Paving the Way for Autonomous Vehicles: Understanding Autonomous Vehicle Adoption and Vehicle Fuel Choice under User Heterogeneity

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Abstract

Vehicle automation, along with vehicle electrification and shared mobility, may transform the existing transportation if they are handled properly. However, they may create unintended consequences if the current market dominance of fossil fuel and privately-owned vehicles persists, and travel patterns and transportation policies remain unchanged. The extent of these potential benefits and unintended consequences depends on the expected AV adoption process, people's preferred vehicle powertrain, and AV-related policy and infrastructural support. This paper seeks to understand the impacts of attitudinal factors and roadway designs on people's intention to use AVs and to purchase battery-electric AVs (EAVs) and gasoline-powered AVs (GAVs) under travel and user heterogeneity. Fourteen latent attitudinal factors related to the perceptions and attitudes towards AV and EV technologies, driving, the environment, and personal innovativeness were considered. An EAV-enabled urban design environments were created, featuring dedicated AV lanes, wireless charging for EAVs, and AV pick-up/drop-off zones. Using a stated preference survey data of over 1,300 responses in the U.S., Multiple Indicators and Multiple Causes models are estimated to understand the relationship among various latent variables and capture heterogeneities within the population based on their sociodemographic and behavioral characteristics. The model estimation results show that the respondents' perception of AVs and EAVs advantages, road safety improvement potential, compatibility with their lifestyles and travel needs, and their attitudes towards driving are key factors of their intention to use AVs and purchase EAVs. Furthermore, some segments of the population based on their sociodemographic and travel behavior characteristics are more likely to have a higher intention to use AVs and buy EAVs. The model estimation results and study insights can be used by policymakers to develop road network design guidelines and policies to nudge consumers towards more sustainable transportation options, minimize the unintended consequences of vehicle automation, and maximize its benefits.

Keywords: autonomous vehicles; battery-electric vehicles; transportation policy; technology adoption; roadway design.

1. Introduction

Vehicle automation, along with vehicle electrification and shared mobility, are considered as three revolutions (i.e., vehicle electrification, vehicle automation, and shared mobility) in urban transportation that have the potential to shape the future of how people travel (Fulton, 2018; Sperling, 2018; Sprei et al., 2018). Vehicle electrification refers to replacing the fossil-based fuel powertrain with electricity powertrain, including hybrid, plug-in hybrid, battery, and fuel cell electric vehicles. The development of electric vehicles (EVs) has come far in the past decade with the advancement of battery technology (cost reduction and range increase), financial incentives, infrastructural support (public and private charging stations), and government mandates in China, Europe, and the U.S. (Weiss et al., 2017). Despite public knowledge about the benefits of EVs in reducing greenhouse gas emissions and strong government support, EVs only counted for around one percent of total vehicle sales in the world (Sperling, 2018). Shared mobility represents shared use of a vehicle for performing a trip which can include sharing a vehicle (carsharing) and sharing a passenger ride (ridesharing and on-demand ride services). This represents one of the fast-growing sectors of the emerging sharing economy and mobility services provided by such companies as Uber and Didi Express are actively competing with public transportation, traditional taxi, and private vehicles for passengers (Jin et al., 2018). It can potentially improve vehicle utilization and reduce vehicle ownership and pollution. However, COVID-19 pandemic may have long lasting impacts on impeding the development of shared mobility services (Hadjidemetriou et al., 2020; Guo et al., 2021d). Vehicle automation refers to technological advances to assist and eventually replace human control in the driving process, ranging from no automated functionality to high-level automation (i.e., SAE Level 4 or Level 5 vehicles, hereafter referred to as "AVs"). At levels 4 and 5 of automation, the vehicle operator is not required to drive or take over the driving task when the automated driving system is engaged (SAE International, 2018). Vehicle automation is expected to lead to the next paradigm shift in transportation field despite that potential benefits and issues associated with it are still being critically evaluated and discussed. Many studies predict AVs will be commercially available by the late 2020s in some countries, but they will not be ubiquitous until as early as 2040 or as late as 2060 (Navigant Research, 2014; Litman, 2020). Bansal and Kockelman (2017) estimated that in the United States (the U.S.) by 2045 AVs market penetration could potentially range from 24% under pessimistic estimation and 87% under optimistic estimation. Over 30 states in the U.S., several countries in the European Union (EU), and China have already introduced related legislation to support AV testing and usage (Xu and Fan, 2019). Traditional auto manufacturers such as Ford and GM, ridesharing providers such as Uber and Didi, and technology companies such as Waymo and Baidu have been actively developing AVs and/or AV transportation services with a targeted release date in the 2020s (Walker, 2018; Waymo, 2020). Thomas and Deepti (2018) argued that the development of vehicle automation can accelerate the growth of shared mobility services and lead to a more sustainable transportation future when combined with the advancement of vehicle electrification.

It is possible that vehicle automation, electrification, and shared mobility can transform the existing transportation system into an ideal system with dramatically decreased accident rate and increased mobility; nevertheless, caution is needed as the same set of changes can lead to increasing vehicle use, rising greenhouse gas emissions, and accelerating urban sprawl. It is yet unclear what the future transportation system will look like, how each revolution will unfold across the globe, and whether they will create unintended negative consequences. Understanding traveler decision-making process related to AV adoption, powertrain choice (gasoline-powered vs. electric) when buying the vehicle, and ownership choice (privately-owned vs. shared) can be the first step of answering these questions. It is also important to understand how government can influence those decisions through providing the infrastructural and policy support to help harmonize these revolutions so they achieve their optimal outcomes. Only with the collaboration among government, private sectors, and individual travelers, these three revolutions can potentially be well integrated together to reduce congestion, travel-related emissions, and urban sprawl, and improve the travel experience, safety, mobility, accessibility, and equity (Fagnant and Kockelman, 2015; Fox-Penner et al., 2018; Axsen and Sovacool, 2019 Bennett et al., 2019; Herrenkind et al., 2019; Spurlock et al., 2019).

Different studies have demonstrated various positive scenarios due to simultaneous adoption of both AVs, and EV, supported by transition to shared mobility. With many people trust that AV can provide safer and more efficient travel mode choice, many travelers become AV users who may not experience driving-related stress and fatigue and can better utilize their in-vehicle time for more productivity or leisure (Litman, 2017). Existing roadway designs will be transformed with wireless charging, AV pickup and drop-off areas, and dedicated AV lanes to be more compatible with electric AVs (EAVs), shared mobility services provided by EAVs, and other sustainable travel mode choices such as automated electric buses and electric scooters. Road accidents caused by human errors such as driving under the influence, distraction, or fatigue, which are the main cause of over 90% of accidents, injuries, and fatalities. They can potentially be avoided with the increased vehicle automation and compatible roadway designs (Kyriakidis et al., 2015; Piao et al., 2016). Travelers who do not have or have lost their ability to drive (e.g., fear of driving, aging, or physical and/or intellectual impairment) can leverage AVs (shared or privately owned) to increase their mobility and accessibility which can lead to social inclusion and improved quality-of-life (Fagnant and Kockelman, 2015; Bennett et al., 2019). The use of AV-based taxis, ridesharing, and vehicle sharing services (hereafter referred to as shared AVs) that are powered by electricity and other alternative fuels instead of driving privately-owned gasoline-powered vehicles can significantly reduce vehicle ownership, vehicle miles traveled (VMT), congestion, total system travel time, parking demand, and greenhouse gas emissions (Greenblatt and Saxena, 2015; Chen et al., 2016).

Several studies have explored scenarios and possible consequences where government takes a laissez-faire approach letting the automobile or technology companies dictate when and how these three revolutions will unfold. Without policies and incentives to promote shared mobility, over half of the people who can afford private AVs are unlikely to or will not participate in shared AV programs, and prefer to replace their current vehicles with privately-owned AVs (Bansal et al., 2016; Krueger et al., 2016; Haboucha et al., 2017). Many people have concern over AVs due to the high purchase and usage costs, as well as liability, licensing, security, and privacy concerns associated with AVs (Fagnant and Kockelman, 2015; Masoud and Jaykrishnan, 2017; Tussyadiah et al., 2017). They may become AV-have-nots. The occupancy rate of buses and subways will fall as more people shift to using AVs and many transit routes may be terminated due to lack of funding. This may widen the mobility and accessibility gap between AV-haves and AV-have-nots. Most people still prefer gasoline-powered AVs (GAVs) over EAVs, and the increasing VMT contributes to congestions and emissions (Bansal et al., 2016; Harper et al., 2016; Taiebat et al., 2018; Stilgoe, 2018; Zhang et al., 2018; Soteropoulos et al., 2019). Existing suburbs will become less affordable as more people who can afford AVs opts for longer commutes, work during the commute, and live further away from the city center. These can lead to intensified urban sprawl which can have profound impacts on land use, property price, etc. (Fagnant and Kockelman, 2015; Guo et al., 2016; Heinrichs, 2016; Guo et al., 2017; Hawkins and Habib, 2019; Guo and Peeta, 2020). Some studies suggested that if the current domination of privately-owned, gasoline-powered vehicles persists and people's travel patterns and transportation policies remain unchanged, the addition of AVs in to the transportation network would lead to increased overall VMT and emissions due to induced travel demand, decreased value of in-vehicle travel time (e.g., people may choose to live further away from their workplace), unoccupied VMT, and increased accidents due to mixed traffic flow of vehicles with different levels of automation (A. Brown et al., 2014; B. Brown et al., 2014; Fagnant and Kockelman, 2015; de Almeida Correia and van Arem, 2016; Bösch et al., 2017; Auld et al., 2018; Zhang et al., 2018; Zhao and Kockelman, 2018).

To sum up, how the future of transportation will upfold depends on people's decisions made related to vehicle automation, vehicle powertrain choice (GAVs or EAVs), and shared mobility. Hence, it is important for policymakers to design infrastructural and policy support to influence how these revolutions will unfold to minimize unintended negative consequences and maximize their benefits. To achieve these, it is important to understand what factors affect these traveler decisions and whether these decisions can be influenced by designing forward-thinking policy and infrastructural support. This study seeks to address these two questions by understanding (i) the impacts of fourteen attitudinal factors on people's intention to use AVs and their intention to purchase GAVs and EAVs while accounting for travel and sociodemographic heterogeneities; and (ii) the impacts of urban roadway designs for accommodating AVs and EAVs on their intention to purchase GAVs and EAVs.

The remainder of the paper is organized as follows. Section 2 highlights the literature review of some publications related to this topic in peer-reviewed journals between 2014 and 2019. Section 3 reviews the methodologies related to the data analysis, model constructs, and hypothesis associated with the model constructs in this study. Section 4 discusses the survey design, survey distribution, and descriptive statistics. Section 5 focuses on study results and model estimation results. Section 6 presents some policy recommendations and Section 7 provides some concluding comments, study limitations, and future work.

2. Literature Review and Research Objectives

2.1. Literature review

An ample number of studies that have investigated various factors that influence people's intention to use (i.e., using services provided by autonomous vehicle technology) and to purchase AVs. Considering that AV technology has yet to reach a mature stage, most studies rely on stated preference survey method to understand the impacts of various factors on public acceptance and adoption decisions of AVs. However, most existing studies in this area did not consider what vehicle fuel type AVs might use. A possible reason is an optimistic assumption that people may not be willing to buy GAVs despite that most vehicles on the road today and most vehicles being sold (except a few countries such as China and Norway) are still gasoline-powered. Such status quo (preference of gasoline-powered vehicles) may unlikely change without being sufficiently challenged. Hence, our literature review includes studies that have focused on people's intention to use AVs and to purchase battery electric conventional vehicles (BEVs) which is one of the most commonly used alternative fuel vehicles.

Tables 1–3 summarize 58 recent studies in related fields and their key findings and Table 4 summarizes their study population, sample size, method of recruitment, and types of variables included. These studies showed that three types of factors influence people's intention to use and to purchase AVs or BEVs, including sociodemographic factors and travel-related factors (Table 1), attitudinal factors (Table 2), and availability of policy measures (Table 3). It is important to note that not all the factors included in the literature review are considered in each study.

Table 1. Literature review summary related to sociodemographic factors and travel-related factors affecting people's intention to use and/or purchase BEVs and AVs

	Intention to use and/or purchase BEVs		**Intention to use and/or purchase AVs**	
Factors	**References**	**Most common findings**	**References**	**Most common findings**
Gender	Jensen et al. (2014) × Nayum and Klöckner (2014) Peters and Dütschke (2014) + Plötz et al. (2014) + Dumortier et al. (2015) × Barth et al. (2016) × Morton et al. (2016) Wang et al. (2017) Berkeley et al. (2018) Huang and Qian (2018) × Westin et al. (2018) Carley et al. (2019) + Okada et al. (2019) Qian et al. (2019) Simsekoglu and Nayum (2019) Sovacool et al. (2019) × Spurlock et al. (2019) ×	The impacts of gender on the intention to use and/or purchase BEVs are **complicated**. Most studies find that gender **does not have a statistically significant impact** on their intention to use and/or purchase BEVs. Among studies that found that gender plays a role, most of them state that **women** have a **greater** intention to use and/or purchase BEVs compared to men.	Payre et al. (2014) × Kyriakidis et al. (2015) Bansal et al. (2016) × Hohenberger et al. (2016) Zmud et al. (2016) Bansal and Kockelman (2017) Haboucha et al, (2017) + Lavieri et al. (2017) × Hulse et al. (2018) Nazari et al. (2018) Shabanpour et al. (2018) × Acheampong and Cugurullo (2019) Berliner et al. (2019) × Cunningham et al. (2019) × Hardman et al. (2019) × Liu et al. (2019) × Sheela and Mannering (2019) Spurlock et al. (2019) Wang and Zhao (2019) Zoellick et al. (2019) ×	The impacts of gender on the intention to use and/or to purchase AVs are **complicated**. Most studies find that gender **does not have a statistically significant impact** on their intention to use and/or to purchase AVs. Among studies that found gender plays a role, most of them found that **men** have a **greater** intention to use and/or purchase AVs compared to women.
Age	Nayum and Klöckner (2014) × Dumortier et al. (2015) Valeri and Danielis (2015) Barth et al. (2016) × Morton et al. (2016) × Wang et al. (2017) × Berkeley et al. (2018) Huang and Qian (2018) × Lane et al. (2018) × Westin et al. (2018) Carley et al. (2019) Okada et al. (2019) Qian et al. (2019) × Simsekoglu and Nayum (2019) × Sovacool et al. (2019) × Spurlock et al. (2019)	The impacts of age on the intention to use and/or purchase BEVs are **complicated**. Most studies find that age **does not have a statistically significant impact** on their intention to use and/or purchase BEVs. Among studies that state that age plays a role, most found that **older people** have a **lesser** intention to use and/or purchase BEVs younger ones.	Payre et al. (2014) × Kyriakidis et al. (2015) Bansal et al. (2016) × Zmud et al. (2016) × Bansal and Kockelman (2017) Haboucha et al, (2017) Lavieri et al. (2017) Hulse et al. (2018) Nazari et al. (2018) Shabanpour et al. (2018) Acheampong and Cugurullo (2019) Berliner et al. (2019) × Cunningham et al. (2019) Hardman et al. (2019) × Liu et al. (2019) × Sheela and Mannering (2019) Spurlock et al. (2019) Wang and Zhao (2019) Zoellick et al. (2019)	**Older people** have a **lesser** intention to use and/or purchase AVs younger ones.

Table 1. (Continued)

	Intention to use and/or purchase BEVs		Intention to use and/or purchase AVs	
Factors	**References**	**Most common findings**	**References**	**Most common findings**
Education	Peters and Dütschke (2014) × Nayum and Klöckner (2014) Dumortier et al. (2015) × Morton et al. (2016) × Wang et al. (2017) × Huang and Qian (2018) Lane et al. (2018) × Westin et al. (2018) Carley et al. (2019) × Simsekoglu and Nayum (2019) × Sovacool et al. (2019) × Spurlock et al. (2019)	People's education level **does not have a statistically significant impact** on the intention to use and/or purchase BEVs. Among studies that state that education plays a role, most found that people with **higher** education have a **greater** intention to use and/or purchase BEVs.	Zmud et al. (2016) × Haboucha et al, (2017) Lavieri et al. (2017) × Acheampong and Cugurullo (2019) Hardman et al. (2019) × Liu et al. (2019) Sheela and Mannering (2019)	People with **higher** education have a **greater** intention to use and/or purchase AVs.
Income	Dumortier et al. (2015) × Valeri and Danielis (2015) Morton et al. (2016) × Wang et al. (2017) × Lane et al. (2018) × Westin et al. (2018) × Carley et al. (2019) + Okada et al. (2019) Simsekoglu and Nayum (2019) × Spurlock et al. (2019)	People's income level **does not have a statistically significant impact** on their intention to use and/or purchase BEVs. Among studies that state that income plays a role, most have found that people with a **higher** income have a **greater** intention to use and/or purchase BEVs.	Kyriakidis et al. (2015) Zmud et al. (2016) × Bansal et al. (2016) Shabanpour et al. (2018) Berliner et al. (2019) × Cunningham et al. (2019) × Hardman et al. (2019) Liu et al. (2019) Sheela and Mannering (2019) Spurlock et al. (2019) Wang and Zhao (2019)	People with a **higher** income have a **greater** intention to use and/or purchase AVs.
Having a driver's license	N/A	N/A	Bansal et al. (2016) × Nazari et al. (2018) × Liu et al. (2019) ×	Whether a person has a driver's license or not **does not have a statistically significant impact** on their intention to use and/or purchase AVs.
Household size	Huang and Qian (2018) Westin et al. (2018) × Carley et al. (2019) × Sovacool et al. (2019) ×	People's household size **does not have a statistically significant impact** on their intention to use and/or purchase BEVs. Among studies that state that household size plays a role, most have found that people with a **larger** household size have a **greater** intention to use and/or purchase BEVs.	Bansal et al. (2016) Bansal and Kockelman (2017) Nazari et al. (2018) Shabanpour et al. (2018) Berliner et al. (2019) × Hardman et al. (2019) × Sheela and Mannering (2019)	People with a **larger** household size have a **greater** intention to use and/or purchase AVs.

Table 1. (Continued)

	Intention to use and/or purchase BEVs		Intention to use and/or purchase AVs	
Factors	**References**	**Most common findings**	**References**	**Most common findings**
Vehicle miles travelled (VMT)	Westin et al. (2018) Carley et al. (2019) ×	One study found people who have a **more** VMT have a **greater** intention to use and/or purchase BEVs. The other one suggested that VMT does not have a statistically significant impact on their intention to use and/or purchase BEVs.	Bansal et al. (2016) × Haboucha et al. (2017) Nazari et al. (2018) + Shabanpour et al. (2018) * Berliner et al. (2019) × Sheela and Mannering (2019)	People who have a **more** VMT have a **greater** intention to use and/or purchase AVs.
Classification of living area or living area density	Westin et al. (2018) × Carley et al. (2019) Spurlock et al. (2019)	People who live in **suburban, rural** or **low population density** areas have a **lesser** intention to use and/or purchase BEVs compared to people who live in urban and high population density areas.	Bansal et al. (2016) Lavieri et al. (2017) × Nazari et al. (2018) Shabanpour et al. (2018) Berliner et al. (2019) ×	People who live in **suburban, rural** or **low population density** areas have a **lesser** intention to use and/or purchase AVs compared to people who live in urban and high population density areas.
Number of previous crash experiences	N/A	N/A	Bansal et al. (2016) × Shabanpour et al. (2018) Sheela and Mannering (2019)	People who have been involved in **more crashes** have a **greater** intention to use and/or purchase AVs.

(× indicates the factor was investigated in the study but was not found to be significant; + indicates the study findings are opposite of the most common findings listed).

Table 2. Literature review summary related to attitudinal factors affecting people's intention to and/or purchase BEVs and AVs

	Intention to use and/or purchase BEVs		Intention to use and/or purchase AVs	
Factors	**References**	**Most common findings**	**References**	**Most common findings**
Perceived vehicle features/attributes				
Relative advantage in terms of vehicle performance (e.g., maintenance and fuel cost savings)	Jensen et al. (2014) Krupa et al. (2014) Barth et al. (2016) White and Sintov (2017) Lane et al. (2018) × Carley et al. (2019) Sovacool et al. (2019) ×	People who think BEVs have a relative **advantage** over gasoline-powered vehicles (GVs) have a **greater** intention to use and/or purchase BEVs.	Payre et al. (2014) Shin et al. (2015) Zmud et al. (2016) König and Neumayr (2017) Kaur and Rampersad (2018) Nordhoff et al. (2018) Nielsen and Haustein (2018) Panagiotopoulos and Dimitrakopoulos (2018) Sanbonmatsu et al. (2018) Cunningham et al. (2019) Liu et al. (2019)	People who think AVs have a relative **advantage** over human-driven vehicles (HVs) have a **greater** intention to use and/or purchase AVs.
Compatibility	N/A	N/A	Payre et al. (2014) Shin et al. (2015) Zmud et al. (2016) König and Neumayr (2017) Kaur and Rampersad (2018) Nordhoff et al. (2018) Nielsen and Haustein (2018) Panagiotopoulos and Dimitrakopoulos (2018) Sanbonmatsu et al. (2018) Cunningham et al. (2019) Liu et al. (2019)	People who believe that using AVs is **compatible** with their lifestyle and needs have a **greater** intention to use and/or purchase AVs.
Complexity or perceived ease of use	N/A	N/A	Payre et al. (2014) Shin et al. (2015) Zmud et al. (2016) König and Neumayr (2017) Kaur and Rampersad (2018) Nordhoff et al. (2018) Nielsen and Haustein (2018) Panagiotopoulos and Dimitrakopoulos (2018) Sanbonmatsu et al. (2018) Cunningham et al. (2019) Liu et al. (2019)	People who believe that AVs are **difficult** to use have a **lesser** intention to use and/or purchase AVs.

Table 2. Continued

	Intention to use and/or purchase BEVs		Intention to use and/or purchase AVs	
Factors	**References**	**Most common findings**	**References**	**Most common findings**
Perceived vehicle features/attributes (continued)				
Environmental benefits	Barth et al. (2016) × Lane et al. (2018) Simsekoglu and Nayum (2019)	People who believe that using BEVs has environmental **benefits** have a **greater** intention to use and/or purchase BEVs.	N/A	N/A
Range anxiety	Valeri and Danielis (2015) Berkeley et al. (2018) Lane et al. (2018) ×	People who have **range anxiety** have a **lesser** intention to use and/or purchase BEVs.	N/A	N/A
Perceived risk and concerns (e.g., data transmission and privacy)	N/A	N/A	Choi and Ji (2015) Kyriakidis et al. (2015) Hohenberger et al. (2016) Lavieri et al. (2017) × Nazari et al. (2018) Cunningham et al. (2019) × Jing et al. (2019) Liu et al. (2019) Wang and Zhao (2019)	People who believe using AVs is **risky** and have higher **concerns** over using them have a **lesser** intention to use and/or purchase AVs.
Perceived safety improvement	N/A	N/A	Kyriakidis et al. (2015) Zmud et al. (2016) Bansal and Kockelman (2017) Haboucha et al. (2017) Hulse et al. (2018) Panagiotopoulos and Dimitrakopoulos (2018) Sanbonmatsu et al. (2018) Shabanpour et al. (2018) Berliner et al. (2019) Liu et al. (2019)	People who believe using AVs can **improve** road safety have a **greater** intention to use and/or purchase AVs.
Social factors				
Subjective norms	Barth et al. (2016) Schmalfuß et al. (2017) Simsekoglu and Nayum (2019)	People who believe that most of the people who are important to them would **approve** of them purchasing and/or using BEVs have a **greater** intention to use and/or purchase BEVs.	Payre et al. (2014) Buckley et al. (2018) Kaur and Rampersad (2018) Nordhoff et al. (2018) Acheampong and Cugurullo (2019) Jing et al. (2019) Liu et al. (2019)	People who believe that most of the people who are important to them would **approve** of them purchasing and/or using AVs have a **greater** intention to use and/or purchase AVs.

Table 2. Continued

	Intention to use and/or purchase BEVs		Intention to use and/or purchase AVs	
Factors	**References**	**Most common findings**	**References**	**Most common findings**
Social factors (continued)				
Image	Huang and Qian (2018) × Lane et al. (2018) ×	People's perceived image of using BEVs **does not have a statistically significant impact** on their intention to use and/or purchase BEVs.	Acheampong and Cugurullo (2019)	People who believe that using AVs has a **positive** image in the society have a **greater** intention to use and/or purchase AVs.
Other types of perceptions and attitude				
Personal innovativeness	Morton et al. (2016) Huang and Qian (2018) × Lane et al. (2018)	People who have a **greater** personal innovativeness have a **greater** intention to use and/or purchase BEVs.	Shin et al. (2015) Zmud et al. (2016) Bansal and Kockelman (2017) Haboucha et al. (2017) Lavieri et al. (2017) Nazari et al. (2018)	People who have a **greater** personal innovativeness have a **greater** intention to use and/or purchase AVs.
Environmental concerns, ecological awareness, or pro-environmental attitudes, values, beliefs, and norms	Krupa et al. (2014) Helveston et al. (2015) Barbarossa et al. (2015) Barth et al. (2016) × Wang et al. (2017) White and Sintov (2017) × Westin et al. (2018) × Carley et al. (2019) × Ingeborgrud and Ryghaug (2019) Okada et al. (2019) Spurlock et al. (2019) ×	People who are **concerned with the** negative environmental impacts of traveling have a **greater** intention to use and/or purchase BEVs.	N/A	N/A
Love of driving and locus of control	N/A	N/A	Payre et al. (2014) + Choi and Ji (2015) Haboucha et al, (2017) × Hardman et al. (2019) +	People's love of driving and locus of control does not have a statistically significant impact on their intention to use and/or purchase AVs. Among studies that state that this factor plays a role, one study found that people who **love** driving have a **lesser** intention to use and/or purchase AVs.

	Intention to use and/or purchase BEVs		Intention to use and/or purchase AVs	
Factors	**References**	**Most common findings**	**References**	**Most common findings**
Experience with the vehicle	Dumortier et al. (2015) Barth et al. (2016) × Schmalfuß et al. (2017) Huang and Qian (2018) Carley et al. (2019) Sovacool et al. (2019)	People who have **positive** experience (e.g., ownership or test driving) with BEVs have a **greater** intention to use and/or purchase BEVs.	Chen et al. (2019) Zoellick et al. (2019)	People who have **positive** experience (e.g., test-driven AVs) with AVs have a **greater** intention to use and/or purchase AVs.
Knowledge and awareness	Barth et al. (2016) Simsekoglu and Nayum (2019) × Sovacool et al. (2019)	People who consider themselves as **knowledgeable** of BEVs have a **greater** intention to use and/or purchase BEVs.	König and Neumayr (2017) Nordhoff et al. (2018) Berliner et al. (2019) Cunningham et al. (2019) Hardman et al. (2019) Jing et al. (2019)	People who consider themselves as **knowledgeable** of AVs have a **greater** intention to use and/or purchase AVs.

(× indicates the factor was investigated in the study but was not found to be significant; + indicates the study findings are opposite of the most common findings listed).

Table 3. Literature review summary related to the availability of policies measures affecting people's intention to use and/or purchase BEVs and AVs

	Intention to use and/or purchase BEVs		**Intention to use and/or purchase AVs**	
Policies	**References**	**Most common findings**	**References**	**Most common findings**
Financial incentive policy measures	Krupa et al. (2014) Helveston et al. (2015) Wang et al. (2017) Huang and Qian (2018) Lane et al. (2018) Carley et al. (2019) Ingeborgrud and Ryghaug (2019)	Financial incentives can **promote** the adoption of BEVs.	Harper et al. (2016) Sparrow and Howard (2017)	Financial incentives can **promote** the adoption of AVs.
Information provision policy measures	Dumortier et al. (2015) Wang et al. (2017) Ingeborgrud and Ryghaug (2019)	Information provision policy can **promote** the adoption of BEVs.	Du et al. (2019a, b) Lee et al. (2019) Sheela and Mannering (2019)	Information provision policy can **promote** the adoption of AVs.
Convenience policy and infrastructural support measures	Jensen et al. (2014) Krupa et al. (2014) Dumortier et al. (2015) Wang et al. (2017) Schmalfuß et al. (2017) White and Sintov (2017) × Huang and Qian (2018) Lane et al. (2018) Westin et al. (2018) × Carley et al. (2019) × Ingeborgrud and Ryghaug (2019) Qian et al. (2019) Sovacool et al. (2019)	Convenience policy and infrastructural support measures can **promote** the adoption of BEVs.	Shabanpour et al. (2018) Chen (2019)	Convenience policy and infrastructural support measures can **promote** the adoption of AVs.

Note: The classification of policy measures is based on Wang et al. (2017).
(× indicates the factor was investigated in the study but was not found to be significant; + indicates the study findings are opposite of the most common findings listed).

Table 4. Survey characteristics

Reference	Factors			Region	Sample Size	Recruitment method	Type
	Socio	Attitude	Policy				
Jensen et al. (2014)	✓	✓		Denmark	1,176	Self-distribution	BEV
Krupa et al. (2014)		✓		USA	911	MTurk	BEV
Nayum and Klöckner (2014)	✓	✓		Norway	1,421	Self-distribution	BEV
Payre et al. (2014)	✓	✓		France	421	Self-distribution	AV
Peters and Dütschke (2014)	✓	✓		Germany	969	Self-distribution	BEV
Plötz et al. (2014)	✓	✓		Germany	210	Self-distribution	BEV
Barbarossa et al. (2015)		✓		Denmark, Belgium & Italy	2,005	Survey companies	BEV
Choi and Ji (2015)		✓		South Korea	552	Self-distribution	AV
Dumortier et al. (2015)	✓		✓	USA	2,759	Qualtrics	BEV
Helveston et al. (2015)		✓		China & USA	832	MTurk	BEV
Kyriakidis et al. (2015)	✓	✓		109 countries	5,000	Figure Eight	AV
Shin et al. (2015)	✓	✓		South Korea	675	Face-to-face interview	AV
Valeri and Danielis (2015)	✓	✓		Italy	1,452	Face-to-face interview	BEV
Bansal et al. (2016)	✓	✓		USA	347	Neighborhood association	AV
Barth et al. (2016)	✓	✓		Germany	548	WorkHub	BEV
Hohenberger et al. (2016)	✓	✓		Germany	1,603	Self-distribution	AV
Morton et al. (2016)	✓	✓		UK	506	Mail	BEV
Zmud et al. (2016)	✓	✓		USA	556	Not specify	AV
Bansal and Kockelman (2017)	✓			USA	2,167	Qualtrics	AV
Daziano et al. (2017)		✓		USA	1,260	Qualtrics	AV
Haboucha et al, (2017)	✓	✓		Israel & NA	721	Social media	AV
König and Neumayr (2017)	✓	✓		Mostly from Austria	489	Personal network	AV
Lavieri et al. (2017)	✓	✓		USA	1,832	Open source data	AV
Schmalfuß et al. (2017)		✓		Germany	286	Social media & personal email list	BEV
Wang et al. (2017)	✓	✓	✓	China	324	Auto S4 shops	AV
White and Sintov (2017)	✓	✓	✓	USA	355	Mail list	BEV
Berkeley et al. (2018)	✓	✓		UK	26,195	Automobile Association	BEV
Buckley et al. (2018)		✓		USA	74	Self-distribution	AV
Huang and Qian (2018)	✓	✓		China	348	Shopping malls	BEV
Hulse et al. (2018)	✓	✓		UK	925	Self-distribution	AV
Kaur and Rampersad (2018)		✓		Australia	101	University	AV
Lane et al. (2018)	✓	✓	✓	USA	1,080	Qualtrics	BEV

Table 4. Continued

Reference	Factors			Region	Sample Size	Recruitment	Type
	Socio	Attitude	Policy				
Nordhoff et al. (2018)	✓	✓		116 countries	7,755	Figure Eight	AV
Nielsen and Haustein (2018)		✓		Denmark	3,040	Public sector	AV
Panagiotopoulos and Dimitrakopoulos (2018)		✓		Greece	483	Self-distribution	AV
Sanbonmatsu et al. (2018)		✓		USA	114	MTurk	AV
Shabanpour et al. (2018)	✓		✓	USA	1013	Qualtrics	AV
Westin et al. (2018)	✓	✓		Sweden	1,192	Statistic Sweden	BEV
Acheampong and Cugurullo (2019)	✓	✓		Ireland	507	Self-distribution	AV
Berliner et al. (2019)	✓	✓		USA	2,697	Public projects	AV
Carley et al. (2019)	✓	✓		USA	2,038	Growth from Knowledge	BEV
Chen (2019)	✓	✓		China	700	Face-to-face interview	AV
Cunningham et al. (2019)	✓	✓		Australian & New Zealand	6,133	Qualtrics	AV
Du et al. (2019a)	✓	✓		USA	32	University	AV
Du et al. (2019b)	✓	✓		USA	61	University	AV
Hardman et al. (2019)	✓	✓		USA	2,715	Mail	AV
Ingeborgrud and Ryghaug (2019)		✓	✓	Norway	16,087	Norwegian EV Association	BEV
Jing et al. (2019)		✓		China	906	SoJump	AV
Lee et al. (2019)		✓		South Korea	313	Macromill Embrain	AV
Liu et al. (2019)	✓	✓		China	1,355	Face-to-face interview	AV
Okada et al. (2019)		✓		Japan	10,6982	Not specify	BEV
Qian et al. (2019)	✓			China	1,076	Face-to-face interview	BEV
Simsekoglu and Nayum (2019)	✓	✓		Norway	205	Public database	BEV
Sheela and Mannering (2019)	✓			USA	2,338	American Automobile Association	AV
Sovacool et al. (2019)	✓	✓	✓	China	805	Universities	BEV
Spurlock et al. (2019)	✓	✓		USA	1,026	Mail	BEV & AV
Wang and Zhao (2019)	✓	✓		Singapore	1,142	Survey companies	AV
Zoellick et al. (2019)	✓			Germany	125	Face-to-face interview	AV

In terms of sociodemographic and travel-related factors, some studies suggest that factors such as *gender* (Jensen et al., 2014; Dumortier et al., 2015; Huang and Qian, 2018; Sovacool et al., 2019; Spurlock et al., 2019), *age* (Nayum and Klöckner, 2014; Barth et al., 2016; Morton et al., 2016; Wang et al., 2017; Huang and Qian, 2018; Lane et al., 2018; Simsekoglu and Nayum, 2019; Sovacool et al., 2019), *education*

(Peters and Dütschke, 2014; Dumortier et al., 2015; Barth et al., 2016; Morton et al., 2016; Wang et al., 2017; Lane et al., 2018; Carley et al., 2019; Simsekoglu and Nayum, 2019; Sovacool et al., 2019), *income* (Dumortier et al., 2015; Morton et al., 2016; Wang et al., 2017; Lane et al., 2018; Westin et al., 2018; Simsekoglu and Nayum, 2019), *household size* (Westin et al., 2018; Carley et al., 2019; Sovacool et al., 2019), and *vehicle miles traveled* (Carley et al., 2019) does not have a statistically significant impact on their intention to use and/or purchase BEVs (Table 1). Only *the living area classification* was found to be significant in some studies (Carley et al., 2019; Spurlock et al., 2019) in which people who live in suburban, rural or low population density areas have a lesser intention to use and/or purchase BEVs.

Some studies show that a *greater* intention to use and/or purchase AVs was associated with *younger age* (Kyriakidis et al., 2015; Bansal and Kockelman, 2017; Haboucha et al., 2017; Lavieri et al., 2017; Hulse et al., 2018; Nazari et al., 2018; Shabanpour et al., 2018; Acheampong and Cugurullo, 2019; Sheela and Mannering, 2019; Spurlock et al., 2019; Wang and Zhao, 2019; Zoellick et al., 2019), *higher education* (Haboucha et al,, 2017; Acheampong and Cugurullo, 2019; Liu et al., 2019; Sheela and Mannering, 2019), *higher income* (Kyriakidis et al., 2015; Bansal et al., 2016; Shabanpour et al., 2018; Hardman et al., 2019; Liu et al., 2019; Sheela and Mannering, 2019; Spurlock et al., 2019; Wang and Zhao, 2019), *larger household size* (Bansal et al., 2016; Bansal and Kockelman, 2017; Nazari et al., 2018; Shabanpour et al., 2018; Sheela and Mannering, 2019), *more vehicle miles traveled* (Haboucha et al., 2017; Sheela and Mannering, 2019), and *living in urban area* (Bansal et al., 2016; Nazari et al., 2018; Shabanpour et al., 2018)

Attitudinal factors can be classified into three large categories: perceived vehicle features/attributes (the perception of a certain vehicle features/attributes compared to its competitors'), social factors, and other types of perceptions and attitudes (Table 2). Unlike sociodemographic and travel characteristics, most of the studies reached similar conclusions in terms of attitudinal factors' impacts on people's intention to use and/or purchase BEVs or AVs. *Relative advantage* is defined as the perceived performance advantage (e.g., cost and travel time savings) of using AVs and BEVs compared to using human-driven vehicles (HVs) and gasoline-powered vehicles (GVs), respectively. Some studies suggested that people who think BEVs have a relative advantage over GVs have a greater intention to use and/or purchase BEVs (Jensen et al., 2014; Krupa et al., 2014; Barth et al., 2016; White and Sintov, 2017; Carley et al., 2019). *Compatibility* represents the compatibility of using AVs with their work and lifestyle needs and *complexity* is used to capture the perceived difficulty or level of complication involved in operating AVs. Many studies reached similar conclusions that people who think AVs have a relative advantage over HVs, using AVs is compatible with their lifestyle and needs, or AVs are easy to use have a greater intention to use and/or purchase AVs (Payre et al., 2014; Shin et al., 2015; Zmud et al., 2016; König and Neumayr, 2017; Kaur and Rampersad, 2018; Nordhoff et al., 2018; Nielsen and Haustein, 2018; Panagiotopoulos and Dimitrakopoulos, 2018; Sanbonmatsu et al., 2018; Cunningham et al., 2019; Liu et al., 2019).

Both *perceived environmental benefits* and *range anxiety* are related to BEVs only. Lane et al. (2018) and Simsekoglu and Nayum (2019) concluded that people who believe that using BEVs has environmental benefits have a greater intention to use and/or purchase BEVs. Valeri and Danielis (2015) and Berkeley et al. (2018) suggested that people who have range anxiety have a lesser intention to use and/or purchase BEVs. *Perceived risk and concerns* are related to the perceived risks (e.g., privacy and liability concerns) associated with operating an AV. Some studies found out that people who believe using AVs is risky and have higher concerns over using them have a lesser intention to use and/or purchase AVs (Choi and Ji, 2015; Kyriakidis et al., 2015; Hohenberger et al., 2016; Nazari et al., 2018; Jing et al., 2019; Liu et al., 2019; Wang and Zhao, 2019). Many studies showed that people who believe using AVs can improve road safety have a greater intention to use and/or purchase AVs (Kyriakidis et al., 2015; Zmud et al., 2016; Bansal and Kockelman, 2017; Haboucha et al., 2017; Hulse et al., 2018; Panagiotopoulos and Dimitrakopoulos, 2018; Sanbonmatsu et al., 2018; Shabanpour et al., 2018; Berliner et al., 2019; Liu et al., 2019). In terms of social factors, Barth et al. (2016), Schmalfuß et al. (2017), and Simsekoglu and Nayum (2019) suggested that *subjective norms* (i.e., approval for purchasing and/or using BEVs from the most people who are important to them) positively impact participant intention to use and/or purchase BEVs, while many studies found the same relationship for AVs (Payre et al., 2014; Buckley et al., 2018; Kaur and Rampersad, 2018; Nordhoff et al., 2018; Acheampong and Cugurullo, 2019; Jing et al., 2019; Liu et al., 2019). Acheampong and Cugurullo (2019) also suggested that people who believe that using AVs has a positive image in society have a greater intention to use and/or purchase AVs.

Other attitudinal factors that affect BEV and AV adoption attitudes include *personal innovativeness*, *environmental concerns* (ecological awareness, or pro-environmental attitudes, values, beliefs, and norms), *love of driving and locus of control* (i.e., people who believes that they can control events), *experience with the vehicle*, and *knowledge and awareness* are among other attitudinal factors that affect BEV and AV adoption. People who have greater personal innovativeness have a greater intention to use and/or purchase BEVs (Morton et al., 2016; Lane et al., 2018) and AVs (Shin et al., 2015; Zmud et al., 2016; Bansal and Kockelman, 2017; Haboucha et al., 2017; Lavieri et al., 2017; Nazari et al., 2018). People who have positive experience (e.g., ownership or test-driving) with the BEVs and AVs have a greater intention to use and/or purchase BEVs (Dumortier et al., 2015; Schmalfuß et al., 2017; Huang and Qian, 2018; Carley et al., 2019; Sovacool et al., 2019) and AVs (Chen et al., 2019; Zoellick et al., 2019), respectively. People who consider themselves as knowledgeable of BEVs and AVs have a greater intention to use and/or purchase BEVs (Barth et al., 2016; Sovacool et al., 2019) and AVs (König and Neumayr, 2017; Nordhoff et al., 2018; Berliner et al., 2019; Cunningham et al., 2019; Hardman et al., 2019; Jing et al., 2019), respectively. Many studies suggested that people who are concerned with the negative environmental impacts of traveling have a greater intention to use and/or purchase BEVs (Krupa et al., 2014; Helveston et al., 2015; Barbarossa et al., 2015; Wang et al., 2017; Ingeborgrud and Ryghaug, 2019; Okada et al., 2019). Choi and Ji (2015) found that people who love driving have a lesser intention to use and/or purchase AVs.

In terms of the policy impacts, financial incentive policy measures, information provision policy measures, convenience policies, and infrastructural support measures have been explored in their impacts on promoting BEV and AV adoption (Wang et al., 2017). Financial incentive policy measures refer to promoting BEV or AV adoption by reducing vehicle purchasing and operating costs, through policies such as direct subsidies and road tolling exemption. Information provision policy measures present using behavioral intervention strategies to provide information (e.g., battery life information) to potential users for promoting adoption, and infrastructural support measures means using policies (e.g., access to high occupancy vehicle (HOV) lanes) and infrastructure (e.g., dedicated lanes and dedicated parking) support to provide convenience to potential users to promote BEV or AV adoption. The findings related to these policies are relatively consistent and most studies show that these policy measures can potentially facilitate BEV and AV adoption (Krupa et al., 2014; Dumortier et al., 2015; Helveston et al., 2015; Chen et al., 2016; Harper et al., 2016; Wang et al., 2017; Huang and Qian, 2018; Lane et al., 2018; Carley et al., 2019; Chen, 2019; Du et al., 2019a; Ingeborgrud and Ryghaug, 2019; Lee et al., 2019; Sheela and Mannering, 2019).

In terms of the study region, only 7 out of 58 studies investigated the AV or BEV adoption in more than one country (Table 4). Among the remaining 51 studies, the U.S. (19), the EU (19), and China (7) are the most commonly studied regions. The median sample size of these studies is 918 and only 4 studies covered all three types of factors (i.e., Wang et al., 2017; White and Sintov, 2017; Lane et al., 2018; Sovacool et al., 2019).

Studies in Table 3 highlight the similarities and differences in terms of the factors affecting AV and BEV adoption. These studies also show that the impacts of various factors on AV or BEV adoption can be very different, sometimes contradicting, based on the underlying assumptions, experiment setup, and the study nature and survey sample size. These studies provide valuable insights to policymakers for designing effective behavioral intervention strategies and policies for promoting AV or BEV adoption. However, to the best of our knowledge, none of the existing studies have addressed: (i) the potential similarities and differences among the factors that affect people's intention to purchase gasoline-powered AVs (GAVs) and battery-electric AVs (EAVs); and (ii) the impacts of the availability of dedicated AV lanes and EAV wireless charging options on people's intention to purchase GAVs and EAVs.

2.2. Research objectives

To address these gaps, a model framework is developed to capture the impacts of various attitudinal factors on people's intention to use AVs, purchase GAVs and EAVs, and how these intentions can be affected by infrastructural support that enables EAVs. These attitudinal factors, sociodemographic and travel characteristics, and their hypothesized relationships were identified using information from published literature pertaining to AV or BEV adoption. Seven travel and sociodemographic variables were introduced to capture the potential heterogeneities among observations, including gender, age, highest completed level of education, annual household income, the area they live in (urban, suburban, or rural), household size, and the most commonly used mode of transportation for the commute.

To evaluate the proposed model and test the hypothesized relationships, a stated-preference survey was designed with a targeted population of U.S. travelers over the age of 18 years. Participants answered questions that captured various attitudinal factors and their intention to use AVs and to purchase GAVs and EAVs. Then, they were asked how their intention to purchase GAVs and EAVs would change if an *EAV-enabled roadway design* is used on most of the routes they usually travel on. This design features a dedicated AV lane and roadside parking is replaced with AV pick-up/drop-off zones. The dedicated AV lane has a higher speed limit and includes a wireless charging option for EAVs. Such design can potentially promote EAV adoption as it provides more infrastructural support for EAVs (i.e., higher speed limit, wireless charging, and pick-up/drop-off zones) while reducing some support for human-driven vehicles (i.e., removed roadside parking). Over 1,300 completed surveys were collected and analyzed using Multiple Indicators Multiple Causes (MIMIC) modeling, a special case of Structural Equation Modelling (SEM). Understanding these impacts can assist policymakers in designing effective behavioral intervention strategies and policies to facilitate the desired co-evolutions of vehicle automation, vehicle electrification, and shared mobility to minimize their unintended negative consequences, and promote smooth and sustainable transition to a new transportation system.

3. Methodological Approach

3.1 Methodological review

SEM has been widely used in travel behavior research and other fields such as marketing research, psychology, sociology, and education (Golob, 2003). It is considered a suited method to address some modeling challenges, including studies in which some variables are unobservable (i.e., latent) and are measured using one or more exogenous variables, handling a large number of endogenous and exogenous variables, and addressing complex underlying social phenomena (Washington et al., 2020). The latent variables represent abstract concepts or phenomena such as attitudes, perceptions, social experiences, and emotions that cannot be directly observed or measured (Golob, 2003; Zheng et al., 2020). In addition, SEM can accommodate regression relationships among latent variables and between observed and latent variables. Furthermore, SEM enables users to estimate in one model where one or multiple variables are predicted and predictor variables at the same time (Bowen and Guo, 2012).

SEMs contain two components: a measurement model for the endogenous (dependent) variables (η_2) and exogenous (independent) variables (η_1), and a structural model (Figure 1). The measurement model specifies how well various measured exogenous (observed) variables measure latent (unobserved) variables. A measurement model within an SEM incorporates estimates of the weighted average of exogenous variables in the system, which are called indicators (y_m and z_n) of the latent constructs. These weights are also called factor loadings. The structural model is concerned with how various variables are interrelated. A hypothetical conceptual model is created to present these interrelationships based on the existing literature and hypotheses made, and the model estimation results can be used to validate these hypotheses (Washington et al., 2020).

MIMIC model, a special case of SEM model, enables users to capture the possible heterogeneities in the measurement of latent variables between different groups of the population when using a SEM (Posey et al., 2014). The MIMIC approach can be used to restrict a group-invariant covariance matrix for the observed response variables represented by regressors (Figure 1). It means that users can estimate group differences on the perceptions of the latent variable by using MIMIC, where the latent variables are regressed on one or more binary indicators (exogenous observed variables, x_p) that represent group membership. It enables users to analyze the potential subpopulation differences without partitioning the population into subsamples at the modeling stage (Kline, 2015). Furthermore, users can test several different grouping variables all at once without performing a multigroup analysis with one variable at a time.

To sum up, the MIMIC modeling approach enables users to include a set of relevant explanatory variables to investigate the hypotheses of invariance across subpopulations. This can be important when analyzing the behavior among a highly heterogeneous population. For example, for a binary regressor such as "gender", where 0 means Male, and 1 represents Female; if the variable "gender" has a statistically significant and negative sign associated with a latent construct based on model estimation results, this would mean that, in general, female users perceive this latent construct more negatively compared to male users.

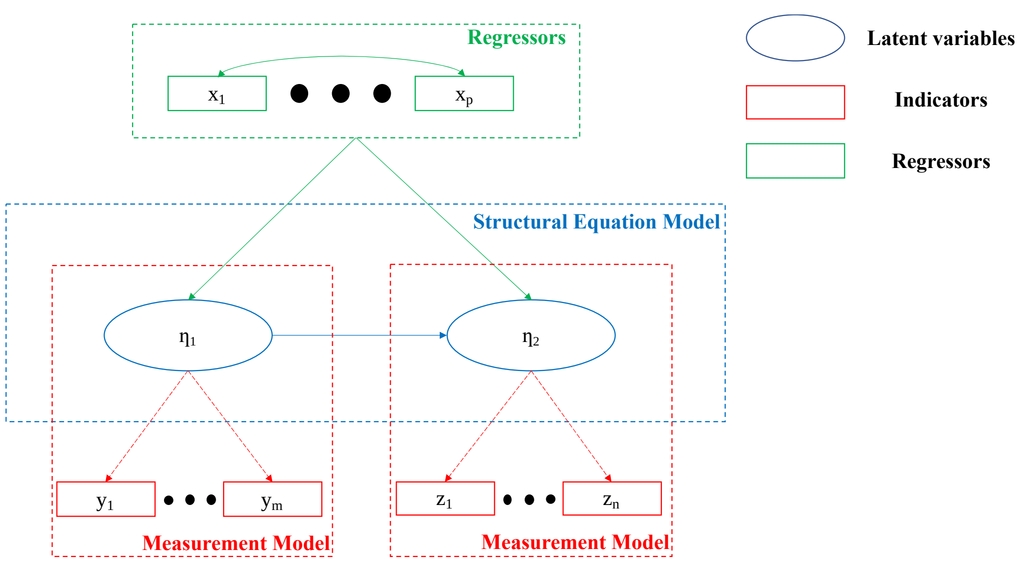

Figure 1. A simplified illustration of a MIMIC model

To validate a MIMIC model, a five-step validation method used in Allen et al. (2018), and Washington et al. (2020), and Zheng et al. (2020) is implemented. The first step is to evaluate if the information come from one sign factor using Herman's single facto score. Second, exploratory factor analysis can be used to evaluate if the number of hypothesized latent constructs is correct. Third, confirmatory factor analysis should be considered to evaluate the internal consistency among measurement models. Fourth, the different constructs' internal reliability should be evaluated. the degree of conceptual overlap among formative indicators should be evaluated to limit potential issues related to multicollinearity.

3.2. Model construct and hypothesis development

As described in section 3.1, a model framework was first conceptualized based on literature review related to AV and BEV adoption, and seventeen hypotheses were established (Figure 2). The fourteen attitudinal factors that were included, are drawn from literature and can be categorized as follows: (i) perceived vehicle features/attributes (relative advantage, compatibility, complexity, road safety improvement, user concerns, and range anxiety), (ii) social impacts (image and subjective norm), and (iii) perception related to new technologies, environment, and driving. It is important to note that the positive (negative) signs in Figure 2 mean a latent variable at the arrow tail have a positive (negative) impacts on the outcomes of the variable at the arrowhead.

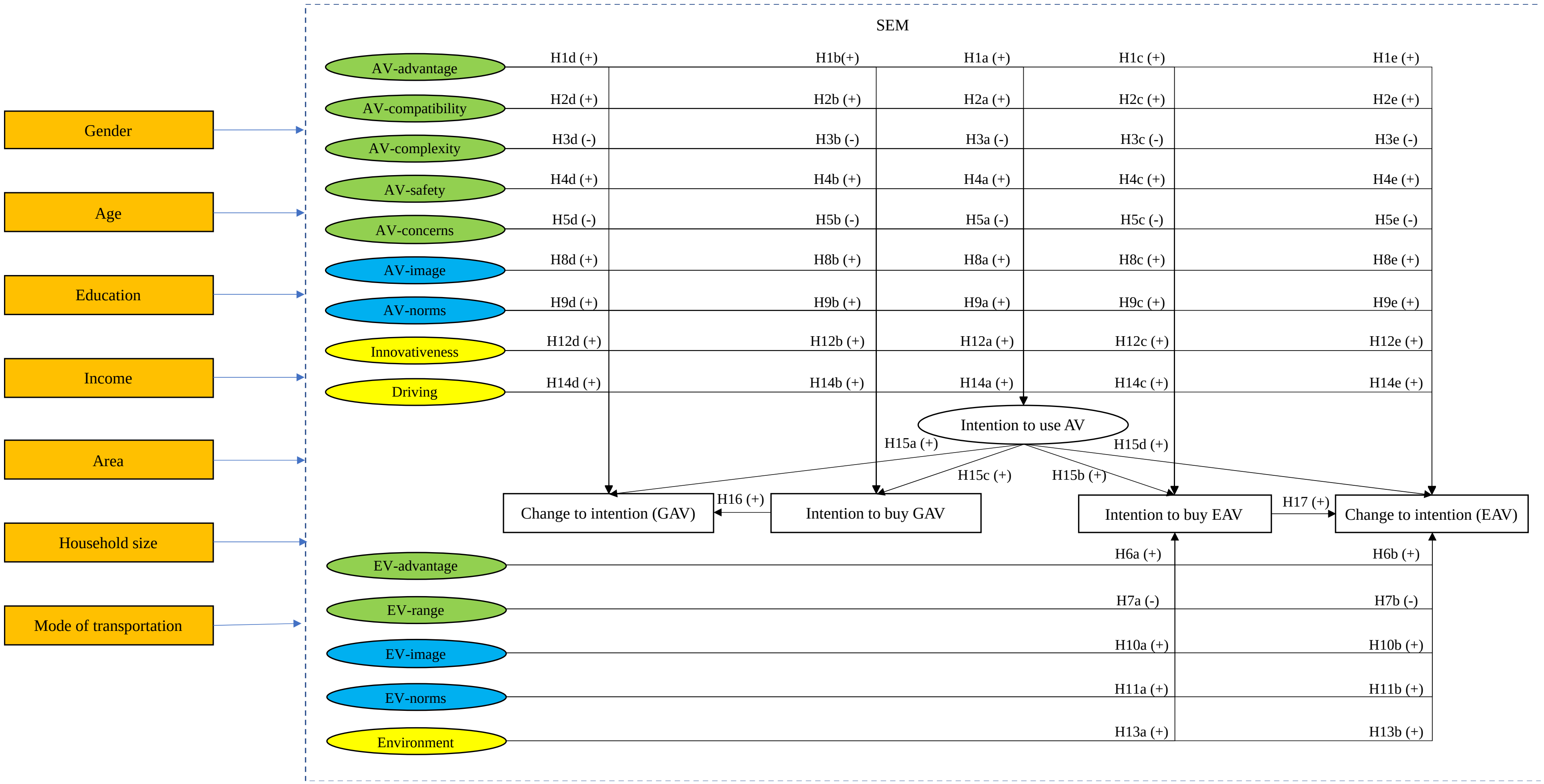

Figure 2. Proposed research model for investigating the impacts of attitudinal factors and roadway design features on AV adoption and fuel choice. (+ suggests a positive correlation while - suggests a negative correlation)

The model specification and hypothesis development draw inspiration from Technology Acceptance Model (Davis et al., 1989), Technology Diffusion Theory proposed by Rogers (2010), and a wide range of applied literature exploring AVs acceptance and adoption. These methods been widely used in studying AV related adoption (Acheampong and Cugurullo, 2019; Berliner et al., 2019). In Technology Acceptance Model, Technology Diffusion Theory, and their later expansions, a wide range of latent variables (e.g., relative advantage and complexity) were proposed that contributed to a new technology being accepted (e.g., intention to use and willingness to buy). Rogers (2010) highlighted the four key elements that can impact the adoption of new technology including the technology itself, communication channels between marketers and consumers, time, and a social system. According to Technology Diffusion Theory, in the context of AV adoption, it is important to identify potential AV early adopters and their characteristics, and policymakers can potentially use various types of policies and infrastructural support to influence technology diffusion process.

Relative performance advantage, compatibility, and complexity (i.e., ease-of-use) have been considered as primary factors that influence the adoption of new technologies (Rogers, 2010; Kulviwat et al., 2007; Herrenkind et al., 2019). In this study, *AV/EV-advantage* is defined as the perceived performance advantage (e.g., cost and travel time savings) of using AVs and BEVs compared to using HVs and GVs, respectively. *AV-compatibility* represents the compatibility of using AVs with their work and lifestyle needs and *AV-complexity* is used to capture the perceived complexity of operating AVs. *AV-safety* is defined as the perceived safety improvement related to using AVs instead of HVs. The factor "*AV-concerns*" is used to capture the perceived risks (e.g., privacy and liability concerns) associated with operating an AV and *EV-range* is aimed at understanding users' perceived range anxiety (e.g., limited charging stations) of operating an EV. The hypotheses related to these factors are summarized as follows:

H1: The **greater** the perceived AV-advantage, the **greater** intention (a) to use AVs, (b) to purchase GAVs, and (c) to purchase EAVs, and the **increased** greater intention to purchase (d) GAVs and (e) EAVs under the EAV-enabled Roadway Design.

H2: The **greater** the perceived AV-compatibility, the **greater** intention (a) to use AVs, (b) to purchase GAVs, and (c) to purchase EAVs, and the **increased** intention to purchase (d) GAVs and (e) EAVs under the EAV-enabled Roadway Design.

H3: The **greater** the perceived AV-complexity, the **lesser** intention to (a) use AVs, (b) purchase GAVs, and (c) purchase EAVs, and the **decreased** intention to purchase (d) GAVs and (e) EAVs under the EAV-enabled Roadway Design.

H4: The **greater** the perceived AV-safety, the **greater** intention to (a) use AVs, (b) purchase GAVs, and (c) purchase EAVs, and **increased** intention to purchase (d) GAVs and (e) EAVs under the EAV-enabled Roadway Design.

H5: The **greater** the perceived AV-concerns, the **lesser** intention to (a) use AVs, (b) purchase GAVs, and (c) purchase EAVs, and the **decreased** intention to purchase (d) GAVs and (e) EAVs under the EAV-enabled Roadway Design.

H6: The **greater** the perceived EV-relative advantage, the **greater** intention to (a) purchase EAVs, and the **increased** intention to purchase (b) EAVs under the EAV-enabled Roadway Design.

H7: The **greater** the perceived EV-range anxiety, the **lesser** intention to (a) purchase EAVs, and the **decreased** intention to purchase (b) EAVs under the EAV-enabled Roadway Design.

AV/EV-image and AV/EV-subjective norms are used to capture the impacts of social influence on AV adoption and fuel choice. In this study, *AV/EV-image* is defined as one's perception that adopting AV/EV can improve his or her reputation within a group or social system. The construct of *subjective norms* refers to the belief that personally important individuals (i.e., people whose opinions can influence that person) approve or support their decision to adopt AV/EV (i.e., AV/EV-norms).

H8: The **greater** the perceived AV-image, the **greater** intention to (a) use AVs, (b) purchase GAVs, and (c) purchase EAVs, and the **increased** intention to purchase (d) GAVs and (e) EAVs under the EAV-enabled Roadway Design.

H9: The **greater** the perceived AV-norms, the **greater** intention to (a) use AVs, (b) purchase GAVs, and (c) purchase EAVs, and the **increased** intention to purchase (d) GAVs and (e) EAVs under the EAV-enabled Roadway Design.

H10: The **greater** the perceived EV-image, the **greater** intention to (a) purchase EAVs, and the **increased** intention to purchase (b) EAVs under the EAV-enabled Roadway Design.

H11: The **greater** the perceived EV-norms, the **greater** intention to (a) purchase EAVs, and the **increased** intention to purchase (b) EAVs under the EAV-enabled Roadway Design.

Personal innovativeness, environmental concerns, and attitude towards driving have also been identified in the literature as factors affecting AV and EV adoption. *Innovativeness* is described as the attitude that an individual is attracted to new products or innovations and have a desire to try and purchase them (Ozaki and Dodgson, 2010). *Environment* is related to a potential user's concerns of negative environmental impacts related to their behavior and have a desire to behave in an ecological friendly manner. *Driving* is used to capture a potential user's desire to control the vehicle operation, fondness of driving and driving responsibility, and confidence in their driving skills.

H12: The **greater** the personal innovativeness, the **greater** intention to (a) use AVs, (b) purchase GAVs, and (c) purchase EAVs, and the **increased** intention to purchase (d) GAVs and (e) EAVs under the EAV-enabled Roadway Design.

H13: The **greater** the perceived environmental concerns, the **greater** intention to (a) purchase EAVs, and the **increased** intention to purchase (b) EAVs under the EAV-enabled Roadway Design.

H14: The **greater the negative** attitude towards driving, the **greater** intention to (a) use AVs, (b) purchase GAVs, and (c) purchase EAVs, and the **increased** intention to purchase (d) GAVs and (e) EAVs under the EAV-enabled Roadway Design.

Apart from these hypotheses related to various factors affecting AV adoption and fuel choice, three hypotheses were established related to relationship among people's intention to use AVs, intention to purchase GAVs and EAVs, and changes to the purchasing intention under the EAV-enabled Roadway Design.

H15: The **greater** intention to use AVs, the **greater** intention to (a) purchase GAVs, and (b) purchase EAVs, and the **increased** intention to purchase (c) GAVs and (d) EAVs under the EAV-enabled Roadway Design.

H16: The **greater** intention to purchase GAVs, the **increased** intention to purchase GAVs under the EAV-enabled Roadway Design.

H17: The **greater** intention to purchase EAVs, the **increased** intention to purchase EAVs under the EAV-enabled Roadway Design.

For each latent variable, a measurement model is built to capture how various observed variables measure latent variable. In addition, seven travel and sociodemographic variables were introduced to capture the potential heterogeneities among observations for each latent variable. These variables are all binary indicator variables: gender (male as 1 and female as 0), age (millennials or younger as 1, otherwise

0), highest completed level of education (college or above as 1, otherwise 0), annual household income ($75,000 or above as 1, otherwise 0), area lived in (urban as 1, otherwise 0), household size (one or two as 1, otherwise 0), and the most commonly used mode of transportation for daily commute (drive alone or drive with family members as 1, otherwise 0). Using the variable "AV-advantage" as an example, Figure 3 illustrates the relationship among this latent variable, its three indicators (observable), and seven travel and sociodemographic indicator. Millennials or younger are defined as anyone that was born after 1981 (younger than 39 years of age at the time of survey) (Pew Research Center, 2019). The median household income is $68,703 in 2019 (United States Census Bureau, 2019) and a person with an annual household income higher than $75,000 suggests that he or she has a relatively high income. Apart from these seven characteristics, a few additional variables were also considered, including marital status, whether they have a valid driver's license or not, and employment status. However, they were removed due to their high correlation with other variables.

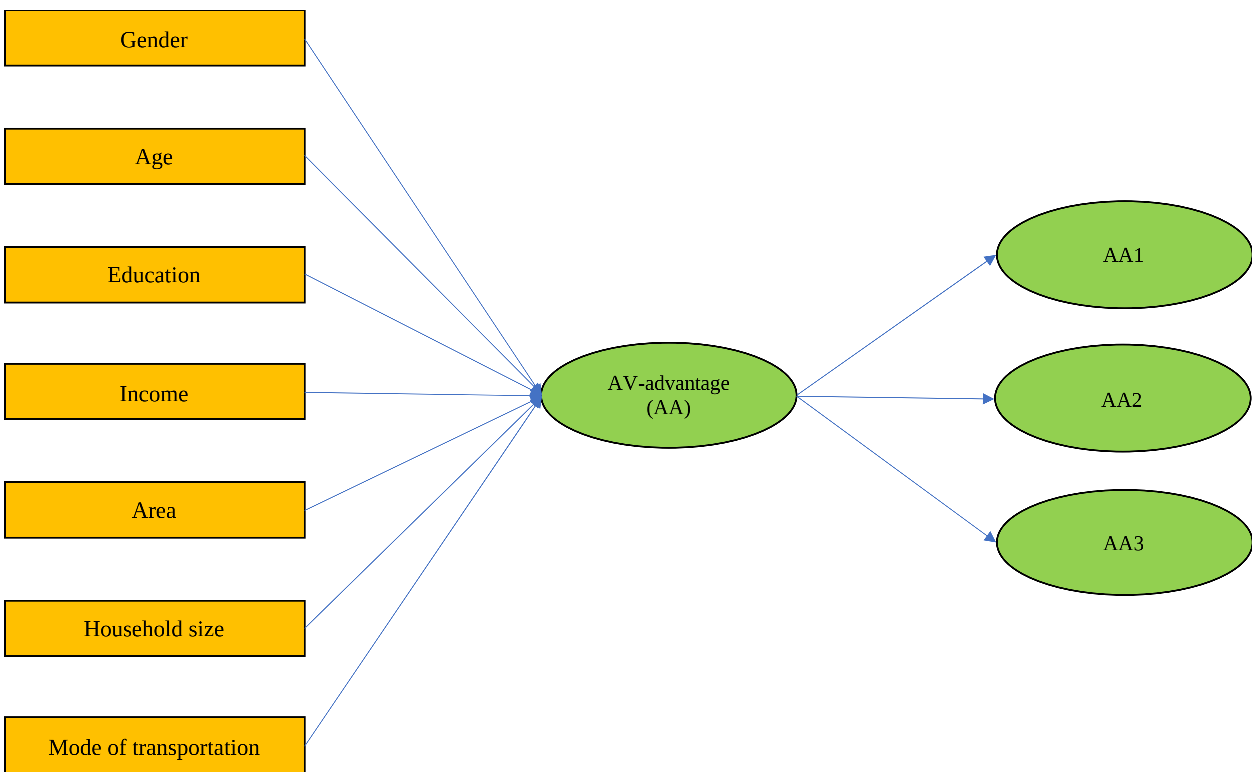

Figure 3. The relationship among a latent variable (green AA), its indicators (green AA1, AA2, and AA3), and seven travel and sociodemographic variables (orange)

3.3. Survey design and distribution

A draft survey questionnaire was designed to evaluate the hypotheses made in section 2.2. After that, a pilot study was conducted among a group of students (i.e., 50) at Purdue University to evaluate the survey questions. Feedback from the pilot study regarding the survey features (for example, the survey length and level of difficulty of the questions) was used to further enhance the survey instrument. The final survey flow is shown in Figure 4.

The survey contains three main sections. In Section I, respondents were asked questions related to their gender, age, highest completed level of education, annual household income, the area they live in (urban, suburban, or rural), household size, and the most commonly used mode of transportation for the commute (colored in yellow in Figure 4). In Section II, respondents were first given the definition of AV. The term "self-driving cars" was used instead of "AVs". Its definition is based on the SAE Intentional (2018) for vehicles with level-4 automation: "Self-driving cars can perform all driving tasks – essentially, do all the driving – in certain conditions (e.g., urban environment and most highways). You do not need to take over driving in those conditions". It is important to note that survey respondents need to understand the definition of AVs (self-driving cars) as people's understanding about the term can be very different. Based on the literature review (Tables 2-3), the descriptions of AVs vary. The most commonly used method to use standard definitions provided by institutions or government bodies (18 out of 33), such as SAE (Bansal et al., 2016; Buckley et al., 2018; Nielsen and Haustein, 2018; Panagiotopoulos and Dimitrakopoulos, 2018; Sanbonmatsu et al., 2018; Berliner et al., 2019; Cunningham et al., 2019; Hardman et al., 2019; Liu et al., 2019; Spurlock et al., 2019), the National Highway Traffic Safety Administration (NHTSA) (Payre et al., 2014; Choi and Ji, 2015; Hohenberger et al., 2016; Zmud et al., 2016; Bansal and Kockelman, 2017; Daziano et al., 2017; Kaur and Rampersad, 2018; Acheampong and Cugurullo, 2019; Zoellick et al., 2019), and others (Kyriakidis et al., 2015). Nordhoff et al. (2018) choose to provide their own description of AVs, Chen (2019) surveyed people who have used the autonomous shuttle in Kaohsiung City, China, and Du et al. (2019a) and Du et al. (2019b) designed an AV in a driving simulator environment using SAE standard. In the rest of the studies, the authors did not provide their definition of AVs or self-driving cars (Shin et al., 2015; Haboucha et al., 2017; König and Neumayr, 2017; Lavieri et al., 2017; Wang et al., 2017; Hulse et al., 2018; Shabanpour et al., 2018; Jing et al., 2019; Lee et al., 2019; Sheela and Mannering, 2019; Wang and Zhao, 2019). Hence, in this study, the SAE definition for AVs (self-driving cars) was used and it was provided to the participants.

The 14 attitudinal factors presented in Section 2.2 are latent variables and the items in their latent constructs (i.e., each item represents one question in the survey and is a measurable indicator variable in the model) were established from literature. All indicator questions were measured on a 7-point Likert scale from 1 = "strongly disagree" to 7 = "strongly agree" except (i) people's intention to purchase GAVs and EAVs which are from 1 = "very weak" to 7 = "very strong", and (ii) changes to people's intention to purchase GAVs and EAVs which are from 1 = "definitely decrease" to 7 = "definitely increase". The latent constructs are presented in Table 5. It means that for each latent variable, it can be the estimates of the weighted average of exogenous variables for these item constructs. For example, AV-relative advantage (AA) has three items, namely, "I think using a self-driving car in my day-to-day commuting would be better than using my daily forms of travel. (AA1)"; "I think a self-driving car would be faster than my daily forms of transportation. (AA2)"; and "I believe that self-driving cars, in comparison to human-driven cars, would have lower follow-up costs (e.g., maintenance). (AA3)".

Finally, Section III focuses on the change in a person's intention to purchase GAVs and EAVs for an existing roadway design (Figure 5) and a prospective roadway design (Figure 6), termed here as "EAV-enabled Roadway Design". This design was developed to improve the mobility and accessibility of AVs, reduce range anxiety related to using EAVs, and, as a result to promote AVs adoption. It features a dedicated lane for AVs (i.e., an AV-only lane) with a higher speed limit (10 mph higher) compared to 30 mph for human-driven vehicle lanes, wireless charging for EAVs with electricity costs similar to charging an EAV at home, and replacing all roadside parking with pick-up and drop-off areas for AVs and buses. Visual illustrations were created to effectively show the differences between the EAV-enabled Roadway Design from the existing design to the participants. A standard one-way street was used to illustrate such differences. This roadway features three driving lanes and roadside parking on both sides (Figure 1), and its design is recreated (including lane width and markings) based on a portion of East Washington Street located in downtown Indianapolis, Indiana, USA. Detailed descriptions of each design were provided to participants at the time of survey.

Two important assumptions were made. Assumption 1: people are equally likely to have the same intention to use GAVs and EAVs but may have different intentions to buy a GAV or an EAV. As shown in

Table 5, the intention to use AV is a latent variable with three indicators, namely "I could imagine myself using a self-driving car instead of a human-driven car. (WA1)"; "If it were affordable, I would use a self-driving car. (WA2)"; "If I have a choice, I would use a self-driving car instead of a human-driven car. (WA3)". Based on the literature review of 28 studies in the related domain, the impacts of AV service's fuel type on the intention to use AVs were not studied. In addition, based on the literature related to existing transportation service such as ridesharing industry (Sarriera et al., 2017; Moody et al., 2019; Narayanana, et al., 2020), fuel type was also not included as a factor that affects users' choice. As these studies have shown, service users are more concerned about the service fee and service quality when making their mode choice. For example, most people are unlikely to reject an Uber car service because it is a Toyota Prius (hybrid electric) or Toyota Corolla (gasoline-powered). However, as a service provider or a car owner, fuel type can be important for them as this is directly related to maintenance, cost, etc.

Assumption 2: people's intention to use AVs does not change significantly from original design to EAV-enabled roadway design as most of the design features as most of the new features (e.g., wireless charging) can be beneficial to the people who own the vehicle (e.g., reduced range anxiety and vehicle charging time) but may have little impact on people who use AV services (e.g., most bus riders do not worry about whether a bus has enough power take them to their destination). Both assumptions were evaluated in the pilot survey study by adding questions related to people's intention to use GAVs and EAVs and only 1 out of 50 test subjects' responses disagreed with Assumption 2 (i.e., their intention to use AVs changes in EAV-enable roadway design). Furthermore, based on the pilot study results, questions related the intention to use EAVs and GAVs and the changes of these intentions (12 questions) were reduced to the intention to use AVs (3 questions) to reduce survey response time. The average survey response time in the pilot study was over 25 minutes and the major complaint received was the survey length. As studies have shown (Höhne et al., 2017; Revilla and Ochoa, 2017), relatively longer web-based surveys can potentially lead to relatively low response rate and response quality, and higher cognitive burden. Based on these reasons, a trade-off was made, and these questions were removed from the survey.

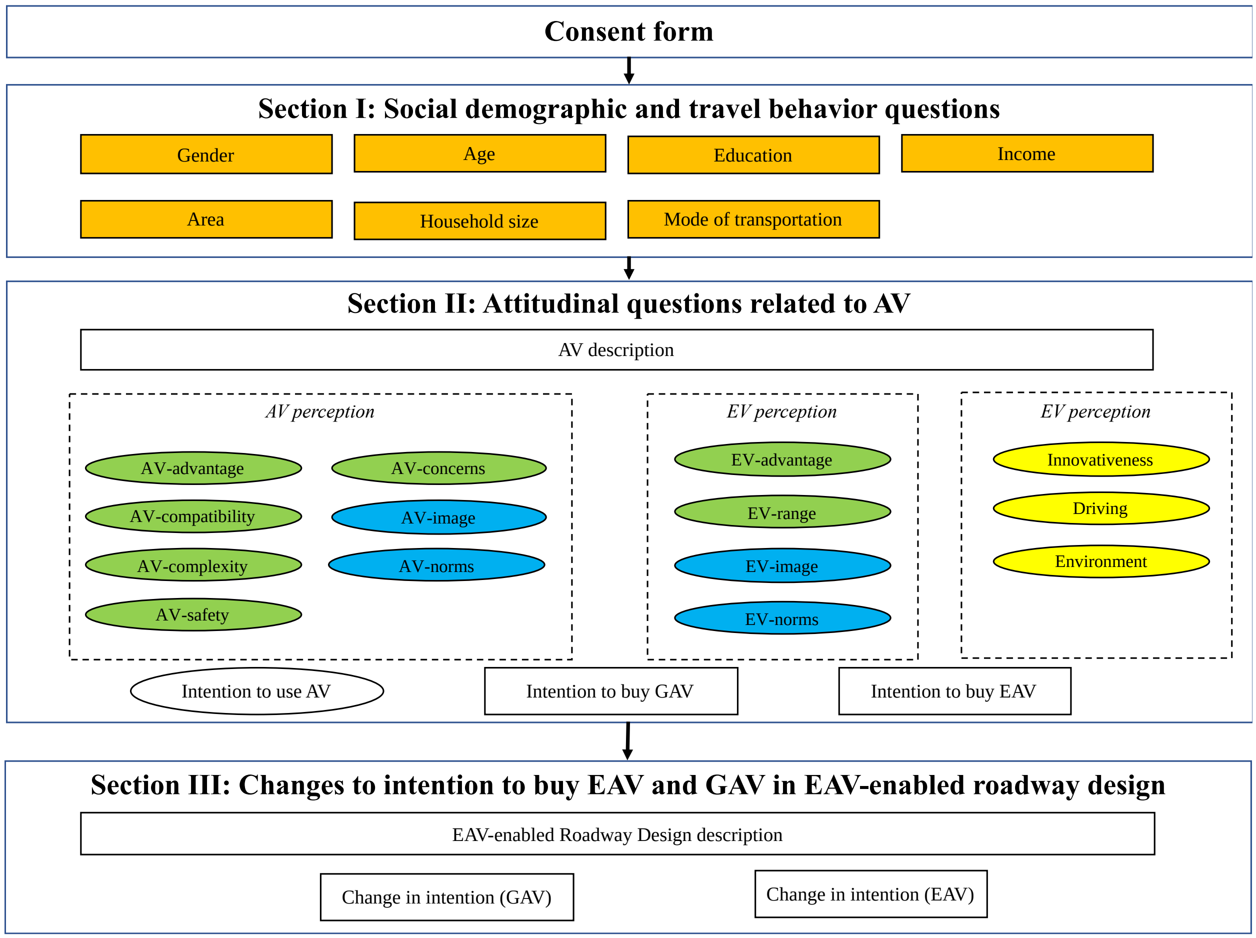

Figure 4. Survey flow (sociodemographic and travel behavior factors in orange, perceived vehicle features/attributes in green, social factors in blue, and other attitudinal factors in yellow)

Table 5. Measurement items (questions in the survey) for latent variables of the MIMIC construct and the relevant references for each question

Latent variables	Items	References
AV-relative advantage (AA)	I think using a self-driving car in my day-to-day commuting would be better than using my daily forms of travel. (AA1)	Arts et al. (2011) Haboucha et al. (2017)
	I think a self-driving car would be faster than my daily forms of transportation. (AA2)	
	I believe that self-driving cars, in comparison to human-driven cars, would have lower follow-up costs (e.g., maintenance). (AA3)	
AV-compatibility (AP)	I believe that using self-driving cars is compatible with my work travel needs. (AP1)	Karahanna et al. (2006)
	I believe that using self-driving cars is compatible with my lifestyle needs. (AP2)	
AV-complexity (AX)	I think a self-driving car would be easy to understand how to use. (AX1+)	From the authors
	It would not take me long to learn how to use a self-driving car. (AX2+)	
AV-safety (AS)	I believe that human error is responsible for most of the road accidents. (AS1)	Haboucha et al. (2017)
	I believe that self-driving cars will reduce the amount of road accidents. (AS2)	
	I believe that the interactions between self-driving and human-driving cars are unsafe. (AS3+)	
	I believe that the interactions between self-driving and pedestrian/cyclists are unsafe. (AS4+)	
AV-concerns (AC)	I would be afraid of legal liability when using a self-driving car. (AC1)	Haboucha et al. (2017)
	I would be afraid of system and vehicle security from hackers. (AC2)	
	I would be afraid of the privacy issues relate to using a self-driving car. (AC3)	
	I would be afraid of using a self-driving car for fear of equipment or system failure and I cannot take back vehicle control. (AC4)	
EV-relative advantage (EA)	Using an all-electric car could potentially saving money in the long run. (EA1)	Krupa et al. (2014)
	Using an all-electric car could cut my greenhouse gas emission significantly. (EA2)	
EV-range anxiety (ER)	Public charging stations are not sufficient for me to use just BEVs. (ER1)	Berkeley et al. (2018)
	BEVs have limited driving range and cannot satisfy my day driving needs. (ER2)	
	I would be worried about driving range if I was driving BEVs. (ER3)	
AV-image (AI)	Owning an AV would make it clear to others that I am on the forefront of new technology. (AI1)	From the authors
	Owning an AV would make a statement regarding my strong innovative values. (AI2)	
	Owning an AV would increase my reputation in my environment positively. (AI3)	
AV-subjective norms (AN)	My social environment would tend to expect me to use a self-driving car. (AN1)	From the authors
	My friends and family would think that I should use a self-driving car. (AN2)	
	People who influence my behavior tend to think that I should use a self-driving car. (AN3)	
EV-image (EI)	Owning an all-electric car would make it clear to others that I am on the forefront of new technology. (EI1)	Krupa et al. (2014)
	Owning an all-electric car would make a statement regarding my strong environmental values. (EI2)	
	Owning an all-electric car would increase my reputation in environment positively. (EI3)	
EV-subjective norms (ES)	My social environment would tend to expect me to use a BEV. (ES1)	Krupa et al. (2014)
	My friends and family would think that I should use a BEV. (ES2)	
	People who influence my behavior tend to think that I should use a BEV. (ES3×)	
Personal innovativeness (AT)	I try new products before my friends and neighbors. (AT1)	Ewing and Sarigöllü (2000)
	I know more than others on latest new products. (AT2)	
	I often purchase new technology products, even though they are expensive. (AT3)	Roehrich (2004)
	I am excited by the possibilities offered by new technologies. (AT4×)	Jensen et al. (2014)
	I have little to no interest in new technology. (AT5×+)	
	I think global climate change is mostly attributed to human activities. (EC1)	Krupa et al. (2014)

Environmental concerns (EC)	I think global climate change is a great threat to humanity. (EC2) I think it is important to reduce energy consumption to improve energy independence. (EC3) I feel responsible to mitigate global climate change. (EC4) Environmental problems have been greatly exaggerated. (EC5×) We need to be proactive in protecting the environment as we cannot rely on modern technology to solve environmental problems. (EC6)	Bennett and Vijaygopal (2018)
Attitude towards driving (AD)	I prefer not to have the responsibility of driving. (AD1) I feel nervous when driving. (AD2) I feel uncomfortable driving next to bicyclists. (AD3×) I feel safer driving myself rather than others driving me. (AD4×+) I enjoy driving. (AD5+)	Devarasetty et al. (2014)
Intention to use AVs (WA)	I could image myself using a self-driving car instead of a human-driven car. (WA1) If it were affordable, I would use a self-driving car. (WA2) If I have a choice, I would use a self-driving car instead of a human-driven car. (WA3)	Haboucha et al. (2017)

Note: Items that were removed because of low factor loadings are marked with ×.
Items that were reverse scored are marked with +.

Figure 5a. Bird’s eye view of original roadway design

Figure 5b. Eye level view of original roadway design

Figure 5. Original one-way street design.

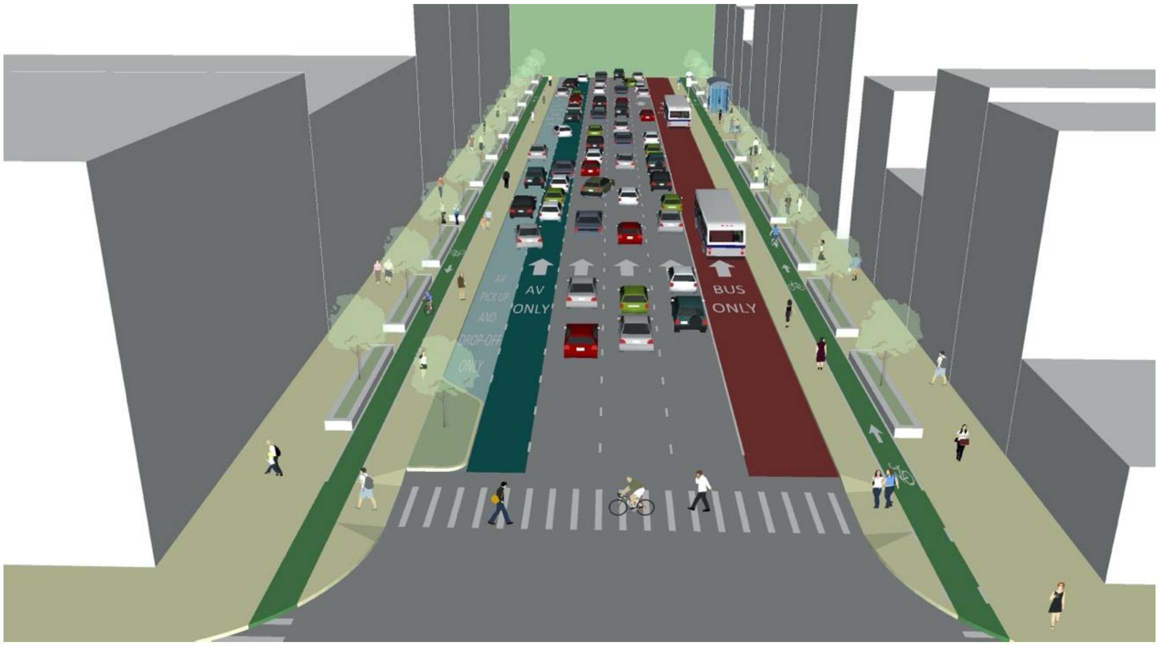

Figure 6a. Bird’s eye view of EAV-enabled Roadway Design

Figure 6b. Eye level view of EAV-enabled Roadway Design.

Figure 6. EAV-enabled Roadway Design.

Three commonly used methods for survey respondent recruitment in the literature (Table 4) were considered, namely the self-distribution method, using crowdsourcing websites, and using survey companies. Self-distribution method was removed due to its limitations such as social media filter bubbles and the inability to reach participants from broader geographical regions which can limit the quality of the data collected (Groshek and Koc-Michalska, 2017). Distributing the survey on crowdsourcing websites was chosen over survey companies as the more economical option. The average cost per response of using survey companies is about three times higher than using crowdsourcing websites and both methods can provide similar level of reliability in terms of the quality of the response (Guo and Peeta, 2015; Walters et al., 2018; Jing et al., 2019; Rouse, 2019; Li et al., 2019; Guo et al., 2021a; Guo et al., 2021b; Tang et al., 2021). Hence, in this study, the crowdsourcing websites were used for data collection.

The study participants were recruited through a commonly used crowdsourcing website, MTurk. MTurk has been used in many recent studies due to its large potential participant pool, relatively fast data collection speed, and relatively high participant attentiveness compared to other online survey platforms (Huff and Tingley, 2015; Hauser and Schwarz, 2016). In this study, MTurk Masters were used as these workers are identified by MTurk as people who have maintained a high level of performance over a long period of time. These MTurk Masters are paid 5 percentage higher than the average MTurk workers. Using MTurk masters can potentially improve survey response quality. The survey was conducted between May 2019 and July 2019. All participants were at least 18 years old and lived in the U.S. In addition, three attention check questions were embedded in the survey and only the responses of participants who answered these questions correctly were considered as valid responses. This study was approved by Purdue University's Institutional Review Board and took approximately 25 minutes to complete with participants receiving $1.25 for valid completions.

The data was cleaned up and 37 responses were removed because respondents failed to provide correct answers to attention check questions, complete the survey too fast (i.e., under 10 minutes), or had an IP address that is outside of the U.S. After three months of data collection and data clean up, 1,302 valid responses were collected. The average response time is 23.4 minutes (standard deviation 5.7). The sample size is larger than both the median sample size of all studies in the literature review and the median sample size of all U.S.-based studies in the literature review (Table 4).

4. Study Results

4.1. Descriptive statistics of the respondents' sociodemographic and travel behavior characteristics

Table 6 shows the descriptive statistics of the respondents' sociodemographic and travel behavior characteristics. 50.2% of the 1,302 participants identify themselves as a female. The youngest respondent was 22 years old and the oldest was 89 years old. 53.6% of the respondents are Millennials or post-Millennials (born after 1980, or younger than 39 years old at the time of the survey), 32.9% of them are Generation X (born between 1965 and 1980 or aged between 39 and 54), and the rest are older generations. The average age of the respondents is 40.1 with a standard deviation of 11.0. Most of the respondents have a college degree or above (56.5%) and live in suburban areas (52.1%). The household income composition is 11% below $15,000 (about the 10th percentile for U.S household income in 2019), 40.7% between $15,000 and $49,999 (between the 11th and 40th percentile), 38.0% between $50,000 and $99,999 (between the 41th and 71th percentile), and 10.3% over $100,000. The average household size was 2.72 (standard deviation 1.47) and the average number of cars per household was 1.63 (standard deviation 0.85) compared to 2.60 and 1.88 on average in the U.S., respectively. Over 72% of them reported that they either choose driving by themselves or driving with family members as their most common mode of transportation to work/school. Apart of the descriptive statistics presented in Table 6, additional questions were asked related to their race, employment type, marital status, and if they have a valid U.S. driver's license. Most common types of the participants are Caucasian (75.0%), full-time employees (65.3%), have a valid U.S. driver's license (over 91%), or are married or have a domestic partnership (48.5%).

Table 6. Descriptive statistics of the respondents' sociodemographic and travel behavior characteristics

Variables	Items	Percentage
Gender	Male	49.8
	Female	50.2
Age	Millennials or post-Millennials	53.6
	Generation X (born between 1965 and 1980 or aged between 39 and 54)	32.9
	Older generation	13.5
Education	High school graduate (diploma or the equivalent) or lower	11.5
	Some college credit, no degree	21.5
	Technical college degree	10.5
	College degree	46.6
	Post graduate degree	9.9
Income	Below $15,000	11.0
	Between $15,000 and $49,999	40.7
	$50,000 and $99,999	38.0
	Over $100,000	10.3
Area living in	Urban	31.3
	Suburban	51.9
	Rural	16.8
Most common mode of transportation	Drive alone or drive with family members	72.7
	Public transport	4.5
	Bike, walk, or motorcycle	4.3
	Ridesharing or carpooling	0.6
	Don't need to go to work or school	17.9

4.2. Model construct validation

The model construct validation (section 4.2) as well as the MIMIC model estimation (section 4.3) were performed using the open-source package Lavaan in R (RStudio Version 1.1456, R Version 3.5.1) (Rosseel, 2012).

To validate the model construct, the five-step validation method introduced in Section 2.1 was used. First, Herman's single factors score was used which showed that the information does not come from one single factor. Second, an exploratory factor analysis was used, and the results support the idea of 14 underlying factors (Kaiser-Mayer-Olkin criterion = 0.88 and the Bartlett's test $p<0.001$). Third, confirmatory factor analysis was used to test the internal consistency and the results are presented in Table 5. The results show that all measures of fit met their requirements: the root mean square error of approximation (RMSEA) = 0.052 (recommended RMSEA < 0.080); standardized root mean square residual (SRMR) = 0.044 (recommended SRMR < 0.080); comparative fit index (CFI) = 0.931 (recommended CFI ≥ 0.9); and Tucker-Lewis Index (TLI) = 0.920 (recommended TLI ≥ 0.900) (Hu and Bentler, 1999; Hooper et al., 2008). Items with factor loadings under 0.7 were eliminated from the analysis, as suggested by Herrenkind et al. (2019), to guarantee that the item extracts sufficient variance from that latent variable. The fourth step is to test constructs' internal reliability using Cronbach's Alpha and average variance extracted (Table 7). Both tests showed that the constructs are beyond the recommended threshold (over 0.7 for Cronbach's Alpha and over 0.5 for average variance extracted) (Bagozzi and Yi, 1988; Bhattacherjee and Premkumar, 2004). These validation methods showed that the underlying constructs demonstrate validity and reliability for estimating the proposed MIMIC. The final step is to evaluate the potential multicollinearity using variance inflation factors (VIFs). All of the VIFs were in the specified 3.3 cut-off recommended by Petter et al. (2007) to avoid potential multicollinearity.

Table 7. Measurement model for each latent variable using factor loadings, Cronbach's Alpha, and average variance extracted to validate the mode construct

	Items	Average (*SD*)	Factor loadings	Cronbach's Alpha	Average variance extracted
AV-relative advantage (AA)	AA1	3.52 (1.83)	0.831	0.812	0.753
	AA2	4.21 (1.84)	0.733		
	AA3	4.02 (1.77)	0.708		
AV-compatibility (AP)	AP1	2.78 (1.56)	0.826	0.788	0.721
	AP2	3.71 (1.78)	0.780		
AV-complexity (AX)	AX1	2.77 (1.39)	0.944	0.827	0.741
	AX2	2.64 (1.46)	0.740		
AV-safety (AS)	AS2	3.09 (1.64)	0.771	0.771	0.711
	AS3	3.91 (1.64)	0.760		
	AS4	4.07 (1.67)	0.751		
AV-concerns (AC)	AC1	4.36 (1.84)	0.870	0.921	0.823
	AC2	4.43 (1.86)	0.812		
	AC3	4.20 (1.91)	0.902		
	AC4	3.74 (1.97)	0.844		
EV-relative advantage (EA)	EA1	5.40 (1.31)	0.769	0.750	0.698
	EA2	5.75 (1.22)	0.771		
EV-range anxiety (ER)	ER1	3.35 (0.94)	0.811	0.809	0.731
	ER2	3.14 (0.97)	0.773		
	ER3	2.28 (0.87)	0.811		
AV-image (AI)	AI2	4.13 (1.99)	0.818	0.772	0.721
	AI3	3.65 (2.03)	0.709		
AV-subjective norms (AN)	AN2	4.18 (1.79)	0.887	0.814	0.735
	AN3	3.72 (1.81)	0.849		
EV-image (EI)	EI1	4.63 (1.44)	0.810	0.838	0.752
	EI2	4.96 (1.55)	0.842		
	EI3	4.65 (1.57)	0.731		
EV-subjective norms (EN)	EN1	4.39 (2.12)	0.871	0.801	0.725
	EN2	4.59 (2.15)	0.881		
Personal innovativeness (AP)	AP1	4.10 (1.59)	0.922	0.874	0.801
	AP2	4.14 (1.62)	0.863		
	AP3	3.52 (1.71)	0.816		
Environmental concerns (EC)	EC1	5.48 (1.66)	0.867	0.910	0.812
	EC2	5.63 (1.62)	0.912		
	EC3	5.89 (1.29)	0.766		
	EC4	4.82 (1.77)	0.746		
	EC5	5.22 (1.93)	0.712		
	EC6	5.58 (1.39)	0.744		

Table 5. (continued)

	Items	Average (*SD*)	Factor loadings	Cronbach's Alpha	Average variance extracted
Attitude towards driving (AD)	AD1	4.78 (1.98)	0.812	0.832	0.749
	AD2	5.02 (1.90)	0.786		
	AD5	4.84 (1.74)	0.772		
Changes to the intention to purchase GAVs under the EAV-enabled Roadway Design		4.16 (1.35)	N/A	N/A	N/A
Changes to the intention to purchase EAVs under the EAV-enabled Roadway Design		4.72 (1.46)	N/A	N/A	N/A

4.3. Model estimation results

The model estimation results including the standardized path coefficients (std. estimate), their standard errors (std. error), and the *p*-value are presented in Tables 8-11. Only when $p < 0.05$, the proposed hypothesis was considered *supported*, implying that the latent variable has a statistically significant relationship with a variable. RMSEA, SRMR, CFI, and TLI are used to evaluate the performance of the proposed model. The observed RMSEA = 0.061 and SRMR = 0.051 suggest a good model fit (Hu and Bentler, 1999). The observed CFI = 0.915 and TLI = 0.904, comparing the model to an independent model, also indicated a good model fit (Little et al., 2007; Hooper et al., 2008). The final model results are presented in Figure 7 (from the framework in Figure 2) and the statistically significant results are bold. All the numbers in the Figure 7 are standardized path coefficients which represent the correlation between two variables connected by an arrow. Bold numbers indicate that such correlations are statistically significant. The magnitude of standardized coefficients can be directly compared to make inferences about the relative strength of relationship among latent variables (Washington et al., 2020). It is important to note that a larger standardized path coefficient for one variable does not mean that it can explain more variance in the response compared to a variable with a smaller standardized path coefficient. It can only be interpreted as relative influence on the mean of the response. A positive standardized path coefficient means that the explanatory variable changing from 0 to 1 (as all the latent variables are binary variables) lead to an increase in the mean of the explained variable, while a negative standardized path coefficient means that the explanatory variable changing from 0 to 1 lead to a decrease in the mean of the explained variable.

The supported hypotheses can be summarized as follows (Tables 8-11). The greater the perceived AV-advantage, the greater intention to use AVs, to purchase GAVs, and to purchase EAVs, and the increased intention to purchase GAVs and EAVs under the EAV-enabled Roadway Design (H1). The greater the perceived AV-compatibility, the greater intention to use AVs, and the increased intention to purchase GAVs and EAVs under the EAV-enabled Roadway Design (H2). The greater the perceived AV-complexity, the lesser intention to use AVs, purchase GAVs, and purchase EAVs (H3). The greater the perceived AV-safety, the greater intention to use AVs, purchase GAVs, and purchase EAVs, and increased intention to purchase GAVs and EAVs under the EAV-enabled Roadway Design (H4). The greater the perceived AV-concerns, the lesser intention to use AVs, purchase GAVs, and purchase EAVs, and the decreased intention to purchase GAVs and EAVs under the EAV-enabled Roadway Design (H5). The greater the perceived EV-relative advantage, the greater intention to purchase EAVs, and the increased intention to purchase EAVs under the EAV-enabled Roadway Design (H6). The greater the perceived EV-range anxiety, the lesser intention to purchase EAVs (H7). In terms of the social factors' impacts, the greater the perceived AV-image, the greater intention to use AVs (H8), while the rest of the factors do not have a statistically significant impacts on the decision variables.

In terms of other variables, the greater the personal innovativeness, the greater intention to use AVs, purchase GAVs, and purchase EAVs (H12), and the greater the negative attitude towards driving, the greater intention to use AVs, purchase GAVs, and purchase EAVs, and the increased intention to purchase GAVs and EAVs under the EAV-enabled Roadway Design (H14). In terms of the relationship among people's intention to use AVs, intention to purchase GAVs and EAVs, and changes to these purchasing intention under the EAV-enabled Roadway Design, the mode estimation results show that the greater intention to use AVs, the greater intention to purchase GAVs, and purchase EAVs, and the increased intention to purchase GAVs and EAVs under the EAV-enabled Roadway Design (H15); the greater intention to purchase GAVs, the increased intention to purchase GAVs under the EAV-enabled Roadway Design (H16); and The greater intention to purchase EAVs, the increased intention to purchase EAVs under the EAV-enabled Roadway Design (H17).

Table 12 summarizes the MIMIC model estimation results related to how sociodemographic and travel characteristics impact the latent variables. A positive (negative) standard estimate associate with a latent variable suggests some subpopulations have a higher (lower) value of that latent variable. The

“Gender” factor is the only factor that significantly impacts any AV-related decision variables. Male respondents are more likely to rate higher on AV’s and EV’s image, EV’s relative advantage, their personal innovativeness, environment concerns related to their negative environmental impacts, and view driving more positively to compared to their female counterparts. At the same time, they are more likely to rate lower towards AV’s relative advantage, compatibility, complexity, and safety compared to their female counterparts. Furthermore, most of them also have a higher intention to purchase GAVs and EAVs, and a larger increase in the intention to purchase GAVs and EAVs under the EAV-enabled Roadway Design.

In terms of other six sociodemographic and travel behavior characteristics, they do not have statistically significant direct impacts on AV-related decision variables. However, they have indirect impacts on these variables through other variables as these sociodemographic and travel behavior characteristics have a statistically significant relationship with latent variables that affect AV-related decision variables. Most millennials or younger are more likely to rate higher on perceived AV’s relative advantage, safety advantage, and image, and personal innovativeness compared to older generations. Most people with a college degree or above are more likely to rate higher in terms of AV’s relative advantage, safety, image, and subjective norms, EV’s relative advantage, image, and subjective norms, personal innovativeness, and environmental concerns related to their negative environmental impacts, while they rate lower on AV’s compatibility, complexity, and concerns compared to people who do not have a college degree.

Most respondents with relatively higher annual household income (more than $75,000) are more likely to rate higher on AV’s safety, image, and subjective norms, EV’s subjective norms, personal innovativeness, intention to use AVs, and a negative attitude towards driving, while they rate lower on EV’s relative advantage and their negative environmental impacts compared to respondents with lower income. Most respondents who lived in urban area are more likely to give higher ratings to AV’s relative advantage, compatibility, and image, and EV’s subjective norms, while giving lower ratings to AV’s concerns compared to people living in suburban and rural areas.

People who have a relatively small household size (one or two people in the household) are more likely to rate higher on AV’s compatibility, intention to use AVs, EV’s relative advantage and image, personal innovativeness, and their negative environmental impacts, while rate lower on AV’s complexity and concerns compared to people living in a relatively larger household. Most people who drive alone or drive with family members as their most commonly used mode of transportation for commute are more likely to rate higher on AV’s relative advantage, image, and subjective norms, EV’s subjective norms, and positively attitude towards driving, while rate lower on AV’s safety, concerns, and EV’s image compared to people who used other modes of transportation as most commonly used mode of transportation for daily commute.

The model estimation result discussion and policy implications are presented in sections 6 and 7.

Table 8. Hypotheses related to participants' perceived vehicle features/attributes (if the relationship is statistically significant, it is a supported hypotheses)

	Std. Estimate	Std. Error	*p*-value	Conclusion
H_1: The **greater** the perceived AV-relative advantage,				
…the **greater** intention to use AVs	0.237	0.036	0.000	**Supported**
…the **greater** intention to purchase GAVs	0.204	0.072	0.005	**Supported**
…the **greater** intention to purchase EAVs	0.209	0.041	0.000	**Supported**
…the **increased** intention to purchase GAVs under the EAV-enabled Roadway Design	0.058	0.029	0.041	**Supported**
…the **increased** intention to purchase EAVs under the EAV-enabled Roadway Design	0.177	0.033	0.000	**Supported**
H_2: The **higher** the perceived AV-compatibility,				
…the **greater** intention to use AVs	0.504	0.033	0.000	**Supported**
…the greater intention to purchase GAVs	0.064	0.079	0.418	Not supported
…the greater intention to purchase EAVs	0.084	0.051	0.099	Not supported
…the **increased** intention to purchase GAVs under the EAV-enabled Roadway Design	0.053	0.029	0.041	**Supported**
…the **increased** intention to purchase EAVs under the EAV-enabled Roadway Design	0.177	0.033	0.000	**Supported**
H_3: The higher the perceived AV-complexity,				
…the **lesser** intention to use AVs	-0.433	0.042	0.000	**Supported**
…the **lesser** intention to purchase GAVs	-0.185	0.087	0.033	**Supported**
…the **lesser** intention to purchase EAVs	-0.331	0.057	0.000	**Supported**
…the decreased intention to purchase GAVs under the EAV-enabled Roadway Design	-0.044	0.034	0.201	Not supported
…the decreased intention to purchase EAVs under the EAV-enabled Roadway Design	-0.012	0.297	0.766	Not supported
H_4: The **higher** the perceived AV-safety,				
…the **greater** intention to use AVs	0.115	0.029	0.000	**Supported**
…the **greater** intention to purchase GAVs	0.148	0.058	0.011	**Supported**
…the **greater** intention to purchase EAVs	0.197	0.039	0.000	**Supported**
…the **increased** intention to purchase GAVs under the EAV-enabled Roadway Design	0.055	0.013	0.000	**Supported**
…the **increased** intention to purchase EAVs under the EAV-enabled Roadway Design	0.058	0.017	0.000	**Supported**
H_5: The **higher** the perceived AV-concerns,				
…the **lesser** intention to use AVs	-0.157	0.024	0.000	**Supported**
…the **lesser** intention to purchase GAVs	-0.143	0.020	0.000	**Supported**
…the **lesser** intention to purchase EAVs	-0.083	0.033	0.011	**Supported**
…the **decreased** intention to purchase GAVs under the EAV-enabled Roadway Design	-0.101	0.020	0.000	**Supported**
…the **decreased** intention to purchase EAVs under the EAV-enabled Roadway Design	-0.047	0.023	0.038	**Supported**
H_6: The **higher** the perceived EV-relative advantage,				
…the **greater** intention to purchase EAVs	0.450	0.043	0.000	**Supported**
…the **increased** intention to purchase EAVs under the EAV-enabled Roadway Design	0.133	0.027	0.000	**Supported**
H_7: The **higher** the perceived EV-range anxiety,				
…the **lesser** intention to purchase EAVs	-0.100	0.023	0.000	**Supported**
…the decreased intention to purchase EAVs under the EAV-enabled Roadway Design	-0.073	0.077	0.339	Not supported

Table 9. Hypotheses related to social impacts on AV adoption and fuel choice (if the relationship is statistically significant, it is a supported hypotheses)

	Std. Estimate	**Std. Error**	***p*-value**	**Conclusion**
H_8: The **higher** the perceived AV-image,				
…the **greater** intention to use AVs	0.348	0.020	0.000	**Supported**
…the greater intention to purchase GAVs	0.073	0.052	0.160	Not supported
…the greater intention to purchase EAVs	0.022	0.034	0.519	Not supported
…the increased intention to purchase GAVs under the EAV-enabled Roadway Design	0.011	0.059	0.847	Not supported
…the increased intention to purchase EAVs under the EAV-enabled Roadway Design	0.065	0.079	0.417	Not supported
H_9: The higher the perceived AV-subjective norms,				
…the greater intention to use AVs	0.013	0.030	0.669	Not supported
…the greater intention to purchase GAVs	0.011	0.058	0.845	Not supported
…the greater intention to purchase EAVs	0.012	0.041	0.768	Not supported
…the increased intention to purchase GAVs under the EAV-enabled Roadway Design	0.009	0.023	0.682	Not supported
…the increased intention to purchase EAVs under the EAV-enabled Roadway Design	0.045	0.026	0.091	Not supported
H_{10}: The higher the perceived EV-image,				
…the greater intention to purchase EAVs	0.035	0.031	0.249	Not supported
…the increased intention to purchase EAVs under the EAV-enabled Roadway Design	0.054	0.031	0.092	Not supported
H_{11}: The higher the perceived EV-subjective norms,				
…the greater intention to purchase EAVs	0.016	0.025	0.526	Not supported
…the increased intention to purchase EAVs under the EAV-enabled Roadway Design	0.008	0.039	0.864	Not supported

Table 10. Hypotheses related to personal innovativeness, environmental concerns, and attitude towards driving on AV adoption and fuel choice (if the relationship is statistically significant, it is a supported hypotheses)

	Std. Estimate	Std. Error	*p*-value	Conclusion
H_{12}: The **higher** the perceived personal innovativeness,				
…the **greater** intention to use AVs	0.113	0.020	0.000	**Supported**
…the **greater** intention to purchase GAVs	0.081	0.040	0.044	**Supported**
…the **greater** intention to purchase EAVs	0.067	0.027	0.013	**Supported**
…the increased intention to purchase GAVs under the EAV-enabled Roadway Design	0.010	0.016	0.514	Not supported
…the increased intention to purchase EAVs under the EAV-enabled Roadway Design	0.019	0.018	0.294	Not supported
H_{13}: The higher the perceived environmental concerns,				
…the greater intention to purchase EAVs	0.013	0.030	0.669	Not supported
…the increased intention to purchase EAVs under the EAV-enabled Roadway Design	0.004	0.015	0.775	Not supported
H_{14}: The **higher the negative** attitude towards driving,				
…the **greater** intention to use AVs	0.145	0.020	0.000	**Supported**
…the **greater** intention to purchase GAVs	0.087	0.042	0.037	**Supported**
…the **greater** intention to purchase EAVs	0.080	0.029	0.000	**Supported**
…the **increased** intention to purchase GAVs under the EAV-enabled Roadway Design	0.040	0.017	0.015	**Supported**
…the **increased** intention to purchase EAVs under the EAV-enabled Roadway Design	0.044	0.019	0.020	**Supported**

Table 11. Hypotheses related to the intention to use AVs, and intention to purchase GAVs and EAVs (if the relationship is statistically significant, it is a supported hypotheses)

	Std. Estimate	Std. Error	*p*-value	Conclusion
H_{15}: The **higher** intention to use AVs,				
…the **greater** intention to purchase GAVs	0.277	0.057	0.000	**Supported**
…the **greater** intention to purchase EAVs	0.500	0.067	0.000	**Supported**
…the **increased** intention to purchase GAVs under the EAV-enabled Roadway Design	0.057	0.019	0.000	**Supported**
…the **increased** intention to purchase EAVs under the EAV-enabled Roadway Design	0.048	0.018	0.009	**Supported**
H_{16}: The **higher** intention to purchase GAVs,				
…the **increased** intention to purchase GAVs under the EAV-enabled Roadway Design	0.032	0.011	0.003	**Supported**
H_{17}: The **higher** intention to purchase EAVs,				
…the **increased** intention to purchase EAVs under the EAV-enabled Roadway Design	0.048	0.018	0.009	**Supported**

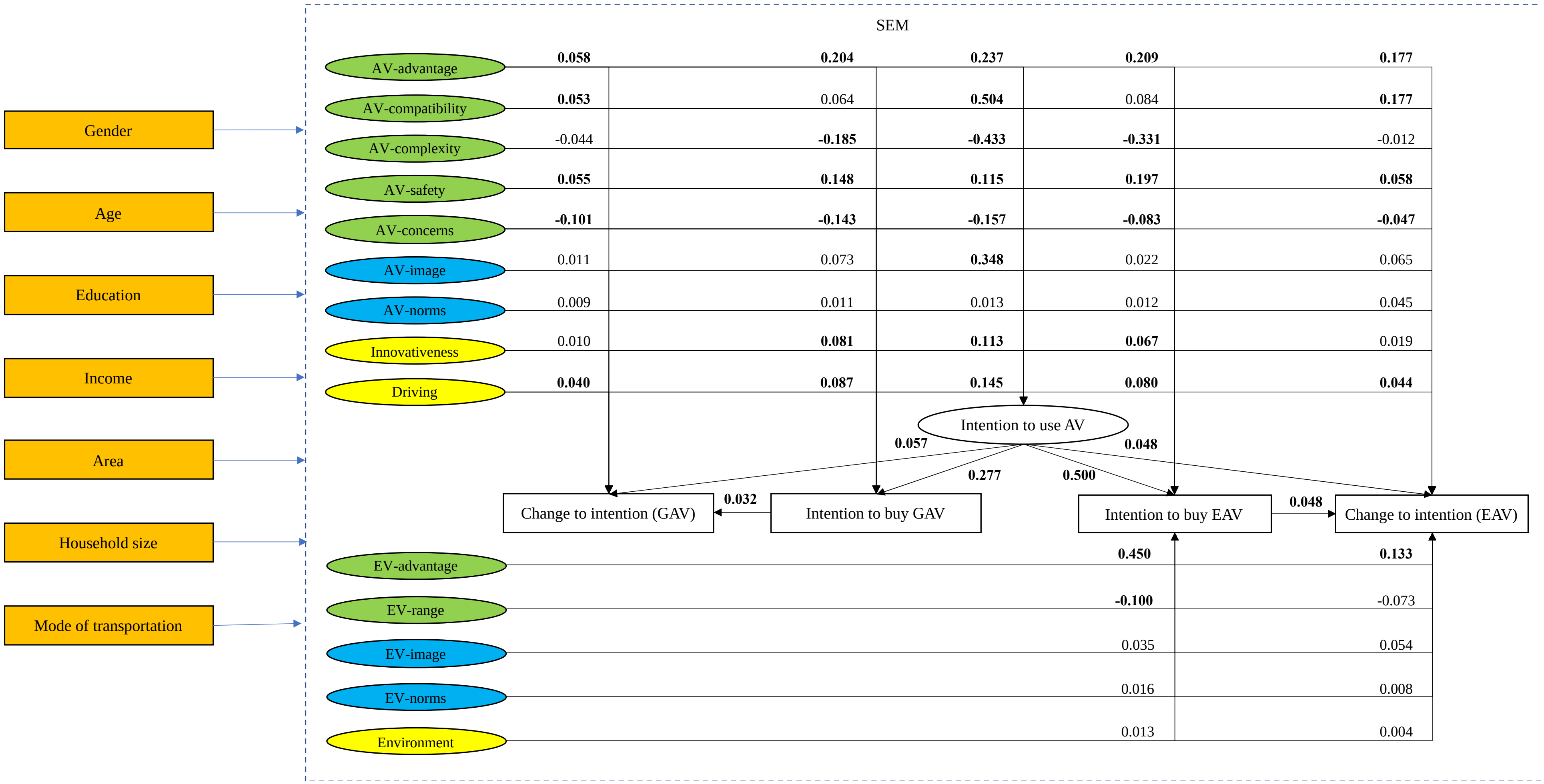

Figure 7. Mode estimation results for investigating the impacts of attitudinal factors and roadway design features on AV adoption and fuel choice. (+ suggests a positive correlation while - suggests a negative correlation)

Table 12. Sociodemographic and travel characteristics' relationship with latent variables (bold results suggest a statistically significant relationship)

	Std. Estimate	Std. Error	*p*-value
Gender: most **male** respondents are more likely to … compared to female respondents			
… **doubt AV's relative advantage** over HVs…	-0.143	0.031	0.000
… **doubt AV's compatibility**…	-0.206	0.043	0.000
… **doubt AV's complexity**…	-0.192	0.037	0.000
… **doubt AV's safety** advantage over HVs…	-0.130	0.036	0.000
… **doubt** the **concerns** of using AVs…	-0.254	0.046	0.000
… **believe EV's relative advantage** over GVs…	0.155	0.042	0.000
… *does not have a statistically significant impact* on the perceived EV-range anxiety…	0.003	0.015	0.789
… **believe** that using **AVs** have a positive **image**…	0.114	0.054	0.035
… *does not have a statistically significant impact* on the perceived AV-subjective norms…	-0.049	0.033	0.137
… **believe** that using **EVs** have a positive **image**…	0.167	0.048	0.000
… *does not have a statistically significant impact* on the perceived EV-subjective norms…	0.042	0.052	0.418
… **believe** that they have high **personal innovativeness**…	0.109	0.049	0.027
… **believe** negative **environmental impacts** related to their behavior (environmental concerns) …	0.112	0.053	0.035
… have a **positive** attitude towards **driving** (i.e., negative towards negative driving attitude) …	-0.120	0.051	0.018
… *does not have a statistically significant impact* on the intention to use AVs…	-0.065	0.036	0.068
… have **higher** intention to **purchase GAVs**…	0.411	0.067	0.000
… have **higher** intention to **purchase EAVs**…	0.378	0.047	0.000
… have **larger increase in** intention to **purchase GAVs** under the EAV-enabled Roadway Design…	0.616	0.027	0.000
… have **larger increase in** intention to **purchase EAVs** under the EAV-enabled Roadway Design…	0.220	0.031	0.000
Age: most millennials or younger are more likely to …. compared to older generations			
… **believe** AV's relative advantage over HVs…	0.196	0.049	0.000
… *does not have a statistically significant impact* on the perceived AV-compatibility…	0.093	0.068	0.171
… *does not have a statistically significant impact* on the perceived AV-complexity…	0.042	0.058	0.469
… **believe** AV's **safety** advantage over HVs…	0.139	0.058	0.017
… *does not have a statistically significant impact* on the perceived AV-concerns…	-0.036	0.074	0.624
… *does not have a statistically significant impact* on the perceived EV-relative advantage…	0.056	0.077	0.466
… *does not have a statistically significant impact* on the perceived EV-range anxiety…	0.005	0.066	0.924
… **believe** that using **AVs** have a positive **image**…	0.201	0.088	0.022
… *does not have a statistically significant impact* on the perceived AV-subjective norms…	0.099	0.055	0.070
… *does not have a statistically significant impact* on the perceived EV-image…	0.056	0.077	0.466
… *does not have a statistically significant impact* on the perceived EV-subjective norms…	0.002	0.090	0.988
… **believe** that they have high **personal innovativeness**…	0.174	0.080	0.030
… *does not have a statistically significant impact* on the perceived environmental concerns…	0.107	0.086	0.214
… *does not have a statistically significant impact* on the attitude towards driving…	-0.048	0.082	0.554
… *does not have a statistically significant impact* on intention to use AVs…	0.032	0.054	0.556

… *does not have a statistically significant impact* on intention to purchase GAVs…	0.043	0.103	0.674
… *does not have a statistically significant impact* on intention to purchase EAVs…	0.149	0.105	0.159
… *does not have a statistically significant impact* on the changes to intention to purchase GAVs under the EAV-enabled Roadway Design…	0.147	0.106	0.164
… *does not have a statistically significant impact* on the changes to intention to purchase EAVs under the EAV-enabled Roadway Design…	0.009	0.047	0.844
Education: most respondents with a college degree or above are more likely to … compared to those who don't have			
… **believe** AV's relative advantage over HVs…	0.349	0.037	0.000
… **doubt** AV's **compatibility**…	-0.587	0.052	0.000
… **doubt** AV's **complexity**…	-0.492	0.047	0.000
… **believe** AV's **safety** advantage over HVs…	0.391	0.043	0.000
… **doubt** the **concerns** of using AVs…	-0.569	0.053	0.000
… **believe EV's relative advantage** over GVs…	0.308	0.048	0.000
… *does not have a statistically significant impact* on the perceived EV-range anxiety…	0.019	0.078	0.811
… **believe** that using **AVs** have a positive **image**…	0.737	0.063	0.000
… **believe** that AV-subjective norms…	0.081	0.039	0.039
… **believe** that using **EVs** have a positive **image**…	0.263	0.055	0.000
… **believe** that EV-subjective norms…	0.219	0.034	0.000
… **believe** that they have high **personal innovativeness**…	0.150	0.056	0.008
… **believe** the negative **environmental impacts** related to their behavior (environmental concerns) …	0.355	0.061	0.000
… *does not have a statistically significant impact* on the attitude towards driving…	-0.050	0.058	0.392
… *does not have a statistically significant impact* on the intention to use AVs…	0.027	0.054	0.618
… *does not have a statistically significant impact* on the intention to purchase GAVs	0.019	0.099	0.848
… *does not have a statistically significant impact* on the intention to purchase EAVs	0.035	0.032	0.277
… *does not have a statistically significant impact* on the changes to the intention to purchase GAVs under the EAV-enabled Roadway Design	0.037	0.039	0.340
… *does not have a statistically significant impact* on the changes to the intention to purchase EAVs under the EAV-enabled Roadway Design	0.010	0.047	0.822
Annual household income: most respondents with relatively high annual household income (more than $75,000) are more likely to … compared to those who have relatively low annual household income.			
… *does not have a statistically significant impact* on the perceived AV-relative advantage…	0.018	0.029	0.550
… *does not have a statistically significant impact* on the perceived AV-compatibility…	0.056	0.041	0.176
… *does not have a statistically significant impact* on the perceived AV-complexity…	0.061	0.035	0.082
… **believe** AV's **safety** advantage over HVs…	0.244	0.036	0.000
… *does not have a statistically significant impact* on the perceived AV-concerns	0.007	0.044	0.869
… **doubt EV's relative advantage** over GVs…	-0.126	0.041	0.002
… *does not have a statistically significant impact* on the perceived EV-range anxiety	0.002	0.089	0.986
… **believe** that using **AVs** have a positive **image**…	0.206	0.053	0.000

… **believe** that AV-subjective norms…	0.175	0.045	0.000
… *does not have a statistically significant impact* on the perceived EV-image	0.006	0.046	0.903
… **believe** that EV-subjective norms…	0.228	0.051	0.000
… **believe** that they have high **personal innovativeness**…	0.562	0.048	0.000
… **doubt** the negative **environmental impacts** related to their behavior (environmental concerns) …	-0.228	0.052	0.000
… have a **negative** attitude towards **driving** (i.e., positive towards negative driving attitude) …	0.240	0.050	0.000
… have a **higher** intention to **use AVs**…	0.084	0.036	0.019
… *does not have a statistically significant impact* on the intention to purchase GAVs	0.046	0.069	0.499
… *does not have a statistically significant impact* on the intention to purchase EAVs	0.132	0.080	0.099
… *does not have a statistically significant impact* on the changes to intention to purchase GAVs under the EAV-enabled Roadway Design	0.011	0.027	0.674
… *does not have a statistically significant impact* on the changes to intention to purchase EAVs under the EAV-enabled Roadway Design	0.038	0.032	0.235
Area lived in: most respondents who live in urban region are more likely to … compared to people who live			
… **believe AV's relative advantage** over HVs…	0.268	0.057	0.000
… **believe AV's compatibility**…	0.145	0.078	0.061
… *does not have a statistically significant impact* on the perceived AV-complexity…	0.061	0.035	0.082
… *does not have a statistically significant impact* on the perceived AV-safety…	0.031	0.066	0.642
… **doubt** the **concerns** of using AVs…	-0.383	0.084	0.000
… *does not have a statistically significant impact* on the perceived EV-relative advantage…	-0.020	0.077	0.790
… *does not have a statistically significant impact* on the perceived EV-range anxiety…	0.127	0.082	0.121
… **believe** that using **AVs** have a positive **image**…	0.463	0.100	0.000
… *does not have a statistically significant impact* on the perceived AV-subjective norms…	-0.078	0.060	0.194
… *does not have a statistically significant impact* on the perceived EV-image…	-0.157	0.088	0.074
… **believe** that **EV-subjective norms**…	0.533	0.097	0.000
… *does not have a statistically significant impact* on the perceived personal innovativeness…	-0.074	0.091	0.414
… *does not have a statistically significant impact* on the perceived environmental concerns…	-0.061	0.098	0.536
… *does not have a statistically significant impact* on the attitude towards driving…	0.030	0.317	0.751
… *does not have a statistically significant impact* on the intention to use AVs…	0.100	0.063	0.110
… *does not have a statistically significant impact* on the intention to purchase GAVs…	0.071	0.120	0.552
… *does not have a statistically significant impact* on the intention to purchase EAVs…	0.148	0.105	0.160
… *does not have a statistically significant impact* on the intention to purchase GAVs under the EAV-enabled Roadway Design…	-0.003	0.047	0.950
… *does not have a statistically significant impact* on the intention to purchase EAVs under the EAV-enabled Roadway Design…	0.079	0.055	0.150
Household size: most people who have fewer than three people in their household are more likely to … compared to those who have three or more people in their household			
… *does not have a statistically significant impact* on the perceived AV-relative advantage…	0.026	0.036	0.473

… **believe** AV's **compatibility**…	-0.194	0.050	0.000
… **doubt** AV's **complexity**…	-0.184	0.043	0.000
… *does not have a statistically significant impact* on the perceived AV-safety…	-0.071	0.043	0.099
… **doubt** the **concerns** of using AVs…	-0.250	0.054	0.000
… **believe EV's relative advantage** over GVs…	0.180	0.050	0.000
… *does not have a statistically significant impact* on the perceived EV-range anxiety…	0.009	0.090	0.917
… **believe** that using **AVs** have a positive **image**…	0.244	0.064	0.000
… *does not have a statistically significant impact* on the perceived AV-subjective norms…	0.055	0.039	0.160
… **believe** that using **EVs** have a positive **image**…	0.154	0.056	0.006
… *does not have a statistically significant impact* on the perceived EV-subjective norms…	0.019	0.076	0.798
… **believe** that they have high **personal innovativeness**…	0.133	0.059	0.023
… **believe** the negative **environmental impacts** related to their behavior (environmental concerns) …	0.170	0.063	0.007
… *does not have a statistically significant impact* on the attitude towards driving	0.099	0.060	0.101
… have a **higher** intention to **use AVs**…	0.160	0.041	0.000
… *does not have a statistically significant impact* on the intention to purchase GAVs	0.132	0.080	0.099
… *does not have a statistically significant impact* on the intention to purchase EAVs	0.148	0.105	0.160
… *does not have a statistically significant impact* on the intention to purchase GAVs under the EAV-enabled Roadway Design	0.035	0.032	0.277
… *does not have a statistically significant impact* on the intention to purchase EAVs under the EAV-enabled Roadway Design	0.014	0.037	0.704
The most commonly used mode of transportation for daily commute: most people who drive alone or drive with family members are more likely to … compared to those who use other modes of transportation for commute			
… **believe** AV's relative advantage over HVs…	0.115	0.049	0.018
… *does not have a statistically significant impact* on the perceived AV-compatibility…	0.051	0.067	0.452
… *does not have a statistically significant impact* on the perceived AV-complexity…	0.087	0.057	0.130
… **doubt** AV's **safety** advantage over HVs…	-0.129	0.058	0.026
… **doubt** the **concerns** of using AVs…	-0.175	0.073	0.016
… **doubt EV's relative advantage** over GVs…	-0.243	0.076	0.001
… *does not have a statistically significant impact* on the perceived EV-range anxiety…	0.020	0.060	0.735
… **believe** that using **AVs** have a positive **image**…	0.215	0.087	0.013
… **believe** that AV-subjective norms…	0.274	0.084	0.001
… **doubt** that using **EVs** have a positive **image**…	-0.243	0.076	0.001
… **believe** that **EV-subjective norms**…	0.274	0.084	0.001
… *does not have a statistically significant impact* on the perceived personal innovativeness	-0.087	0.079	0.273
… *does not have a statistically significant impact* on the perceived environmental concerns	0.043	0.086	0.618
… have a **positive** attitude towards **driving** (i.e., negative towards negative driving attitude) …	-0.464	0.083	0.000
… *does not have a statistically significant impact* on the intention to use AVs	0.087	0.055	0.113
… *does not have a statistically significant impact* on the intention to purchase GAVs	0.127	0.104	0.221
… *does not have a statistically significant impact* on the intention to purchase EAVs	0.148	0.105	0.160

… *does not have a statistically significant impact* on the intention to purchase GAVs under the EAV-enabled Roadway Design	0.041	0.041	0.325
… *does not have a statistically significant impact* on the intention to purchase EAVs under the EAV-enabled Roadway Design	0.067	0.048	0.162

5. Discussions of Results

5.1. Impacts of EAV-enabled design on the change to the willingness to buy GAVs and EAVs

As shown in Figure 8(a), under current condition (i.e., existing roadway design), about 66.6% of the respondents have strong (i.e., “a little strong”, “somewhat strong”, or “very strong”) intention to buy EAVs and 59% of the respondents have strong intention to buy GAVs.

Respondents' stated intentions to buy AVs of different fuel types revealed that they might only be open to purchasing AVs of their preferred fuel type. Less than half of all respondents (47%) have affirmative (i.e., “a little strong”, “somewhat strong”, or “very strong”) intentions to buy AVs of either powertrain type. It is important to note that many respondents only prefer one of the AV fuel types. 12% of all respondents only have strong (i.e., “a little strong”, “somewhat strong”, or “very strong”) intention to buy GAVs over EAVs (i.e., “neutral”, “a little weak”, “somewhat weak”, or “very weak” intention to buy EAVs). 19% of all respondents only have strong (i.e., “a little strong”, “somewhat strong”, or “very strong”) intention to buy EAVs over GAVs (i.e., “neutral”, “a little weak”, “somewhat weak”, or “very weak” intention to buy GAVs). The rest (22%) had a weak to neutral intention to buy either type of AVs (i.e., “neutral”, “a little weak”, “somewhat weak”, or “very weak” intention to buy GAVs or EAVs). These results suggest that (i) about half of the respondents may choose either fuel type and their choices can affect the overall impacts of AVs on environment and CO2 emissions; and (ii) some people may only want to buy GAVs.

The EAV-enabled design has very little impacts on the change in respondents’ willingness to buy GAVs. Although this design has some features (e.g., increased speed limit) that can also benefit GAVs, only about 28% of the respondents suggest that their willingness to buy GAVs is “somewhat likely”, “likely”, or “definitely” going to increase in this design. However, around 50% of the respondents suggest that their willingness to buy EAVs is “somewhat likely”, “likely”, or “definitely” going to increase in this design with “wireless charging” as the only features differentiating between the benefits towards GAVs and EAVs. This highlights the importance of (i) increasing the EAV range by EAV manufactures and (ii) reducing people’s range anxiety through information programs and public infrastructure support; these can play key roles in reducing people’s range anxiety and promoting EAV adoption over GAV when both types of AVs become available.

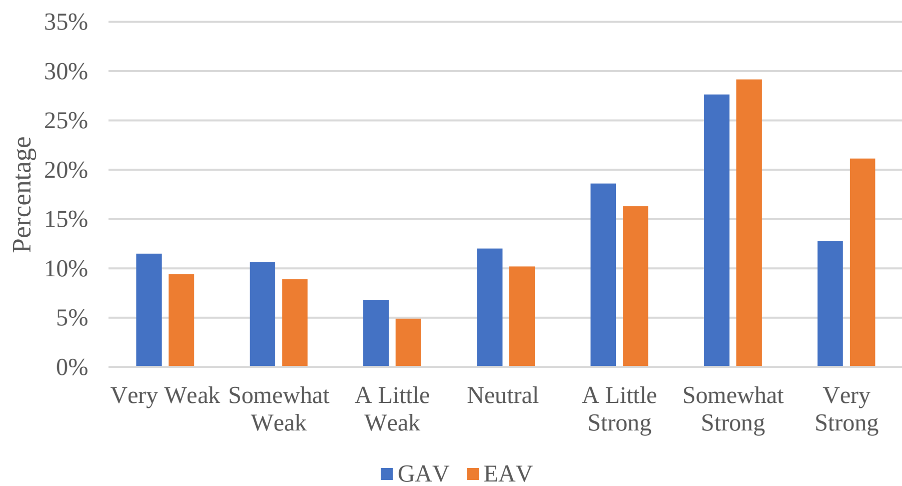

Figure 8(a). Respondents’ willingness to buy GAVs and EAVs

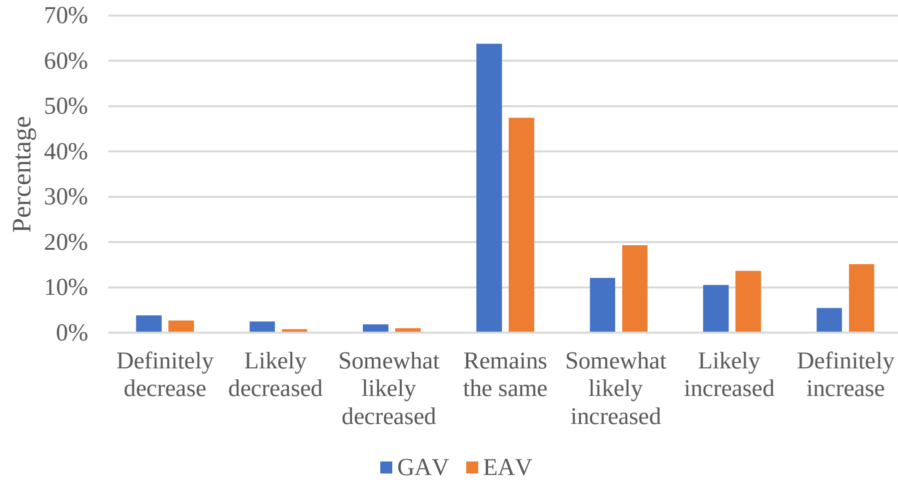

Figure 8(b). Respondents' change to the willingness to buy GAVs and EAVs in EAV-enabled design

Figure 8. Impacts of EAV-enabled design on the change to the willingness to buy GAVs and EAVs

5.2. Perceived vehicle features and attributes

Six key findings can be identified based on model estimation results. First, this study demonstrates the impacts of the variable "relative performance advantage" (i.e., the perceived AV's relative performance advantages over existing forms of transportation) on people's stated intention to use AVs. Among all the attitudinal variables considered, "AV-relative advantage" was the most important factor that influenced participants' AV-related decisions. Many studies (Cunningham et al., 2019; Liu et al., 2019) have similar findings and this highlights the importance of improving the performance of AVs and EAVs for promoting their adoption among potential users. Second, individuals who believe that AV usage is compatible with their work and lifestyle needs have greater intention to use AVs, and the increased intention to purchase GAVs and EAVs under the EAV-enabled Roadway Design. Previous studies such as Payre et al. (2014) and Shin et al. (2015) also mentioned the importance of compatibility in AV adoption process. Third, the results revealed that if people perceive AVs are safer than the existing transportation modes, they are more likely to use AVs and purchase GAVs and EAVs. Similar findings can be found in the literature that people who believe that removing human from the driving process has the potential of improving transportation safety are more likely to use AVs (Kyriakidis et al., 2015; Zmud et al., 2016).

Fourth, people who perceived AVs are difficult to operate are more likely to have less intention to use AVs, to buy GAVs, or EAVs. This is consistent with studies like Zmud et al. (2016) and König and Neumayr (2017) and highlights the importance of proper training and human-machine interface design. Fifth, the perceived risk (e.g., privacy concerns and accident liability) associated with using an AV plays an important role in AV adoption. As more and more people are concerned about their digital footprints and personal data safety, studies such as Choi and Ji (2015) and Kyriakidis et al. (2015) highlighted the importance of reducing the perceived risk in AV adoption. Lastly, peoples' perceived advantages of BEVs and their range anxiety have statistically significant relationships with their intention to purchase EAVs and changes to their intention to purchase EAVs in the EAV-enabled Roadway Design environment, while their range anxiety only affects their intention to purchase EAVs. This is similar to studies related to intentions to purchase BEVs (e.g., Valeri and Danielis, 2015; Berkeley et al., 2018).

5.3. Social influence factors

Of the four social factors considered in this study, only AV-image was found to have a statistically significant positive relationship with intentions to use AVs. This highlights the mixed results regarding the impacts of social factors on AV adoption and purchase. Studies like Axsen and Sovacool (2019) suggested that social factors are important factors affecting AV-related decisions, while studies such as Liu et al. (2019) concluded differently. In the literature, there is a tendency toward a positive, but still mixed, effects of pro-AV and/or pro-EV social influence (e.g., subjective norms towards using AVs and EVs and positive image related to using AVs and EVs) on people's intention to use AVs and purchase EAVs (Panagiotopoulos and Dimitrakopoulos, 2018; Gkartzonikas and Gkritza, 2019; Herrenkind et al., 2019). There are several possible reasons for such discrepancies, including experiment design differences, such as considered variables, survey population differences, and so on. For example, some social factors such as subjective norms can vary greatly between individuals across different studies, perhaps due to a lack of understanding, experience, or clarity on what to expect from AVs in their current nascent stage of development and deployment. Hence, terminology used in the questionnaire and provided information can significantly impact survey results. Additional studies are needed to better understand these differences, and more time and education might be necessary before such social factors stabilize.

5.4. Personal innovativeness, environmental concerns, and attitude towards driving

The participants who perceive themselves as "innovative" (e.g., love to try and/or purchase new technologies and purchasing new products) were found to have greater intention to use AVs. This observation suggests that people who demonstrate strong technology-related interest or have a greater personal innovativeness, have a tendency to try new products even where these products may be expensive and/or are at their nascent stages of development (e.g., Haboucha et al., 2017). Similar findings have also been observed in other domains related to new technologies (Hurt et al., 1977).

In terms of the environmental concerns, the model estimation results show that respondents' level of environmental concerns does not have a statistically significant relationship with their intention to purchase EAVs or changes to their intention to purchase EAVs in the EAV-enabled Roadway Design environment. Of the eleven previous studies listed in the literature review (Table 2), five studies similarly showed that respondents' intention to purchase BEVs was not significantly associated with their environmental concerns, ecological awareness, pro-environment attitudes, values, and beliefs (Barth et al., 2016; White and Sintov, 2017; Westin et al., 2018; Carley et al., 2019; Spurlock et al., 2019). There is a multitude of reasons that lead to the mixed results observed in the literature. A plausible reason is that the impacts of environmental concerns on people's intention to purchase EAVs diminish when other performance- and cost-related variables are included. Participants who dislike driving were found to exhibit a greater intention to use AVs, and purchase EAVs and GAVs. This observation is similar to previous studies that people who love driving or have a strong desire to exert control have a lesser intention to use and purchase AVs (Howard and Dai, 2014; Payre et al., 2014; Haboucha et al., 2017).

Finally, the model estimation results show that people with a greater intention to use AVs are more likely to have a greater intention to purchase GAVs and EAVs, and increased intention of purchasing GAVs and EAVs under the EAV-enabled Roadway Design environment. These results also show that people's intention to purchase GAVs and EAVs are positively correlated to their changes to the intention to purchase GAVs and EAVs in the EAV-enabled Roadway Design.

5.5. Sociodemographic and travel behavior characteristics

Among the seven sociodemographic and travel behavior characteristics, "gender" factor is the only factor that have statistically significant direct impacts on AV-related decision variables. However, other characteristics have indirect impacts on these variables through other variables by having a statistically significant relationship with latent variables that affect AV-related decision variables. The results show that male (similar to Peters and Dütschke, 2014; Kyriakidis et al., 2015), millennials or younger (similar to Westin et al., 2018; Cunningham et al., 2019), with a college degree or above (similar to Nayum and

Klöckner, 2014; Haboucha et al., 2017), having relatively high annual household income (more than $75,000) (similar to Okada et al., 2019; Wang and Zhao, 2019), living in urban areas (similar to Nazari et al., 2018; Carley et al., 2019), having a relatively small household size (contradicting to Bansal et al., 2016; Bansal and Kockelman, 2017; Nazari et al., 2018; Shabanpour et al., 2018; Sheela and Mannering, 2019), or using drive alone or drive with family members as their most commonly used mode of transportation for commute are more likely to have a higher intention to use AVs, intention to purchase GAVs and EAVs, and larger changes in their intention to purchase GAVs and EAVs in the EAV-enabled design.

6. Policy Implications

Model estimation results and descriptive statistics can be used by policymakers and transportation planners, in collaboration with AV manufacturers to design various infrastructural and policy support to mitigate unintended negative consequences of the three revolutions and maximize their benefits.

6.1. Minimizing unintended negative consequences

First, in terms of people's preference of privately-owned AVs over shared mobility operated by AVs, most people are more likely to be private AV owners instead of sharing them (Figure 8) which may signal the potential challenges for facilitating promotion of shared mobility operated by AVs. In addition, the recent pandemic may heighten the perceived need to privately owned vehicles over shared ones (e.g., previous riders may be COVID-19 patients or carry other types of viruses that may affect the next rider) as suggested in Guo et al. (2021c). If most AVs are still gasoline-powered and privately owned, it may lead to increasing VMT and GHG emissions due to induced demand, zero occupancy vehicle ridership, and increased mobility. These contemporary societal choices (favoring AV ownership) can determine the outcomes of the AV adoption (Haugland and Skjølsvold, 2020). Hence, policymakers may consider policies such as restricting privately-owned empty AVs' access the road at congestion regions or during peak hours, introducing measures to improve the shared AV interior to reduce potential disease spreading through them, restoring public's confidence in shared vehicles, and other measures to promote shared AVs and encourage shared AV service providers to offer more shared EAVs instead of shared GAVs.

Second, in terms of people's concerns over vehicle automation, legal liability ("I would be afraid of legal liability when using a self-driving car"), system and vehicle security ("I would be afraid of system and vehicle security from hackers"), and privacy ("I would be afraid of the privacy issues relate to using a self-driving car") are remaining to be of high concern among respondents (Table 7). It may require both continued autonomy and algorithmic enhancement by automakers and academia, and policymakers adopt the concept of technology governance. If AVs are promised to be safe and environmentally beneficial compared to conventional vehicles, yet fail to deliver on either of these promises due to the fuel type or ownership model, public trust in them may be undermined and their long-term potential curtailed (Stilgoe, 2018). A diversified approach that capitalizes on the inherent strengths of vehicle electrification, vehicle automation, and shared ownership/ridership might assure that these emergent technologies and trends are greater than the sum of their parts (Sperling, 2018). The concept of governance as social learning (how people learn socially and how societies learn) is pertinent to AV technology and other new technologies. Good governance should engage both the technological outcomes and the processes and purposes of innovation. It is important for policymakers and AV manufacturers to focus on both technical security (e.g., improving system security) and legal measures (e.g., laws and policies related to accident liability) to address these legitimate concerns. It is also important for policymakers, planners, and AV manufacturers to develop a transparent plan that allows the public to better understand the technological and legislative efforts to address these concerns and ease the valid anxieties of skeptical individuals.

Third, in terms of infrastructural and policy design process for preparing for the coming of three revolutions, it is important to incorporate public in designing AV-related rules and regulations. This can be critical for democracy and democratic processes and public participation should not be limited to educational or marketing purposes. This study, along with studies such as Stilgoe (2018) and Haugland and Skjølsvold (2020), represent one of the early attempts to understand public attitude, expectations, and concerns of AVs and AV-related roadway designs. Public hearings, surveys, and other methods can be implemented to ensure that both AV design and the regulations that govern them meet the needs of the general public, and that public needs supersede business interests (Marres, 2020; Haugland and Skjølsvold, 2020).

Fourth, it is important to factor the needs of socially and economically disadvantaged subpopulations when designing AV-related rules and regulations. The model estimation results show that for people who are older (Generation X or older) or lower-income (have less than $75,000 compared to the U.S. median at $68,703 in 2019) are less likely to use AV. Ideally, AVs should provide new mobility options to older or lower-income travelers as they may have limited driving ability or affordable travel options, and, as a result, increase their access to various types of opportunities. However, this study results show that these people are more skeptical on AVs and may lag behind in the AV adoption process. Therefore, the introduction of AVs may widen the gaps in terms of travel options and access to various opportunities between early adopters (younger or high-income) and those lagging behind (older or low-income). In addition, most existing AV-related advertisements developed by automakers only targeted male and Caucasian drivers (Hildebrand and Sheller, 2018). It is important for policymakers to identify creative policies and regulations to incentivize automakers to incorporate the needs of these subpopulations. It is also important to factor the potential cultural and regional differences during the policy design process. Furthermore, older adults are willing to try other kinds of new, useful technologies (Demiris et al., 2004), and perhaps increased visibility of AVs' benefits in other populations may move them to see how they might also benefit.

Finally, high market penetrations of the AVs, EAVs, and shared mobility give tremendous opportunities for updating the existing urban landscape and roadway design guidelines and regulations. Existing ones may be inadequate in addressing such changes brought by the three revolutions. For example, parking minimums (private businesses and residences need to provide at least a certain number of off-street parking) that are used in most states lead to the urban centers mostly occupied by parking structures, roadside parking, and other parking facilities. Some of these parking facilities may not be needed when a sizeable number of vehicles on the street are AVs (i.e., they can drive back home or park at some remote locations). Some of such changes can be used for targeted promotion of AVs, EAVs, and/or shared mobility in the future. Without updating these guidelines and regulations may lead to unintegrated three revolutions with unintended negative consequences.

6.2. Maximizing benefits

The study results also show that additional efforts can be spent to facilitate seamless integration of vehicle automation and electrification with shared mobility to maximize benefits from these revolutions.

In terms of perceived vehicle features and attributes, the following plans can be considered to promote AVs, EAVs and/or shared mobility if needed. (i) It is important to emphasize the potential benefits of EAVs over GAV options. Some of the advantages to highlight include reduced life-time vehicle costs through energy consumption reduction (e.g., platooning), increased convenience and flexibility, and reduced congestion through increased road capacity (e.g., reduced vehicle headway due to platooning). (ii) Individuals whose work and/or lifestyle require frequent, flexible, and/or long-distance travel may likely be early EAV adopters, and they can potentially create a positive image of shared AV and EAV use. (iii) These results highlight the potential of introducing some of the measures and policies for BEV adoption to promote purchasing EAVs over GAVs. Financial incentive policy measures such as direct subsidies and/or tax exemptions could potentially make EAVs more cost competitive relative to GAVs. Government can also potentially introduce programs that are similar to “Cash for Clunkers” to support private vehicle buying services to suppose people to trade in HVs with poor fuel economy for EAVs with improved EPA-estimated mileage. Or local government can potentially limit the number of GAVs that can be licensed each year similar to what many cities in China (Beijing and Shanghai) are doing to promote BEVs. Information provision policies that help to inform potential users on favorable EAV attributes (i.e., those that put EAVs’ relative advantages on display compared to GAVs), including their life-time cost, driving range, charging time, battery life, environmental performance and other issues related to using EAVs can also be introduced, and should play a critical role in peoples’ adoption decisions. Convenience policies and infrastructural support such as the dedicated AV lanes and wireless charging mentioned earlier in this paper can potentially provide both tangible and intangible benefits to the future EAV users that can further influence people’s fuel choice when purchasing AVs or using an AV related service, but such emphasis on convenience might directly clash with the desirable goal of promoting shared AV services. Additional studies are needed to better understand the full impact of such policies on AV adoption and fuel choice, and how shared AV options might be made more attractive transportation options.

In terms of the potential policy implications related to social influence factors, it is important to create social (e.g., family and friends), media, and societal environments that promote the adoption of EAVs and build positive image related to using EAVs over GAVs, as well as shared mobility. These environments can be created through developing media reports, advertising campaigns, and organizing community outreach programs to better inform the general public on related issues. In addition, it is also important for federal- and state-level public organizations to act as potential early adopters of shared EAVs and promote shared EAV visibility, familiarity, and adoption. These early adopters can potentially serve as a reference group for the broader masses to positively promote EAV usage over GAVs and shared EAVs over privately-owned EAVs.

In terms of participants’ concerns over complexity, the results highlight the importance of making AV operation less complex, such as improving human machine interface so that potential users of different ages, of varying technological ability/sophistication, varying levels of sensory, cognitive, and/or physical ability can operate the AVs with less stress, adding fail safe measures to reduce the anxiety associated with users initiating the wrong order (e.g., pressing the wrong button, saying the wrong voice command, etc.). This can potentially make AVs more appealing to more potential users which will hopefully maximize their benefits.

In terms of the policy implications related to perceived personal innovativeness, environmental concerns, and attitude towards driving, a few conclusions can be derived from the model results. (i) People with high personal innovativeness can likely be considered as possible early adopters of AVs. They can potentially boost the initial diffusion of AVs as they are inclined to take risks when it comes to such new technologies. It is important to attract this class of potential users by offering test ride opportunities with AVs, particularly EAVs, and shared EAV services to provide them with first-hand experience of AV and EAV technologies, and services provided by shared EAVs. (ii) Although environmental concern was not found to be statistically significantly correlated with GAV or EAV purchase, it does not imply environmental concerns do not play a role in their choice between GAVs and EAVs. Results suggest that when promoting EAV adoption, a more effective, multifaceted advertising strategy could focus on the life-time cost-saving benefits and other performance- and safety-related benefits of EAVs over GAVs rather than solely focus on the environmental-related benefits of electrification. This may also be a factor that affect their decisions related shared mobility. Additional studies are needed to understand the impacts of individuals' environmental concerns, ecological awareness, pro-environment attitudes, values, and beliefs on their AV fuel choice and intention to use shared mobility services provided by EAVs. (iii) People who would rather not drive could potentially be early adopters of AVs as well. People's desire to exert vehicle control or love for sensation-seeking through driving may be one of the main barriers for AV adoption among some people, particularly at the beginning of the transition period. (iv) The proposed design features such as dedicated lanes, wireless charging, and pick-up/drop-off zones for AVs can potentially promote EAV adoption over GAVs. It is possible that these design features can also help to promote shared mobility services provided by EAVs.

The model results also highlight subpopulations that are more likely to use AVs and buy EAVs. These include males, those that are millennials or younger, highly educated (college degree or higher), those that have a relatively high annual household income (more than $75,000 compared to the U.S. median at $68,703 in 2019), those living in urban areas, those with a relatively smaller household size (fewer than 3 people compared to the U.S. average at 2.72 in 2019), or those driving alone or driving with family members as their most commonly used mode of transportation for commute. These results facilitate the identification of subpopulations who are more likely to be the early adopters of the EAVs and shared mobility to promote a smoother transition from HVs to shared EAVs in the near future.

7. Conclusions, Limitations, and Future Research

Technological advances in AVs have immense potential to improve mobility of the currently underserved populations, improve road safety, and increase transportation system efficiency. They can potentially also bring negative externalities such as increasing VMT and emissions if the majority of the road users still prefer privately-owned gasoline-powered vehicles. There is an ample number of studies focused on AV adoption and human-driven vehicle fuel choice. However, none of the previous studies addressed the potential similarities and differences among the factors that affect people's intention to purchase GAVs and EAVs. Neither did the past studies investigate the effect of new roadway designs and facilities (such as dedicated AV lanes, removal of parking, and wireless charging options) on people's intention to purchase GAVs and EAVs or subscribe to such services. To address this gap, the present study developed a comprehensive framework that uses 14 attitudinal factors to investigate factors that potentially affect AV adoption and fuel choice while capturing the potential heterogeneities among people based on their sociodemographic and travel behavior characteristics.

The purpose of this study is to pose useful questions (e.g., "are people's willingness to buy EAVs and GAVs similar or different"), to gather data (e.g., people's attitude towards self-driving vehicle), to generate first evidence (e.g., people's willingness to buy EAVs and GAVs have similarities and differences), to provide relevant insights (e.g., how to use roadway designs to promote EAVs over GAVs), and to foster future research the focal concept (e.g., potential differences among different countries in terms of AV adoption). This can be critical in shaping the extent and direction of AV technology's impacts on the transportation system as AVs are still yet to be commercially available (Haugland and Skjølsvold, 2020).

Apart from the policy implications in Section 6, this study can potential contribute to academia, policymakers, and automobile industry in the following aspects. First, this study is the first one to factor the potential impacts of a wide range of sociodemographic and behavioral characteristics and attitudinal factors on AV usage, intention to purchase GAVs, and intention to purchase EAVs *concurrently*. Most of the existing studies have yet to include vehicle powertrain as a factor affecting AV adoption process. Study results also highlight that people still prefer vehicle ownership and GAVs. Transparent federal- and state-level policies can also be developed to address people's concerns of using AVs and EAVs such as information privacy, accident liability, and range anxiety.

Second, this study highlights the importance of differentiating the people's willingness to purchase EAVs and GAVs in understanding AV adoption process as many people still prefer AV ownership and

GAVs. The needs for vehicle ownership over shared vehicles may be heightened during the global pandemic as more people may prefer driving over other modes of transportation (e.g., crowded space and mandated mask wearing requirements) and worry about the disease spreading through shared vehicles. Policymakers may consider policies such as restricting privately-owned empty AVs from accessing the road at congested regions or during peak hours, dedicated EAV lanes, reduced freeway tolls for EAVs, and other measures to discourage personal GAV ownership and promote EAV purchases for transportation providers. For future AV ridesharing service providers, they may consider restoring public's confidence in shared vehicles through marketing and adopting measures to disinfect shared AV interiors to reduce the potential risk of diseases spreading through shared AVs.

Third, this study is one of the first studies that attempts to capture the impacts of EAV-enabled designs on AV and EAV adoption process. Policymakers can potentially leverage the knowledge and experience from promoting alternative fuel vehicles to developing financial incentive policies (e.g., tax exemption for EAVs), information provision policies (e.g., life-time cost-savings for using EAVs compared to using GAVs), convenience policies (e.g., EAV users can use HOV lanes), and infrastructural support (e.g., EAV charging infrastructure) for AV and EAV adoption. Considering that AV technology is not yet mature, it is critical to develop these policies and measures early before habitual behaviors are formed (e.g., choosing to purchase GAVs instead of EAVs). This can also be applied to promotion of the shared EAVs (EAV-based taxis, ridesharing, and vehicle-sharing services) and other forms of shared alternative fuel AVs. Automakers may potentially consider collaborating with policymakers and various public institutions to address the infrastructural supports that are needed for AVs to facilitate a safe and smooth transition from the existing transportation system to an environment with both AVs and HVs.

Fourth, federal- and state-level agencies can potentially collaborate with AV automakers and become early AV and EAV adopters (e.g., government vehicle fleet and public transit) and develop community-level outreach programs that offer first-hand AV and EAV experience to the general public. Such programs could be used to identify potential early AV and EAV adopters. These potential users can include people with strong personal innovativeness, and those who dislike driving but need to make long, frequent, or flexible trips. These users' experiences can demonstrate the relative performance and safety advantages of AVs and EAVs to a wider audience and accelerate the diffusion of AVs and EAVs among potential users to become early adopters, and these early adopters can later serve as a reference group (e.g., form positive subjective norms) to promote AV and EAV usage.

Fifth, the process of AV adoption (shared vs. owned and GAVs vs. EAVs) depends on contemporary societal choices. It is important for public participation in AV-related rule and regulation designs and vehicle designs that can address the needs of travelers, particularly for people who have social and economic disadvantages.

Sixth, improving the AV's capabilities and maintaining a good safety track record still play the most critical role in AV adoption process as it shapes people's perception of relative advantage, safety, and concerns of EAVs and AVs, while policy and infrastructural support and educational, informational, and marking campaigns can play a complimentary role in the process. Policymakers can focus on designing standards, regulations, and incentives that promote automakers to invest in EAVs instead of GAVs. For example, although EV-related technology has been available for nearly a hundred years, automakers had limited incentives to design low-cost and long-range EVs (e.g., GM's ill-fated EV1). After California introduced more stringent fuel economy and vehicle emissions standards in the 2010s, many automakers in the U.S. started to invest in EV technology innovations leading to many popular EV models in the U.S., ranging from Nissan LEAF to Tesla. Similarly, as many cities in China such as Beijing and Shanghai introduced tougher regulations for GVs to be licensed, many Chinese home-grown models such as Wuling Hong Guang Mini (priced at around $4,500 in 2021), BYD's Han (priced at around $40,000 in 2021), and Xpeng's P7 (priced at around $37,000) were introduced to compete with Tesla and other international brands.

Finally, it is important to note that a collective effort should be made among automakers, policymakers, and academia to minimize the potential negative impacts of AV and maximize the potential positive impacts of AV. Such process may not be limited to promoting continued autonomy and algorithmic enhancement and glorifying the benefits of AVs by some automakers, academia may not assume that most people will choose shared AVs over owning AVs and EAVs over GAVs in their analysis, and policymakers may not rely on a "hands-off" approach to let automakers setting the AV standards and may consider a proactive approach with sufficient efforts in public education and engagement.

This study has several limitations that can be addressed through future studies. First, the study participants were recruited through MTurk which may limit the types of participants in the study in terms of their sociodemographic characteristics. Other types of data collection methods can be used to validate the findings of this study. Second, previous studies have shown that AV-related travel experience can potentially influence AV adoption (Chen et al., 2019; Zoellick et al., 2019). Future research could use roadway designs in a virtual reality or driving simulator environment where the EAV operator experiences more realistically, some of the potential benefits of EAVs vis-à-vis a gasoline-powered vehicle in operating and refueling in that driving environment. Third, in this study, all the survey participants were from the U.S. It would be insightful to carry out a similar survey in different countries and to explain any differences in the behavior of prospective AV users. Several recent studies have shown that there is a wide gap, across countries, between people's intention to use AVs and other travel-related behavior (Guo et al., 2018; Vidhi and Shrivastava, 2018; Jing et al., 2019; Li et al., 2019; Guo et al., 2020; Guo et al., 2021a). OC&C (2019) suggested that 28% of participants in China "would like to be one of the first to try an autonomous vehicle" compared to 13% in the U.S. The same study also showed that 40% of participants in the U.S. "would be very unlikely to use an autonomous car" compared to 5% for participants in China. In future work, the differences can be evaluated to design various policies to promote AV and EAV adoption in other countries. Fourth, in this study, it is assumed that people's intention to use AVs (i.e., transportation services provided by AVs instead of HVs) do not change from the original design to the EAV enabled design. Additional studies are needed to understand if there are any differences among these intentions. Fifth, although this study has a relatively large sample size compared to the existing literature, the larger sample size accomplished with longitudinal study can give better understanding of people attitude toward AVs, as well as give insights in its possible evolution. Sixth, in this study, the description for AVs (self-driving cars) is from SAE and it has its limitations which include but not limited to (i) assuming that the automation increases linearly and displace human work (i.e., the more automation is better), (ii) not adequately addressing human-machine cooperation, (iii) not including components critical to AVs, such as infrastructure, environment, and context of use, and (iv) subjecting to misuse (i.e., a system can be labeled with a level that only applies to part of their operation or future operation) (Stayton and Stilgoe, 2020). Future studies should consider providing a definition that can address these limitations. Seventh, this study used a wide range of existing classic literature such as Technology Acceptance Model and Technology Diffusion Theory to study AV adoption process. It is still can be considered as a simplified process to describe AV adoption process. Future studies can consider address this issue by designing a more comprehensive framework for understanding AV adoption process.

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