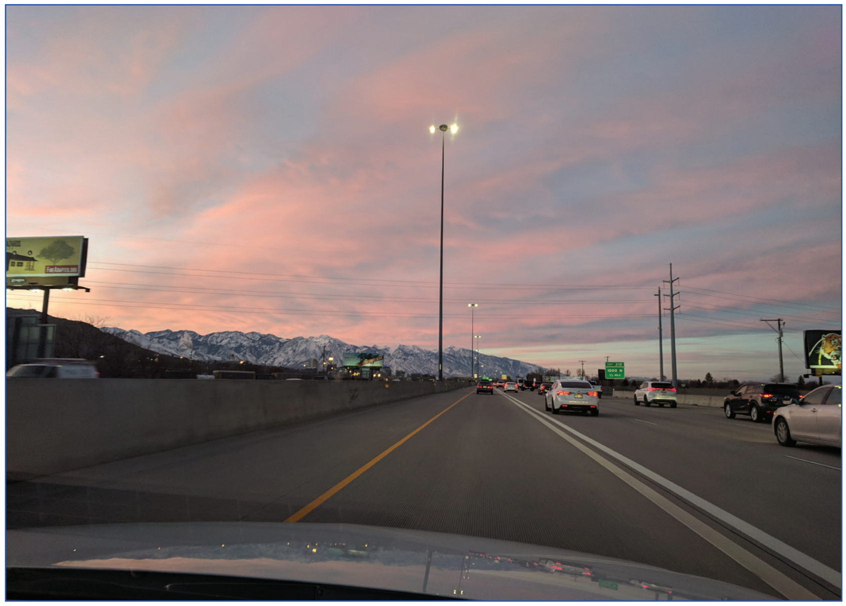
MOUNTAIN-PLAINS CONSORTIUM

MPC 21-439 | S. Acharya and M. Mekker

Public Perception of the Collection and Use of Connected Vehicle Data



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Connected vehicles (CV) offer various potential improvements to the existing transportation system. However, to maximize these benefits, sufficient market penetration is needed. The existing literature lacks understanding of public perception of CV adoption. Past studies highlighted data privacy and security as possible barriers to CV acceptance. The objectives of this study were to understand CV data sharing intention, ascertain associations between data issues and CV acceptance, and to develop a CV acceptance model. To accomplish these objectives, exploratory and confirmatory factor analyses and structural equation models were fitted to survey data.

The results showed that perceived data privacy and security was found to lower the CV acceptance directly and indirectly through data sharing intention. Perceived data privacy and security was also found to lower the trust towards CVs. These findings imply that stakeholders should act to reduce the data issues associated with CV and educate users about such efforts. The data sharing intention was found to depend on the use of CV data but not the type of data. Thus, stakeholders should assure the public about the specific intended uses of data. It was found that enforcement and fees assessment were the least desirable use of CV data. Another contribution of this study is the development of a novel connected vehicle acceptance model, which explains the overall development of public attitude and behavioral intention to use CVs. The associations of individual characteristics with CV acceptance and its determinants were also investigated. Finally, possible ways to improve CV acceptance are discussed.

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Public Perception of the Collection and Use of Connected Vehicle Data

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This study was approved by the Utah State University Institutional Review Board (IRB Protocol #11317). All data collection and management practices adhere to Institutional Review Board requirements and policies.

ABSTRACT

With the recent increase in connectivity in vehicle technologies, connected vehicles (CVs) offer a number of potential improvements (e.g., safety, mobility, environmental efficiency, etc.) to the existing transportation system. However, to maximize these benefits, sufficient market penetration of CV is needed. The existing literature on CV technology (CVT) lacks in-depth understanding of public perception regarding the adoption of CVs in the near future. Past studies have highlighted data privacy and security associated with CVT as possible barriers to acceptance of CV. Thus, the objectives of this study were to understand the data sharing intention among the public for CV applications, ascertain the associations of CV data privacy and security with data sharing intention and CV acceptance, and to develop the acceptance model of CV. To accomplish these objectives, a number of exploratory and confirmatory factor analyses and structural equation models were fitted.

The results showed that perceived data privacy and security about CVT was found to lower the CV acceptance directly and indirectly through data sharing intention. Perceived data privacy and security was also found to lower the trust toward the technology. These findings imply that CV developers and stakeholders should act to reduce the data issues associated with CVT by strengthening the technology and by educating users about their data privacy and security efforts. In addition, this study investigated the data sharing intention for CVT. The data sharing intention was found to depend on the use of CV data but not the type of data. Thus, CV stakeholders should assure the public about the specific intended uses of data. Overall, it was found that enforcement and fee assessments were the least desirable use of CV data. Another contribution of this study is the development of a novel connected vehicle acceptance model (CAVM), which explains the overall process of development of public attitude and behavioral intention to use CVs. The associations of individual characteristics (socio-demographic, driving related, etc.) with CV acceptance and its determinants were also investigated. Finally, the number of possible ways to improve CV acceptance is discussed.

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ABI	Attitude and Behavioral Intention to Use
AV	Autonomous Vehicle
AVE	Average Variance Extracted
CA	Cronbach's Alpha
CAR	Center for Automotive Research
CAV	Connected and Autonomous Vehicle
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CR	Composite Reliability
CV	Connected Vehicle
CVAM	Connected Vehicle Acceptance Model
CVT	Connected Vehicle Technology
DOT	Department of Transportation
DSI	Data Sharing Intention
DWLS	Diagonally Weighted Least Squares
EF	Enforcement and Fees Based on Usage
EFA	Exploratory Factor Analysis
IoT	Internet of Things
IoV	Internet of Vehicles
ITS-JPO	Intelligent Transportation System Joint Program Office
ITS	Intelligent Transportation System
KMO	Kaiser, Meyer, Olkin measure of sampling adequacy
MDOT	Michigan Department of Transportation
MIMIC	Multiple Indicator Multiple Cause Model
TLI	Tucker-Lewis Index
ICP	Driver Information, Congestion Assessment and Reduction, and Pavement and Infrastructure Assessment and Improvement
PEU	Perceived Ease of Use
PPS	Perceived Data Privacy and Security
PT	Perceived Trust
PU	Perceived Usefulness
RC	Road Side Assistance and Crash Investigation
RMSEA	Root Mean Square Error of Approximation
RP	Research Purpose
SAVE	Square Root of Average Variance Extracted
SEM	Structural Equation Modeling
SRMR	Standardized Root Mean Square Residual
TAM	Technology Acceptance Model
V2C	Vehicle to Cloud
V2I	Vehicle to Infrastructure
V2P	Vehicle to Pedestrian
V2V	Vehicle to Vehicle
V2X	Vehicle to Everything
UDOT	Utah Department of Transportation
USDOT	U.S. Department of Transportation

EXECUTIVE SUMMARY

The landscape of the transportation system is changing rapidly, in part due to the recent introduction of connectivity in vehicle technology. With connectivity, vehicles can “talk” to each other and surrounding infrastructure to improve system safety and efficiency. These types of vehicles are called connected vehicles (CVs). A number of benefits can be expected from CV technology (CVT), which includes, but is not limited to, the domains of safety, mobility, environmental efficiency, traffic studies, monitoring road infrastructures, and so on. To maximize these broad domains of benefits, sharing of CV data is necessary. CV data encompasses speed, position, windshield activation, tire pressure, acceleration, braking intensity, etc. Due to public wariness about government entities tracking their personal data, users might not consider sharing CV data and may be less likely to adopt CVs. However, the market penetration of CVs is important to achieve the benefits that the technology offers to the transportation system. In this context, understanding of the public’s intention about sharing CV data and CV adoption is important, but the literature lacks such studies. To fill this research gap, this study carried out a questionnaire survey of 2,400 U.S. adults with three primary objectives: (1) define the CV data sharing intention of the public, (2) ascertain how CV data sharing intention is associated with CV adoption, and (3) understand the overall process of development of behavioral intention to adopt CVs.

First, a concept called “data sharing intention” was defined based on the respondents’ intentions to share eight types of CV data for 10 different use categories. After developing a series of structural models, it was found that data sharing intention is dependent upon the purpose for which data will be used rather than the type of CV data. This finding has a number of implications. CV stakeholders should focus on utilizing CV data for public-intended and approved purposes only. For example, respondents were found to be highly interested in sharing CV data for the purpose of informing drivers about incidents ahead but least interested for enforcement purposes. Alternatively, CV developers and transportation agencies are recommended to assure the public about the intended uses of CV data.

Second, the association of data sharing intention with CV acceptance was assessed. The acceptance of CVT was found to relate to the data sharing intention, with higher acceptance if the data sharing intention was higher. In addition, public perception about data privacy and security was found to be related to CV acceptance directly and indirectly through data sharing intention. Thus, this study concludes that data privacy and security issues associated with CVT reduce the data sharing intention and overall acceptance of CVT. Based on these findings, CV developers and related stakeholders are recommended to work on strengthening the data privacy and security systems in CVT. In addition, dissemination of data storage and encryption policies is necessary to inform the public about the safe and intended use of data.

Third, the process of development of public attitude toward adoption of CVs was ascertained. A novel connected vehicle acceptance model (CVAM) was developed by extending the widely used technology acceptance model (TAM). The CVAM was able to explain the CV adoption as represented by attitude and behavioral intention to use CVs. The CV adoption was found to be related to perceived data privacy and security perceived trust, perceived usefulness, and perceived ease of use. Based on the results, it was concluded that the public consider data privacy and security issues to be major barriers to CV adoption. These issues lower the public trust toward the technology. Thus, the CVT stakeholders should work on improving public perception about data privacy and security issues associated along with the ease of using and usefulness of the technology. From this theoretical standpoint, this study investigated the role of perceived trust in the acceptance model. It was found that the role of perceived trust in relation to perceived ease of use and perceived usefulness could go both ways: mediating the effects of perceived usefulness and ease of use on CV adoption or acting as an antecedent of perceived ease of use and usefulness. These results could come as a result of limited actual interaction of respondents with CVT.

In addition, this study also investigated the associations of socio-demographic and other individual characteristics of respondents with data sharing intention and CV acceptance and its determinants. These results could be helpful to CV stakeholders to formulate different plans and policies for various socio-demographic groups in order to increase the acceptance of CVs. For example, familiarity with connected features was found to be associated with an increase in data sharing intention and CV acceptance. Thus, a marketing strategy to increase CV acceptance could focus on educating experienced drivers about the advantages of connectivity and providing inexperienced drivers opportunities to test drive CVs, thus increasing familiarity with connected features.

1. INTRODUCTION

The landscape for connected vehicle technology (CVT) is changing rapidly. No longer are the deployment dates 20 years into the future; connected and autonomous vehicles (CAV) are here today. What is more, significant advancements in the technology are expected in the next three to five years. The traveling public has limited involvement with these technologies and significant reasons not to trust or embrace the technologies. From an agency standpoint, there are potential benefits of a safer and more efficient transportation system. Gathering public perception and determining sentiment is critically important to the deployment and use of these technologies.

Connected vehicles (CVs) are those that can communicate and exchange information with other vehicles and/or the environment. Generally, five types of communications are available or anticipated (shown in Figure 1.1): vehicle to infrastructure (V2I), vehicle to vehicle (V2V), vehicle to cloud (V2C), vehicle to pedestrian (V2P) and vehicle to everything (V2X). Bidirectional exchange of data between the vehicles and roads is possible in V2I technology. This communication enhances the safety, mobility, and environmental benefits of the transportation system. In V2V communication, the information regarding the speed and position of surrounding vehicles can be shared, which could contribute to the reduction of traffic crashes and congestion. V2C communication allows for the exchange of information to and from the system cloud. The vehicle can use the information provided by other cloud connected industries. Unidirectional and/or bidirectional detection of surrounding vehicles and/or pedestrians and cyclists can be done via V2P communication technology, which has the potential to increase safety for active transportation modes. V2X technology can accommodate communication between all of the areas discussed above as well as other modes of transportation, such as ships, trains, and aircrafts.

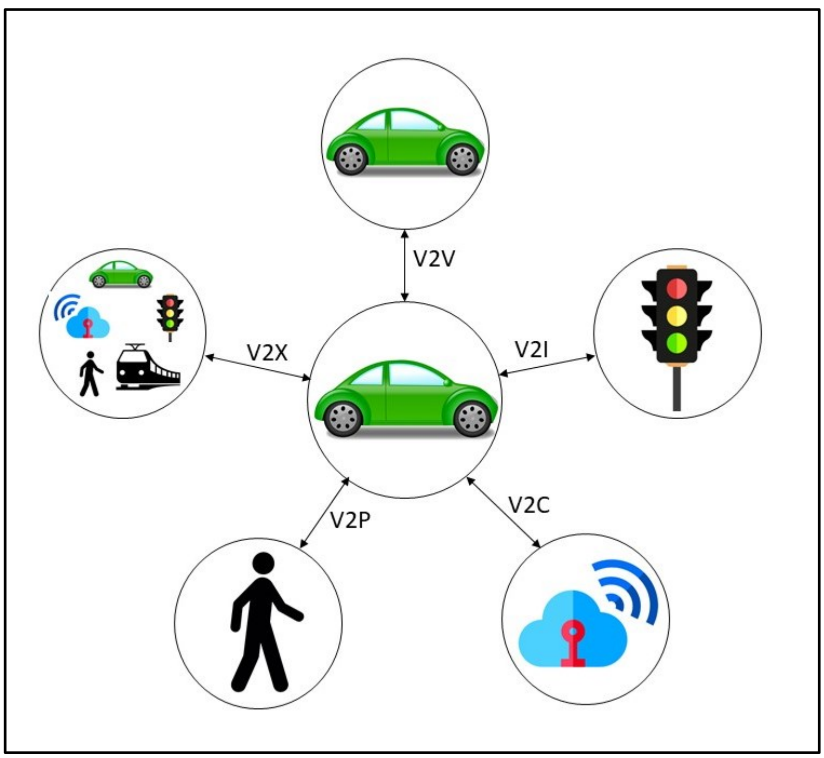

Figure 1.1 Communications in connected vehicles

Currently, two types of communications, V2V and V2I, are in the testing and implementation stage in the United States. The U.S. Department of Transportation (USDOT) is currently involved in research, development, and pilot testing of technologies for the advancement and implementation of CVs in the United States through the Intelligent Transportation System Joint Program Office (ITS-JPO). The office is currently overseeing a number of pilot deployments of CV technology (CVT), including New York, Wyoming, and Florida. Integration of in-vehicle wireless devices, mobile devices, and roadside devices has been and is currently being conducted to measure the performance of the deployed technology. USDOT has also planned to test the V2P communication technology at the Turner Fairbank Highway Research Center with the aim of substantially reducing intersection and mid-block crashes between vehicles and pedestrians/cyclists (ITS-JPO, 2020a). Many state departments of transportation (DOT), academic institutions, and private organizations are also involved in testing and implementing CVT, such as the Utah Department of Transportation (UDOT, 2018, 2019).

1.1 Problem Statement

With the continued development and increasing prevalence of CVs, there is a growing need to understand the public perception of this technology across the United States. In particular, CVs represent a potential source of immensely valuable data for traffic operations and planning. The successful collection and use of these data are directly related to public opinion and acceptance. CV data are expected to encompass a variety of valuable metrics for traffic operations and planning. These may include speed, traction, lateral/vertical acceleration, windshield wiper activation, headlight activation, braking intensity, etc. These metrics can be used in a number of ways to improve a transportation agency's operations, such as for pavement maintenance and monitoring, incident detection, and weather response. For planning purposes, CV data could potentially provide detailed trip data at a network level. There have been many studies on the small-scale collection and use of such data (Pu et al., 2011; Riveiro et al., 2015; Yu et al., 2014; and others.). The importance of these data cannot be downplayed. Public opinion can significantly affect the degree to which transportation agencies can collect and utilize these data.

It is important to understand public opinion and acceptance of the collection and use of what will be commonly viewed as private data. Anecdotally, the U.S. population is very wary of government entities being able to track their movements and day-to-day activities (Bridget, 2017). There have been limited studies evaluating public perception on data sharing intention for CV applications. The results of this research, detailed in this report, will provide transportation agencies with guidance for future management of CV data and public education on the technology.

The Utah Department of Transportation (UDOT) conducted focus groups in the fall of 2018 to gain a baseline analysis of the public sentiment toward CAV technology. The focus group results showed:

- On a rating scale of 1-7, when asked "What is your perception of CAV technology," gave an average mean rating of 5.71.
- On average, participants' perceptions decreased slightly after learning more about CAV technology, likely because the discussion sparked questions they had not thought of previously.
- Focus group participants had a significant disadvantage when discussing CAV technology because they were misinformed or completely unaware of the specific details of the technologies.

The focus group conclusions and recommendations showed that public messaging emphasizing safety, convenience, and time savings were a good way to increase public sentiment. This research project will build upon this and other similar research efforts to direct and guide future outreach.

As a part of the Internet of Things (IoT), CVs increase the possibility of frauds, hacks, and data-breach incidents with their gradual increase in market penetration. A study has revealed that the number of automotive cyber security incidents has increased exponentially from 2010 to 2019, with an average annual growth rate of 94% since 2016 and 99% since 2019 (Upstream Security, 2020). On one hand, the automotive industry and researchers are working to develop safety and security measures for CVT. On the other hand, the market penetration of CVs is increasing rapidly day by day. In this context, the study of users and public perception of this technology is vital in light of widespread development and prevalence. Prior to this one, very few studies have been conducted to study public perception of CVT, and those studies are rarely related to public perception on collection and use of CV data, particularly in regard to data privacy and security.

1.2 Objectives and Goals

The main goal of this study was to understand the public's perception on the data issues (e.g., privacy, security, etc.) and public intentions toward sharing various types of data (e.g., speed, traction, position, etc.) via CVT applications. Furthermore, the relationships between these attitudes and intentions of future purchase and use of CVs were studied. Structural equation models were developed to understand the path of relationship between data issues, data sharing intention, and behavioral intention to use CVs in the near future. The results of this study address the following research questions:

1. What is the public intention toward sharing different types of data through CVs?
2. How are the prevalent data issues of CV technology associated with public data sharing intention and overall acceptance of CVs?
3. What is the process of development of public perception toward the acceptance of CVs?

The main objectives of this study were:

1. To ascertain the data sharing intention of the public for a number of CV applications.
2. To ascertain how the data privacy and security issues of CVT affect the public data sharing intention for CV applications and overall CV acceptance.
3. To identify the psychological factors affecting the CV acceptance and overall process of development of attitude and behavioral intention to use CVs.

To accomplish these goals, a questionnaire survey of 2,400 U.S. adults was conducted through an online Qualtrics Panel from November 2020 to February 2021. Based on the data collected, a series of structural equation models were proposed and developed. The structural models developed explained the CV data sharing intention, how data sharing intention affects the acceptance of CV, and the overall process of CV acceptance development. In addition, the associations of socio-demographic and other individual characteristics with data sharing intentions and the predictors of CV acceptance were also determined.

1.3 Outline of Report

This report summarizes the work conducted as part of this study. First, a literature review is summarized and discussed. Then the data collection methodology is outlined. Third, three different data models and their results are discussed: a data sharing intention model, a data sharing intention and CV usage intention model, and a CV acceptance model. Lastly, the results of the survey and models informed the development of the conclusions, recommendations, and suggestions for future work.

2. LITERATURE REVIEW

2.1 Internet of Things and Intelligent Transportation Systems

The Internet of Things (IoT) is the basis of connected vehicle technology (CVT). IoT is a system of interrelated computing devices, mechanical and digital machines, objects, animals, or people that are provided with unique identifiers and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction. A network comprises physical objects capable of gathering and sharing electronic information. The IoT includes a wide variety of "smart" devices, from industrial machines that transmit data about the production processes to sensors that track information about the human body and more (Atzori et al., 2010). Often, these devices use Internet Protocol (IP), the same protocol that identifies computers over the World Wide Web and allows them to communicate with one another. This framework has applications in a wide range of spaces, including home computerization, modern robotization, clinical guides, versatile medicinal services, transportation networks, and numerous others (Bellavista et al., 2013). Vehicular categories of IoT are sometimes referred to as Internet of Vehicles (IoV). As CVT involves the collection and exchange of data between vehicles, roadside units, mobile devices and other intelligent transportation system technologies, it falls under the umbrella of IoT and IoV.

Intelligent transportation systems (ITS) are the application of advanced communication and information technology to the field of transportation in order to improve safety, efficiency, and sustainability. The technological application may fall within any of the three main components of transportation: vehicles, infrastructure, and users (e.g., drivers, pedestrians). ITS is a broad concept. There are many applications that have already been explored and just as many more still in the research stage. Within the USDOT, the Intelligent Transportation System Joint Project Office (ITS-JPO) is responsible for overseeing research in the area of ITS. Some other technologies that have been the subject of ITS-JPO research include electronic data collection, ramp meters, red light cameras, traffic signal priority, and traveler information systems. Some of the resulting applications from ITS-JPO research include: Next Generation 9-1-1, Cooperative Intersection Collision Avoidance Systems, Integrated Vehicle Based Safety Systems, Integrated Corridor Management Systems, Clarus, Emergency Transportation Operations, Mobility Services for All Americans, Electronic Freight Manifest, and ITS Operational Testing for Congestion Mitigation (ITS-JPO, 2020b). The study and pilot implementation of CVT, as a part of ITS, is also being carried out by ITS-JPO.

2.2 Uses of CVT

CVT, as a part of ITS, has a wide range of applications and benefits. The applications/benefits of the technology fall into the general categories of safety, mobility, environment, infrastructure condition assessment, traffic studies, and miscellaneous, which are presented in **Error! Reference source not found.** and described briefly in the subsections below.

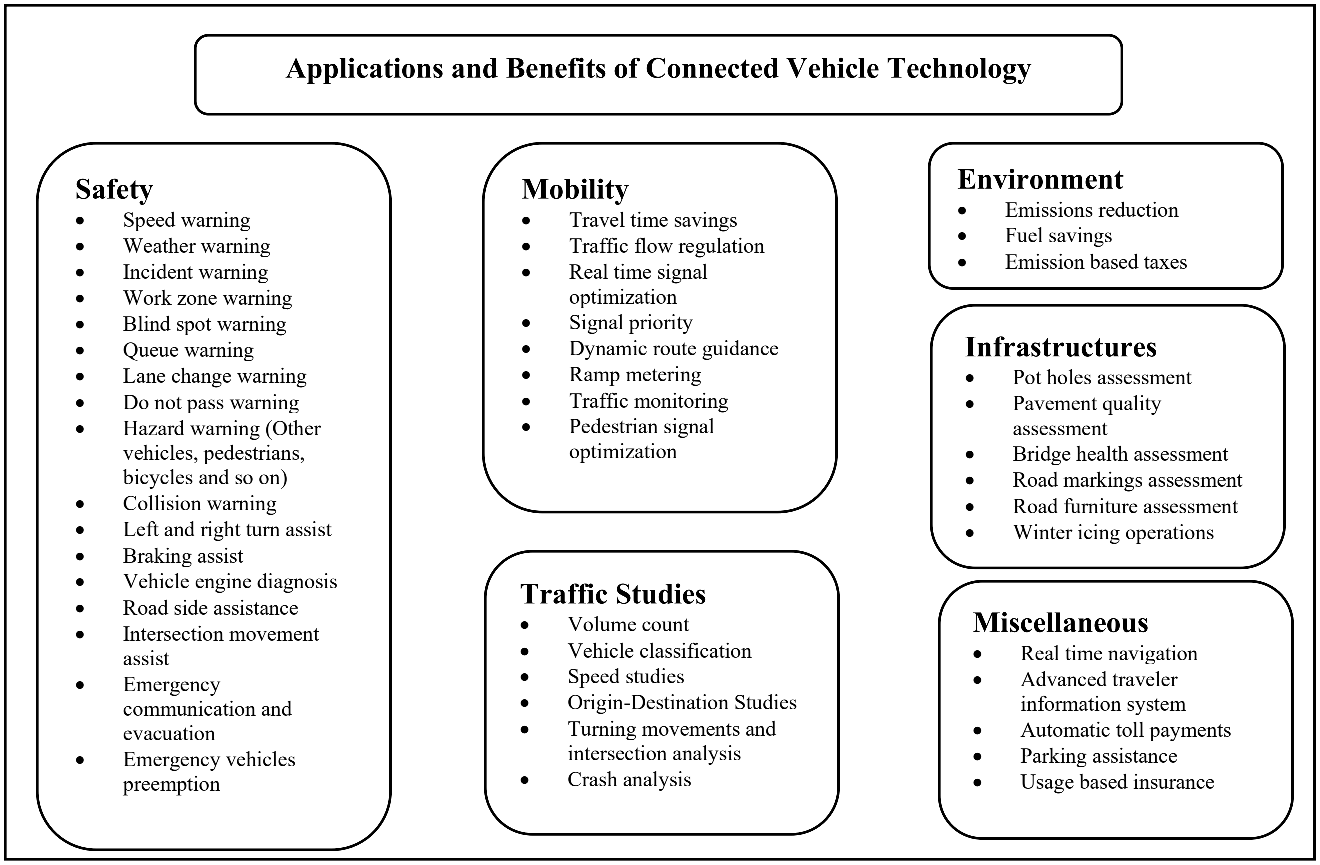

Figure 2.1 Applications of CVT

2.2.1 Safety

The data collected from individual vehicles in a connected system can be used to improve the safety of road users and the overall transportation system. This can be achieved via a variety of applications, including, but not limited to, speed warning (Zhang et al., 2017), weather warning (Siegel et al., 2017), incident warning (Kattan et al., 2012), work zone warning (Genders & Razavi, 2016), blind spot warning (Uhlemann, 2015), queue warning (Khazraeian et al., 2017), lane change warning (Williams et al., 2018), do not pass warning (Doecke & Anderson, 2014), hazard warning (other vehicle, pedestrian, bicycle, and so on) (Nair et al., 2017), collision warning (Zhang et al., 2017), left- and right-turn assist (Jadaan et al., 2017), braking assist (Njobelo et al., 2018), vehicle condition monitoring (Zhang et al., 2009), road side assistance (Siegel et al., 2017), intersection movement assist (Wang et al., 2020), emergency communication and evacuation (Bahaaldin et al., 2017), emergency vehicles preemption (Noori et al., 2016), and many more.

2.2.2 Mobility

CV data can be used for real-time signal optimization and signal priority (Feng et al., 2015), dynamic route guidance (Liu et al., 2019), and ramp metering (Yang et al., 2018), which can reduce travel delay. Real-time traffic monitoring and flow regulation can also be done through the use of CVT (Khan et al., 2017). Also, the data from CVs and pedestrians can be used to optimize pedestrian signals and timing, thus improving pedestrian safety (Khosravi et al., 2018). Overall, the mobility and operational efficiency of intersections and networks can be improved using this technology.

2.2.3 Environment

The reduction in delay at intersections, reduction of congestion, dynamic traffic assignment, and many more applications of connected data all offer tremendous benefits in terms of emissions reductions and fuel savings (Lee & Park, 2012). As CVs can be designed to monitor the emissions and fuel efficiency of each vehicle, environmental policy measures, such as emission-based taxes, can also be implemented and adapted (ITS-JPO, 2020a).

2.2.4 Infrastructure

CVs can share data regarding conditions both inside and outside the vehicle. The data can be used to assure the quality of roadway infrastructure via applications, including pothole assessment (Dennis et al., 2014), pavement quality assessment (Dennis et al., 2014), bridge condition assessment (Khan et al., 2016), road marking assessment (Veit et al., 2008), and winter icing operations (Steiner et al., 2015).

2.2.5 Traffic Studies

Improvement of the transportation system requires the regular collection and study of traffic data, which include traffic volume, speed, density, and travel time. Significant efforts have been made to capture these data in real time and/or across numerous points within the roadway network. With the deployment of CVT, shared vehicular and trip data could be used to perform traffic studies more economically and quickly. Such studies might include volume studies based on vehicle classifications, speed studies, origin-destination studies, turning movements and intersection analysis, crash analysis, and others (Khan et al., 2017; Zheng & Liu, 2017). These data could also be shared more readily among transportation agencies, universities, and other organizations for research purposes.

2.2.6 Miscellaneous

Some other uses of CVT include real-time navigation (Chen & Du, 2017), advanced traveler information systems (Yang et al., 2017), automatic toll payments (Shladover, 2018), parking assistance (Uhlemann, 2015), and usage-based insurance (Sahebi & Nassiri, 2017). For the most part, these applications are intended more for user convenience and assistance rather than for safety or operational benefits.

2.3 Issues of CVT

Although CVT offers significant potential benefits to the transportation system through the enhancement of safety, mobility, and efficiency, there are several issues with the technology that need to be addressed so that widespread adoption is not hindered. CVT, being a part of the Internet of Things (IoT) and intelligent transportation systems (ITS), shares many of the issues of IoT and ITS. Limited research has been conducted to assess public perception and issues of CVT. From the extensive literature review and the research team’s perspective, the main issues of connected vehicle technology are shown in Figure 2.2. Data, equity, cost, and driver distraction are considered to be the four major issues of the technology.

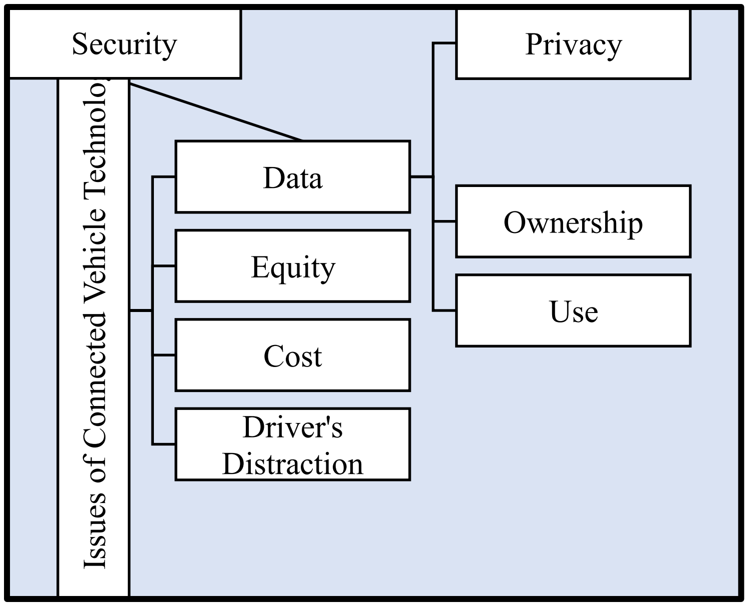

Figure 2.2 Issues of CVT

2.3.1 Data Issues

Among the four main issues, data-related issues are considered the most critical in the implementation and acceptance of CVT. Three types of data could potentially be shared by CVs: driver information, vehicle information, and trip data. Driver information is the least useful for most transportation applications and may include the driver's name, age, license number, driving history, and physical disabilities (if any). However, due to the current climate of data privacy concerns in the United States, these data are very unlikely to be shared outside of restricted administrative purposes. Vehicle information includes such things as tire pressure, mileage, fuel consumption, fuel level, and engine status. The information will likely be most useful to the driver and vehicle manufacturer, though applications do exist for transportation operations. Trip data include origin of trip, destination of trip, speed of vehicle, steering angle, wiper speed, jerking of vehicle, and weather/roadway conditions. These data are anticipated to be the most valuable for transportation applications. Privacy, security, ownership, and use of data collected from CVs are the four key areas of concern regardless of these three CVT data content types.

2.3.1.1 Privacy

Data privacy deals with how the personal data collected from CVs are shared and used in appropriate ways. Unauthorized access, loss, misuse, modification and disclosure of personal information are the major privacy threats of CV technology being a part of IoT. Driver, vehicle, and trip data shared through the technology can be used to track the movement of each user, which may pose a threat to safety of the users. Moreover, users are worried about the misuse of their personal information for advertisements, surveillance, and other unauthorized applications. A questionnaire survey followed by focus group discussion showed that users perceive the disadvantages of CVT to be greater than the potential advantages due to the issues of data privacy and control, illegal access, and identifiability (Schmidt et al., 2016).

2.3.1.2 Security

Data security deals with how the data collected from the connected vehicles are stored and protected from unauthorized access and use, both internally and externally. The information relating to driver, vehicle, and trip is normally collected by the CV system. However, there is inconsistency regarding whether or not the data are stored, and if so, whether the data are stored locally (in-vehicle), in the cloud, or at a remote location. There is a security threat in both the unintended and unauthorized use of data collected and in the dissemination of messages or warnings to the driver. If a fake message is forwarded to the driver due to unauthorized access or misuse of the system, it may lead to severe accidents and crashes.

The data security threats to CV technology are nearly the same as that of IoT and IoV. Huge networks of IoV (connected vehicles and intelligent transportation system) have the risk of authentication and identification attacks, availability attacks, confidentiality attacks, routing attacks, data authenticity attacks, etc. (Sun et al., 2015). A study carried out in Michigan demonstrated that the public perceives security of data as the most concerning issue regarding CVs (Furr, 2017).

2.3.1.3 Ownership

Data ownership deals with who owns the data collected via CV technology. Vehicle owners, transport agencies, traffic safety officers, or vehicle manufactures may all have a claim to ownership of the data collected based on the policies put in place. However, individual users are concerned about the perceived unauthorized use of stored CV data due to the ownership disputes. A questionnaire survey study demonstrated users wanted ownership of the data to be limited to the vehicle owner only (Brell et al., 2019).

2.3.1.4 Use

Data use deals with the purposes for which the data are used. The potential benefit of CVT can be achieved by using the driver, vehicle, and trip data collected as described above. Usage preferences are expected to vary from user to user, so that some data uses are of a concern to some but not all users. However, much of the data collected may be useful for state and federal transportation agencies, researchers, and industry to measure, assess, and improve the transportation system. The data might also be used for enforcement purposes or for usage-base fees. Different users have different perceptions regarding the various uses of data. For example, female drivers generally perceive the higher safety and mobility uses and benefits more than male drivers (Schmidt et al., 2016). One study showed that users want the data to be used for crashes and emergency management purposes only because of excessive privacy concerns (Brell et al., 2019).

2.3.2 Equity

There are some equity-related issues with CVT. Users must follow the instructions provided by the system to properly use the technology and achieve the safety and mobility enhancements. However, there is uncertainty about whether all drivers are capable of perceiving and following the instructions provided due to literacy and physical capability issues. Also, the public's perception regarding CVT varies by gender and age (CAR & MDOT, 2012). A survey by Owens et al., (2015) found that younger users are more likely to feel comfortable with advanced technology but are least likely to own the advanced technology. However, older users were found to be more interested in owning the more advanced technology but least likely to use it.

2.3.3 Cost

Currently, the initial cost of CVs is higher than for conventional vehicles. Often, a subscription cost is also needed to use the connected features. A willingness to pay study concluded that users are interested in the installation of CVT but are concerned about the cost of advanced features (Shin et al., 2015). Cost is one of the main factors impacting the ability of younger users and low-income users (representing the greatest share of potential users) from accessing and utilizing the technology.

2.3.4 Driver Distraction

Any activity that diverts a driver's attention from driving is called driver distraction. Cell phone use, texting, eating, talking, and adjusting music are among the major activities that lead to distracted driving. It is a leading cause of crashes and fatalities. In the United States, driver distraction contributed to 9% of the total fatal crashes (3,166 fatalities in total) in 2017 (NHSTA, 2020). Although distracted driving is a safety threat for all drivers, it is most prominent in younger drivers. Of fatal crashes in 2017, 8% of involved drivers 15 to 19 years of age were noted to have been driving while distracted (NHSTA, 2020).

2.4 Public Perception of CVT

A pioneering study by the Center for Automotive Research (CAR) and the Michigan Department of Transportation (MDOT) was conducted to understand public perceptions toward CVT (CAR & MDOT, 2012). The study was completely based on three series of focus groups, each having 14 participants. Based on the discussions in the focus groups, the potential CVT benefits were grouped into three categories: safety, mobility, and environmental performance. The CVT issues were grouped into five categories: security, driver distraction, complacency, cost, and privacy. Results showed that increased safety was considered to be the most appealing benefit and that security of the connected data was the most concerning issue. The differences in the perception of participants based on gender, age, and educational attainment on each of the benefits and issues of CVT were also summarized in the study. The results indicated that socio-demographic and personal characteristics might influence the perception of technology.

Schoettle and Sivak (2014) conducted a survey of 1,596 individuals in the U.S., U.K., and Australia to understand public opinion about CV and make international comparisons. More than 70% of each country's respondents were unfamiliar with the CVT before the survey but more than 60% had a positive opinion regarding CV. Interestingly, among the three countries, the U.S. had the highest familiarity but lowest positive opinion about using CV. The respondents considered safety as the most important benefit of CVT among the pool of safety, mobility, and environment. In addition, the respondents showed their concerns about issues such as safety, legal liability, security, data privacy, and interaction with environments.

To understand the public's intention toward the use of CVT and willingness to pay for the technology, Shin et al. (2015) carried out a questionnaire-based study where the respondents were asked to choose among the five levels of CVT attributes. The attributes considered were collisions, diver assistance, enhanced safety, roadway information, and travel assistance packages. Calculated utilities for each level (from "none" to "most comprehensive") showed that the respondents were interested to have some CVT features rather than none. Among the five CVT packages, the collision package was found to have highest importance and also had a higher willingness to pay. In addition, the study confirmed that although the public is interested in adopting CVT, the cost for those features might hinder the actual adoption.

An empirical study was carried out by Schmidt et al. (2016) using focus group discussion and a survey to understand public perception toward the V2X technology. From the focus group study (18 participants), safety, comfort, and efficiency (in relation to costs) were classified as the perceived benefits of the technology; whereas data privacy and control, illegal access, and identifiability were categorized as the perceived disadvantages. For each category of advantage and disadvantage, 169 survey participants were asked to rate from 0 (disagree) to 5 (agree). The results showed that participants considered safety (average score: 3.4 out of 5) as the most important advantage, and data privacy and control (average score: 3.8 out of 5) as the major drawback of technology. Secondly, the study analyzed the public's openness to sharing driver and vehicle related data for connected applications. The respondents were categorized into experienced and laypeople, where the use or availability of a driver assistance system was used as the criteria. Experienced drivers were found to have more openness toward sharing driver and vehicle data for CVT than laypeople. However, the openness for data sharing for experienced drivers was 1.43 out of 5 for driver data and 2.8 out of 5 for vehicle data. For laypeople, the openness values were 1.13 and 2.47, respectively, for driver and vehicle data. The study concluded that experience with the connected features is key for the widespread adoption and acceptance of the technology.

A recent study by Zhao et al. (2021) investigated the behavioral intention of using CV at an uncontrolled non-signalized intersection by extending the theory of planned behavior. A hypothetical scenario of an uncontrolled non-signalized intersection was presented first in the questionnaire followed by other questions. The factors related to intentions of using CV at the intersection were found to be subjective norms, attitudes, characteristics and experiences, risk perceptions, perceived behavioral control, and personal traits. Based on the personal traits of drivers, two categories of drivers were identified: high-neurotic and low-neurotic. These two categories of drivers had significant differences in CV driving intentions.

2.5 Summary, Research Gaps, and Rationale of Study

A comprehensive literature review in the field of public perception toward connected vehicle technology was carried out to guide the research efforts and strategies of this study. The literature review started with an introduction to the Internet of Things (IoT) and intelligent transportation systems (ITS), as CVs are considered to be a part of IoT and ITS. This section was followed by a summary of the potential applications of CV data. Then the existing and perceived issues of the connected technology were discussed. Finally, a summary of existing studies related to the public's perception of CVT was presented. This comprehensive literature review demonstrates that there are limited studies related to public perception of CVT, particularly on the collection and use of CV data.

In summary, based on limited preliminary studies, it can be concluded that the public considers CVT to be a promising solution to existing traffic safety problems but are highly concerned about the privacy and security of collected data and might not consider sharing the data. These issues might hinder the widespread adoption of CVs in the near future. However, a detailed and in-depth understanding of these data issues pertaining to CVT is still lacking. The narrowing of this gap is the objective of this study. Thus, this study aims to understand public perception of data privacy and security issues, public openness to sharing CV data, and how these issues may impact adoption of CVs in the near future. Based on the literature review, the following paragraphs explain the research gaps and how three research objectives fill those research gaps.

First, the existing studies in the literature showed that there are a number of potential applications of CV data (shown in **Error! Reference source not found.**). However, it should be realized that these benefits cannot be capitalized on without CV users' data sharing intention. In this scenario, understanding of CV data sharing intention is important to formulate plans and policies to improve the CV data sharing intention. However, the research on this topic is scant in the literature. The only previous study (as per the team's knowledge) that investigated users' intentions or willingness to share CV data was conducted by Schmidt et al., (2016), which hinted that the intention to share CV data depends on the type of data and other personal characteristics of drivers. Thus, in this study, the research team aimed to extend the work of Schmidt et al., (2016) by using eight types of CV data and 10 uses of those data (detailed later) to understand the public intention toward CV data sharing in detail. In addition, the differences in CV data sharing intention for different socio-economic groups and people of different personal and demographic characteristics were also assessed.

Second, there is a gap in the literature regarding how data sharing intention affects public acceptance of CV. Hypothesizing that the data privacy and security issues of CV technology are related to data sharing intention and CV acceptance, this study aimed to evaluate the paths of relationships between these three. In addition, the associations of demographic and other personal characteristics with these factors were also determined.

Third, the literature lacks evaluation of acceptance models in the context of CVs. With the widespread use of a technology acceptance model (TAM) (Davis et al., 1989) – an extension of the theory of planned behavior (Ajzen, 1991) – in determining the acceptance of emerging technologies (including vehicle technologies), electric vehicles (Globisch et al., 2018), ride sharing services (Wang et al., 2018), and autonomous vehicles (Ghazizadeh et al., 2012; Choi & Ji, 2015; Kaur & Rampersad, 2018; Xu et al., 2018; Zhang et al., 2019), this study developed a connected vehicle acceptance model (CVAM) by integrating the role of trust and data privacy and security in the original TAM. In addition, the associations of demographic and other personal characteristics with the predictors of CV acceptance were also determined.

3. DATA COLLECTION AND METHODOLOGY

3.1 Data Collection

A questionnaire was designed to collect the empirical data for this study. The questionnaire was distributed by Qualtrics and data was collected via online participant panels. The questionnaire began with a letter of information, per Institutional Review Board requirements. The overall study (and questionnaire) was approved by the Utah State University Institutional Review Board. After the letter of information, the questionnaire began with a question related to the familiarity of the participant with connected vehicles (CVs) and was followed by a brief introduction to CV, including acronyms and definitions used within the survey. The survey itself was designed to assess public perception toward different aspects of CVT, including data sharing intention and behavioral intention to purchase and use CVs in the near future. In total, there were four sections in the questionnaire. The first section was related to the public's perception of data issues associated with CVT: privacy, security, and management of data collected through CVs. In the second section, the respondents were asked to select (multiple select) the potential uses for which they would be willing to share the particular types of CV data. The third section was about the public's perception of the usefulness, ease of use, trust, attitude, and behavioral intention toward CV use. More details about the questions in the first, second, and third sections of the questionnaire are presented in the following subsections. The complete questionnaire is included in Appendix A.

The fourth section of the questionnaire was related to the socio-demographic and other characteristics of the respondents. Demographic characteristics of the respondents collected in the study included age, gender, race, annual household income, education, number of households, number of children in household, student status, and employment status. Other characteristics of respondents collected in the study included typical daily travel time, possession of driver's license, driving experience, number of vehicles in household, availability of connected features in any one of the vehicles in household, and familiarity with CVT. The questionnaire was distributed to the general U.S. adult population through the online Qualtrics platform from November 2020 to February 2021. In total, 2,400 responses were collected. The summary of demographic and driving characteristics of the respondents is shown in Table 3.1.

Table 3.1 Descriptive statistics of the sample

Variable	Categorical		Continuous	
	#	%	Mean	SD
Age				
18-24 years	248	10.33		
25-44 years	970	40.42		
45-64 years	674	28.08		
65+ years	504	21.00		
Missing	4	0.17		
Gender				
Male	999	41.63		
Female	1394	58.08		
Other/missing	7	0.29		
Race/ethnicity				
White	1806	75.25		
Others	574	23.92		
Missing	20	0.83		
Income				
< $25k	467	19.46		
$25-75k	1006	41.92		
$75-150k	574	23.92		
≥$150k	239	9.96		
Missing	114	4.75		
Education				
No college degree	930	38.75		
Undergraduate degree	902	37.58		
Graduate degree	530	22.08		
Missing	38	1.58		
# households (age ≥18 years)			2.172	0.999
# children (age <18 years)			0.786	1.055
Student: yes	226	9.42		
Employed: yes	1353	56.38		
Daily travel time				
<30 minutes		42.67		
30-60 minutes	672	28.00		
≥ 60 minutes	689	28.71		
Missing	15	0.63		
Driving license: yes	2219	92.46		
Driving experience (years)			23.947	19.117
Vehicle ownership			1.724	1.033
Connected feature: yes	900	37.50		
Familiarity				
Low/none		52.67		
Medium	899	37.46		
High	237	9.88		

3.1.1 Data Issues

The first part of the questionnaire asked respondents about their current level of perception regarding the data issues associated with CVT. Four questions representing data privacy issues and three questions representing data security issues were asked on a 7-point Likert scale ("extremely unlikely" to "extremely likely"). The summaries of these responses are in shown in Figure 3.1 and Figure 3.2, respectively. In addition, four questions regarding the importance of the reputation of the data manager were asked. The summary of those responses is shown in Figure 3.3. Prior to these questions, the data manager was defined as, "The individual or organization that collects, stores, and owns the data collected from connected vehicles and has the authority to provide access to and give permission for the use of that data."

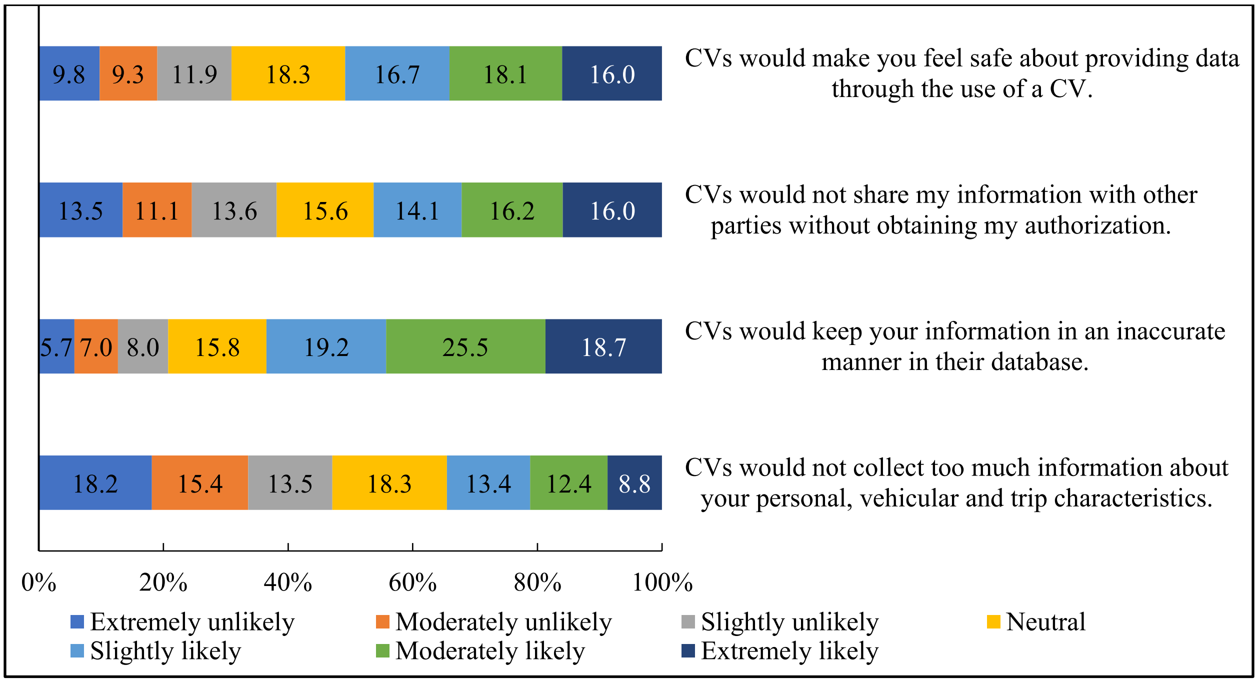

Figure 3.1 Public perception toward data privacy issues

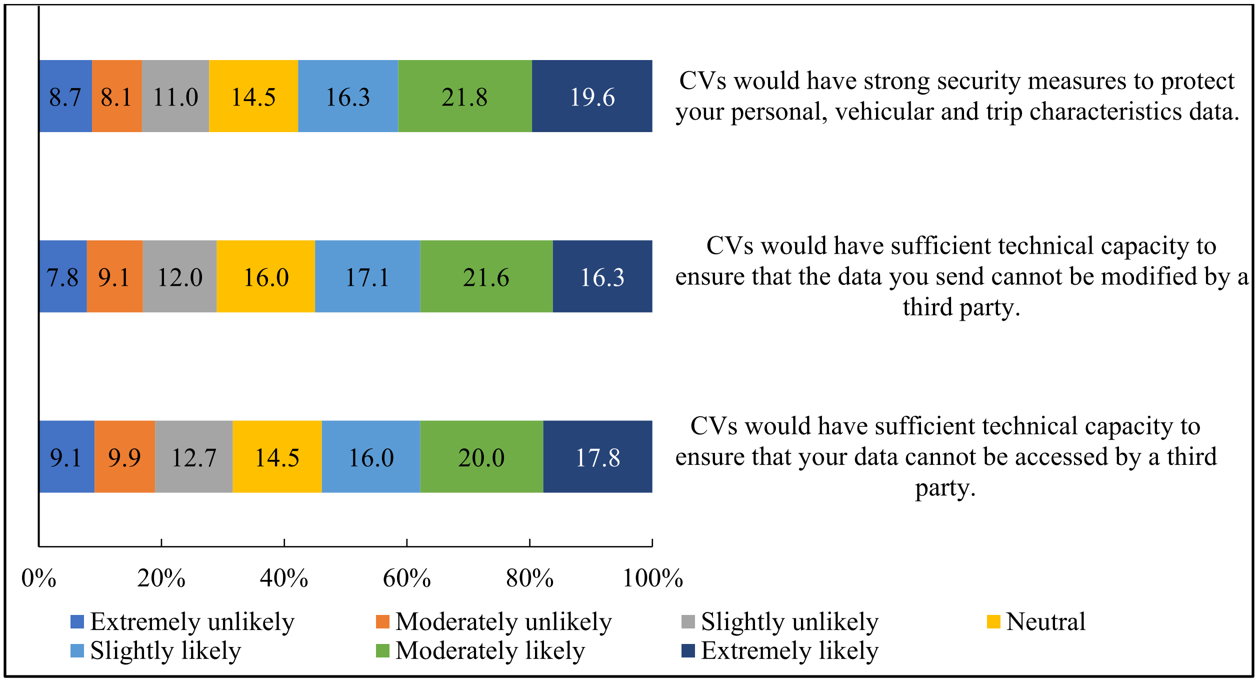

Figure 3.2 Public perception toward data security issues

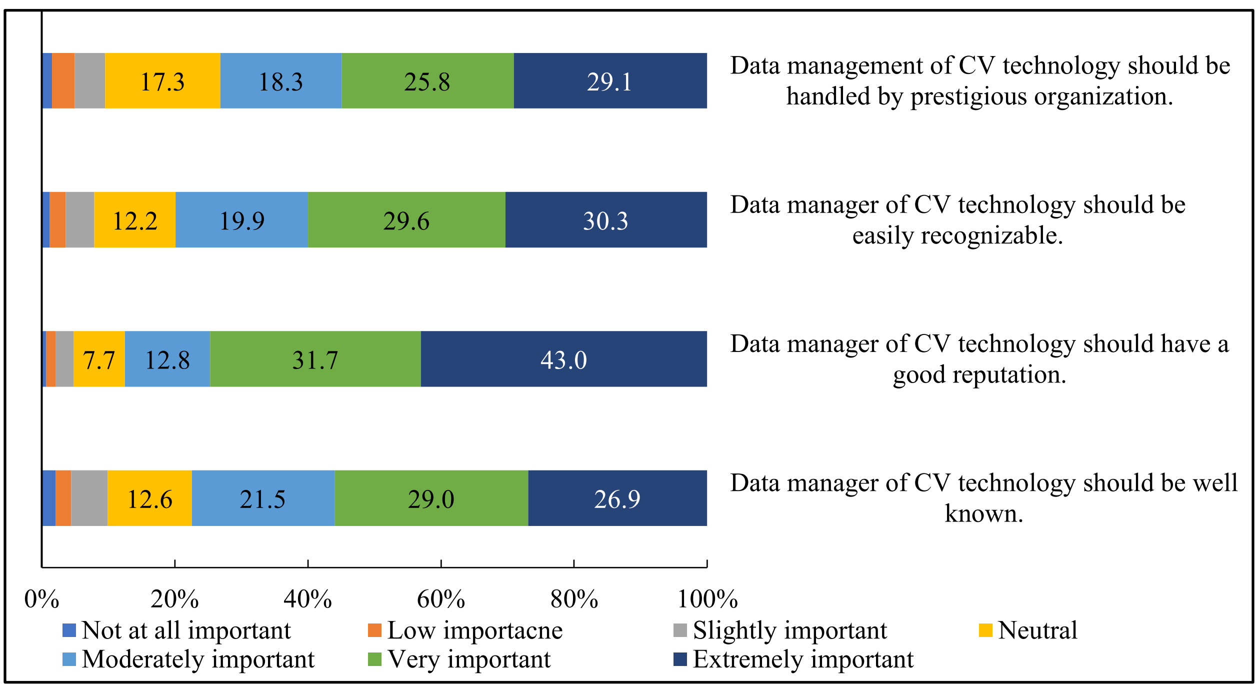

Figure 3.3 Public perception toward importance of reputation of data manager of CVT

3.1.2 Data Sharing Intention

In the second part of questionnaire, eight multiple-select (i.e., select all that apply) questions were asked regarding data sharing intention or willingness.

Based on the detailed review of available literatures, eight types of CV data and 10 uses of those data (shown in Table 3.2) were used for the scale development. For each data type, there were 10 uses of the particular data type, which resulted in 80 items to measure the overall CV data sharing intention. For 80 items, it was difficult to carry out the survey with a Likert scale of 5 or 7 due to time and length restrictions. Therefore, those questions were asked in a binary scale. There were eight questions with varying CV data types and each question had 11 options (10 uses of CV data and none) from which respondents could select the multiple options. The wording of questions followed the format: *"For which of the following applications would you feel comfortable sharing your connected vehicle speed data with a transportation organization? Select all that apply."* The summary of the data collected is shown in Table 3.3, using the same coding as in Table 3.2. The table shows the percentage of respondents intending to share a particular data type (A, B,…, H) for various uses (1, 2, …, 10). In addition, the values in the last column "None" indicates the percentage of respondents not intending to share data of a particular type (A, B, …., H) for any uses (1, 2,….,10).

Table 3.2 Summary of CV data types and their uses

Types of CV data	**Code**
Speed data	A
Braking intensity and traction data	B
Pitch and roll data	C
Mileage data	D
Wiper and headlight intensity data	E
Make/model and ownership data	F
Trip information (location, origin, destination, trajectory) data	G
Onboard diagnostics (vehicle condition) data	H
Uses of CV data	**Code**
Information for drivers (route and weather information, speed and hazard warnings, etc.)	1
Congestion assessment and reduction	2
Safety assessment and improvement	3
Pavement and infrastructure assessment and improvement	4
Roadside assistance	5
Crash investigation	6
Enforcement of traffic laws and regulations	7
Research purposes	8
Future transportation and project planning	9
For assessment of fees based on usage	10

Note: Codes in the table represent the notations to be used further in the paper to represent specific CV data type (alphabets) and purpose of use of CV data (numeric).

Table 3.3 Data sharing intention survey results summary

Data type	Percentage of respondents intending to share data for … use of data (%)										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**None**
A	38.71	26.04	33.67	22.42	32.04	29.21	18.83	19.25	21.13	11.29	5.46
B	34.29	22.71	34.67	23.71	25.46	29.38	16.13	21.17	18.79	9.58	5.58
C	27.96	18.29	28.63	19.25	22.63	25.46	14.50	21.71	16.42	8.79	8.71
D	26.67	19.21	23.63	17.33	21.71	17.96	14.63	24.83	21.29	14.29	7.33
E	31.08	16.29	31.67	13.79	20.25	19.96	13.79	23.54	15.21	8.42	6.50
F	20.96	12.50	22.17	12.25	21.29	19.71	13.33	23.00	15.13	9.17	10.79
G	29.08	19.42	20.17	15.29	23.83	17.71	12.67	18.92	17.54	9.04	10.58
H	23.71	14.63	28.88	13.13	24.08	22.00	11.29	23.08	14.04	9.25	7.25

3.1.3 Behavioral Intention

The third part of the questionnaire dealt with behavioral intentions regarding the use of CVs and the potential predictors of those intentions. In this part, five questions related to the usefulness of CVs and four questions related to ease of using CVs were asked with a 7-point Likert scale ("not confident at all" to "extremely confident"). Summaries of the responses are presented in Figure 3.4 and Figure 3.5, respectively. Second, public trust toward the technology was assessed by three questions. The summary of responses is shown in Figure 3.6. Lastly, four questions about attitude toward and three questions about behavioral intention to use CVs were asked. The response summaries are shown in Figure 3.7 and Figure 3.8, respectively.

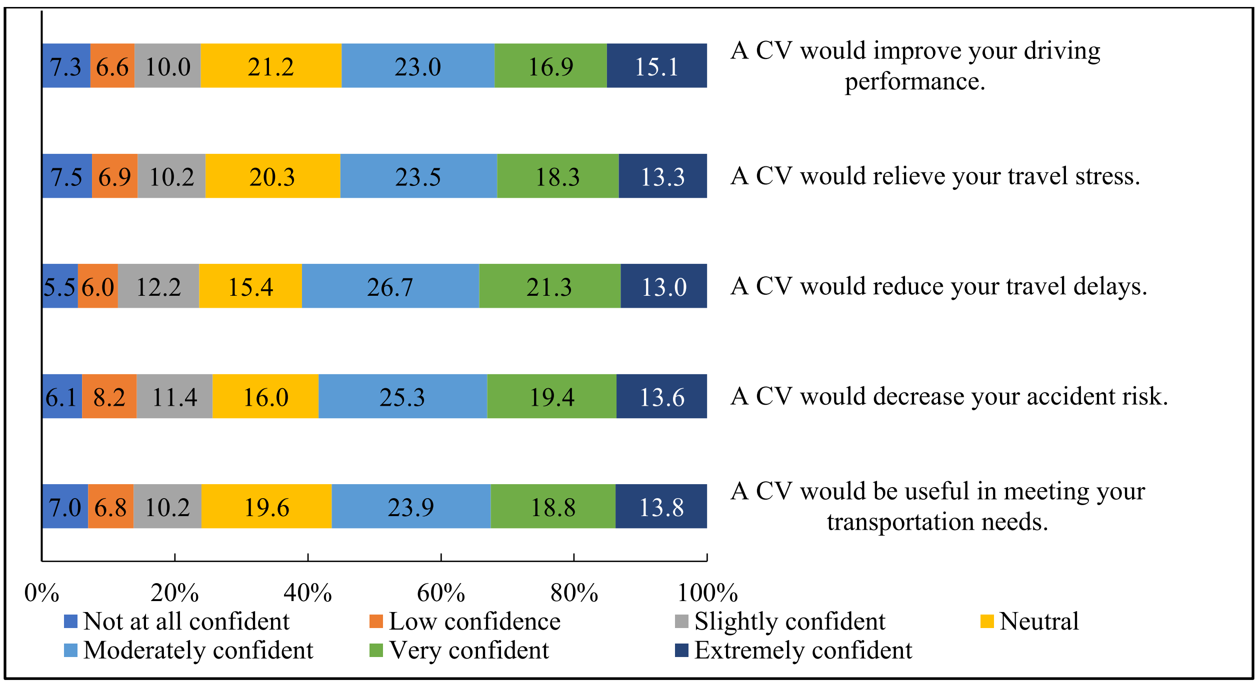

Figure 3.4 Public perception toward usefulness of CVs

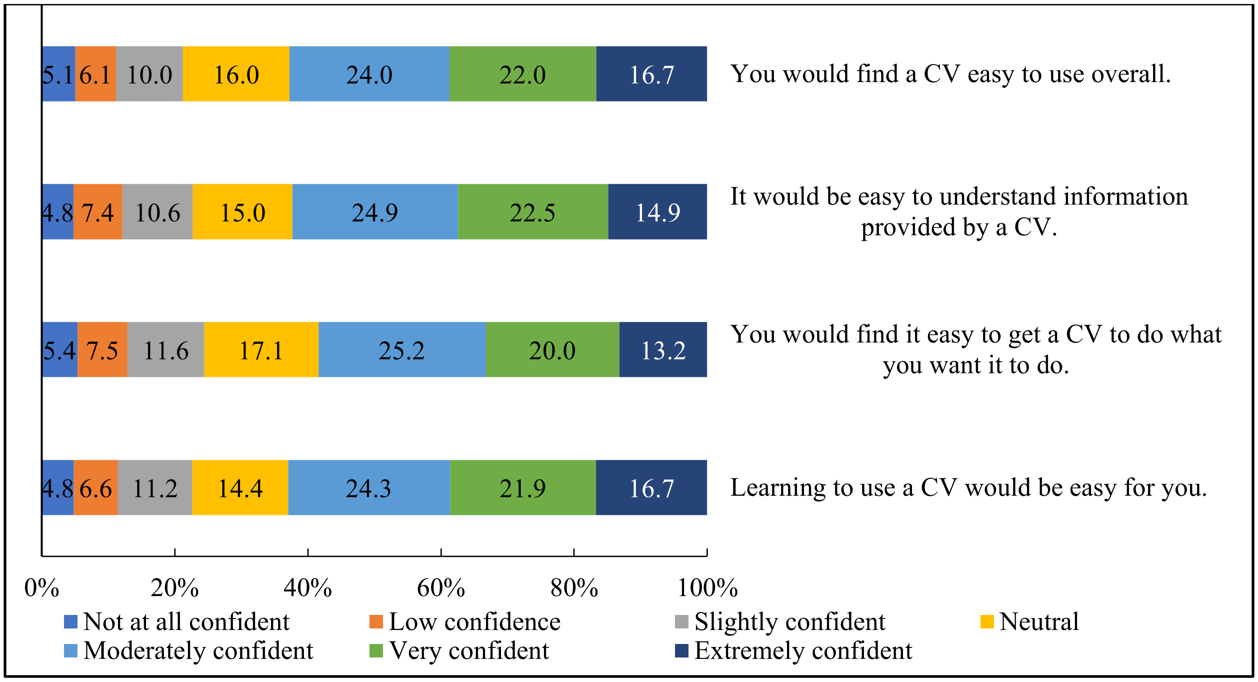

Figure 3.5 Public perception toward ease of using CVs

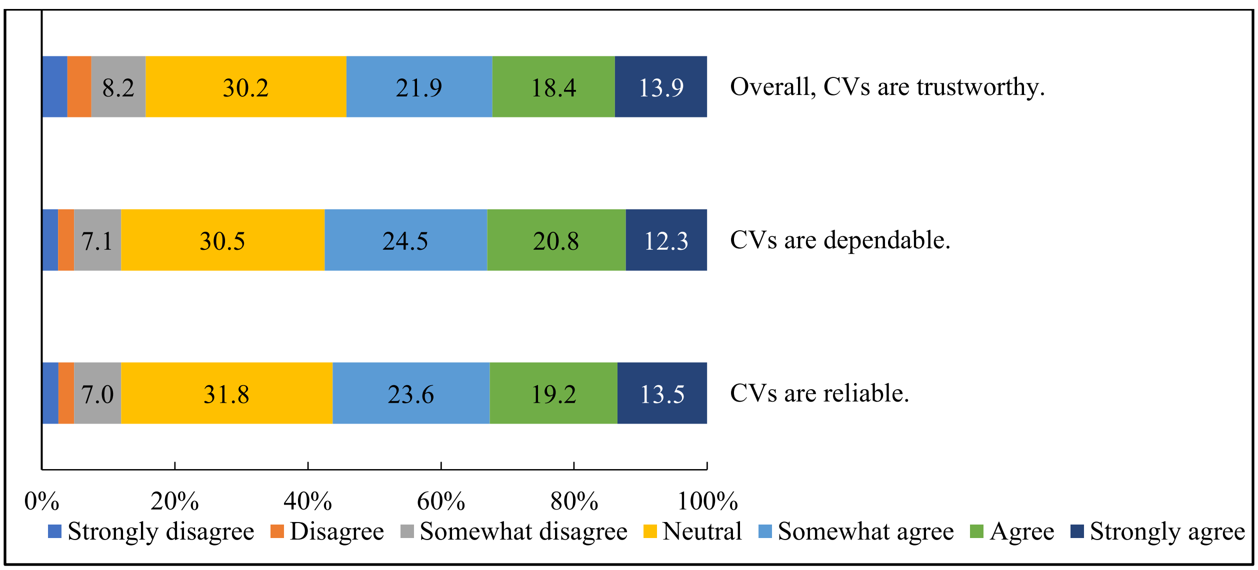

Figure 3.6 Public trust toward CVs

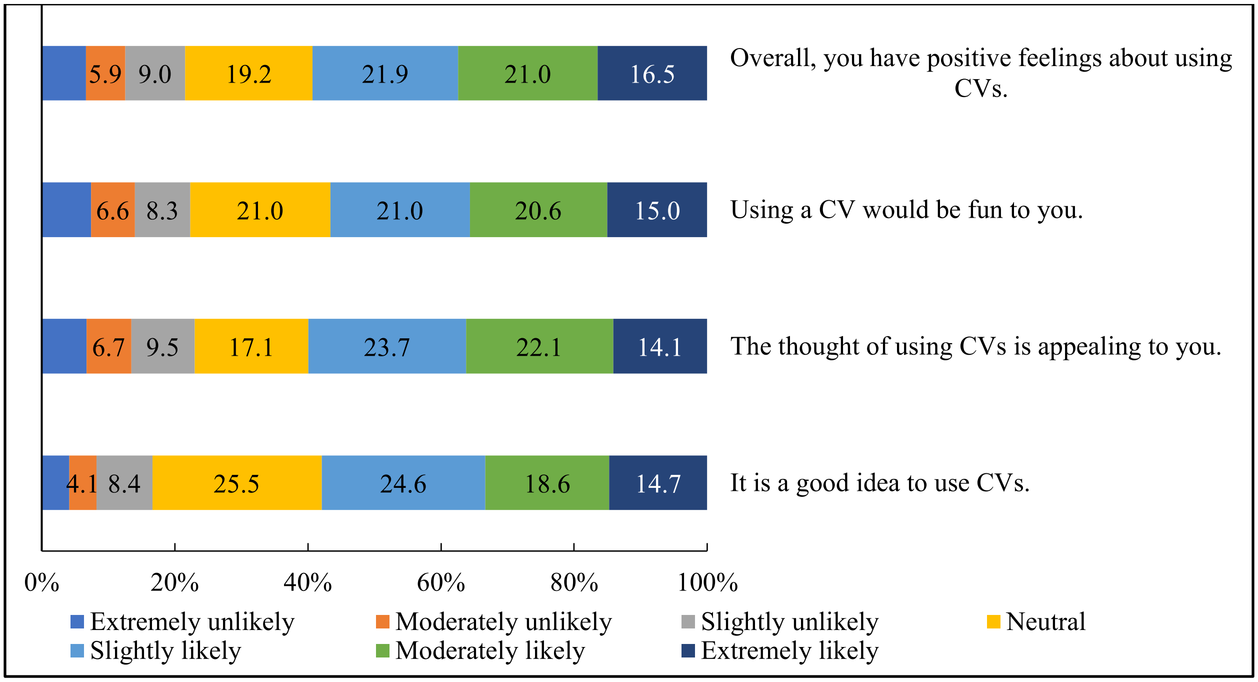

Figure 3.7 Public attitudes toward using CVs

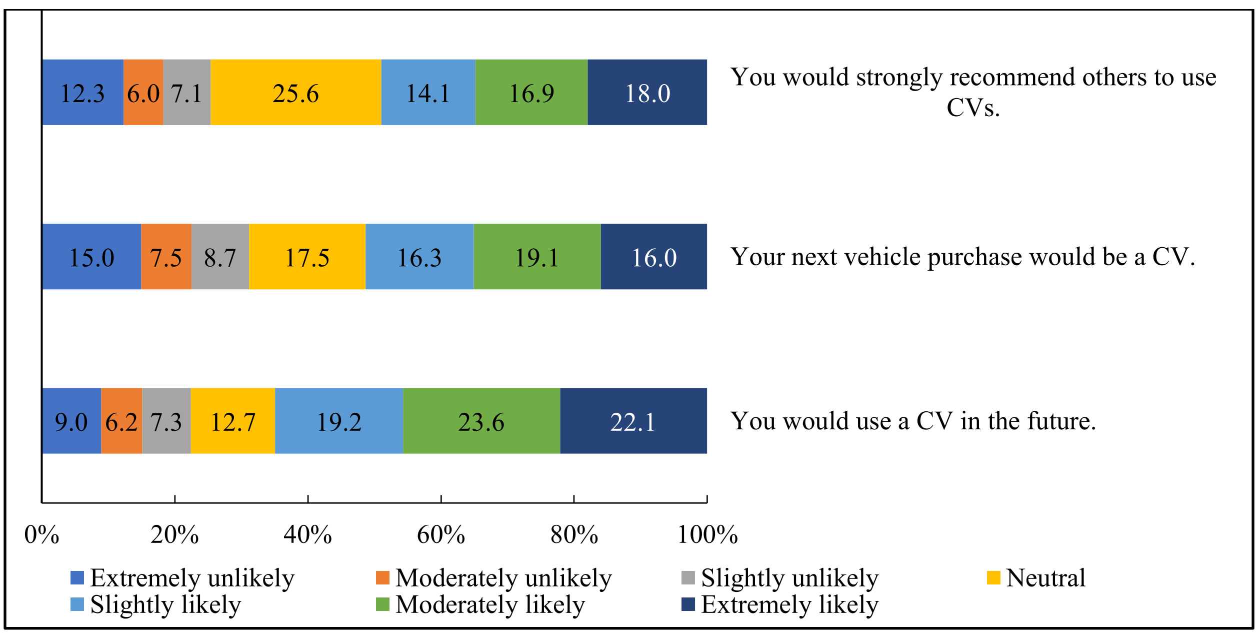

Figure 3.8 Behavioral intentions of public toward using CVs

3.2 Analysis Methods

To analyze the data collected in this study, a number of research models were proposed. Ultimately, a structural equation modeling (SEM) approach was used to statistically examine the survey results. This section explains the overall methodology used in the study. The specific procedures adopted and the details of the proposed models in each analysis are presented in Chapter 4.

The overall modeling approach followed the recommended process of psychological scale development where two subsequent analyses, exploratory factor analysis (EFA), and confirmatory factor analysis (CFA) were used to develop and confirm the factor structure (Furr, 2017). EFA is a statistical technique used to identify the underlying latent constructs that explain the variability of datasets. CFA is used to confirm an already established or proposed factor structure. The factor structure as a result of EFA can be used as a starting point for CFA, especially when the concept is relatively new and not well understood. The suitability of data for EFA was checked using the Kaiser, Meyer, Olkin (KMO) measure of sampling adequacy (Kaiser, 1970) and Barlett's test of sphericity (Bartlett, 1951). The results of Horn's parallel analysis (Horn, 1965) and examination of scree plots of eigenvalues helped to determine the number of factors to be used in EFA. Based on the nature of the measured items, different types of correlation are required as the input of EFA. In this study, the measured items in the scale of 1-7 were considered continuous in nature where a Pearson correlation between the variables was used as the input in analysis. However, when the measured variables are binary in nature, tetrachoric correlation between measured variables was used. A similar approach has been used in past studies (e.g., Singleton & Clifton, 2019). Finally, EFA was then carried out using principal axis factoring with oblimin rotation in a psych package (Revelle, 2020) of R.

SEM is a statistical technique to measure the structural relationship between the variables (Furr, 2017). A measurement model and a structural model are the two major components of the SEM technique. The measurement model defines the relationship between the unobserved latent variable with the observed indicators. Once the measurement model is fitted, the structural model is fitted to assess the relationship between the latent variables. A variable is said to be exogenous if it is introduced in the model by determining the value outside the model. On the other hand, if the value of the variable is determined inside the model, it is called an endogenous variable (Kline, 2015). The structural model determines the relationships and paths among the endogenous and exogenous variables in the model. As the number of links and paths are established between the variables in the structural model, it is sometimes called simultaneous equation modeling. The measurement model and structural models of SEM are represented by equations (1) and (2), respectively, below (Kim et al., 2011):

$$v_i = \lambda_i F_i + e_i \text{ ……………………… } (1)$$

where, v_i, λ_i, F_i, *and* e_i represent the vector of observed variables, parameters, latent variables and measurement errors, respectively.

$$F_i^{**} = B_i F_i^{*} + \Gamma_i F_i + r_i \text{ ……….. } (2)$$

where F_i is the sum of exogenous effects of latent variables, F_i^{*} is the sum of endogenous effects of mediating variables, r_i is the vector of residuals, and F_i^{**} is the function of endogenous variables where B_i and Γ_i represent the parameter vectors.

The measurement models of the concepts for CFA were proposed based on theoretical and conceptual frameworks. For the sake of improving the models' fit and making the models conceptually sound, the number of further modifications were done as required and suggested by the existing literature and concepts. Once the measurement models were finalized, the structural equation models were run based on the proposed path of relationships between the factors and variables. The chi-square value is a widely-used measure of goodness of fit for CFA/SEM models as it tests the null hypothesis that the data fit well to the theoretical model. Thus, a lower chi-square value and higher p-value indicate a good fit of the model. However, a higher value of chi-square is common for models having relatively large sample sizes (Hatcher & O'Rourke, 2013). Recall that this study has sample size of 2,400. Thus, for CFA/SEM with larger sample size, other fit indices, such as comparative fit index (CFI), Tucker-Lewis index (TLI), standardized root mean square residual (SRMR), and root mean square error of approximation (RMSEA), are warranted and were adopted in this study. The cutoff values of CFI ≥ 0.9, TLI ≥ 0.9, SRMR < 0.08, and RMSEA < 0.08 were adopted as the good fit criteria in this study as suggested by Hooper et al., (2008) and Kline (2015).

In order to determine the causal effects of exogenous variables on latent variables, a special structural model consisting of two parts – a measurement model of a latent variable indicating its relationship with measured items and a structural model indicating the relationship between a latent variable and exogenous variables – called a multiple indicators multiple causes (MIMIC) model was used (Jöreskog & Sörbom, 1996). In this case, the exogenous variables were the demographic and other personal characteristics of respondents.

For a measurement or structural model, the items and constructs should be internally consistent and have acceptable convergent and discriminant validity. Internal consistency is a measure of reliability of survey by assessing how well the several items within a construct actually measure the construct. Common ways to test the internal consistency of the constructs include using Cronbach's alpha (CA) and composite reliability (CR). Internal consistency is said to be achieved if the values of CA and CR exceed 0.7 (Fornell & Larcker, 1981; Hatcher & O'Rourke, 2013). A convergent validity test measures whether the items within the construct are able to significantly explain the variance of the latent construct or not (Furr, 2017). For a construct to have convergent validity, factor loadings of the measured items on the construct should be statistically significant and greater than 0.6, and the average variance extracted (AVE) for the construct should be greater than 0.5 (Hair, 2009). Discriminant validity assesses whether the constructs in a model are empirically different from each other (Furr, 2017). A construct is said to have discriminant validity if the square root of average variance extracted (SAVE) is greater than the bivariate correlation with other constructs (Fornell & Larcker, 1981). Using the mentioned criteria, all three tests – internal consistency, convergent validity, and discriminant validity – were carried out for this study.

4. DATA ANALYSIS, MODELING, AND RESULTS

4.1 Data Sharing Intention for CVT

In this subsection, the analysis, model, and results for data sharing intention is discussed. Following the research gaps stated in Chapter 2, there are no prior studies to support the development of scales of CV data sharing intention. Thus, the development of scale for measuring data sharing intention of CVT using a Likert scale was discussed in Section 3.1.2. The data definitions and coding outline in Table 3.2 of Section 3.1.2 are used in the subsequent texts. The research team hypothesized that the measures of CV data sharing intention collected using 80 items (excluding the "None" options) will have a number of dimensionalities such that the measured items will be grouped based on CV data type or based on the uses of CV data. Also, the combination of the groups of items was expected to explain the overall CV data sharing intention. To test the hypothesis, EFA and CFA were carried out.

4.1.1 Exploratory Factor Analysis

For the 80 measured binary variables to be used in factor analysis, the sampling adequacy and significant correlation in the data for factor analysis was confirmed using the KMO measure of sampling adequacy, with a KMO value of 0.97 and Bartlett's test of sphericity with Chisq (3160) = 42950.91 and $p < 0.001$. The eigenvalues and scree plots were examined, which suggested at least two and, at most, seven factors. Thus, the factor analysis was carried out for varying numbers of factors from four to seven, and a factor structure with four factors was found to have the best fit. Thus, a four-factor EFA was carried out using principal axis factoring and oblimin rotation. The results are shown in Table 4.1. Loadings with a value greater than 0.4 are bolded in the table. Out of 80 items, 74 items were loaded into four factors with loadings greater than 0.4. The data sharing intention for CV data uses 1, 2, 3, and 4 were found to contribute Factor 1 (except DSI-A-2, DSI-A-3, DSI-A-4, DSI-B-3, and DSI-E-3). In other words, data sharing intentions for uses 1, 2, 3, and 4 were similar enough to be grouped together. Similarly, data sharing intention for uses 7 and 10 loaded into Factor 2, uses 4 and 5 into Factor 3, and uses 8 and 9 into Factor 4 (except DSI-E-9, DSI-F-9 and DSI-H-9). The four factors were found to explain 42.4% of variance in the dataset. This result of EFA shows that the items are loaded into the factors (or grouped) based on the use of the CV data, not the type of the CV data.

Table 4.1 EFA of items of data sharing intention

Items	Factor 1	Factor 2	Factor 3	Factor 4	Items	Factor 1	Factor 2	Factor 3	Factor 4
DSI-A-1	**0.58**	-0.19	0.21	0.09	DSI-E-1	**0.73**	-0.10	0.07	0.05
DSI-A-2	0.33	-0.35	0.31	0.39	DSI-E-2	**0.58**	0.16	0.11	0.09
DSI-A-3	0.25	0.01	0.31	0.22	DSI-E-3	0.33	-0.05	0.29	0.24
DSI-A-4	0.36	-0.10	0.26	0.28	DSI-E-4	**0.56**	0.21	0.11	0.11
DSI-A-5	0.09	-0.10	**0.69**	0.06	DSI-E-5	0.32	0.16	**0.50**	-0.10
DSI-A-6	-0.18	0.00	**0.77**	0.15	DSI-E-6	0.02	0.18	**0.61**	0.12
DSI-A-7	0.02	**0.44**	0.31	-0.05	DSI-E-7	0.18	**0.62**	0.22	-0.10
DSI-A-8	-0.01	0.08	0.09	**0.68**	DSI-E-8	0.03	-0.02	0.08	**0.76**
DSI-A-9	0.21	0.13	0.03	**0.49**	DSI-E-9	0.34	0.36	-0.10	0.39
DSI-A-10	-0.08	**0.53**	0.15	0.24	DSI-E-10	0.05	**0.70**	0.04	0.22
DSI-B-1	**0.71**	-0.20	0.20	0.06	DSI-F-1	**0.77**	0.22	-0.14	-0.12
DSI-B-2	**0.44**	-0.16	0.26	0.27	DSI-F-2	**0.60**	0.32	-0.05	0.05
DSI-B-3	0.26	-0.08	0.37	0.27	DSI-F-3	**0.45**	0.17	0.10	0.12
DSI-B-4	**0.40**	-0.06	0.18	0.31	DSI-F-4	**0.59**	0.30	-0.02	0.09
DSI-B-5	0.21	0.07	**0.61**	-0.07	DSI-F-5	0.25	0.16	**0.47**	-0.07
DSI-B-6	-0.21	0.06	**0.76**	0.20	DSI-F-6	0.07	0.27	**0.50**	0.04
DSI-B-7	0.09	**0.57**	0.30	-0.10	DSI-F-7	0.19	**0.61**	0.17	-0.10
DSI-B-8	-0.01	0.05	0.11	**0.73**	DSI-F-8	0.08	0.07	0.04	**0.63**
DSI-B-9	0.24	0.27	0.00	**0.46**	DSI-F-9	0.30	**0.45**	-0.13	0.32
DSI-B-10	-0.06	**0.67**	0.14	0.22	DSI-F-10	0.00	**0.69**	0.02	0.21
DSI-C-1	**0.77**	-0.06	0.09	0.03	DSI-G-1	**0.65**	0.05	-0.02	0.04
DSI-C-2	**0.52**	-0.01	0.21	0.20	DSI-G-2	**0.52**	0.05	0.10	0.19
DSI-C-3	**0.41**	-0.06	0.24	0.28	DSI-G-3	**0.54**	0.13	0.07	0.10
DSI-C-4	**0.48**	0.01	0.13	0.28	DSI-G-4	**0.55**	0.19	0.04	0.14
DSI-C-5	0.27	0.12	**0.54**	-0.04	DSI-G-5	0.20	0.13	**0.56**	-0.07
DSI-C-6	-0.07	0.07	**0.67**	0.16	DSI-G-6	0.08	0.27	**0.55**	0.01
DSI-C-7	0.19	**0.58**	0.23	-0.11	DSI-G-7	0.22	**0.61**	0.15	-0.12
DSI-C-8	0.00	0.06	0.06	**0.75**	DSI-G-8	0.14	0.13	-0.03	**0.63**
DSI-C-9	0.29	0.30	-0.03	**0.42**	DSI-G-9	0.23	0.32	-0.07	**0.42**
DSI-C-10	-0.02	**0.68**	0.11	0.21	DSI-G-10	-0.02	**0.70**	0.03	0.24
DSI-D-1	**0.80**	-0.04	0.01	-0.02	DSI-H-1	**0.78**	0.13	-0.10	-0.07
DSI-D-2	**0.56**	-0.03	0.16	0.20	DSI-H-2	**0.54**	0.28	0.06	0.03
DSI-D-3	**0.51**	0.11	0.17	0.11	DSI-H-3	**0.40**	-0.02	0.15	0.25
DSI-D-4	**0.54**	0.08	0.08	0.22	DSI-H-4	**0.54**	0.32	0.00	0.08
DSI-D-5	0.35	0.13	**0.51**	-0.09	DSI-H-5	0.26	0.04	**0.53**	-0.06
DSI-D-6	0.14	0.22	**0.56**	0.05	DSI-H-6	-0.01	0.23	**0.61**	0.05
DSI-D-7	0.20	**0.58**	0.23	-0.11	DSI-H-7	0.24	**0.64**	0.11	-0.10
DSI-D-8	-0.01	0.00	0.09	**0.74**	DSI-H-8	0.05	0.08	0.02	**0.69**
DSI-D-9	0.23	0.25	0.00	**0.42**	DSI-H-9	0.35	**0.41**	-0.06	0.25
DSI-D-10	-0.17	**0.58**	0.09	0.27	DSI-H-10	0.06	**0.70**	0.01	0.15

Notes: DSI-I-j denotes data sharing intention of I data type for j use of data. The codes for data type (I) and use of data (j) are shown in **Table 3.2**.

4.1.2 Confirmatory Factor Analysis

All of the measured items of CV data sharing intention were binary in nature, thus diagonally weighted least square (DWLS) with robust standard errors and a mean adjusted test statistics was used for CFA estimation. First, CFA estimation was carried out using four factors and 74 items (bolded items in Table 4.1) in accordance with the results of EFA (model CFA-1). All the items were found to load significantly into four factors with loadings ≥ 0.6, as expected. The goodness of fit statistics of model A were chi-square: 28404.753 (df = 2621, p-value: 0.000), CFI: 0.978, RMSEA: 0.052, and SRMR: 0.069. The results of EFA – showing loading of items into the factors based on the use of CV data – reflected that the four factors explain the data sharing intentions for several uses of CV data. Thus, few modifications of factors were done in order to make the factors conceptually strong.

As most of the items of CV data uses 1, 2, 3, and 4 loaded significantly into Factor 1 in EFA (with some exceptions), Factor 1 was modified to include all 32 items of uses 1, 2, 3, and 4. Two items of use 9 that were loaded in Factor 2 were removed such that Factor 2 represented 16 measured items of uses 7 and 10. No modification was done on Factor 3, which represented 16 measured items of uses 5 and 6 with no cross loadings. Lastly, Factor 4 was modified to represent all the items of uses 8 and 9. With these modifications, a new four-factor CFA model (model CFA-2) was fitted. All the standardized loadings of items for each construct were found to be higher than the threshold of 0.6 (except one item). The goodness of fit statistics of the model (model CFA-2) were chi-square: 33374.819 (df = 3074, p-value: 0.000), CFI: 0.977, RMSEA: 0.052, and SRMR: 0.070. Model CFA-2 was found superior to model CFA-1 based on the conceptualization but a discriminant validity issue was observed because of a high correlation of Factor 1 with Factors 3 and 4. Thus, to resolve this issue, further modifications were done.

Out of eight items of CV data use 3, three items were not loaded significantly on Factor 1, two of which had their highest loading on Factor 3. Thus, to remove the issues of insignificant loadings and cross loadings, all eight items of use 3 were removed from Factor 1 (considered in model CFA-2) and from whole analysis. In addition, out of the eight items of use 9, two items loaded significantly on Factor 2, but the remaining six items loaded on Factor 4. Thus, all eight items of use 9 were removed from Factor 4 (considered in model CFA-2) and from whole analysis. Thus, in the subsequent CFA models, only 64 items were considered to explain the data sharing intention. Based on the items represented by the four factors, the factors were named as the following: Factor 1: data sharing intention for driver information, congestion assessment and reduction, and pavement and infrastructure assessment and improvement (ICP); Factor 2: data sharing intention for enforcement and fees based on usage (EF); Factor 3: data sharing intention for roadside assistance and crash investigation (RC); and Factor 4: data sharing intention for research purpose (RP). Hence, these four factors essentially represented the four categories of purpose of use of CV data.

With these modifications, another four-factor CFA model (model CFA-3) with 64 items was fitted. All the standardized loadings of items for each construct were found to be higher than the threshold of 0.6. The goodness of fit statistics of the model (model CFA-3) were chi-square: 21336.017 (df = 1946, p-value: 0.000), CFI: 0.978, RMSEA: 0.052, and SRMR: 0.071. Although not much difference in goodness of fit statistics were observed between models CFA-1, CFA-2, and CFA-3, model CFA-3 was considered superior because of the conceptual representation of items in model CFA-3 compared with that of model CFA-1. The discriminant validity issue in model CFA-2 was resolved in model CFA-3. Internal consistency, convergent validity, and discriminant validity for model CFA-3 are shown in **Table 4.2**. The values of composite reliability (CR) and Cronbach's alpha (CA) were greater than 0.7, which confirmed the internal consistency of the measured items of the factors. The values of average variance extracted (AVE) for each construct was greater than 0.5, which proved the convergent validity of the model. The values of square root of average variance extracted (SAVE) for each construct were greater than the correlation values, which indicated the good discriminant validity of the model.

Table 4.2 Internal consistency, convergent validity, and discriminant validity test results for CFA-3

	Correlation				AVE	CR	CA
	ICP	**EF**	**RC**	**RP**			
ICP	**0.754**				0.569	0.935	0.965
EF	0.704	**0.803**			0.645	0.915	0.960
RC	0.731	0.690	**0.753**		0.567	0.905	0.951
RP	0.604	0.557	0.598	**0.826**	0.683	0.877	0.942

Respondents' characteristics were input into the model CFA-3 as exogenous measures of all four latent constructs. This new model is called the MIMIC model. The confirmatory factor analysis (CFA-4) results of the model are shown in Figure 4.1 and Table 4.3. Figure 4.1 shows the overall results of the CFA estimation and Table 4.3 includes the measured items of each latent construct and their respective loadings. All the path coefficients and loadings of the model were found to be statistically significant at 95% confidence interval. The effects of exogenous variables on factors are explained in the following subsection.

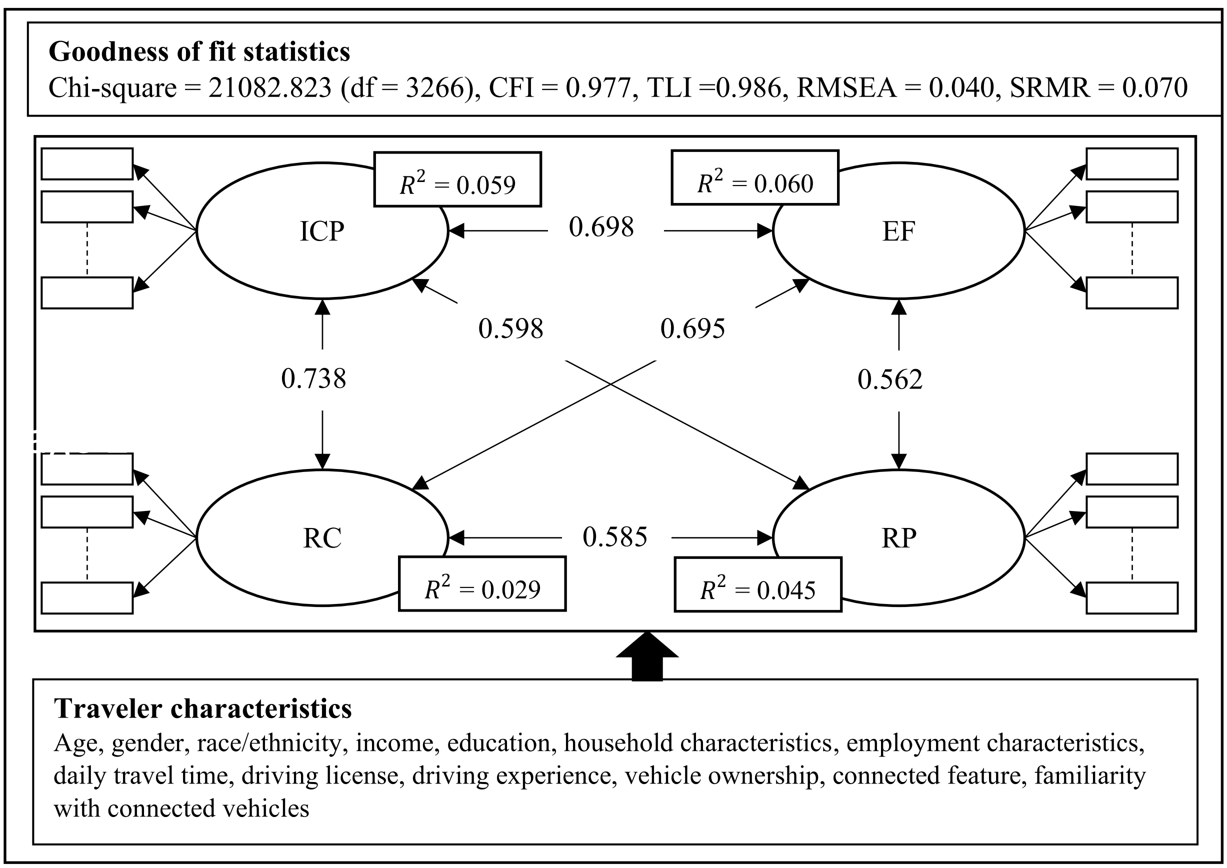

Figure 4.1 Four factor CFA model of CV data sharing intention (model CFA-4)

Table 4.3 Loadings of items as a result of CFA (model CFA-4)

Construct	Item	Loading	Item	Loading	Item	Loading
ICP	DSI-A-1	0.642	DSI-A-2	0.646	DSI-A-4	0.695
	DSI-B-1	0.723	DSI-B-2	0.734	DSI-B-4	0.709
	DSI-C-1	0.770	DSI-C-2	0.808	DSI-C-4	0.777
	DSI-D-1	0.719	DSI-D-2	0.793	DSI-D-4	0.793
	DSI-E-1	0.690	DSI-E-2	0.833	DSI-E-4	0.854
	DSI-F-1	0.708	DSI-F-2	0.833	DSI-F-4	0.835
	DSI-G-1	0.657	DSI-G-2	0.748	DSI-G-4	0.802
	DSI-H-1	0.701	DSI-H-2	0.811	DSI-H-4	0.836
EF	DSI-A-7	0.659	DSI-G-7	0.805	DSI-E-10	0.877
	DSI-B-7	0.786	DSI-H-7	0.820	DSI-F-10	0.818
	DSI-C-7	0.818	DSI-A-10	0.758	DSI-G-10	0.842
	DSI-D-7	0.819	DSI-B-10	0.871	DSI-H-10	0.829
	DSI-E-7	0.834	DSI-C-10	0.880		
	DSI-F-7	0.787	DSI-D-10	0.689		
RC	DSI-A-5	0.694	DSI-G-5	0.744	DSI-E-6	0.800
	DSI-B-5	0.758	DSI-H-5	0.699	DSI-F-6	0.759
	DSI-C-5	0.797	DSI-A-6	0.664	DSI-G-6	0.804
	DSI-D-5	0.822	DSI-B-6	0.702	DSI-H-6	0.753
	DSI-E-5	0.796	DSI-C-6	0.719		
	DSI-F-5	0.747	DSI-D-6	0.833		
RP	DSI-A-8	0.796	DSI-D-8	0.811	DSI-G-8	0.846
	DSI-B-8	0.862	DSI-E-8	0.848	DSI-H-8	0.825
	DSI-C-8	0.845	DSI-F-8	0.798		

4.1.3 MIMIC Model Results

A MIMIC model was estimated for four latent constructs (ICP, EF, RC, and RP) to examine the potential impacts of demographic and driving characteristics on CV data sharing intention. The estimation results are presented in Table 4.4. Most of the demographic and driving characteristics were found to be significantly associated with CV data sharing intention. People aged 45 to 64 years were found to have lower intentions to share CV data for ICP and RP. Conversely, people older than 65 years were found to have higher intentions to share CV data for EF and RC than those less than 25 years old. However, no statistical difference in intention for CV data sharing was observed between people 25 to 44 years old and less than 25 years of age. Females had lower data sharing intentions for all purposes (except for EF, which was insignificant) than those of males. In terms of race/ethnicity, whites were found to have higher data sharing intentions for ICP than other races. In comparison with people of annual household income less than $25k, people with incomes $25 to $75k were found to have higher data sharing intentions for all purposes (except for EF). However, people with incomes $75 to $150k had lower data sharing intentions for EF and EC. People of incomes higher than $150k had lower data sharing intentions for RC than those of people with incomes less than $25k. People with undergraduate degrees had higher data sharing intentions for ICP, RC, and RP than those of people with no college degrees. However, people with graduate degrees were not significantly different from people with no college degree in terms of data sharing intentions except for ICP, where graduate degree holders were found to have higher data sharing intentions. The number of persons in the household ($\geq$ 18 years age) did not have a significant effect on data sharing intentions. However, a higher number of children in the household increased the data sharing intentions for EF but lowered the intentions for RP. Students were found to have higher data sharing intentions for ICP and EF. Except for ICP, which was insignificant, lower data sharing intention was observed for employed individuals compared with unemployed individuals.

People with a typical daily travel time between 30 and 60 minutes were found to have higher data sharing intentions for RP compared with people having a daily travel time less than 30 minutes. However, people having a daily travel time more than 60 minutes were found to have higher data sharing intention for all uses than people with a typical daily travel time less than 60 minutes except for ICP, which was insignificant. Possession of a driving license was found not to impact data sharing intention significantly. However, greater driving experience was associated with a lower data sharing intention except for RP, where a positive intention was observed. People with a higher number of vehicles in the household were also found to have higher data sharing intentions for all uses except for RP, which was insignificant. Similarly, those who had some form of connected features in their vehicle/s were more interested to share CV data for all uses. In comparison to people with no familiarity with CV, people of medium and high familiarity were found to have higher intentions for all the uses except RC and RP, for people with high familiarity. A slightly higher coefficient for high familiarity than for medium familiarity and low familiarity suggested that increasing familiarity slightly increases the data sharing intention for ICP and EF.

Table 4.4 Results of MIMIC model

Variables	ICP		EF		RC		RP	
	B	p	B	p	B	p	B	p
Age								
25-44 years	-0.012	0.453	0.010	0.605	-0.005	0.774	0.036	0.129
45-64 years	-0.043	0.009*	0.015	0.463	0.004	0.841	-0.114	0.000*
65+ years	0.004	0.821	0.112	0.000*	0.054	0.017*	-0.125	0.000*
Gender: female	-0.103	0.000*	-0.019	0.080	-0.036	0.000*	-0.080	0.000*
Race/ethnicity: white	0.037	0.000*	-0.003	0.786	-0.007	0.443	0.007	0.543
Income								
$25-75k	0.050	0.000*	0.025	0.060	0.042	0.001*	0.077	0.000*
$75-150k	-0.001	0.938	-0.038	0.011*	-0.039	0.006*	0.018	0.315
≥$150k	0.020	0.055	0.001	0.958	-0.047	0.000*	0.021	0.196
Education								
Undergraduate degree	0.025	0.006*	0.001	0.897	0.030	0.004*	0.032	0.021*
Graduate degree	0.046	0.000*	-0.003	0.791	0.014	0.258	0.022	0.165
# households (age ≥ 18 years)	-0.002	0.811	-0.008	0.448	-0.017	0.093	-0.010	0.460
# children (age <18 years)	-0.011	0.222	0.048	0.000*	-0.011	0.297	-0.043	0.002*
Student: yes	0.020	0.014*	0.028	0.006*	0.015	0.146	0.022	0.093
Employed: yes	-0.009	0.337	-0.040	0.001*	-0.036	0.001*	-0.051	0.000*
Daily travel time								
30-60 minutes	-0.013	0.110	-0.015	0.144	0.021	0.039*	0.031	0.017*
≥ 60 minutes	0.011	0.177	0.042	0.000*	0.067	0.000*	0.084	0.000*
Driving license: yes	0.016	0.072	-0.001	0.923	0.016	0.142	0.002	0.899
Driving experience (years)	-0.068	0.000*	-0.177	0.000*	-0.122	0.000*	0.063	0.006*
Vehicle ownership	0.043	0.000*	0.056	0.000*	0.080	0.000*	0.025	0.056
Connected feature: yes	0.080	0.000*	0.059	0.000*	0.071	0.000*	0.082	0.000*
Familiarity								
Medium	0.065	0.000*	0.053	0.000*	0.034	0.003*	0.063	0.000*
High	0.092	0.000*	0.121	0.000*	-0.023	0.079	-0.014	0.412
R-squared	0.059		0.060		0.029		0.045	

** Indicates statistically significant at 95% confidence interval.*

4.1.4 Second-Order CFA

For the proposed measurement model (model CFA-3), the correlations among the latent constructs ranged from 0.557 to 0.704. As the four constructs in the model conceptually represented the data sharing intentions for different uses, combining all of them into one might represent the overall data sharing intention. This hypothesis was supported by the significant correlations among the constructs. Thus, a second-order CFA model (model CFA-5) was proposed. Overall data sharing intention (DSI) was the measure of four latent constructs. The results of this second-order CFA (model CFA-5) are shown in Figure 4.2. All four first-order constructs loaded significantly on the second-order construct DSI with positive coefficients and acceptable goodness of fit statistics were obtained in the model. Therefore, model CFA-5 was considered as the preferred model describing the overall data sharing intention. Data sharing intention for ICP was the strongest predictor of overall data sharing intention (DSI), followed by RC, EF, and RP.

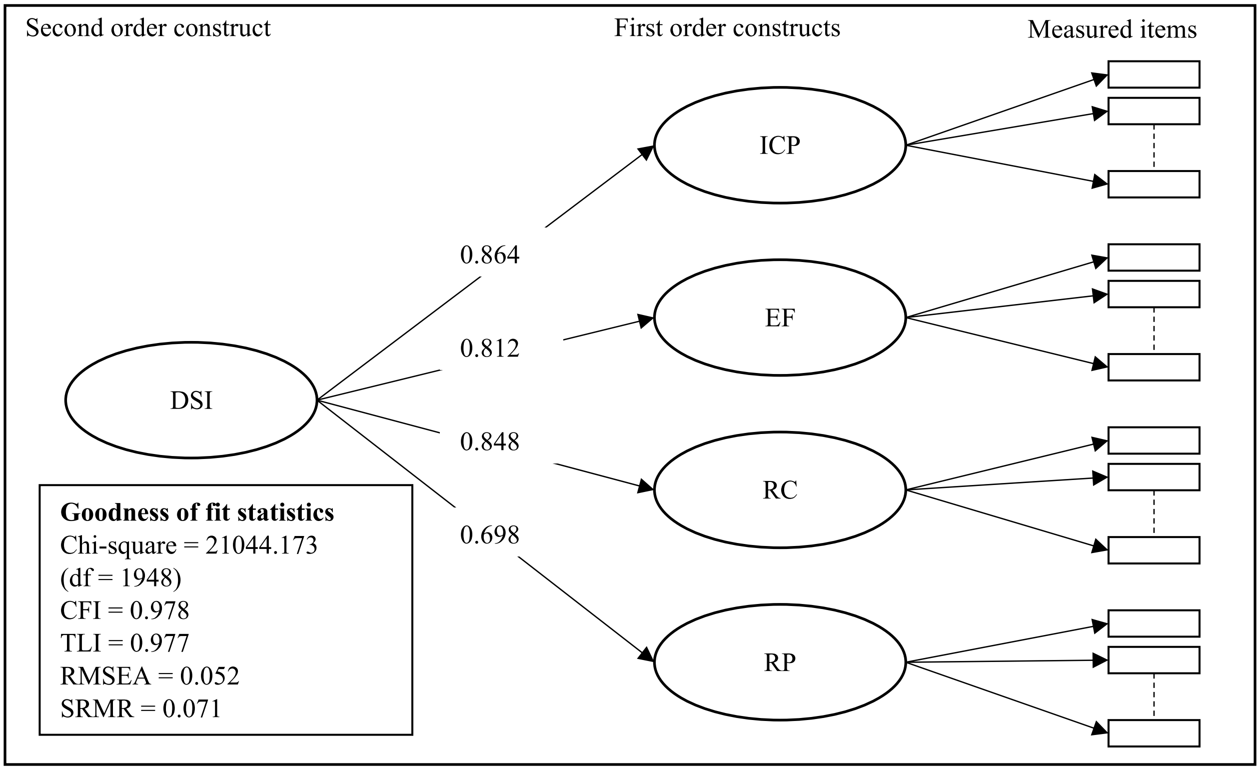

Figure 4.2 Second-order CFA (model CFA-5) for overall data sharing intention (Note: measured items and their loadings are not shown here [they are shown in Table 4.3])

4.1.5 Visual Comparison

To understand the differences in the data sharing intention, a scatter plot was created (Figure 4.3). The horizontal axis shows the different types of CV data. The vertical axis shows the percentage of respondents intending to share the particular type of data for each specific use (shown with different styles and marker colors). The first category of data type (ICP, shown in blue) includes information for drivers, congestion assessment, and pavement and infrastructure assessment and improvement. The second category (EF, shown in red) includes two uses: enforcement of traffic laws and regulations, and for assessment of fees based on usage. RC (shown in green) includes data sharing intention for roadside assistance and crash investigation. Lastly, RP (shown in black) represents data sharing intention for research purposes. Visually inferring from the plot, EF is the least favorable option in terms of sharing CV data. Distinguishable differences between the other three categories could not be observed from the plot.

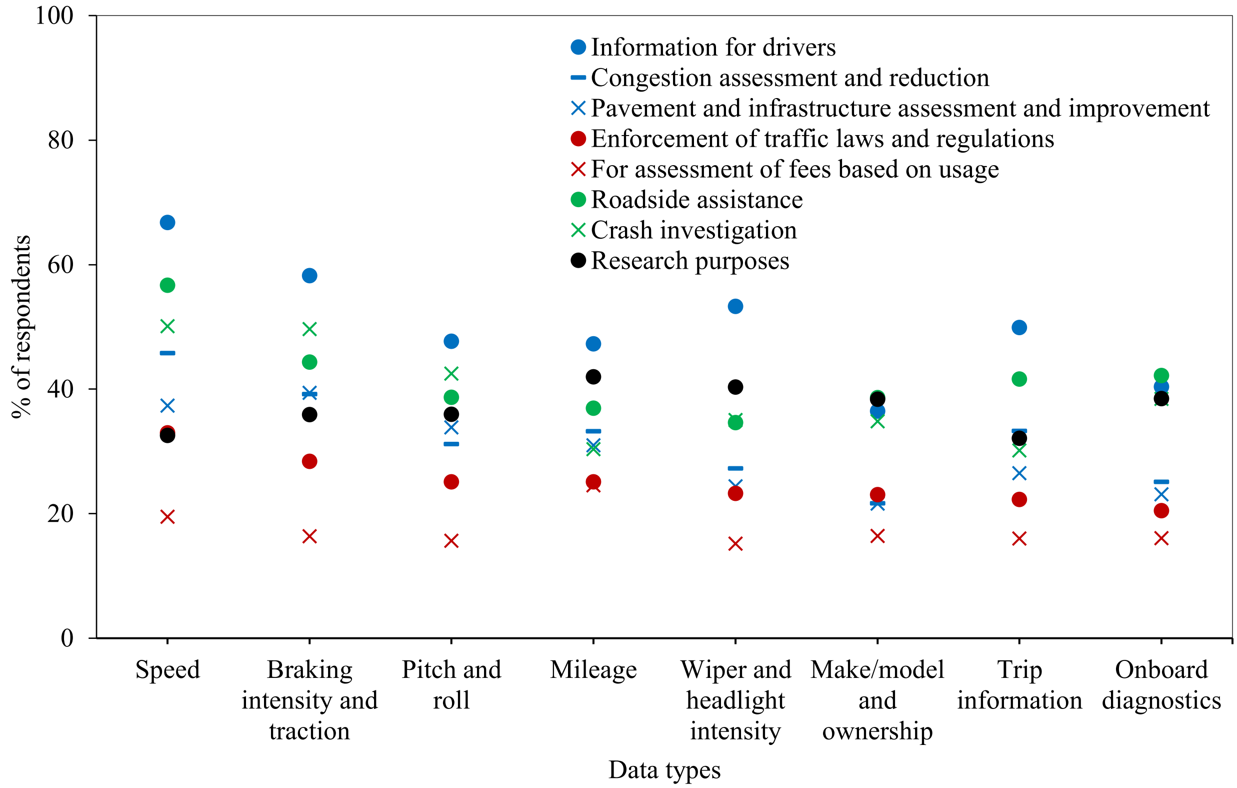

Figure 4.3 Data sharing intention for different uses

4.1.6 Discussion

The findings of this study contribute to the literature of public perception on CV in three ways. First, from the factor analysis of 80 items representing different types of CV data and uses of CV data, it was found that the users consider their data sharing interest based on the uses of data rather than on the types of data. In other words, the type of CV data does not matter to users as much as how the data are used. Thus, transportation agencies should focus on using CV data for users' preferred purposes only or to conduct outreach and educational initiatives to improve perceptions and intentions for less popular uses.

Second, this study concluded that there are four groupings of data sharing intention by purposeful use of CV data: driver information, congestion assessment and reduction, pavement and infrastructure assessment and improvement (ICP), enforcement of traffic rules and fees based on usage (EF), road side assistance and crash investigation (RC), and research purpose (RP). Based on visual comparison of the survey data, the lowest data sharing intention was found for enforcement of traffic laws and regulations and for assessment of fees based on usage (EF). However, the model results concluded that all of four types of intentions (ICP, EF, RC, and RP) combine to represent the overall data sharing intention of CVT. These differences between types of data sharing intention highlights the importance of use of CV data for a number of traffic and transportation applications. For example, the result shows that the use of CV data for enforcement purposes degrades the overall data sharing intention in CVT (and might reduce the overall intention to use CVs). Thus, the research team recommends that stakeholders of CVT recognize and consider the differences in data sharing intention for different applications during their decision- and policy-making processes for CVs.

Third, the CV data sharing intention of individuals of different socio-economic groups and driving characteristics were identified. This result is important to CV developers and marketing agencies to formulate different plans for outreach to different groups of individuals in order to improve the overall data sharing intention and public acceptance of CVs. For example, the data sharing intention was found to be higher for those having higher familiarity with connected features but having low or no driving experience. Thus, one outreach strategy should focus on educating experienced drivers about the advantages of connectivity in their current vehicles. For inexperienced drivers, outreach strategies such as test drive opportunities of CVs (increasing familiarity with connected features) could enhance their overall data sharing intention.

4.2 Data Sharing Intention and Behavioral Intention to Use CV

4.2.1 Model and Hypothesis

After establishing CV data sharing intention and its variability in different socio-economic groups, it was necessary to understand its relationship with attitude and behavioral intention to use CV. To model the behavioral intention to use CV, the research team proposed a model including perception of data issues associated with the technology and CV data sharing intention. The two most common data issues described in the literature, data privacy and data security, were included in the model. The proposed model is shown in Figure 4.4 and the hypotheses are described in following subsections.

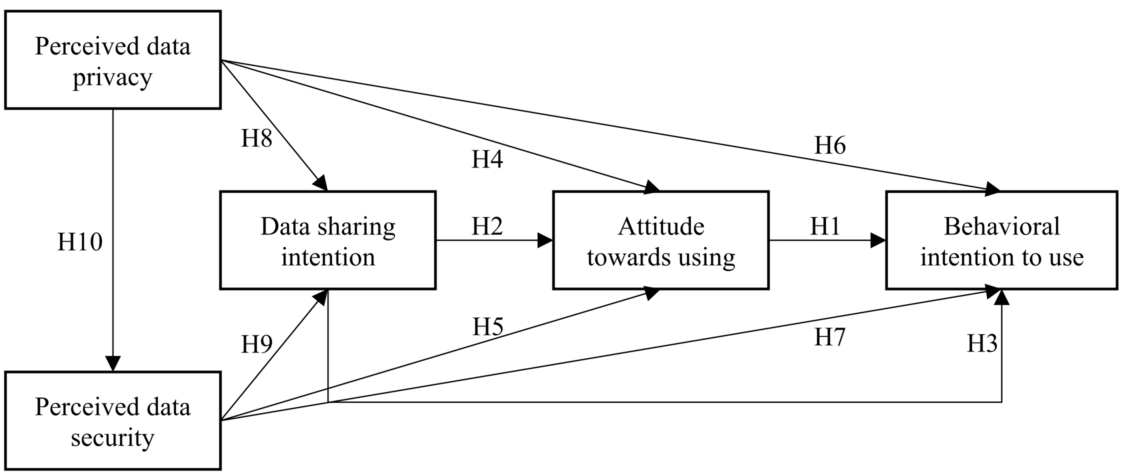

Figure 4.4 Proposed research model

4.2.1.1 Behavioral Intention to Use

Actual use of technology is a key measure of technology acceptance (Davis et al., 1989) but it cannot be assessed before the actual deployment of the technology itself. Behavioral intention to use technology is defined as the degree to which an individual has intention to use CV in future. Several studies, such as (Venkatesh et al., 2003), verified the correlation between actual use and behavioral intention to use technology. This leads to the use of behavioral intention to use the technology as a construct to measure the acceptance of CV.

4.2.1.2 Attitude Towards Using

Attitude reflects an individual's inclination towards the technology. Here, attitude towards using technology is defined as the degree to which an individual has a positive or negative feeling about using CV. The positive or negative feelings developed towards the technology form the intention towards using the technology (Davis et al., 1989). The research team proposed hypothesis H1 based on the technology acceptance model (Davis et al., 1989) and its adoptions in vehicular settings (Ghazizadeh et al., 2012; Zhang et al., 2019).

H1: Attitude towards using CV has a positive effect on the behavioral intention to use CV.

4.2.1.3 Data Sharing Intention

The data sharing intention concept is relatively new in the literature of vehicle technology. In the case of CVs, the research team defined data sharing intention as the degree to which an individual has a positive or negative feeling about sharing CV data. The scales of measurement of this factor were defined in the above section. Thus, according to the results of the above section, data sharing intention was proposed to be used as a second-order factor in the proposed model. The "data sharing intention" concept used here was found to be similar to "willingness to share information" concept (though different items were used to measure willingness to share information) in a study by Anastasopoulou et al. (2018) where a positive association was found between willingness to share information and intention to use connected autonomous vehicles. It was assumed that the attitude and behavioral intention to use CV would be higher for those with a higher intention to share data for several data applications and uses. Similarly, one study found that information/data sharing via social media was significantly associated with an increase in behavioral intention to use social media (Muslim et al., 2020). Thus, to explore the relationship of data sharing intention with attitude and behavioral intention to use CV and verify the assumption, hypotheses H2 and H3 were made.

H2: Data sharing intention has positive effect on the attitude towards using CV.
H3: Data sharing intention has positive effect on the behavioral intention to use CV.

4.2.1.4 Perceived Data Privacy and Security

Perceived data privacy is the degree to which an individual is concerned about the collection and use of his or her personal, vehicular, and trip data. Perceived data security refers to the degree to which an individual is concerned about the unauthorized access and protection of their data. Data privacy and security are considered to be two major reasons behind the distrust of new technology and hence can be considered as major barriers to acceptance. The relationship of data privacy and security with attitude towards using the technology and behavioral intention to use the technology is well established in the literature (in the case of online technologies but not in case of vehicle technologies). For instance, in the case of social media, behavioral intention to purchase the technology was found to be affected directly by the data privacy concerns associated with it (Lin & Kim, 2016). Similarly, privacy concerns were found to affect the intention to use location-based services (Zhou, 2012) and health care technology (Dhagarra et al., 2020). Data privacy and security concerns were found to be the significant antecedents of attitude towards using online shopping applications (Vijayasarathy, 2004). In the case of vehicle technology, perceived security and perceived risks were found to be the antecedents of behavioral intention to use autonomous vehicles (Xu et al., 2018) and ride sharing services (Wang et al., 2018), respectively. In the case of CVT, perceived data privacy and perceived data security can be considered as the risks associated with the technology. Thus, based on the previous evidence of the relationships between data privacy and security with attitude and behavioral intention in various technologies; and the relationship between security and risk concerns with behavioral intention in emerging vehicle technologies, the research team hypothesized H1 and H2.

H4: Perceived data privacy has a positive effect on attitude towards using CV.
H5: Perceived data security has a positive effect on attitude towards using CV.
H6: Perceived data privacy has a positive effect on behavioral intention to use CV.
H7: Perceived data security has a positive effect on behavioral intention to use CV.

Though, the path of relationship between perceived data privacy risk and willingness to share data in connected autonomous vehicles was not found to be significant in Anastasopoulou et al. (2018), the research team still assumed that data sharing intention is affected by perceived data privacy and security in order to explore and test the path of relationships. It is expected that there will be higher data sharing intention for those having higher confidence in the privacy and security of CV data. Thus, the research team hypothesized H8 and H9.

H8: Perceived data privacy has a positive effect on CV data sharing intention.
H9: Perceived data security has a positive effect on CV data sharing intention.

There is a complex relationship between data privacy and security. Privacy refers to the safeguarding of personal data by legal measures and good practices of data handling whereas security is linked to the protection of privacy by legal measures and good practices of data handling. Sometimes data privacy and security are used interchangeably but these two terms are different as per the previously stated definitions. As the privacy of data can be maintained only if the security of system is assured, privacy is sometimes considered as a subset of security. Thus, the research team proposed the hypothesis H10 considering that the perceived data security mediates the effect of perceived data privacy on CV technology (Shin, 2010).

H10: Perceived data privacy has a positive effect on perceived data security.

4.2.2 Measuring the Model

To validate the proposed model, the scale of measurements of constructs was necessary. Thus, for each construct in the proposed model, items of measurement were developed by modifying the verified scales presented in existing literature. The list of items used to measure the constructs and their sources are shown in

Table **4.5**. In the questionnaire, items of perceived data privacy and perceived data security were asked in the first section. The items of attitude towards using CV and behavioral intention to use CV were included in the third section of the survey. All of these items were asked in the Likert scales of 1-7 (1: extremely unlikely - 7: extremely likely). The measurement of data sharing intention, a second-order construct, was described in Section 4.1.

Table 4.5 Latent constructs and survey items

Constructs	Survey Items	Sources
Perceived data privacy	1. CVs would not collected too much information about your personal, vehicular, and trip characteristics. *(privacy1)* 2. CVs would keep your information in an accurate manner in their database. *(privacy2)* 3. CVs would not share your information with other parties without obtaining your authorization. *(privacy3)* 4. CVs would make you feel same about providing data through the use of a connected vehicle. *(privacy4)*	(Roca et al., 2009; Xu, 2007; Yun et al., 2013)
Perceived data security	1. CVs would have sufficient technical capacity to ensure that your data cannot be accessed by a third party. *(security1)* 2. CVs would have sufficient technical capacity to ensure that the data you sent cannot be modified by a third party. *(security2)* 3. CVs would have strong security measures to protect your personal, vehicular, and trip characteristics data. *(security3)*	(Roca et al., 2009)
Attitude towards using	1. It is a good idea to use CVs. *(attitude1)* 2. The thought of using CVs is appealing to you. *(attitude2)* 3. Using a CV would be fun to you. *(attitude3)* 4. Overall, you have positive feelings about using CVs. *(attitude4)*	(Venkatesh et al., 2003)
Behavioral intention to use	1. You would use a CV in the future. *(intention1)* 2. Your next vehicle purchase would be a CV. *(intention2)* 3. You would strongly recommend others to use CVs. *(intention3)*	(Venkatesh et al., 2003; Xu et al., 2018)

4.2.3 Exploratory Factor Analysis

As the factor structure of data sharing intention was examined and confirmed separately (Section 4.1), an EFA was conducted for remaining items describing perceived data privacy, perceived data security, attitude towards using, and behavioral intention to use CV. There were 17 measured items for this EFA. The sampling adequacy and significant correlation in the data for factor analysis was confirmed using KMO measure of sampling adequacy with a KMO value of 0.95 and Bartlett's test of sphericity with (Chisq (91) = 32581.88, $p < .001$). Horn's parallel analysis and examination of the eigen values and scree plots suggested three factors. Thus, an exploratory factor analysis was carried out for three factors. The factor loadings of oblimin rotations using principal axis factoring are shown in Table 4.6. Loadings with value greater than 0.4 are bold in the table. Three factors were found to explain 73% of variance in dataset.

Table 4.6 Exploratory factor analysis results

	Factor 1	Factor 2	Factor 3
privacy1	0.03	-0.08	**0.63**
privacy2	0.05	0.02	**0.57**
privacy3	-0.06	0.04	**0.83**
privacy4	0.09	0.06	**0.74**
security1	0.02	**0.88**	0.02
security2	-0.01	**0.97**	-0.04
security3	0.03	**0.77**	0.13
attitude1	**0.81**	0.07	0.03
attitude2	**0.92**	0.05	-0.05
attitude3	**0.85**	0.04	-0.01
attitude4	**0.88**	0.08	-0.02
intention1	**0.92**	-0.06	-0.01
intention2	**0.87**	-0.07	0.03
intention3	**0.89**	-0.05	0.06

The results of EFA confirmed that three factors are - Factor 1: attitude and intention towards CV adoption, Factor 2: perceived security of data, and Factor 3: perceived privacy of data. Additionally, the two factors for perceived privacy (Factor 3) and perceived security of data (Factor 2) were found to have high correlation (0.893) with each other, which might create discriminant validity issue. Therefore, four measured items of perceived data privacy (privacy1, privacy2, privacy3, and privacy4) and three measured items of perceived data security (security1, security2, and security3) were merged into one factor called perceived data privacy and security for further analysis.

4.2.4 Revised Research Model and Hypotheses

First, merging two concepts - data privacy and data security - into one is supported by the existing body of literature. These two concepts have been used interchangeably and/or in combination in several studies. For instance, to model the behavioral intention towards electronic commerce, seven items were used to measure a privacy construct, and those items reflected both data privacy and security issues (Liu et al., 2005). A higher correlation between data privacy and data security factors was observed in a study related to a website done by Flavián and Guinalíu (2006) such that a second-order factor called security in handling private data was proposed, which represented privacy and security concerns.

Second, the results of EFA suggested that two constructs – attitude towards using and behavioral intention to use – which were initially assumed to be distinct are actually the same with the significant loading of seven items (of both attitude and behavioral intention) into one factor. These two constructs were distinct in the original TAM with the direct effect of attitude on behavioral intention (Davis et al., 1989). However, in the later extensions of the model, an attitude construct was not included (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Similarly, an attitude construct was not used in a few perception-based studies of vehicle technology (e.g. (Choi & Ji, 2015; Wang et al., 2018; Xu et al., 2018). With this evidence and precedence from the literature and in accordance with the results of the EFA, the research team considered the attitude and behavioral intention as one factor represented by seven items.

With the results of EFA and necessary modifications, the five factors originally proposed in the research model dropped to three. Thus, the revision of research model, paths of relationships between the factors, and hypotheses was necessary. The revised research model is presented in Figure 4.5.

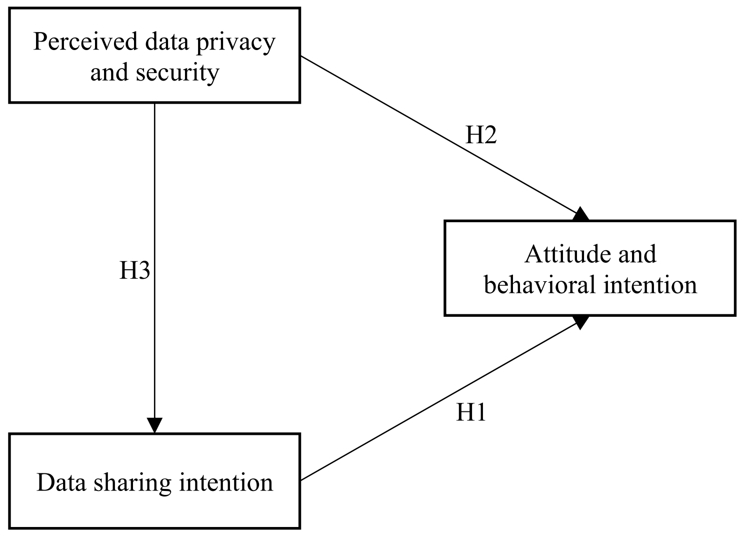

Figure 4.5 Revised research model

For this revised research model, the hypotheses were:

H1: Data sharing intention has a positive effect on behavioral intention to use CV.
H2: Perceived data privacy and security has a positive effect on attitude and behavioral intention to use CV.
H3: Perceived data privacy and security has a positive effect on CV data sharing intention.

4.2.5 Confirmatory Factor Analysis

Two factors as a result of some modifications on the results of EFA (perceived data privacy and security; attitude and behavioral intention to use CV) and one second-order factor (data sharing intention) were used in a confirmatory factor analysis. The second-order factor, data sharing intention, was represented by four factors (ICP, EF, RC, and RP) and their measured items were described in Section 4.1. In addition, travelers' characteristics were the inputs of the model as the exogenous variables affecting all three factors, so the model is called a MIMIC model. The results of the CFA are shown in Figure 4.6.

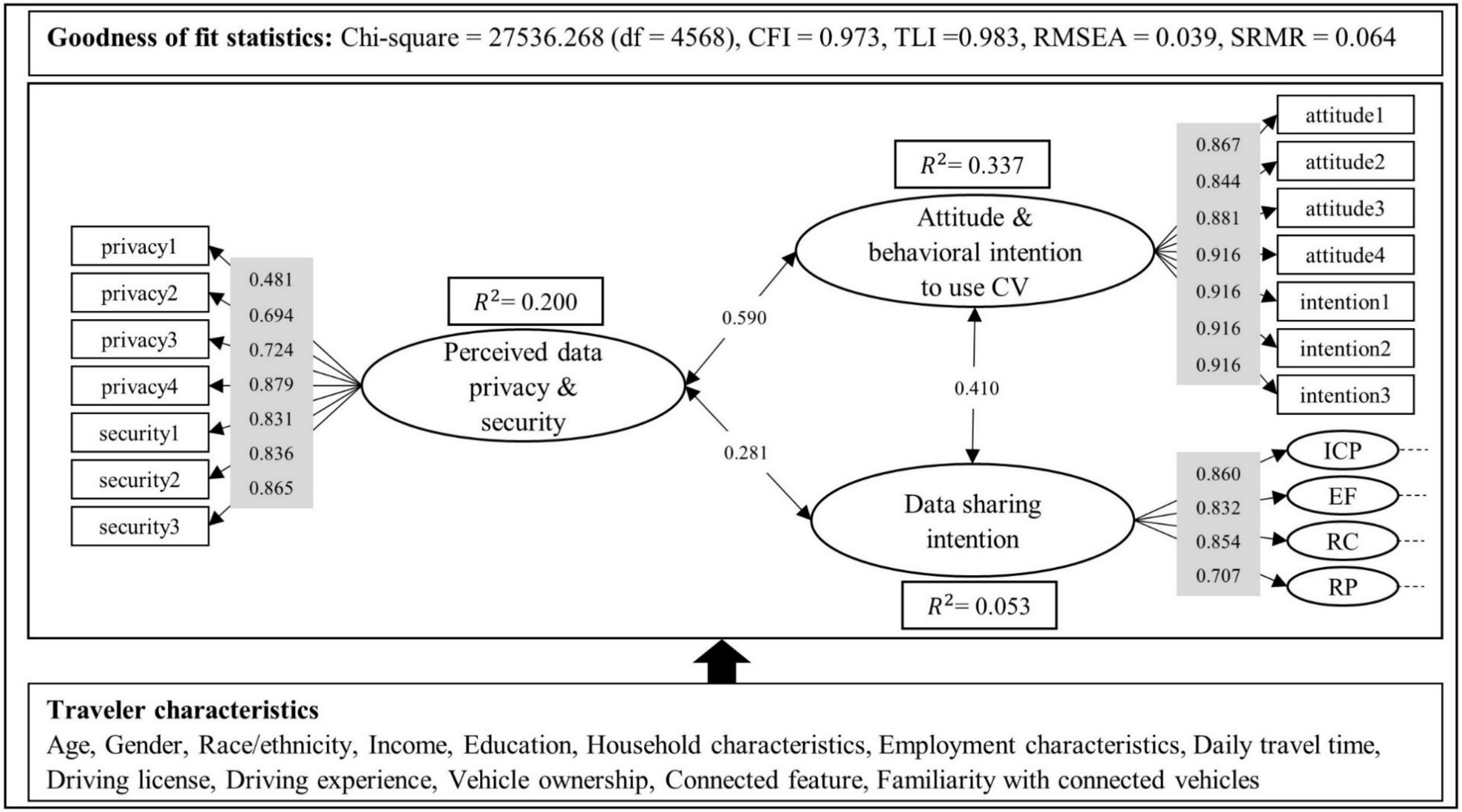

Figure 4.6 Confirmatory factor analysis results

4.2.6 MIMIC Model Results

The estimates of exogeneous variables in the MIMIC model are presented in Table 4.7 and only the significant variables are described here. Females were found to have significantly lower data sharing intention as well as attitude and behavioral intention to use CV compared to males. Whites had lower attitude and behavioral intention to use CV that that of other races. In terms of income, the only significance observed was the positive attitude and intention to use CV for people of annual household income more than \$150k when compared with people of income less than \$25k. Graduate degree holders had higher perception on data privacy and security than that of people with no college degree. The number of adults (more than 18 years) and number of children (less than 18 years) in the household were both found to increase the data privacy and security perception. In addition, a higher number of children in the household was associated with a higher attitude and behavioral intention to use CV. People with a typical daily travel with time greater than one hour a day had higher data sharing intention and higher attitude and behavioral intention to use CV than that of people having a daily travel time less than half an hour. Driving license holders had higher perception on data privacy and security and higher attitude and behavioral intention to use CV. However, an increase in driving experience was associated negatively with all three factors. Number of vehicles owned in a household was associated positively with data sharing intention but negatively with attitude and behavioral intention to use CV. People having some forms of connected features in the vehicle/s of their household were found to have higher positive perception on data privacy and security, data sharing intention, and attitude and behavioral intention to use CV. Increase in familiarity with CV was associated with an increase in positive perception regarding data privacy and security and attitude and behavioral intention to use CV.

Table 4.7 MIMIC model results

Variables	Perceived data privacy and security		Data sharing intention		Attitude and behavioral intention	
	B	**p**	**B**	**p**	**B**	**p**
Age						
25-44 years	0.041	0.318	0.002	0.971	0.025	0.493
45-64 years	0.033	0.455	-0.032	0.524	0.004	0.918
65+ years	0.084	0.085	0.031	0.588	0.009	0.831
Gender: female	-0.025	0.251	-0.077	0.003*	-0.042	0.034*
Race/ethnicity: white	-0.001	0.971	0.015	0.527	-0.058	0.002*
Income						
$25-75k	-0.008	0.770	0.055	0.110	0.036	0.136
$75-150k	-0.015	0.631	-0.020	0.584	0.027	0.314
≥$150k	-0.001	0.973	-0.002	0.949	0.069	0.010*
Education						
Undergraduate degree	-0.017	0.479	0.026	0.342	-0.009	0.662
Graduate degree	0.069	0.014*	0.028	0.388	0.020	0.415
# households (age ≥ 18 years)	0.061	0.008*	-0.010	0.692	0.025	0.191
# children (age <18 years)	0.065	0.007*	-0.002	0.955	0.049	0.020*
Student: yes	0.011	0.598	0.025	0.295	-0.013	0.520
Employed: yes	0.000	0.996	-0.035	0.243	0.029	0.162
Daily travel time						
30-60 minutes	0.017	0.456	0.001	0.963	0.008	0.693
≥ 60 minutes	0.041	0.079	0.052	0.048*	0.046	0.026*
Driving license: yes	0.053	0.030*	0.013	0.666	0.072	0.000*
Driving experience (years)	-0.192	0.000*	-0.109	0.017*	-0.176	0.000*
Vehicle ownership	-0.038	0.103	0.065	0.018*	-0.049	0.015*
Connected feature: yes	0.095	0.000*	0.089	0.001*	0.200	0.000*
Familiarity						
Medium	0.068	0.006*	0.065	0.041*	0.163	0.000*
High	0.253	0.000*	0.066	0.063*	0.330	0.000*

4.2.7 Structural Equation Modeling

With acceptable goodness of fit statistics from the CFA, structural equation modeling (SEM) was then carried out to understand the path of relationship between the factors. The hypotheses and paths of relationships between the factors were set up according to the theoretical model proposed above. Based on the model proposed, structural equation modeling was carried out and the results are presented in Figure 4.7.

Goodness of fit statistics: Chi-square = 27876.361 (df = 2918), CFI = 0.975, TLI =0.975, RMSEA = 0.048, SRMR = 0.066

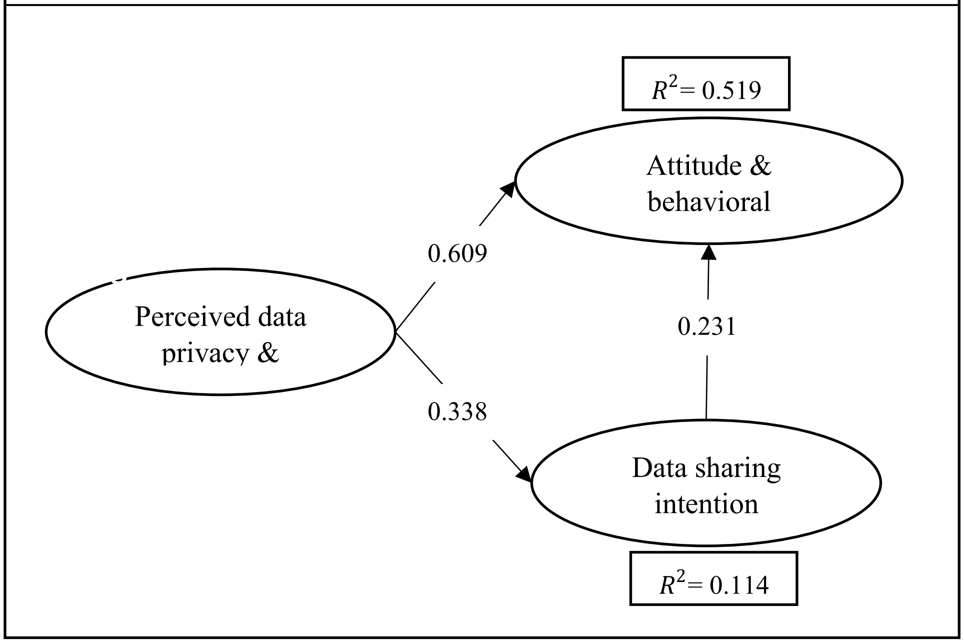

Figure 4.7 Structural equation model results

The hypotheses proposed in the research model were tested and the results are shown in Table 4.8. The results support all three proposed hypotheses. Based on the results, attitude and behavioral intention to use CV was directly affected by the perception towards data privacy and security in the technology and data sharing intention in the technology. Additionally, an indirect effect of perceived data privacy and security on attitude and behavioral intention to use CV through data sharing intention was found to be significant with a standardized magnitude of 0.078. This effect was relatively smaller in comparison to its direct effect on attitude and behavioral intention to use CV which was 0.609, combining to a total effect of 0.687.

Table 4.8 Results of hypothesis testing

Hypotheses	B	z-value	p-value	Supported?
H1: DSI → ABI	0.231	10.617	0.000	Yes
H2: PPS → ABI	0.609	15.100	0.000	Yes
H3: PPS → DSI	0.338	10.915	0.000	Yes

4.2.8 Discussion

The objective of this study was to understand the relationship between data issues in CVT and their influence on data sharing intention and, ultimately, the acceptance of CVs. The results show that data privacy and security issues in CVT lower the acceptance of CV directly and through data sharing intention. The data sharing intention was also found to be reliant on the data issues. This highlights the importance and need of data privacy protection and security in CVT. The proposed model was able to explain more than half of the variance in attitude and behavioral intention to use CVs. In addition, the associations of the socio-demographic and driving related characteristics with CV acceptance and their predictors (data sharing intention and perceived data privacy and security) were also determined.

4.3 Connected Vehicle Acceptance Model

4.3.1 Research Model and Hypotheses

Because CVT represents a promising future of vehicle technology, it is necessary to understand the behavioral intention to use and accept the technology. Although there are some preliminary past studies that tried to assess the public perception of CVT, the research team could find no studies that have investigated the psychological determinants of the acceptance of CVT as detailed in Chapter 2. To fill this research gap, this study aimed to model the acceptance to CVT using theories of human behavior.

A connected vehicle (CV) is considered to be a part of internet of things (IoT). There is precedent in the use of TAM to model the acceptance and adoption of emerging technologies, including IoT. Though there are few cases of its use for vehicles technologies (electric vehicles, AV, ride sharing, etc.), these studies provide the basis for the adoption of TAM to model the acceptance and behavioral intention to use CVs. As the development of public trust is necessary for successful deployment of advanced vehicle technology (Hoffman et al., 2006), the research team modified the original TAM model by incorporating perceived trust towards connected technology. In addition, the effects of perceived data privacy and security issues were also incorporated in the proposed connected vehicle acceptance model (CVAM) such that it consisted of seven constructs and twenty-one hypotheses, each of which are described in the following subsections. The proposed research model is shown in Figure 4.8. In the figure, the solid lines indicate the original TAM (Davis et al., 1989) and the dashed lines represent other hypothesized paths.

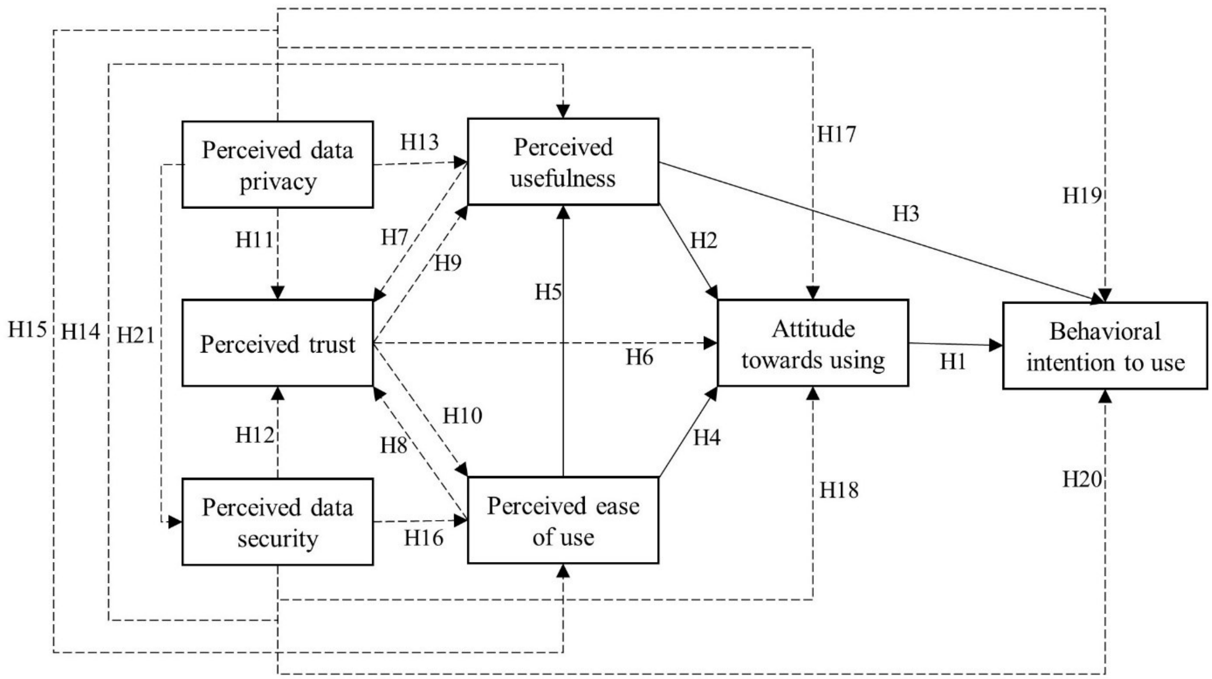

Figure 4.8 Proposed connected vehicle acceptance model

4.3.1.1 Behavioral Intention to Use

Actual use of technology is a key measure of technology acceptance (Davis et al., 1989) but it cannot be assessed before the actual deployment of the technology itself. Behavioral intention to use technology is defined as the degree to which an individual has intention to use CV in future. Several studies, such as (Venkatesh et al., (2003), verified the correlation between actual use and behavioral intention to use technology. This leads to the use of behavioral intention to use the technology as a construct to measure the acceptance of CV.

4.3.1.2 Attitude toward Using

Attitude reflects the individual's inclination toward the technology. Here, attitude toward using technology is defined as the degree to which an individual has a positive or negative feeling about using CV. The positive or negative feelings developed toward the technology form the intention toward using the technology (Davis et al., 1989). The research team proposed hypothesis H1 based on the original TAM and its adoptions in vehicular settings (Ghazizadeh et al., 2012; Zhang et al., 2019).

H1: Attitude toward using CV has a positive effect on the behavioral intention to use CV.

4.3.1.3 Perceived Usefulness

In the original TAM model, Davis et al. (1989) defined perceived usefulness (PU) as "the prospective user's subjective probability that using a specific application system will increase his or her job performance within an organizational context." By definition, PU refers to the thought that describes how useful and helpful the technology is or will be. Thus, in this CV setting, PU is defined as the degree to which an individual finds CV useful to fulfill his or her driving expectations. The potential uses of CVT in order to enhance the safety, mobility, and environmental benefits of transportation systems have been discussed in Section 2.2. These uses and benefits might help to develop the positive attitude and intention to use connected vehicles. Thus, the researchers hypothesized H2 and H3 as suggested by Davis et al. (1989) in the original TAM and by Zhang et al. (2019) in the AV acceptance model.

H2: Perceived usefulness has a positive effect on attitude toward using CV.
H3: Perceived usefulness has a positive effect on behavioral intention to use CV.

4.3.1.4 Perceived Ease of Use

Perceived ease of use (PEU) as defined by Davis et al. (1989) is "the degree to which the prospective user expects the target system to be free of effort." It shows the extent of users' thoughts on how easy and effortless the technology is. Here, PEU is defined as the degree to which an individual finds the use of CV easy. Warnings and information are disseminated by the CV system and drivers are supposed to follow the instructions. Some effort may be needed to use this vehicle technology, which will influence the development of the attitudes regarding the technology and its perceived usability. Thus, the researchers hypothesized H4 and H5 as suggested by Davis et al. (1989) in the original TAM and by Zhang et al. (2019) in the AV acceptance model.

H4: Perceived ease of use has a positive effect on attitude toward using CV.
H5: Perceived ease of use has a positive effect on perceived usefulness of CV.

4.3.1.5 Perceived Trust

Driver, vehicular, and trip data exchange is necessary in CVT to capture the potential benefits of the technology. The system controller uses the data and disseminates instructions that are supposed to be followed by the driver in order to achieve the safety, mobility, and environmental benefits. The users don't have any actual control over the data and instructions provided, so the role of trust is vital in these types of human-system interactions for the acceptance of the technology (Choi & Ji, 2015). Here, perceived trust is defined as the degree to which an individual finds CVT and the instructions provided by CV reliable, dependable, and trustworthy. The data issues of the CVT have been discussed in Section 2.3. From past studies of public perception of CVT, it can be concluded that users have greater concerns about data-related issues. These issues lower the public trust in the technology and influence the development of negative attitudes toward the technology, which ultimately affects its use intention. To assess the trust of CVT, the researchers proposed two determinants: perceived data privacy and perceived data security. Hypothesis H6 was proposed assuming that these two determinants define the trust developed toward the technology and that trust affects the intention to use CV mediated by attitudes toward using CV.

H6: Perceived trust has a positive effect on attitude toward using CV.

The relationships of trust with PEU and PU are somewhat ambiguous as different studies have proposed and confirmed different natures of the relationships. Considering that trust influences cognitive processes of evaluating whether or not to accept technology, trust was found to affect technology acceptance through perceived usefulness and ease of use (Choi & Ji, 2015; Ghazizadeh et al., 2012; Xu et al., 2018). On the other hand, considering the formation of trust as a result of credibility and benevolence (Ganesan & Hess, 1997), perceived usefulness and ease of use were found to be the antecedents of the trust toward the technology (Roca et al., 2009; Zhang et al., 2019). Credibility refers to the intention and ability of a system to fulfill the commitments, which could be achieved in the case of CV by providing reliable weather information, offering fewer signal delays, and other factors. Benevolence is related to the quality of the system, which tends to offer welfare to the users even by compromising the profits in order to meet the users' expectations. Performance of CVT to avoid the misuse and unauthorized transfer of personal information could be referred to as benevolence in this case. This ambiguity in the relationships of trust with PU and PEU in the case of various technologies, including vehicles, did not give specific support to propose the hypothetical relationships. Thus, the researchers hypothesized that either perceived trust is the antecedent of PU and PEU (H7 and H8) or PU and PEU are the antecedents of perceived trust (H9 and H10).

H7: Perceived usefulness of CV has a positive effect on perceived trust.
H8: Perceived ease of use of CV has a positive effect on perceived trust.
H9: Perceived trust on CV has positive effect on perceived usefulness.
H10: Perceived trust on CV has positive effect on perceived ease of use.

4.3.1.6 Perceived Data Privacy and Security

Perceived data privacy is the degree to which an individual is concerned about the collection and use of his/her personal, vehicular, and trip data. The degree to which an individual is concerned about the unauthorized access and protection of data refers to perceived data security. Data privacy and security are the major reasons behind the distrust of new technology and hence can be considered as the major barriers to acceptance. Thus, hypothesis H11 and H12 were proposed in line with the previous studies on social network services (Shin, 2010), online trading (Roca et al., 2009), computer-based systems (Hoffman et al., 2006), healthcare (Alraja et al., 2019) and others.

H11: Perceived data privacy has a positive effect on trust of CV.
H12: Perceived data security has a positive effect on trust of CV.

The effects of perceived privacy and security on the factors of TAM were incorporated differently in different studies. Perceived security was used as an antecedent of behavioral intention to use AV (Xu et al., 2018). Perceived risk associated with the technology was found to have a direct effect on perceived usefulness and behavioral intention to use ride sharing services (Wang et al., 2018). Two types of concerns of advertising on social media, intrusiveness and privacy concerns, were hypothesized to affect PU, PEU, attitude toward using, and purchase intent (Lin & Kim, 2016). As a result, all the hypothesized paths were supported except the direct effect of intrusiveness concerns on purchase intent. Data privacy and security were found to be the antecedents of attitude toward using online shopping (Vijayasarathy, 2004). Privacy concerns associated with healthcare technology were found to be the antecedents of PU, PEU, and behavioral intention to use (Dhagarra et al., 2020). Similarly, privacy concerns were found to affect the usage intention of location-based services directly and through trust (Zhou, 2012). Due to the varied evidence from the literature, the research team decided to test the relationships of perceived data privacy and security with all the TAM components.

H13: Perceived data privacy has a positive effect on perceived usefulness of CV.
H14: Perceived data security has a positive effect on perceived usefulness of CV.
H15: Perceived data privacy has a positive effect on perceived ease of use of CV.
H16: Perceived data security has a positive effect on perceived ease of use of CV.
H17: Perceived data privacy has a positive effect on attitude toward using CV.
H18: Perceived data security has a positive effect on attitude toward using CV.
H19: Perceived data privacy has a positive effect on behavioral intention to use CV.
H20: Perceived data security has a positive effect on behavioral intention to use CV.

There is a complex relationship between data privacy and security. Privacy refers to the safeguarding of personal data by legal measures and good practices of data handling; whereas, security is linked to the protection of privacy by legal measures and good practices of data handling. Sometimes data privacy and security are used interchangeably but these two terms are different as per definitions. As the data privacy can be maintained only if the security of a system is assured, privacy is sometimes considered as a subset of security. Thus, the research team proposed the hypothesis H21 considering that the perceived data security mediates the effect of perceived data privacy on CVT (Shin, 2010).

H21: Perceived data privacy has a positive effect on perceived data security.

4.3.2 Measuring the Model

To validate the proposed CVAM, the scale of measurements of constructs was necessary. Thus, for each construct in the proposed model, items of measurement were developed by modifying the verified scales presented in the existing literature. The list of items used to measure the constructs and their sources are shown in Table 4.9. In the first section of the questionnaire, items of perceived data privacy and perceived data security were asked using the Likert scale of 1-7 (1: extremely unlikely to 7: extremely likely). The items of perceived usefulness and perceived ease of use were asked in the third section of the questionnaire using the Likert scale of 1-7 (1: not at all confident to 7: extremely confident). Similarly, the questions of trust, attitude, and behavioral intention were included in the third section and asked in the Likert scale of 1-7, but the scale was strongly disagree to strongly agree for trust and attitude, and extremely unlikely to extremely likely for items of behavioral intention. The detailed wording of the questionnaire is included in Appendix A.

Table 4.9 Latent constructs and survey items

Constructs	Survey Items	Sources
Perceived data privacy	1. CVs would not collect too much information about your personal, vehicular, and trip characteristics. *(privacy1)* 2. CVs would keep your information in an accurate manner in their database. *(privacy2)* 3. CVs would not share your information with other parties without obtaining your authorization. *(privacy3)* 4. CVs would make you feel same about providing data through the use of a connected vehicle. *(privacy4)*	(Roca et al., 2009; Xu, 2007; Yun et al., 2013)
Perceived data security	1. CVs would have sufficient technical capacity to ensure that your data cannot be accessed by a third party. *(security1)* 2. CVs would have sufficient technical capacity to ensure that the data you sent cannot be modified by a third party. *(security2)* 3. CVs would have strong security measures to protect your personal, vehicular, and trip characteristics data. *(security3)*	(Roca et al., 2009)
Perceived usefulness	1. A CV would be useful in meeting your transportation needs. *(usefulness1)* 2. A CV would decrease your accident risk. *(usefulness2)* 3. A CV would reduce your travel delay. *(usefulness3)* 4. A CV would relieve your travel stress. *(usefulness4)* 5. A CV would improve your driving performance. *(usefulness5)*	(Davis et al., 1989; Wang et al., 2018)
Perceived ease of use	1. Learning to use a CV would be easy for you. *(use1)* 2. You would find it easy to get a CV to do what you want it to do. *(use2)* 3. You would find it easy to understand information provided by a CV. *(use3)* 4. You would find a connected vehicle easy to use overall. *(use4)*	(Davis et al., 1989; Zhang et al., 2019)
Perceived trust	1. CVs are reliable. *(trust1)* 2. CVs are dependable. *(trust2)* 3. Overall, CVs are trustworthy. *(trust3)*	(Choi & Ji, 2015; Xu et al., 2018; Zhang et al., 2019)
Attitude toward using	1. It is a good idea to use CVs. *(attitude1)* 2. The thought of using CVs is appealing to you. *(attitude2)* 3. Using a CV would be fun to you. *(attitude3)* 4. Overall, you have positive feelings about using CVs. *(attitude4)*	(Venkatesh et al., 2003)
Behavioral intention to use	1. You would use a CV in the future. *(intention1)* 2. Your next vehicle purchase would be a CV.*(intention2)* 3. You would strongly recommend others to use CVs. *(intention3)*	(Venkatesh et al., 2003; Xu et al., 2018)

4.3.3 Exploratory Factor Analysis

All 26 measured variables shown in Table 4.9 were used in the EFA. Before running the analysis, the sampling adequacy and significant correlation in the data for factor analysis was confirmed using KMO measure of sampling adequacy with a KMO value of 0.97 and Bartlett's test of sphericity with Chisq (325) = 65165.28, $p < .001$. Horn's parallel analysis with examination of the eigenvalues and scree plots suggested six factors. Thus, the EFA was carried out for six factors. The factor loadings of oblimin rotations using principal axis factoring are shown in Table 4.10. Loadings with a value greater than 0.4 are bolded in the table. Three factors were found to explain 76% of variance in the dataset.

Table 4.10 Exploratory factor analysis results

Items	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
privacy1	0.03	-0.02	0.12	-0.06	-0.01	**0.56**
privacy2	-0.09	0.16	-0.02	0.03	0.15	**0.51**
privacy3	0.00	-0.02	0.01	0.07	0.02	**0.76**
privacy4	0.11	0.04	0.02	0.10	0.00	**0.67**
security1	-0.01	0.01	0.00	**0.87**	0.04	0.02
security2	0.00	0.02	0.00	**0.97**	-0.02	-0.03
security3	0.03	-0.01	0.03	**0.77**	0.00	0.12
usefulness1	0.21	0.06	**0.53**	0.05	0.05	0.01
usefulness2	0.01	0.01	**0.85**	0.05	0.00	-0.05
usefulness3	-0.03	0.07	**0.78**	0.00	0.01	0.01
usefulness4	-0.02	-0.01	**0.91**	-0.02	-0.02	0.03
usefulness5	0.04	-0.01	**0.77**	-0.02	0.04	0.06
ease1	0.01	**0.92**	-0.03	0.02	-0.04	0.00
ease2	0.00	**0.85**	0.03	0.00	0.04	0.03
ease3	-0.02	**0.89**	0.04	-0.01	0.02	-0.01
ease4	0.05	**0.86**	0.01	0.01	0.03	-0.01
trust1	-0.02	0.05	0.01	0.01	**0.89**	0.02
trust2	-0.01	0.02	0.01	-0.01	**0.92**	0.00
trust3	0.18	-0.04	0.02	0.07	**0.69**	0.03
attitude1	**0.56**	-0.04	0.12	0.05	0.26	0.00
attitude2	**0.83**	0.01	0.07	0.07	0.00	-0.04
attitude3	**0.74**	0.04	0.05	0.06	0.03	-0.01
attitude4	**0.76**	0.00	0.05	0.09	0.08	-0.02
intention1	**0.89**	0.09	-0.05	-0.03	-0.03	0.01
intention2	**0.87**	0.02	-0.03	-0.04	-0.01	0.05
intention3	**0.86**	-0.02	0.04	-0.03	0.01	0.07

The results of the EFA confirmed that the six factors are: Factor 1, attitude and behavioral intention to use CV; Factor 2, perceived ease of use; Factor 3, perceived usefulness; Factor 4, perceived data security; Factor 5, perceived trust; and Factor 6, perceived data privacy. Additionally, two factors (perceived privacy and perceived security of data) were found to have high correlation (0.893) with each other, which might create a discriminant validity issue. Therefore, four measured items of perceived data privacy (privacy1, privacy2, privacy3, and privacy4) and three measured items of perceived data security (security1, security2, and security3) were merged into one factor called perceived data privacy and security for further analysis.

4.3.4 Revised Research Model and Hypotheses

First, merging two concepts – data privacy and data security – into one is supported by the existing body of literature. These two concepts have been used interchangeably and/or in combination in several studies. For instance, to model the behavioral intention toward electronic commerce, seven items were used to measure privacy construct, and those items reflected the data privacy and security issues (Liu et al., 2005). A higher correlation between data privacy and data security factors was observed in a study related to acceptance of a website such that a second-order factor called security in handling private data, which represented privacy and security concerns, was proposed (Flavián & Guinalíu, 2006).

Second, the results of the EFA suggested that two constructs – attitude toward using and behavioral intention to use – which were initially assumed to be distinct, are actually the same with the significant loading of seven items (of both attitude and behavioral intention) into one factor. These two constructs were distinct in the original TAM with the direct effect of attitude on behavioral intention (Davis et al., 1989). However, an attitude construct was not included in TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008), indicating that perceived usefulness and perceived ease of use have a direct effect on behavioral intention without the mediation of attitude. Similarly, an attitude construct was not used in a few TAM adoptions in the case of vehicle technologies (e.g., Choi & Ji, 2015; Wang et al., 2018; Xu et al., 2018). With the precedence from the literature and in accordance with the results of the EFA, the research teams considered the attitude and behavioral intention as one factor represented by seven items.

With the results of the EFA and necessary modifications, the seven factors originally proposed in the research model dropped to five. Thus, the revision of the research model, paths of relationships between the factors, and hypotheses was necessary. The revised research model is presented in Figure 4.9.

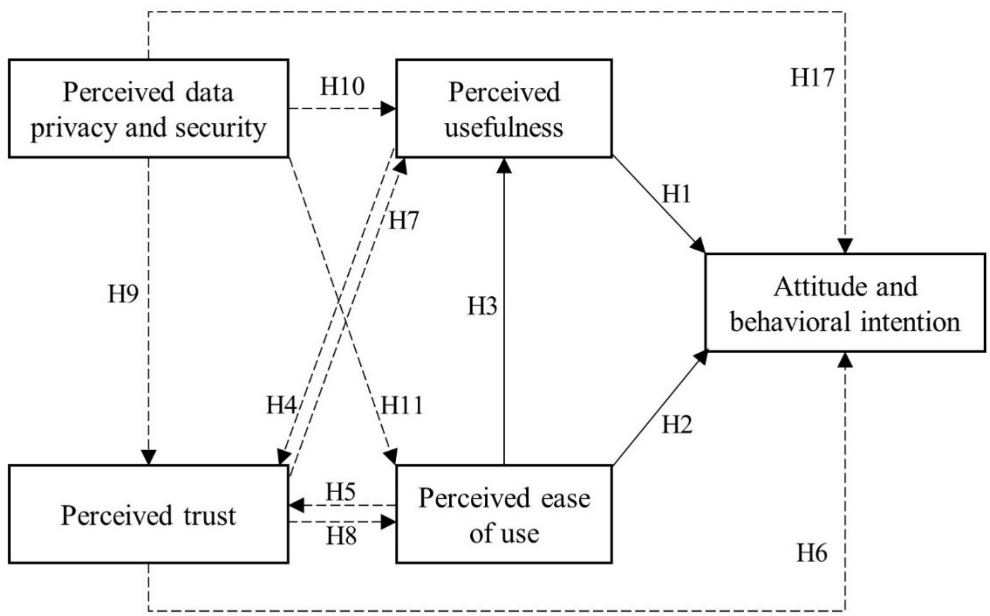

Figure 4.9 Revised connected vehicle acceptance model

For this revised research model, the hypotheses are:

H1: Perceived usefulness has a positive effect on attitude and behavioral intention to use CV.
H2: Perceived ease of use has a positive effect on attitude and behavioral intention to use CV.
H3: Perceived ease of use has a positive effect on perceived usefulness of CV.
H4: Perceived usefulness of CV has a positive effect on perceived trust.
H5: Perceived ease of use of CV has a positive effect on perceived trust.
H6: Perceived trust has a positive effect on attitude and behavioral intention to use CV.
H7: Perceived trust on CV has a positive effect on perceived usefulness.
H8: Perceived trust on CV has a positive effect on perceived ease of use.
H9: Perceived data privacy and security has a positive effect on perceived trust of CV.
H10: Perceived data privacy and security has a positive effect on perceived usefulness of CV.
H11: Perceived data privacy and security has a positive effect on perceived ease of use of CV.
H12: Perceived data privacy and security has a positive effect on attitude and behavioral intention to use CV.

4.3.5 Confirmatory Factor Analysis

As a result of some modifications on the results of the EFA, five factors (perceived data privacy and security [PPS], perceived trust [PT], perceived ease of use [PEU], perceived usefulness [PU], and attitude and behavioral intention to use CV [ABI]) were used for the confirmatory factor analysis. In addition, travelers' characteristics were the inputs of both models as the exogenous variables affecting all five factors, so the model is called a multiple indicator multiple cause (MIMIC) model. The result of CFA is shown Figure 4.10.

The internal consistency, convergent validity, and the discriminant validity of the constructs in the model were tested. The results of these tests are shown in Table 4.11. The values of composite reliability (CR) and Cronbach's alpha (CA) were greater than 0.7 and confirmed the internal consistency of the measured items of the factors. The values of average variance extracted (AVE) for each construct were greater than 0.5 and proved the convergent validity of the model. The values of square root of average variance extracted (SAVE) for each construct were greater than the correlation values, which indicated the good discriminant validity of the model.

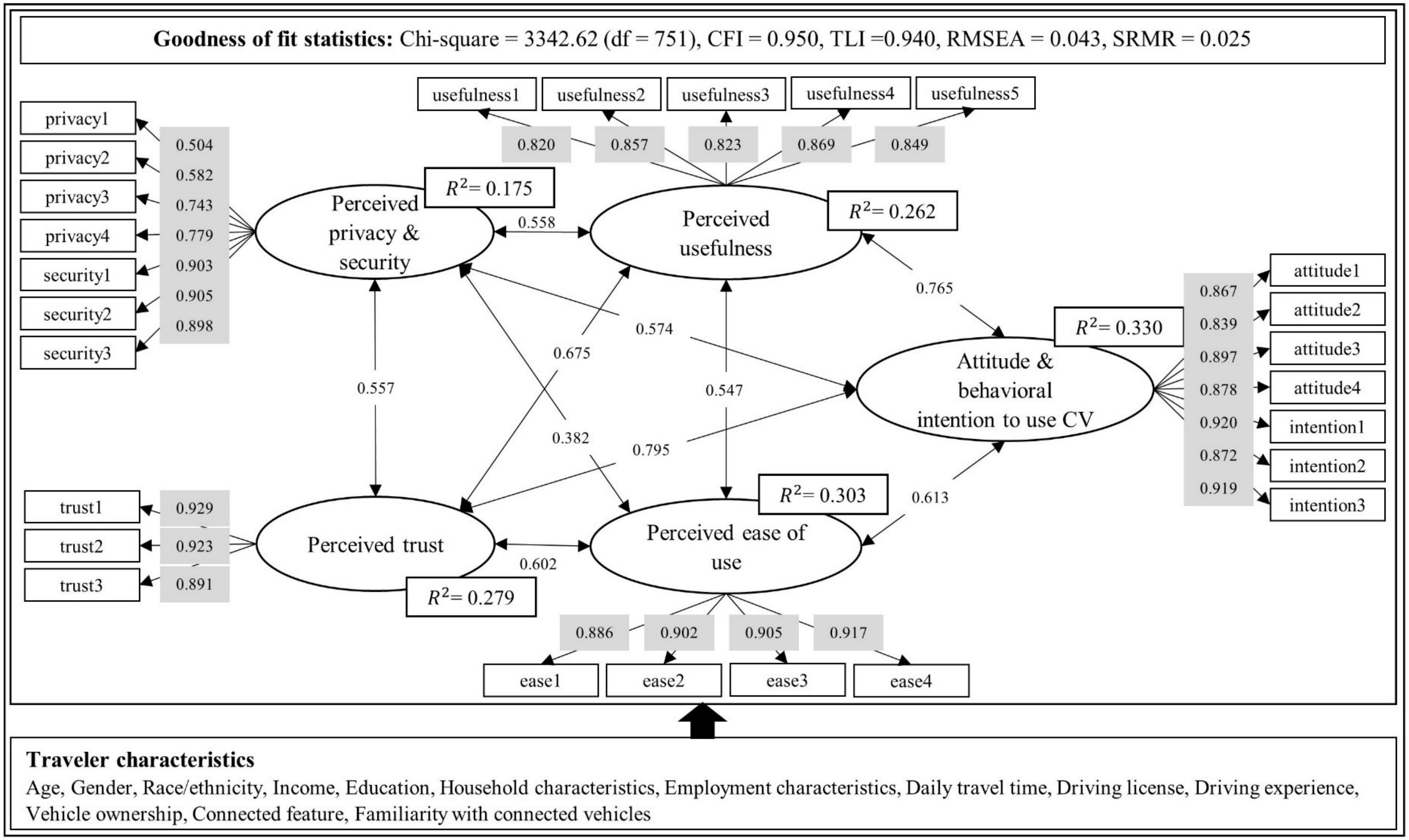

Figure 4.10 Confirmatory factor analysis results

Table 4.11 Internal consistency, convergent validity, and discriminant validity test

	Correlation					AVE	CR	CA
	PPS	**PT**	**PEU**	**PU**	**ABI**			
PPS	**0.776**					0.602	0.910	0.908
PT	0.650	**0.914**				0.835	0.938	0.937
PEU	0.508	0.754	**0.903**			0.816	0.947	0.947
PU	0.652	0.756	0.664	**0.846**		0.716	0.926	0.925
ABI	0.661	0.850	0.726	0.825	**0.884**	0.782	0.962	0.961

4.3.6 MIMIC Model Results

The estimates of exogenous variables in the MIMIC model are presented in Table 4.12 and only the significant variables are described here. Those aged 65-plus years had a positive association with perceived trust and usefulness of CV compared with people less than 25 years of age. Females were found to have significantly lower trust, ease, and attitude and behavioral intention of using CV than males. In terms of race, white people were found to have lower perceived ease of use and attitude and behavioral intention to use CV than other races. People with annual household incomes greater than or equal to \$150k perceived CV as easy to use and had a higher attitude and behavioral intention to use CV than people of annual household incomes less than \$25k. Graduate degree holders had significantly higher confidence in data privacy and security than those with no college degree. An increase in the number of adults in the household (18 and older) was positively associated with data privacy and security perception and perceived usefulness. Similarly, a higher number of children in the household was associated positively with all five factors. Employed people had higher perceived ease of use and usefulness of CV.

People with a typical daily travel time of 30 to 60 minutes were found to have higher ease of use then people with a daily travel time less than half an hour. Similarly, people having more than a one-hour typical daily travel time had higher trust and attitude and intention to use CV than people having less than 30 minutes of typical daily travel time. Driving license holders had higher perceived trust, ease of use, perceived usefulness, and attitude and intention of using CV. However, an increase in driving experience was associated negatively with perceived trust, perceived data privacy and security, perceived usefulness, perceived ease of use, and attitude and behavioral intention of using CV. The number of vehicles owned in a household was associated negatively with attitude and behavioral intention to use CV. People having some form of connected features in their households' vehicle/s were found to have higher confidence in data privacy and security, trust, and attitude and behavioral intention to use CV. In comparison with people with no familiarity with CVT, those with medium and high familiarity had a higher positive perception of data privacy and security, trust toward technology, ease of use, usefulness, and attitude and behavioral intention to use CV. Higher coefficients of high familiarity than that of medium familiarity for all the factors signify that familiarity is important in building positive perception toward data privacy and security, trust, ease of use, usefulness, and attitude and intention to use CV.

Table 4.12 MIMIC model results

Variables	PPS		PT		PEU		PU		ABI	
	B	p	B	p	B	p	B	p	B	p
Age										
25-44 years	0.042	0.312	0.048	0.220	0.011	0.777	0.054	0.163	0.022	0.539
45-64 years	0.040	0.389	0.075	0.083	-0.031	0.465	0.078	0.069	0.002	0.965
65+ years	0.087	0.116	0.145	0.004*	-0.040	0.402	0.133	0.010*	0.010	0.834
Gender: female	-0.013	0.566	-0.042	0.049*	-0.080	0.000*	-0.038	0.079	-0.041	0.044*
Race/ethnicity: white	0.001	0.945	-0.003	0.886	-0.054	0.005*	-0.036	0.077	-0.057	0.002*
Income										
$25-75k	-0.010	0.739	-0.010	0.739	0.052	0.072	-0.004	0.895	0.033	0.232
$75-150k	-0.010	0.764	-0.016	0.607	0.056	0.067	-0.035	0.271	0.026	0.378
≥$150k	0.002	0.950	0.032	0.221	0.066	0.007*	0.019	0.461	0.067	0.006*
Education										
Undergraduate degree	-0.027	0.265	-0.007	0.768	0.008	0.713	-0.022	0.360	-0.010	0.669
Graduate degree	0.059	0.034*	0.016	0.522	0.045	0.072	0.014	0.601	0.019	0.444
# households (age ≥ 18 years)	0.056	0.010*	0.023	0.285	0.020	0.337	0.050	0.019*	0.026	0.185
# children (age <18 years)	0.062	0.006*	0.089	0.000*	0.059	0.006*	0.062	0.004*	0.050	0.020*
Student: yes	0.012	0.580	-0.014	0.526	-0.023	0.310	0.007	0.717	-0.013	0.512
Employed: yes	0.000	0.995	0.021	0.398	0.049	0.043*	0.051	0.046*	0.030	0.224
Daily travel time										
30-60 minutes	0.018	0.418	0.030	0.155	0.045	0.031*	0.018	0.411	0.007	0.742
≥ 60 minutes	0.039	0.083	0.043	0.041*	0.039	0.055	0.041	0.059	0.046	0.021*
Driving license: yes	0.047	0.052	0.074	0.001*	0.070	0.002*	0.063	0.006*	0.071	0.001*
Driving experience (years)	-0.185	0.000*	-0.198	0.000*	-0.111	0.002*	-0.223	0.000*	-0.177	0.000*
Vehicle ownership	-0.036	0.117	-0.032	0.130	-0.025	0.246	-0.015	0.490	-0.050	0.013*
Connected feature: yes	0.084	0.000*	0.153	0.000*	0.107	0.000*	0.120	0.000*	0.195	0.000*
Familiarity										
Medium	0.058	0.030*	0.127	0.000*	0.183	0.000*	0.094	0.000*	0.159	0.000*
High	0.238	0.000*	0.344	0.000*	0.342	0.000*	0.318	0.000*	0.328	0.000*

Note: * indicates statistical significance at 95% confidence interval.

4.3.7 Structural Equation Modeling

With acceptable goodness of fit statistics from the CFA, structural equation modeling (SEM) was then carried out to understand the path of relationships between the factors. The hypotheses and paths of relationships between the factors were set up according to the theoretical model proposed above. Based on the model proposed, two structural equation models were estimated: (1) PU and PEU mediating the effect of perceived trust (model A, with paths H7 and H8 between trust and PU and PEU); and (2) trust mediating the effect of PU and PEU (model B, with paths H4 and H5 between trust and PU and PEU) on attitude and behavioral intention to use CV. The results of SEM of model A and B are presented in Figure 4.11 and Figure 4.12, respectively.

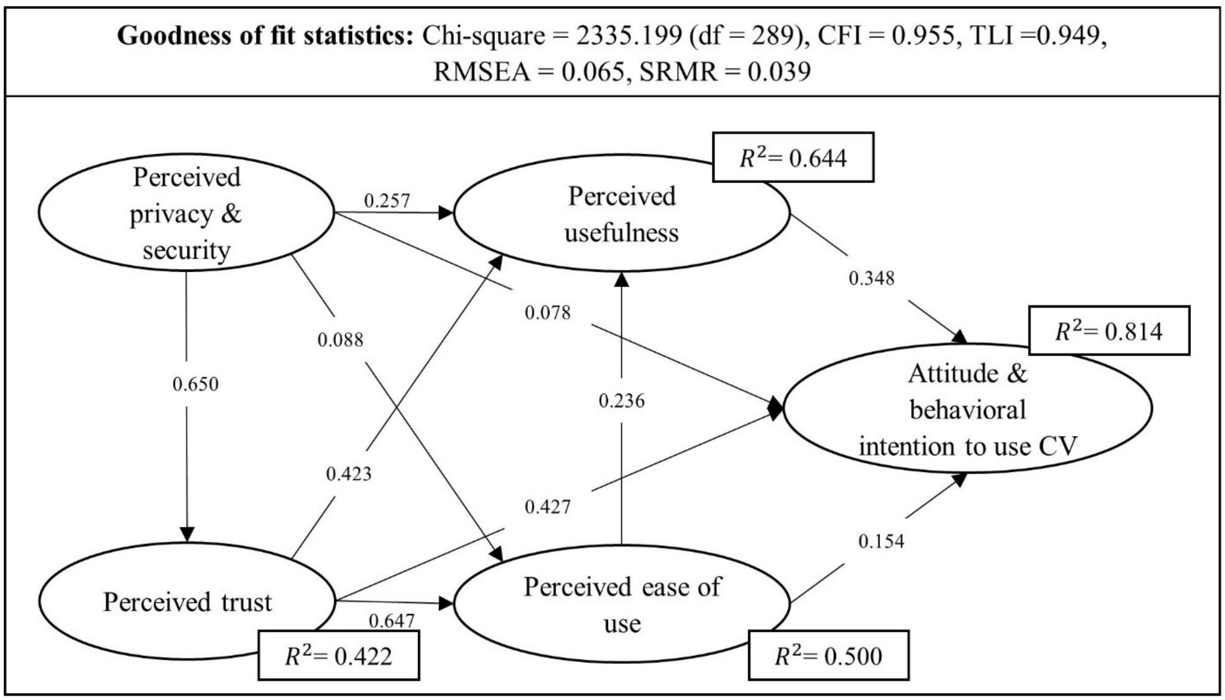

Figure 4.11 SEM results of model A (perceived trust as an antecedent of perceived usefulness and ease of use)

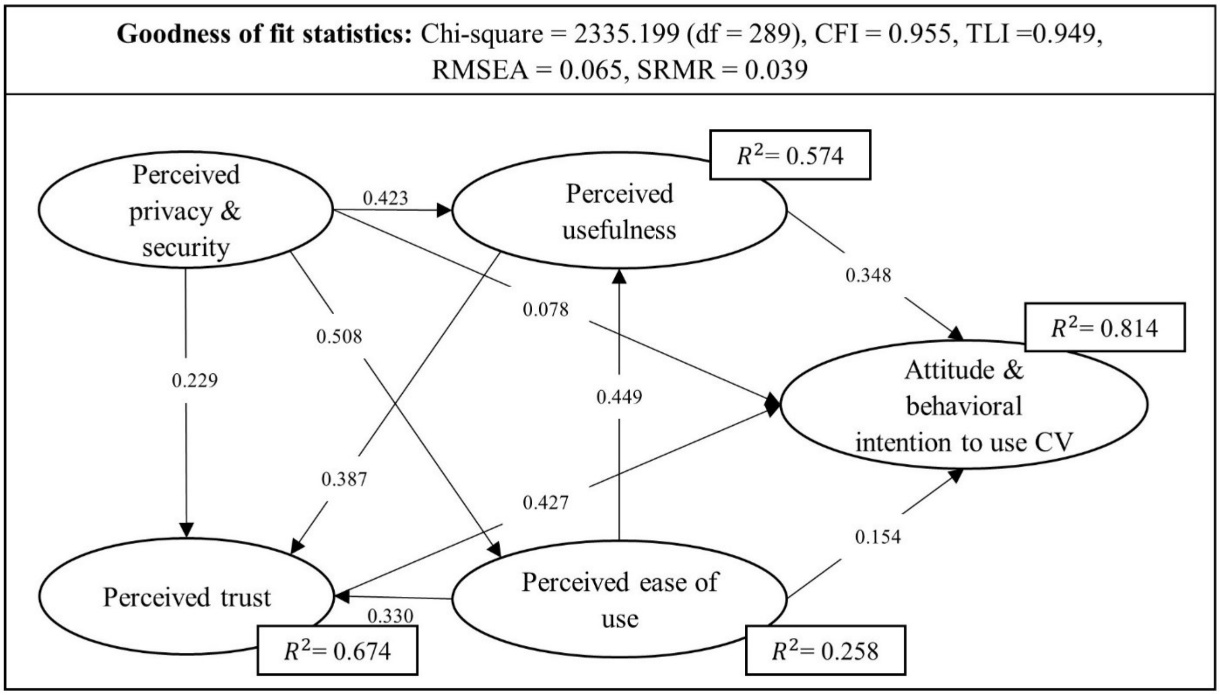

Figure 4.12 SEM results of model B (perceived usefulness and ease of use as antecedents of perceived trust)

The hypotheses regarding path of relationships between the factors were tested through the structural model and the results are presented in Table 4.13. All the paths of relationships hypothesized in model A and B were found significant. As both model A and B were found to have equally goodness fit statistics, neither model is preferred over the other. This concludes that the role of perceived trust on the acceptance of CV technology is still not clear. In other words, more research is required to determine if perceived trust mediates PU and PEU or if PU and PEU mediate the role of perceived trust on attitude and behavioral intention to use CV. Thus, the mediation effects of several factors on attitude and behavioral intention to use CV were estimated and presented in Table 4.14.

Table 4.13 Results of hypothesis testing

Hypothesis	**Path**	**B**	**Supported?**	**Hypothesis**	**Path**	**B**	**Supported?**
(Model A)				*(Model B)*			
H1	PU-ABI	0.348	Yes	H1	PU-ABI	0.348	Yes
H2	PEU-ABI	0.154	Yes	H2	PEU-ABI	0.154	Yes
H3	PEU-PU	0.236	Yes	H3	PEU-PU	0.449	Yes
H6	PT-ABI	0.427	Yes	H4	PU-PT	0.387	Yes
H7	PT-PU	0.423	Yes	H5	PEU-PT	0.330	Yes
H8	PT-PEU	0.647	Yes	H6	PT-ABI	0.427	Yes
H9	PPS-PT	0.65	Yes	H9	PPS-PT	0.229	Yes
H10	PPS-PU	0.257	Yes	H10	PPS-PU	0.423	Yes
H11	PPS-PEU	0.508	Yes	H11	PPS-PEU	0.508	Yes
H12	PPS-ABI	0.078	Yes	H12	PPS-ABI	0.078	Yes

Table 4.14 Mediation effects on attitude and behavioral intention to use CV (ABI)

Variable	Indirect effect through			Total indirect	Direct effect	Total effect
	Trust	Ease	Usefulness			
(Model A)						
PPS	0.278	0.014	0.089	0.381	0.078	0.458
PT	-	0.100	0.147	0.247	0.427	0.675
PEU	-	-	0.082	0.082	0.154	0.237
PU	-	-	-	-	0.348	0.348
(Model B)						
PPS	0.098	0.079	0.147	0.324	0.078	0.402
PT	-	-	-	-	0.427	0.427
PEU	0.141	-	0.156	0.297	0.154	0.452
PU	0.166	-	-	0.166	0.348	0.514

The direct and indirect effects of all the factors on attitude and behavioral intention to use CV were calculated using standardized coefficients. They were found to be statistically significant and are reported in Table 4.14. In model A, PPS was mediated by PT, PEU, and PU and the highest magnitude of mediation was done by PT (0.278) as compared with PEU (0.014) and PU (0.089). PU and PEU mediated PT with the magnitudes of 0.100 and 0.147, respectively. About half of the direct effect (0.154) of PEU on ABI was mediated by PU (0.082). In model B, the indirect effect of PPS on ABI was consistent with the results of model A. The mediation of PT and PU on the effects of PEU on ABI was about equal with magnitudes 0.141 and 0.156, respectively. Additionally, the indirect effect of PU on ABI through PT was about half (0.166) of the direct effect (0.348). These results further confirmed that there is no clear path of relationships of PT with PU and PEU but it could be concluded that PT can be both the mediator and the antecedent of PU and PEU. These inconclusive results might be because of limited actual interaction of respondents with the CVs.

4.3.8 Discussion

4.3.8.1 Theoretical implications

This study proposed a connected vehicle acceptance model by extending the technology acceptance model (TAM). According to TAM, the main predictors of acceptance of technology are the usefulness and ease of using the technology. This study confirms TAM theory, indicating that the adoption of CV is largely dependent upon the usefulness and ease of using CV. To the researchers' knowledge, this is the first adoption of TAM in the case of CV, concluding that TAM theory is able to explain the acceptance of CV. This is the first theoretical contribution of this study. Second, this study explored the path of the relationship of data privacy and security issues and the acceptance of CV. In the proposed model, data privacy and security issues were found to lower the adoption both directly and indirectly through all the antecedents. This result confirms that data issues related to privacy and security are a major barrier toward the acceptance of CV.

The role of trust has a significant effect on the acceptance of technology. However, the actual ways in which trust can affect technology acceptance is not clear. There are opposing opinions on the role of trust in the acceptance of technology: trust mediates perceived usefulness and perceived ease of use (Roca et al., 2009; Zhang et al., 2019) versus perceived usefulness and ease of use mediate the role of trust in technology acceptance (Choi & Ji, 2015; Ghazizadeh et al., 2012; Xu et al., 2018). To understand this, two models were proposed and tested empirically in this study. Surprisingly, both the models were found to have acceptable and almost identical goodness of fit statistics, suggesting that the role of trust on the acceptance of CVs can go both ways. The mediation analysis showed that perceived trust can significantly affect CV adoption through perceived usefulness and ease of use. At the same time, the effect of perceived usefulness and ease of use on CV adoption can be mediated by perceived trust. CVs being in the early stage of adoption might be a possible explanation for this result. The public is not familiar with the technology yet, so perceived trust, perceived usefulness, and perceived ease of use are often based on limited information or misinformation. Trust toward the technology is affected by the risk and uncertainty involved; here, data privacy and security played an important role in the development of trust in addition to usefulness and ease of use. From a theoretical standpoint, the importance of the role of trust and its antecedents in the adoption of emerging technologies is the third theoretical contribution of this study.

4.3.8.2 Practical implications

The findings of this study suggest the number of ways to increase the acceptance and adoption of CVs. First, the perceived usefulness of CVs should be improved by assuring users that their driving needs will be met. Second, perceived ease of use should be made clear (and actual ease of use should be optimized). The use of information and messages sent to drivers through the system should be easily understood and followed; and should not distract the drivers. Third, trust of the vehicle must be high for adoption to succeed. Apart from usefulness and ease, the trust and, ultimately, the acceptance of CV can be improved by reducing the data-related issues associated with the technology. In other words, public perception of data privacy and security in CV technology should be high. Vehicle developers, agencies, and policy makers should assure the public about the protection of data by improving data management and protection systems, introducing data privacy protection laws, and informing the public about such data privacy, security, and management efforts.

The role of familiarity with CV technology and the availability of some form of connectivity in respondents' current vehicle/s were found to play a vital role in developing a positive perception of privacy and security, trust, usefulness, ease of use, and attitude and behavioral intention to use. This signifies that with the gradual increase of CV market penetration, the acceptance and adoption of CV should increase. However, the current CV market penetration is very low, so alternative ways of achieving this are necessary. Advertising the benefits, features, and usability of CV could boost public perception by increasing familiarity. Additionally, alternative outreach strategies, such as providing low-pressure test drive opportunities, could help increase the familiarity and acceptance of CV. The acceptance of CV and its antecedents were found to differ based on demographic and respondents' driving characteristics (presented in Section 4.3.6), and vehicle developers and policy makers should refer to those results in formulating their plans and policies to increase the acceptance and adoption of CV within those groups.

5. CONCLUSIONS AND RECOMMENDATIONS

This study investigated the different aspects of public perception related to the adoption of CVs in the near future. First, it was found that data sharing intention depends on the use of data but not the type of data. For example, a higher data sharing intention was observed for using all CV data types for informing drivers about hazards ahead. However, a lower data sharing intention was observed for data usage for enforcement purposes. Based on the results, agencies and stakeholders should focus on assuring users about the use of CV data for intended purposes only in order to increase the data sharing intention for CVs.

Second, the relationship between data sharing intention and CV acceptance was established. The direct positive impact of data sharing intention on CV acceptance was observed, implying that an increase in data sharing intention is necessary to increase CV acceptance. In addition, the effect of perceived data privacy and security was also included in the relationship. It was found that a decrease in perceived data privacy and security lowers data sharing intention and CV acceptance. Thus, this finding recommends that CV stakeholders strengthen data privacy and security practices and inform the public of such efforts.

Third, the overall process of developing the behavioral intention to use CV was ascertained by developing a novel connected vehicle acceptance model (CVAM). The CVAM, an extension of TAM, was able to explain the relationships between CV acceptance and its determinants. The determinants of CV acceptance, represented by attitude and behavioral intention to use CV, were found to be perceived usefulness, perceived ease of use, perceived trust, and perceived data privacy and security. Based on the path of relationships between the CV acceptance factors, it was found that the role of perceived trust on CV acceptance can go both ways: either it mediates the effects of perceived usefulness and ease of use on CV acceptance or it acts as an antecedent of perceived usefulness and ease of use. In addition, a significant role of perceived data privacy and security was found to develop the trust and, subsequently, the acceptance of CVT. Thus, the authors recommend that CVT stakeholders aim to increase public trust in the protection and use of CV data collected along with implementing measures to increase perceived CV usefulness and ease of use.

Finally, the role of socio-demographic and other individual characteristics of the individuals on the data sharing intention and the CVAM was ascertained. This result is important to CV developers and marketing agencies to formulate different plans to engage different groups of individuals in order to improve the overall data sharing intention and public acceptance of CV. For example, data sharing intention and CV acceptance were found to be higher for those having higher familiarity with connected features and for those having low or no driving experience. Thus, the marketing strategy should focus on educating experienced drivers about the advantages of connectivity. However, for inexperienced drivers, marketing strategies such as CV test drive opportunities (increasing familiarity with connected features) could enhance their overall data sharing intention and CV acceptance.

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APPENDIX A: SURVEY QUESTIONNAIRE

We anticipate that this survey will take around 15 minutes or less to complete. You will be asked questions in four sections (Parts 1-4). You can track your progress with the bar at the top of the screen.

Before we start, we would like to know your familiarity with connected vehicle technology and provide you with some relevant definitions.

1. How familiar are you with the connected vehicle and/or its technology?
    a. Extremely familiar
    b. Very familiar
    c. Moderately familiar
    d. Slightly familiar
    e. Not familiar at all

Connected vehicle: A vehicle that is capable of two-way communication with other vehicles, infrastructure, the cloud, smart devices, etc. A connected vehicle may disseminate information, such as weather warnings, hazard warnings, detour information, desired speed, etc., to the driver. It may also collect and transmit data pertaining to vehicle speed, position, headlight status, wiper intensity, driver characteristics, trip information, etc., to recipients out-of-vehicle. A connected vehicle may be a personal vehicle, public transit vehicle, ride-share vehicle, rental vehicle, etc.

Data manager: The individual or organization that collects, stores, and owns the data collected from connected vehicles and has the authority to provide access to and give permission for the use of that data.

Transportation organization: A private company, professional organization, or government entity that does work within the transportation industry, such as providing consulting services, conducting research, providing certification or licensure, owning and operating roads, etc.

Part 1: Data Privacy, Security, and Management

2. How likely do you think that connected vehicle technology would have the following data privacy measures? (1: Extremely unlikely, 7: Extremely likely)
    Connected vehicles would…
    a. Not collect too much information about your personal, vehicular, and trip characteristics.
    b. Keep your data in an accurate manner in their database.
    c. Not share your data with other parties without obtaining your authorization.
    d. Make you feel safe about providing data through the use of a connected vehicle.

3. How likely do you think that connected vehicle technology would have the following data security measures? (1: Extremely unlikely, 7: Extremely likely)
    Connected vehicles would have…
    a. Sufficient technical capacity to ensure that your data cannot be accessed by a third party.
    b. Sufficient technical capacity to ensure that the data you send cannot be modified by a third party.
    c. Strong security measures to protect your personal, vehicular, and trip characteristics data.

4. How important are the following characteristics of the data manager of connected vehicle technology to you? (1: Not at all important, 7: Extremely important)
    a. The data manager of connected vehicle technology should be well known.
    b. The data manager of connected vehicle technology should have a good reputation.
    c. The data manager of connected vehicle technology should be easily recognizable.
    d. The data management of connected vehicle technology should be handled by a prestigious organization.

______________________________Page Break______________________________

Part 2: Data Sharing Preferences

5. For which of the following applications would you feel comfortable sharing your connected vehicle **speed** data with a transportation organization? Select all that apply.
    a. Information for drivers (route and weather information, speed and hazard warnings, etc.)
    b. Congestion assessment and reduction
    c. Safety assessment and improvement
    d. Pavement and infrastructure assessment and improvement
    e. Roadside assistance
    f. Crash investigation
    g. Enforcement of traffic laws and regulations
    h. Research purposes
    i. Future transportation and project planning
    j. For assessment of fees based on usage
    k. None of the above

6. For which of the following applications would you feel comfortable sharing your connected vehicle **braking intensity and traction** data with a transportation organization? Select all that apply.
    a. Information for drivers (route and weather information, speed and hazard warnings, etc.)
    b. Congestion assessment and reduction
    c. Safety assessment and improvement
    d. Pavement and infrastructure assessment and improvement
    e. Roadside assistance
    f. Crash investigation
    g. Enforcement of traffic laws and regulations
    h. Research purposes
    i. Future transportation and project planning
    j. For assessment of fees based on usage
    k. None of the above

7. For which of the following applications would you feel comfortable sharing your connected vehicle **pitch and roll** data with a transportation organization? Select all that apply.
    a. Information for drivers (route and weather information, speed and hazard warnings, etc.)
    b. Congestion assessment and reduction
    c. Safety assessment and improvement
    d. Pavement and infrastructure assessment and improvement
    e. Roadside assistance
    f. Crash investigation

g. Enforcement of traffic laws and regulations
h. Research purposes
i. Future transportation and project planning
j. For assessment of fees based on usage
k. None of the above

8. For which of the following applications would you feel comfortable sharing your connected vehicle **mileage** data with a transportation organization? Select all that apply.
   a. Information for drivers (route and weather information, speed and hazard warnings, etc.)
   b. Congestion assessment and reduction
   c. Safety assessment and improvement
   d. Pavement and infrastructure assessment and improvement
   e. Roadside assistance
   f. Crash investigation
   g. Enforcement of traffic laws and regulations
   h. Research purposes
   i. Future transportation and project planning
   j. For assessment of fees based on usage
   k. None of the above

9. For which of the following applications would you feel comfortable sharing your connected vehicle **wiper and headlight intensity** data with a transportation organization? Select all that apply.
   a. Information for drivers (route and weather information, speed and hazard warnings, etc.)
   b. Congestion assessment and reduction
   c. Safety assessment and improvement
   d. Pavement and infrastructure assessment and improvement
   e. Roadside assistance
   f. Crash investigation
   g. Enforcement of traffic laws and regulations
   h. Research purposes
   i. Future transportation and project planning
   j. For assessment of fees based on usage
   k. None of the above

10. For which of the following applications would you feel comfortable sharing your connected vehicle **make/model and ownership** data with a transportation organization? Select all that apply.
    a. Information for drivers (route and weather information, speed and hazard warnings, etc.)
    b. Congestion assessment and reduction
    c. Safety assessment and improvement
    d. Pavement and infrastructure assessment and improvement
    e. Roadside assistance
    f. Crash investigation
    g. Enforcement of traffic laws and regulations
    h. Research purposes
    i. Future transportation and project planning
    j. For assessment of fees based on usage
    k. None of the above

11. For which of the following applications would you feel comfortable sharing your connected vehicle **trip information (location, origin, destination, trajectory)** data with a transportation organization? Select all that apply.
    a. Information for drivers (route and weather information, speed and hazard warnings, etc.)
    b. Congestion assessment and reduction
    c. Safety assessment and improvement
    d. Pavement and infrastructure assessment and improvement
    e. Roadside assistance
    f. Crash investigation
    g. Enforcement of traffic laws and regulations
    h. Research purposes
    i. Future transportation and project planning
    j. For assessment of fees based on usage
    k. None of the above

12. For which of the following applications would you feel comfortable sharing your connected vehicle **onboard diagnostics (vehicle condition)** data with a transportation organization? Select all that apply.
    a. Information for drivers (route and weather information, speed and hazard warnings, etc.)
    b. Congestion assessment and reduction
    c. Safety assessment and improvement
    d. Pavement and infrastructure assessment and improvement
    e. Roadside assistance
    f. Crash investigation
    g. Enforcement of traffic laws and regulations
    h. Research purposes
    i. Future transportation and project planning
    j. For assessment of fees based on usage
    k. None of the above

Part 3: Perception of Connected Vehicles

13. How confident are you in getting the following advantages by using connected vehicles? (1: Not at all confident, 7: Extremely confident)
    A connected vehicle would…
    a. Be useful in meeting your transportation needs.
    b. Decrease your accident risk.
    c. Reduce your travel delays.
    d. Relieve your travel stress.
    e. Improve your driving performance.

14. How confident are you in the following statements about ease of using connected vehicles? (1: Not at all confident, 7: Extremely confident)
    a. Learning to use a connected vehicle would be easy for you.
    b. You would find it easy to get a connected vehicle to do what you want it to do.
    c. It would be easy to understand information provided by a connected vehicle.
    d. You would find a connected vehicle easy to use overall.

15. Based on your current knowledge, how much do you agree with the following statements about connected vehicles? (1: Strongly disagree and 7: Strongly agree)
    a. Connected vehicles are reliable.
    b. Connected vehicles are dependable.
    c. Overall, connected vehicles are trustworthy.

16. How much do you agree with the following statements regarding attitudes towards using connected vehicles? (1: Strongly disagree and 7: Strongly agree)
    a. It is a good idea to use connected vehicles.
    b. The thought of using connected vehicles is appealing to you.
    c. Using a connected vehicle would be fun to you.
    d. Overall, you have positive feelings about using connected vehicles.

17. How likely do you think that …? (1: Extremely unlikely, 7: Extremely likely)
    a. You would use a connected vehicle in the future.
    b. Your next vehicle purchase would be a connected vehicle.
    c. You would strongly recommend others to use connected vehicles.

Part 4: Personal Characteristics

18. Do you have a driver's license?
    a. Yes
    b. No

19. (If option a. is selected in QN. 18) How many years has it been since you got your driver's license?

    [short answer] years

20. How many motor vehicles are available at your home? Only count those motor vehicles in working condition that are privately owned or leased. Do not count vehicles that are used purely for recreation (RVs, ATVs, etc.).
    a. 0
    b. 1
    c. 2
    d. 3
    e. 4
    f. 5+

21. Do any of the motor vehicles available at your home have any connected features (e.g. information about weather or traffic ahead, emergency phone calls, etc.)?
    a. Yes
    b. No
    c. Don't know

22. How long is your typical daily travel time? Please include all of your two-way trips' (e.g. work commute, shopping, etc.) time in minutes.

    [short answer] minutes

23. What is your gender?
    a. Female
    b. Male
    c. Other: …
    d. Prefer not to answer

24. What is your age?
    a. 18 to 19 years
    b. 20 to 24 years
    c. 25 to 34 years
    d. 35 to 44 years
    e. 45 to 54 years
    f. 55 to 64 years
    g. 65 to 74 years
    h. 75 to 84 years
    i. 85 years and over
    j. Prefer not to answer

25. How do you describe yourself? Check all that apply.
    a. White
    b. Hispanic or Latino
    c. Asian
    d. Black or African American
    e. American Indian or Alaska Native
    f. Native Hawaiian or other Pacific Islander
    g. Other: …
    h. Prefer not to answer

26. How many people of 18 years or older (including yourself) live in your household?
    [short answer]

27. How many people below 18 years old live in your household?
    [short answer]

28. What is your approximate total household income?
    a. Less than $10,000
    b. $10,000 to $14,999
    c. $15,000 to $24,999
    d. $25,000 to $34,999
    e. $35,000 to $49,999
    f. $50,000 to $74,999
    g. $75,000 to $99,999
    h. $100,000 to $149,000
    i. $150,000 or more
    j. Don’t know
    k. Prefer not to answer

29. What is the highest degree or level of school you have completed?

a. Less than a high school diploma
b. High school diploma or equivalent (e.g. GED)
c. Bachelor's or associate degree
d. Graduate degree
e. Prefer not to answer

30. Are you currently a student?
    a. Yes
    b. No

31. Are you currently employed?
    a. Yes
    b. No

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