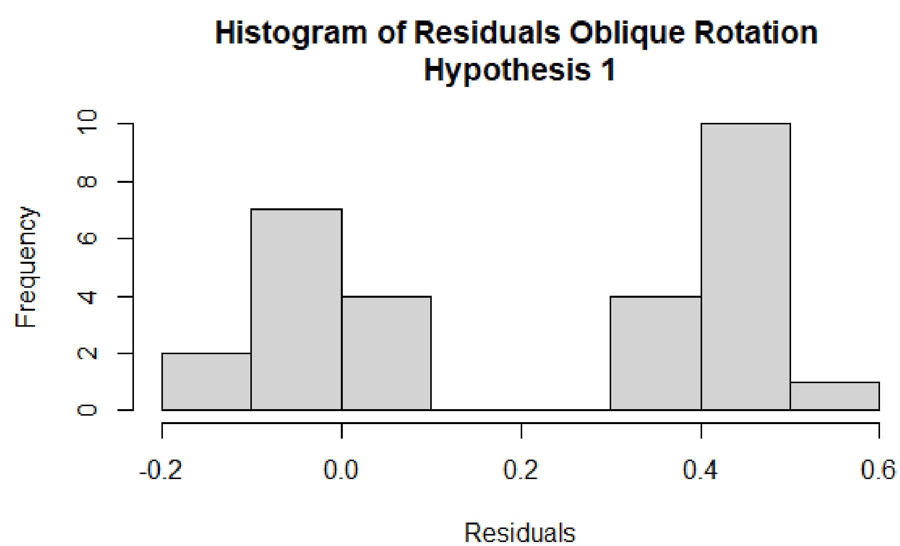


Table 4 below shows the factor loadings after orthogonal rotation onto the two components. Based on the theoretical model, the two components are Perceived Ease of Use from the Technology Acceptance Model and Acceptance and Intention to Use Autonomous Vehicles. Cronbach's Alpha was calculated for each of the factors, resulting in alphas of 0.96 and 0.83 for Component 1 and Component 2, well above the acceptable threshold of 0.70. Therefore, this instrument should be considered reliable in assessing the two-component model.

Table 4. Factor loadings and commonalities using principal component analysis with orthogonal rotation for 8 items

	C1	**C2**	***h2***
Q21	0.92		*0.91*
Q22	0.92		*0.89*
Q25	0.89		*0.88*
Q24	0.87		*0.86*
Q23	0.83		*0.82*
Q19		0.88	*0.83*
Q18		0.87	*0.83*
Q20		0.74	*0.59*
Eigenvalues	4.11	2.51	--
% of Variance	0.51	0.31	--
Cronbach's Alpha	0.96	0.83	--

Factor scores were created for both of the components that emerged from this PCA analysis, with the intent to conduct Simple Linear Regression techniques to determine the relationship between the Perceived Ease of Use construct of the Technology Acceptance Model and Acceptance and Intention to Use Autonomous Vehicles. Results indicated a non-statistically significant relationship between Perceived Ease of Use and Acceptance and Intention to Use Autonomous Vehicles, $F(1,202) = 3.58 \times 10^{-29}$, $p = 1$. The point estimate rounds to 0.000 with a standard error of 7.04×10^{-2}, and an adjusted R-squared value of -0.00495. Therefore, it cannot be concluded that meaningful relationships exist between the PCA scores of the two components, which is contrary to results found in studies such as Nastjuk et al. (2020) and Yuen et al. (2020a).

Hypothesis 2. *There exists a positive relationship between the construct of Perceived Value Theory and Acceptance and Intention to Use Autonomous Vehicles.*

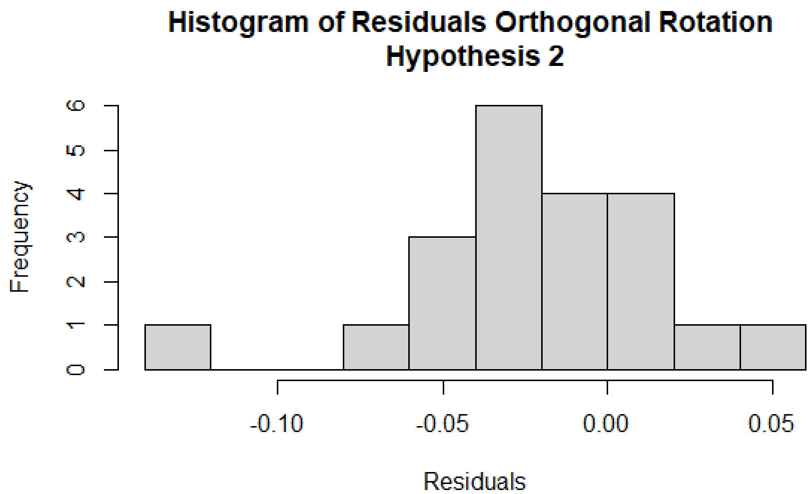
In the survey questionnaire, there were three questions geared towards the construct of Perceived Value Theory and five questions based on the Acceptance and Intention to Use Autonomous Vehicles. As in Hypothesis 1, a PCA was conducted on the eight items of the survey questionnaire for these constructs. Bartlett's test of minimum correlations, $\chi^2(28) = 1776.54$, $p < .001$, indicated that the correlations between the items were sufficiently large for PCA. The determinant of the correlation matrix was greater than 0.00001 (1.36×10^{-4}), indicating no concern of multicollinearity in the data for these constructs. As before, normality of the data was not attained due to the nature of Likert scale data assumed to be not normally distributed.

In starting the factor analysis for this research question, an initial model with orthogonal rotation was created to obtain eigenvalues for each of the eight items in the data. There is one construct in Perceived Value Theory and one factor for Acceptance and Intention to Use Autonomous Vehicles, so the test design was to examine whether two components should be kept for further analysis. However, Question 14 unexpectedly did not load onto the same factor as Questions 13 and 15 based on the test design setup, as these all were questions geared towards the construct of Perceived Value Theory. Therefore, Question 14 was removed from the analysis and a principal component analysis was conducted again with two factors.

In this new two-factor model, Bartlett's test of minimum correlations, $\chi^2(21) = 1510.20$, $p < .001$, indicated that the correlations between the items were sufficiently large for PCA. The determinant of the correlation matrix was greater than 0.00001 (5.22×10^{-4}), indicating no concern of multicollinearity in the data for these constructs for this research question. Again, normality of the data was not attained due to the nature of Likert scale data assumed to be not normally distributed.

Upon examining the results with a two-factor model, all questions loaded onto their expected factors and both components exhibited eigenvalues greater than 1. Together, the two components explained 87% of the variance. The screen plot was also examined and showed inflection points that would support retaining two components. Investigating the residuals of the two-component model revealed that 19% of the residuals were above the threshold of 0.05, which is satisfactory since less than 50% of the residuals fall above this threshold. The root-mean-square of the residuals was equal to 0.04, below the threshold of 0.08. A histogram of the residuals is shown below in Figure 5, indicating that they appear to come from a normal distribution. Also, the fit based upon off diagonal values was equal to 1, another indicator that two components were appropriate here. Finally, the mean h2 values from this model with orthogonal rotation was greater than 0.6, indicating that sample size was not an issue.

Figure 5. Histogram of the residuals for Hypothesis 2



Given the nature of this questionnaire, there was a potential for overlap and higher than normal correlations among the factors. Therefore, an oblique rotation was investigated. Factor correlations are shown below in Table 5. The two factors show a relatively high correlation between each other (0.54), indicating some appropriateness for using the oblique rotation model.

Table 5. Factor Correlations for Hypothesis 2

	FA1	FA2
FA1	1.00	0.54
FA2		1.00

However, upon examining a histogram of the residuals for this model with oblique rotation, there were serious concerns with the residuals appearing to come from a normal distribution, as seen in Figure 6 below. An analysis of the residuals showed that 71% of them were greater than 0.05, indicating a very poor fit with the data. Therefore, a PCA with oblique rotation was not considered for further analysis and the model using orthogonal rotation was used going forward instead.

Figure 6. Histogram of Residuals with Oblique Rotation for Hypothesis 2

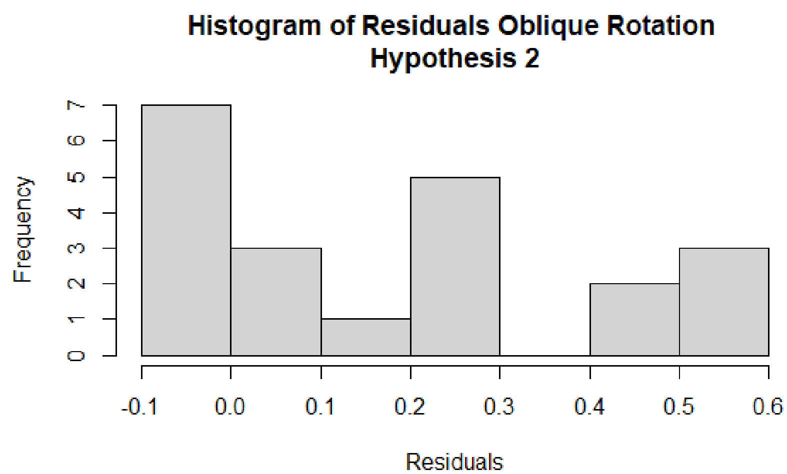


Table 6 below shows the factor loadings after orthogonal rotation onto the two components. Based on the theoretical model, the two components are Perceived Value and Acceptance and Intention to Use Autonomous Vehicles. Cronbach's Alpha was calculated for each of the factors, resulting in alphas of 0.96 and 0.77 for Component 1 and Component 2, well above the acceptable threshold of 0.70. Therefore, this instrument should be considered reliable in assessing the two-component model.

Table 6. Factor loadings and commonalities using principal component analysis with orthogonal rotation for 7 items

	C1	**C2**	***h2***
Q21	0.91		*0.91*
Q25	0.91		*0.88*
Q24	0.89		*0.87*
Q22	0.86		*0.88*
Q23	0.82		*0.83*
Q13		0.94	*0.92*
Q15		0.68	*0.79*
Eigenvalues	4.24	1.83	--
% of Variance	0.61	0.26	--
Cronbach's Alpha	0.96	0.77	--

Factor scores were created for both of the components that emerged from this PCA analysis, with the intent to conduct Simple Linear Regression techniques to determine the relationship between Perceived Value and Acceptance and Intention to Use Autonomous Vehicles. Results indicated a non-statistically significant relationship between Perceived Value and Acceptance and Intention to Use Autonomous Vehicles, $F(1,202) = 1.49 \times 10^{-28}$, $p = 1$. The point estimate rounds to 0.000 with a standard error of 7.04×10^{-2}, and an adjusted R-squared value of -0.00495. Therefore, we cannot conclude that any meaningful relationships exist between the PCA scores of the two components, contrary to the findings in Yuen et al. (2020b).

Hypothesis 3. *There exist positive relationships between the constructs of Innovation Diffusion Theory and the constructs of the Technology Acceptance Model and Perceived Value Theory.*

In the survey questionnaire, there were twelve questions geared towards the constructs of Innovation Diffusion Theory, five questions based on the constructs of the Technology Acceptance Model, and two questions based on the constructs of Perceived Value Theory. As in

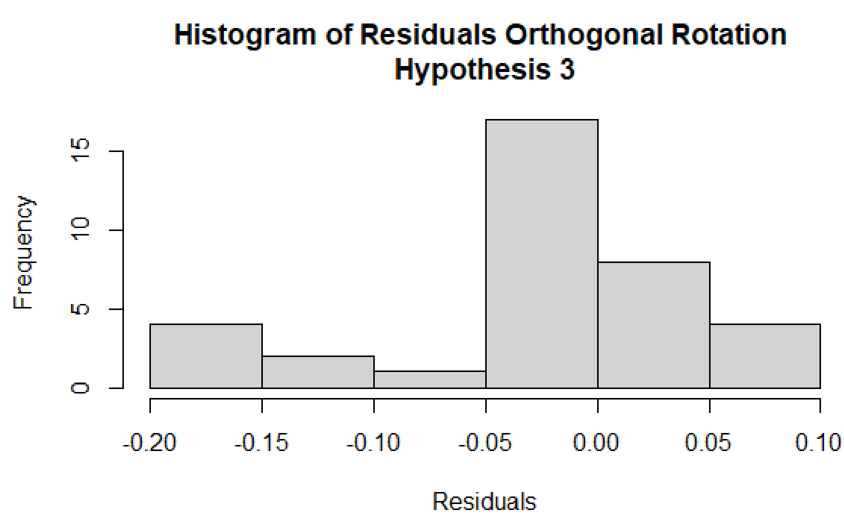
Hypotheses 1 and 2, a PCA was conducted on the 19 items of the survey questionnaire for these constructs. Bartlett's test of minimum correlations, $\chi^2(190) = 2671.92$, $p < .001$, indicated that the correlations between the items were sufficiently large for PCA. The determinant of the correlation matrix was not greater than 0.00001 (1.16×10^{-6}), indicating a slight concern of multicollinearity in the data for these constructs for this research question. As before, normality of the data was not attained due to the nature of Likert scale data assumed to be not normally distributed.

In starting the factor analysis for this research question, an initial model with orthogonal rotation was created to obtain eigenvalues for each of the 19 items in the data for this research question. There are four constructs in Innovation Diffusion Theory, two constructs in the Technology Acceptance Model, and one construct in Perceived Value Theory, so the test design was to examine whether seven components should be kept for further analysis. However, various questions unexpectedly did not load onto their expected factors based on the test design setup. So, only Questions 7 through 11, Question 13, and Questions 18-20 were retained, and a principal component analysis was conducted again with four factors.

In this new four-factor model, Bartlett's test of minimum correlations, $\chi^2(36) = 656.79$, $p < .001$, indicated that the correlations between the items were sufficiently large for PCA. The determinant of the correlation matrix was now greater than 0.00001 (3.69×10^{-2}), indicating no concern of multicollinearity in the data for these constructs for this research question after those questions had been removed from the data. Normality of the data was not attained due to the nature of Likert scale data assumed to be not normally distributed.

Upon examining the results with a four-factor model, all questions loaded onto their expected factors and both components exhibited eigenvalues greater than 1. Altogether, the four components explained 77% of the variance. The screen plot was also examined and showed inflection points that would support retaining three components. Investigating the residuals of the four-component model revealed that 31% of the residuals were above the threshold of 0.05, which is satisfactory since less than 50% of the residuals fall above this threshold. The root-mean-square of the residuals was equal to 0.07, below the threshold of 0.08. A histogram of the residuals is shown below in Figure 7, indicating that they appear to come from a normal distribution. Also, the fit based upon off diagonal values was equal to 1, another indicator that two components were appropriate here. Finally, the mean h2 values from this model with orthogonal rotation was greater than 0.6, indicating that sample size was not an issue.

Figure 7. Histogram of the residuals for Hypothesis 3



Given the nature of this questionnaire, there was a potential for overlap and higher than normal correlations among the factors. Therefore, an oblique rotation was investigated. Factor correlations are shown below in Table 7. Some factors showed moderately high correlations among each other, but nothing that was alarming. Therefore, a PCA with oblique rotation was not considered for further analysis and the model using orthogonal rotation was used going forward instead.

Table 7. Factor Correlations for Hypothesis 3

	FA1	FA2	FA3	FA4
FA1	1.00	0.00	0.39	0.33
FA2		1.00	0.05	0.05
FA3			1.00	0.26
FA4				1.00

Table 8 below shows the factor loadings after orthogonal rotation onto the four components. Based on the theoretical model, the components are Perceived Ease of Use, Trialability, Observability, and Perceived Value. Cronbach's Alpha was calculated for each of the factors, resulting in alphas of 0.83, 0.72, and 0.68 for Components 1, 2 and 3, with two of the three above the acceptable threshold of 0.70. An alpha measurement could not be obtained for Component 4 because only one question was retained for this construct. While one alpha measurement fell just below the threshold of 0.70, the researchers in this study argue that this instrument should still be considered reliable in assessing the four-component model.

Table 8. Factor loadings and commonalities using principal component analysis with orthogonal rotation for 9 items

	C1	**C2**	**C3**	**C4**	***h2***
Q20	0.85				*0.73*
Q19	0.81				*0.79*
Q18	0.78				*0.82*
Q8		0.85			*0.74*
Q7		0.81			*0.69*
Q9		0.78			*0.64*
Q11			0.89		*0.82*
Q10			0.77		*0.75*
Q13				0.97	*0.99*
Eigenvalues	2.21	2.01	1.73	1.01	--
% of Variance	0.25	0.22	0.19	0.11	--
Cronbach's Alpha	0.83	0.72	0.68	N/A	--

Factor scores were created for both of the components that emerged from this PCA analysis, with the intent to conduct Simple Linear Regression techniques to determine the relationship between the two individual Innovation Diffusion Theory constructs of Trialability and Observability, and either Perceived Value or Perceived Ease of Use. Results indicated non-statistically significant relationships between Trialability and Perceived Value, $F(1,202) = 9.72 \times 10^{-29}$, $p = 1$, Trialability and Perceived Ease of Use, $F(1,202) = 1.18 \times 10^{-29}$, $p = 1$, Observability and Perceived Value, $F(1,202) = 6.93 \times 10^{-30}$, $p = 1$, and Observability and Perceived Ease of Use, $F(1,202) = 5.98 \times 10^{-29}$, $p = 1$. Therefore, it cannot be concluded that meaningful relationships exist between these constructs, contrary to the findings in Yuen et al. (2020b).

Hypothesis 4. *There exist differences in acceptance and intention to use autonomous vehicles for those that have experience with accidents or driver assisted systems compared to those that have no experience with either.*

Hypothesis 5. *There does not exist a difference in Acceptance and Intention to Use Autonomous Vehicles across gender.*

All three of the hypotheses listed above were investigated using the Wilcoxon Rank-Sum Test. Since the data came from a Likert scale and was assumed to be not normally distributed, this non-parametric test was appropriate to test these assumptions. Tests were performed on the total scores of each participant regarding Q21 - Q25 which relate to the participant's acceptance and intention to use autonomous vehicles. Tables 9 and 10 below show the median scores of each variable tested, its possible values, and results of the various Wilcoxon Rank-Sum Tests performed on the data.

Table 9. Median Scores of Variables in Wilcoxon Rank-Sum Tests

Independent Variable	Values	Median
Accident Experience	Yes	20
	No	19
Experience with Driver Assisted Systems	Yes	19
	No	23
Gender	Female	20
	Male	18

Table 10. Wilcoxon Rank-Sum Test Results

Independent Variable	W	p-value	r (effect size)
Accident Experience	3982	.61	0.036
Experience with Driver Assisted Systems	3210	< .01	0.209
Gender	3855	< .05	0.151

So, the difference in acceptance and intention to use autonomous vehicles for those who have experienced a car accident in the past (median = 20) and those who have not experienced a car accident in the past (median = 19) is not statistically significant, $W = 3982$, $p = .609$, $r = 0.036$. However, the difference in acceptance and intention to use autonomous vehicles for those who had experience with driver assisted systems (median = 19) and those who did not have experience with driver assisted systems (median = 19) is statistically significant with a small-to-medium effect size, $W = 3210$, $p < .01$, $r = 0.209$. Likewise, the difference in acceptance and intention to use autonomous vehicles for females (median = 20) and males (median = 18) is statistically significant with a small effect size, $W = 3855$, $p < .05$, $r = 0.151$.

A gap in the research that this study provides is in providing additional potential predictor variables in determining acceptance and intention to use autonomous vehicles. Three variables that this study examined were age, geographical region, and annual miles driven. Using the Kruskal-Wallis test (a non-parametric ANOVA statistical test) to detect a difference in means across three or more groups, results indicated non-statistically significant differences between age groups ($\chi^2(4) = 6.786$, $p = .148$), geographical region ($\chi^2 (5) = 2.437$, $p = .786$), and annual miles driven ($\chi^2(5) = 4.039$, $p = .544$). These findings are consistent with those presented in Müller (2019), Yuen at al. (2020a), and Yuen et al. (2020b). Although no statistically significant differences were seen among groups of these demographic variables, the researchers of this study did discover some statistically significant findings by creating new groupings among these demographic variables and conducting Wilcoxon Rank-Sum Tests. Tables 11 and 12 below show results of statistically significant findings from these tests.

Table 11. Median Scores of Variables in Additional Wilcoxon Rank-Sum Tests

Independent Variable	Values	Median
Age	40 and under	21
	Over 40	18
	50 and under	21
	Over 50	18

Table 12. Additional Wilcoxon Rank-Sum Test Results

Independent Variable	W	p-value	r (effect size)
Age - break at 40	4298.5	< .05	0.128
Age - break at 50	4011	< .01	0.164

The difference in median scores across the acceptance and intention to use autonomous vehicle questions in the survey for age groups 40 and under (median = 21) and over 40 (median = 18) are statistically significant with a small effect size, $W = 4298.5$, $p < .05$, $r = 0.128$. Similarly, age groups 50 and under (median = 21) and over 50 (median = 18) are statistically significant with a small effect size, $W = 4011$, $p < .01$, $r = 0.164$. These results indicate a small tendency for older people (at least 40 and above) to have a higher acceptance and intention to use autonomous vehicles since their median scores were ranked lower (i.e., closer to a rank of 1).

In this chapter, the questionnaire setup and data cleaning steps were presented, along with descriptives of the survey data and questions included in the survey. The results of the various statistical tests performed to answer the Primary and Secondary Research Questions were also presented and analyzed to determine if any conclusions could be made based on the theoretical framework presented in earlier chapters. The chapter concluded by presenting some additional findings outside of the research questions that can be used for future research.

CHAPTER V: SUMMARY

Chapter V presents a summary of this study and the reasons for conducting such a study in the context of recent research done in this field. A discussion and interpretation of results is then presented based on what was found through the statistical tests performed and presented in the previous chapter. Retrospective thoughts on the significance of this study and contributions to this research field follows, connecting these results and interpretations back to the theoretical framework of this study. Lastly, limitations and recommendations for future research in acceptance and intention to use autonomous vehicles are presented for future readers and researchers aiming to advance the knowledge in this field.

The main focus of this study was to determine theoretical factors that influence the acceptance and intention to use autonomous vehicles, while also building upon the theoretical models developed in recent studies on this topic. The subject of autonomous vehicles has recently become more relevant in many industries, such as in auto manufacturing and insurance. In the recent past, many studies have been conducted to determine factors that influence the acceptance and intention to use autonomous vehicles in the general public. The most common theoretical model used in these studies was the Technology Acceptance Model (TAM). This model has been used in a variety of studies outside of autonomous vehicles, such as in the areas of healthcare, education, and business (Gagnon et al., 2012; Zheng et al., 2020; Park et al., 2014). Many recent studies have used the TAM as a building block to develop new and better factors in determining acceptance and intention to use autonomous vehicles (Koul & Eydgahi, 2018; Müller, 2019; Yuen et al., 2020b; Nastjuk, 2020). However, the study conducted by Yuen et al. (2020b) had the greatest influence on the development of this study.

Incorporating aspects of Innovation Diffusion Theory and Perceived Value Theory, Yuen et al. (2020b) was one of the first studies to incorporate constructs of these theoretical models in determining factors that influence autonomous vehicle acceptance. This study sought to develop an even more predictive model than in Yuen et al.'s study by also including constructs of the TAM as well as demographic variables such as age, gender, approximate annual miles driven, accident experience, and experience with driver assistance systems (e.g., blind spot warning indicator and automatic emergency braking).

Discussion

The data for this study was collected using a survey in Google Forms that asked participants to share their opinions about autonomous vehicles using a Likert scale for each response. A combination of factor analysis, linear regression, and non-parametric t-tests were used to determine if any statistically significant factors emerged from the data in determining acceptance and intention to use autonomous vehicles. Results from factor analysis and linear regression for Hypotheses 1, 2, and 3 indicated many non-statistically significant relationships between the constructs of the TAM, Innovation Diffusion Theory, and Perceived Value Theory in influencing the acceptance and intention to use autonomous vehicles. These results differed from those found in other studies utilizing these theoretical models (Nastjuk et al, 2020; Yuen et al, 2020a; Yuen et al, 2020b).

Intuitively, constructs of these models used in this study should have shown positive influences on the acceptance and intention to use autonomous vehicles. However, none were found through the tests performed in this study. Yet, it would be short-sighted to disregard these factors from having any influence on acceptance and intention to use autonomous vehicles, since many recent studies have proven this to be true. This is merely another data point in the history of studies completed in this field, and these non-statistically significant results should be considered simply as additional findings to those from other studies.

The demographic variables of gender and experience with driver assisted systems showed statistically significant differences in determining acceptance and intention to use autonomous vehicles. Additionally, a few interesting results were obtained from this study within the demographic variable of age. Various cuts of age ranges were analyzed to identify any possible existence of statistically significant relationships, and both the age range groups of over 40 and over 50 showed lower average median score ranks across the acceptance and intention to use autonomous vehicle questions in the survey, compared to the under 40 and under 50 age ranges, respectively. These results indicate that older participants in this study were more open to autonomous vehicles than older participants, at least when grouped together and cut off at either 40 or 50 years old. These are unexpected results since younger generations tend to adapt to new technologies quicker and easier than older generations (Dorsey, 2020). So, while individual age ranges grouped by 10-15 years showed to be non-statistically significant between each other, grouping the ages around a threshold of either 40 or 50 years old showed statistically significant differences in the median ranks of responses to autonomous vehicle acceptance questions.

Significance of the Study

Attitude towards autonomous vehicles has become a popular field of research in recent years, making this study about acceptance and intention to use autonomous vehicles relevant given how recent some of the bigger studies in this field have taken place. Many of those studies employed the Technology Acceptance Model (TAM) to explain how a new technology, such as autonomous vehicles, become accepted into mainstream society. Yuen et al. (2020b) advanced the field of study by incorporating relatively newer constructs of Innovation Diffusion Theory and Perceived Value into their study to determine acceptance and intention to use autonomous vehicles. However, Yuen et al. (2020b) did not include constructs of the TAM into their study, so this study aimed to build upon the available research by incorporating aspects of both the TAM as well as Innovation Diffusion Theory and Perceived Value Theory. This study also included additional demographic variables not previously used in many studies in an attempt to discover additional determinants in acceptance and intention to use autonomous vehicles.

While many of the results were not statistically significant using the statistical techniques of factor analysis, linear regression, and non-parametric tests, this study did contribute to the knowledge in this field by showing statistically significant differences in questions about acceptance and intention to use autonomous vehicles both for participants above and below 40 years old and above and below 50 years old, with the 50 year old cutoff showing a slightly stronger difference between the two. This is an interesting result since older generations tend to receive a worse reputation in regard to acceptance of new technologies, and these results appear to contradict that argument.

Limitations and Recommendations

There were a few limitations to this study. First, while this study was not conducted in one geographical location, many of the participants resided in the Midwest region of the United States. There may have existed an inherent bias either for or against autonomous vehicles that could have presented itself in the data. The other regions included in the study were likely improperly represented to characterize the actual distribution of the United States population across the regions defined in this study. This was a major threat to any generalizability that might have been made about the results of this study. Additionally, while there were a sufficient number of participants included in this study to properly conduct the statistical tests, future studies could attempt to recruit more participants and reach more participants outside of the Midwest region. Improving these two pieces in the collection of data could help produce statistically significant results like those seen in recent studies in this field.

Another limitation is in the theoretical framework that was designed for this study. Results did not show statistically significant relationships between the constructs used and acceptance and intention to use autonomous vehicles, and perhaps introducing different theories to help explain these relationships could prove to be more significant. Modeling the relationship of acceptance and intention to use autonomous vehicles and the factors that determine it is not a linear path, meaning that there likely exist interaction effects between various constructs of theoretical models to best explain how one moves to acceptance and intention to use autonomous vehicles. Future studies could investigate further these interactions and test the significance of new and different factors.

A third limitation of this study is in what resulted when testing Hypothesis 1 with the constructs of the TAM and acceptance and intention to use autonomous vehicles. The two questions related to Perceived Usefulness did not load onto their own factor when conducting principal component analysis on the data, and therefore this variable was dropped completely from the test. Because of this, a large portion of this study's theoretical framework was removed, even though many other recent studies have shown the statistical strength of the Perceived Usefulness construct in determining acceptance and intention to use autonomous vehicles (Koul & Eydgahi, 2018; Müller, 2019; Yuen et al., 2020b; Nastjuk, 2020). However, it was decided that this was the best course of action in order to preserve the ethical standard sought out by this study. Future studies could present different questions about Perceived Usefulness in order to more accurately represent how this construct was meant to be presented to participants through a survey.

Lastly, this study recognizes that autonomous vehicles are a new technology that not everybody included in this study likely had exposure to. Lack of knowledge, combined with possible apathy toward autonomous vehicles, could have resulted in skewed data not representative of the general population nor of how autonomous vehicles will be viewed in the future. Reconducting studies like this in the future could yield different results simply because more time has passed, or people may have become more familiar with autonomous vehicles by that time.

Conclusion

This study sought to build a more predictive model than those presented in recent studies by incorporating constructs of three theoretical models, namely the Technology Acceptance Model, Innovation Diffusion Theory, and Perceived Value theory. Additional demographic variables were also tested to determine statistical strength. Through a combination of factor analysis, linear regression techniques, and non-parametric t-tests, results indicated several non-statistically significant results. However, this study did indicate a statistically significant difference in attitudes toward autonomous vehicles across gender and across experience with driver assisted systems. Statistically significant results were also found among older participants compared to younger participants, with cutoff ages of both 40 and 50 years old. Future studies can build off of these results, as well as find different ways to produce statistically significant results for the theoretical framework constructs used in this study. This study found that there likely exists a variety of contributing factors in determining acceptance and intention to use autonomous vehicles, beyond those presented in this study, making the attempt to model relationships between them a very difficult task to complete.

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Appendix A

Disclosure Statement Preceding Survey Questionnaire

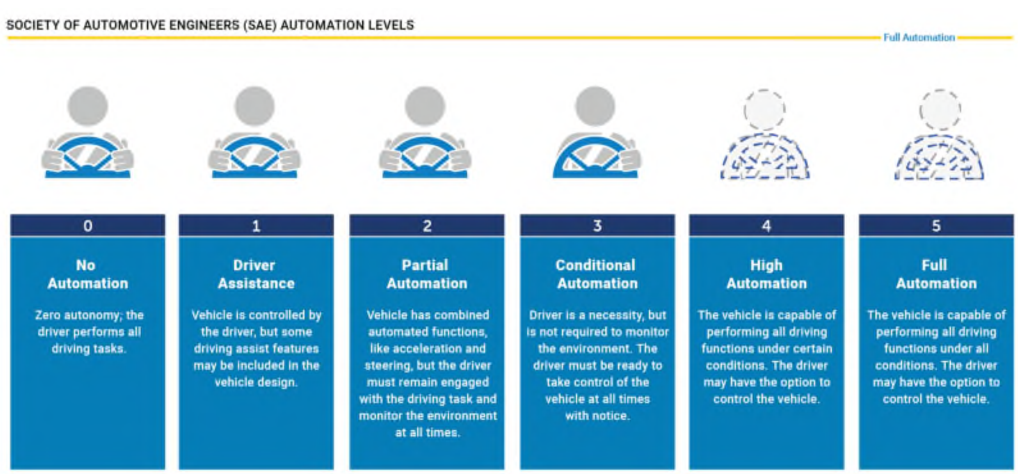
Please only respond to this survey once. If you have already responded to this survey, please close out of this window now. Adherence to this notice is vital to upholding the integrity of this survey and its results. Thank you!

Paragraph About the Study

This study is being conducted to determine the opinions and feelings about autonomous vehicles (i.e., self-driving cars). The following pages contain a brief description of autonomous vehicles followed by some basic demographic questions and 25 survey questions. All responses will be made anonymous to the researcher and demographic information will be kept confidential. This survey should take you no more than 5 minutes to complete.

Autonomous Vehicle Levels

Autonomous vehicles have 6 levels of automation, ranging from No Automation to Full Automation. For this survey questionnaire, assume that the autonomous vehicle in question is a Level 5 Full Automation vehicle.



Appendix B

IRB Form Submitted and Approved

Shawnee State University

Protocol #

Exempt Review Application

Title of Research Project: Determining acceptance and intention to use autonomous vehicles and its implication on the auto insurance industry

Name(s) of Principal Investigators:	Email address:	Faculty	Student	Other
Cal Thomay	thomayc@mymail.shawnee.edu	☐	☑	☐
		☐	☐	☐
		☐	☐	☐
		☐	☐	☐
		☐	☐	☐
		☐	☐	☐

*Please place an asterisk by the investigator name(s) whose NIH certificate(s) is/are already on file with the IRB, if the certificate is less than 3 years old.

Contact Name: Cal Thomay Contact Phone Number: (216) 513-9648

Department(s)/Division/Agency: Mathematics

Please place a check mark next to the category that best describes your research. You may check more than one category.

- ☐ Research conducted in established or commonly accepted educational settings, involving normal educational practices, such as (a) research on regular and special education instructional strategies, or (b) research on the effectiveness of or the comparison among instructional techniques, curricula, or classroom management methods.
- ☑ Research involving the use of educational tests (e.g., cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures or observation of public behavior, unless: (a) data obtained is recorded in such a manner that human subjects can be identified, directly or through identifiers linked to the subjects; and (b) any disclosure of the human subjects' responses outside the research could reasonably place the participants at risk of criminal or civil liability or be damaging to the participants' financial standing, employability, or reputation. No videotaping or photography is allowed for data collection. You may not collect data from appointed public officials or candidate for public office.
- ☐ Research involving the collection or study of existing information, documents, records, pathological specimens, or diagnostic specimens, if these sources are publicly available or if the information is recorded by the investigator in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects.

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- ☐ Research and demonstration projects that are conducted by or subject to the approval of supporting agencies, and which are designed to study, evaluate, or otherwise examine: (a) public benefit or service programs; (b) procedures for obtaining benefits or services under those programs; (c) possible changes in or alternatives to those programs or procedures; or (d) possible changes in methods or levels of payment for benefits or services under those programs.
- ☐ Taste and food quality evaluation and consumer acceptance studies, (a) if wholesome foods without additives are consumed or (b) if a food is consumed that contains a food ingredient at or below the level, and for a use, found to be safe, or agricultural chemical or environmental contaminant at or below the level found to be safe, by the Food and Drug Administration and approved by the Environmental Protection Agency or the Food Safety and Inspection Service of the U.S. Department of Agriculture.

If at least one of these categories does NOT describe your research, then you should complete the "Expedited and Full Review Application" instead of this one.

1. Describe the key demographics (age, SES, ethnicity, geographic locations, gender, etc) of the sample that you wish to obtain. No specific demographic that I will be targeting except for limiting the respondents to being based in the Cleveland area.

1a. What is the greatest number of participants that will be recruited? No limit

1b. How will participants be recruited? As many as possible. A survey will be used and distributed online, so I will take as many that respond to the survey. [redacted]

2. Will participants be remunerated for their participation? Yes No

2a. If so, how will participants be remunerated? Please indicate the type of remuneration and the amount. For instance, the participants will be given a $10 Amazon Gift Card for participation or the participants will receive 3% of their final grade in extra credit in their Introduction course. _____

2b. If participants do not complete the study, will partial or full remuneration be given? Please describe how that will be determined. _____

Shawnee State University Protocol #

____

____

3. What direct benefits (other than remuneration) exist for the participants who participate?

None, other than knowing they will be advancing the research on autonomous vehicle perception and acceptance.

4. What direct risks could the participants potentially face? Check all that apply.

_____ Risk of breach of confidentiality or privacy

_____ Risk of coercion by researcher(s)

_____ Risk of psychological harm

_____ Risk of physical harm

_____ Other potential risk: ______________________________

If you checked any direct risks in Item 4, then you should complete the "Expedited and Full Review Application."

5. Will the participants be informed of the risks and benefits of the study? Yes No

5a. If so, how will the participants be informed?

____

____

5b. Please check each box if the following criteria match your research.

- ☑ The research involves no greater than minimal risk.
- ☐ It is not practicable to conduct the research without a waiver of informed consent or alteration to informed consent.
- ☑ Waiving or altering the informed consent will not adversely affect the subjects' rights and welfare.
- ☐ The consent document would be the only record linking the subject and the research, and the principal risk would come from a breach of confidentiality.

5c. Do you wish to waive the signed informed consent? Yes No

Shawnee State University

Protocol #

In submitting this form and the corresponding documents, I acknowledge that I have completed Human Research Participants training and that I understand and will uphold the rights of human participants. I also verify that all information contained in this form and any other corresponding documentation is correct based on my knowledge. I understand that I may not have contact with any research participants until the Shawnee State University IRB has given me their approval.

Signature of Principal Investigator 1

Signature of Principal Investigator 2

Signature of Principal Investigator 3

Signature of Principal Investigator 4

Signature of Principal Investigator 5

Signature of Principal Investigator 6

Date of Submission: 10/21/20

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Appendix C

Demographic Questions

What is your gender?

- Male
- Female
- Other

What is your age?

- < 16
- 16-30
- 31-40
- 41-50
- 51-60
- > 60

Which region of the country do you live in?

- Midwest - IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, WI
- Northeast - CT, DC, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VT
- Southeast - AL, AR, FL, GA, KY, LA, MS, NC, SC, TN, VA, WV
- Southwest - AZ, NM, OK, TX
- West - AK, CA, CO, HI, ID, MT, NV, OR, UT, WA, WY
- Not in the USA

Approximately how many miles do you drive in your car each year (pre-COVID)?

- < 6,000
- 6,000-7,999
- 8,000-9,999
- 10,000-11,999
- 12,000-13,999
- > 14,000

Have you ever been in a car accident before?

- Yes
- No

Do you have any experience with driver assisted systems (e.g., blind spot warning indicator or automatic emergency braking)?

- Yes
- No

Do you possess a valid driver's license?

- Yes
- No

Survey Questionnaire Items

Q1 Autonomous vehicles would solve problems that I have encountered with conventional vehicles. (RA)

Q2 Autonomous vehicles would increase the time that I need to get to places. (RA)

Q3 Autonomous vehicles would be more advantageous compared to using conventional vehicles. (RA)

Q4 Autonomous vehicles would fit well with my driving habits. (COMP)

Q5 Autonomous vehicles would not suit me well. (COMP)

Q6 Autonomous vehicles would be in line with my everyday life. (COMP)

Q7 Before I decide to buy an autonomous vehicle, I would like to test-drive it. (TRIAL)

Q8 Before I decide to buy an autonomous vehicle, I would like to borrow it for a day or two. (TRIAL)

Q9 Before I decide to buy an autonomous vehicle, I would like to receive training or attend a course on using an autonomous vehicle. (TRIAL)

Q10 I believe I can learn how to use autonomous vehicles. (OBSV)

Q11 I believe I can explain to others how to use autonomous vehicles. (OBSV)

Q12 I don't believe I can benefit from using autonomous vehicles. (OBSV)

Q13 I feel that using autonomous vehicles can enable cost savings (e.g., fuel savings or more optimized trips). (PV)

Q14 I feel that using autonomous vehicles would be pleasant. (PV)

Q15 I feel that using autonomous vehicles would have positive effects on the environment and society. (PV)

Q16 I believe that autonomous vehicles would be useful to me. (PU)

Q17 I believe using autonomous vehicles would increase my productivity. (PU)

Q18 I expect learning to use autonomous vehicles will be easy for me. (PEU)

Q19 I expect autonomous vehicles will be easy to use. (PEU)

Q20 I think that interacting with autonomous vehicles would require a lot of mental effort. (PEU)

Q21 I believe I would consider using autonomous vehicles when they are available in the market. (ACCEPT)

Q22 I believe I would recommend autonomous vehicles to my family and peers. (ACCEPT)

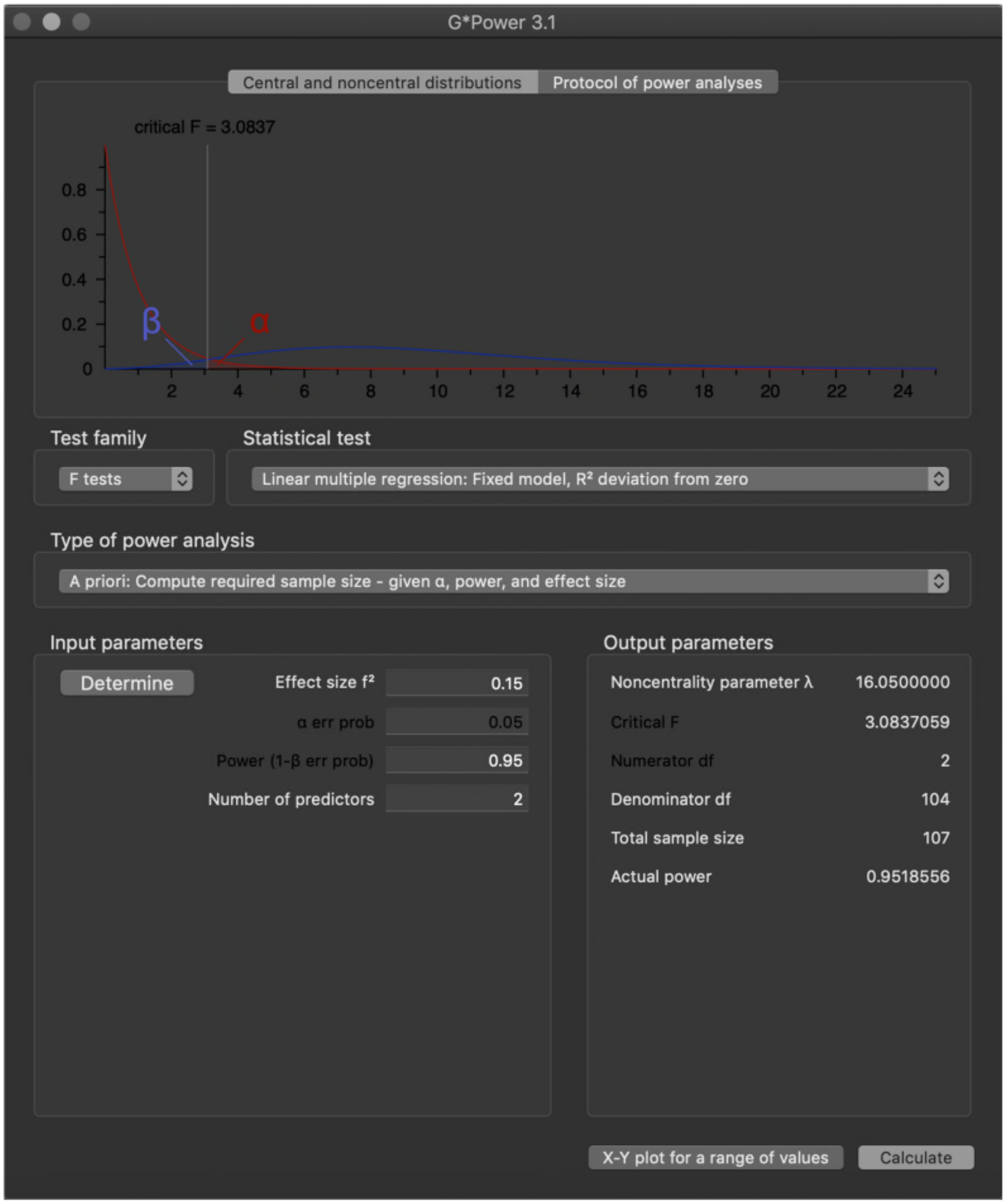
Q23 I have positive things to say about autonomous vehicles. (ACCEPT)

Q24 If I had access to an autonomous vehicle, I predict that I would use it. (ACCEPT)

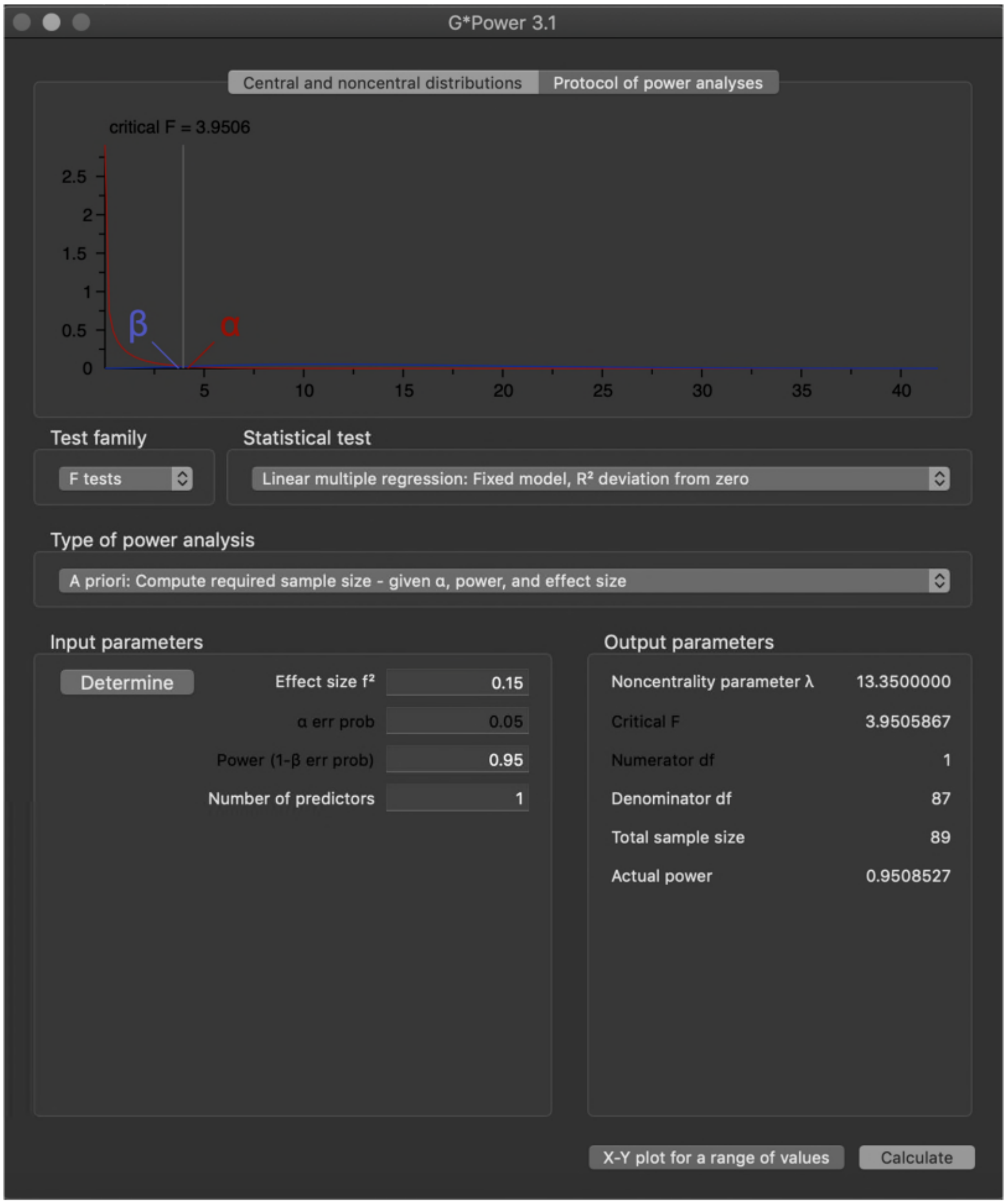
Q25 I intend to use an autonomous vehicle in the future. (ACCEPT)

Appendix D

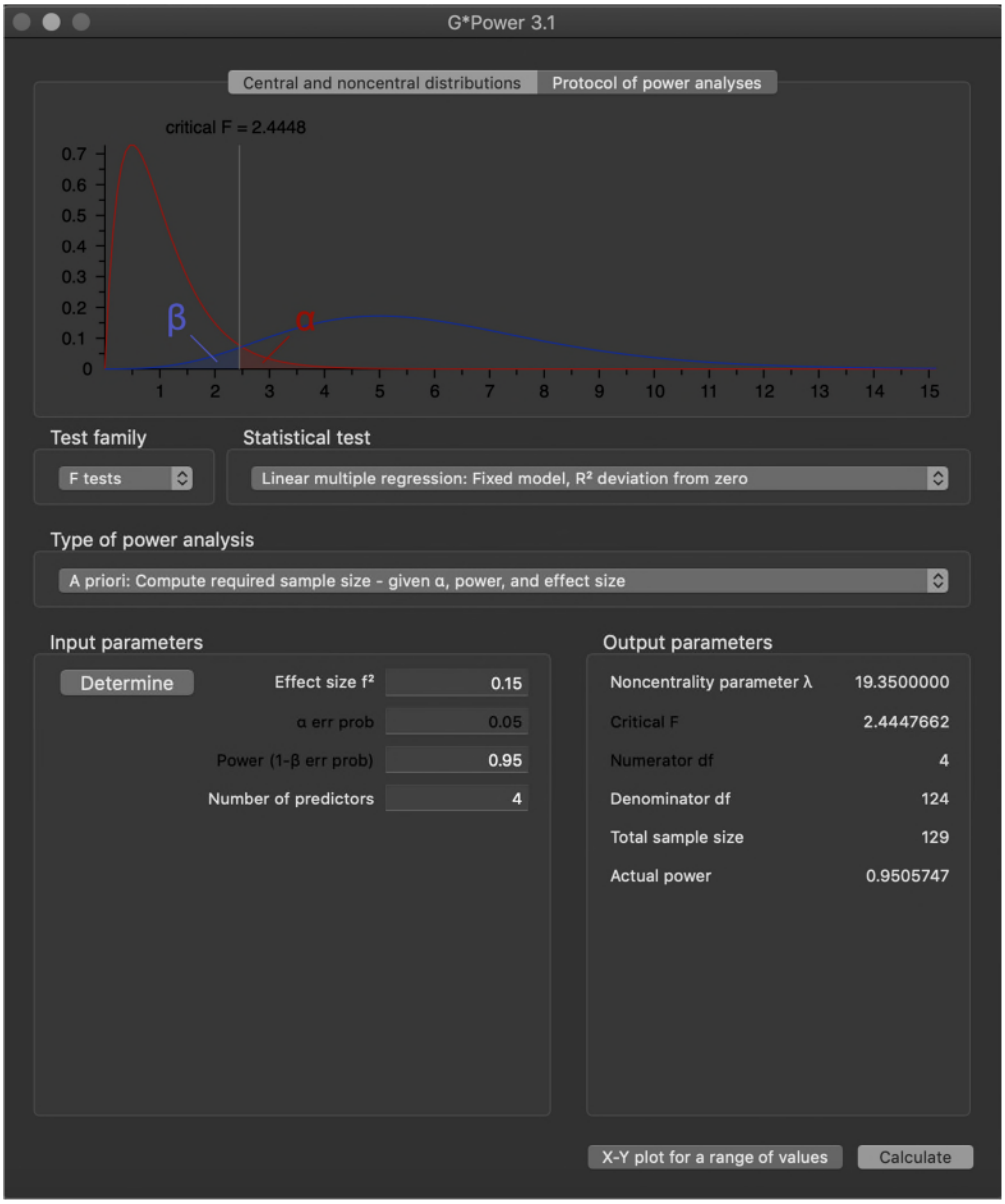
Priori Power for Primary Research Question #1



Priori Power for Primary Research Question #2



Priori Power for Primary Research Question #3



BIBLIOGRAPHY

Cal David Thomay

Candidate for the Degree of

Master of Science Mathematics

Thesis: THE DETERMINANTS OF ACCEPTANCE AND INTENTION TO USE AUTONOMOUS VEHICLES AND ITS IMPLICATION ON THE AUTO INSURANCE INDUSTRY

Major Field: Mathematics

Personal Data: I am currently a Pricing Analyst at Progressive Insurance where I analyze premiums and losses for the state of California. I live in Fairview Park, OH with my wife of 5 years, Mia, and our two boys, Cyrus and Simeon. I enjoy cooking, being active, and I referee high school basketball games during the winter months.

Education: I earned a bachelor's degree in Mathematics from The College of Wooster in 2014.

Completed the requirements for the Master of Science in Mathematics, Portsmouth, Ohio in August 2021.

Dr. Douglas G. Darbro 7/23/2021

ADVISER'S APPROVAL: Douglas Darbro