INVESTIGATING THE DETERMINANTS OF AUTONOMOUS VEHICLES AND THEIR POTENTIAL IMPACTS ON TRAVEL BEHAVIORS AND LAND USE DISTRIBUTION

by

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ABSTRACT

MD. MOKHLESUR RAHMAN. Investigating the Determinants of Autonomous Vehicles and Their Potential Impacts on Travel Behaviors and Land Use Distribution.
(Under the direction of DR. JEAN-CLAUDE THILL)

Autonomous Vehicles (AVs) are imminent and they are not in people's dreams now. Now the burning questions the research community is interested in include how quickly AVs would be implemented for public use, whether people would accept them, and how AVs would change the ecosystem of transportation and the built environment. Stimulated by these questions, this dissertation aims to investigate the factors that influence people's Behavioral Intention (BI) to adopt AVs and Shared AVs (SAVs). In addition, this study is intended to investigate the potential impacts of AVs on land use patterns and people's travel behaviors. This dissertation consists of six papers as discussed hereunder.

The first article presents a state-of-the-art literature review to understand people's perceptions and opinions of AVs and the factors that influence AV adoption. Results show that the socioeconomic profile of individuals and their household, their psychological factors (e.g., usefulness, ease of use, risk), and knowledge and familiarity with AV technologies would affect AV adoption. Additionally, urban form (e.g., density, land use diversity), transportation factors (e.g., travel mode, distance, and time), affinity to new technology, and institutional regulations would influence the AV adoption rate.

The second review study critically analyzes the extant literature and summarizes the short, medium, and long-term effects of AVs based on a SWOT (Strength, Weakness, Opportunity, and Threat) analysis. Results show that AV would influence transportation and human mobility by reducing vehicle ownership, Vehicle Miles Traveled (VMT), congestion, travel costs, energy use, and increasing accessibility, mobility, safety and security, and revenue generation for commercial

operators. AVs would encourage dispersed urban development, reduce parking demand, and enhance network capacity. Additionally, AVs would increase the convenience and productivity of passengers by providing amenities for multitasking opportunities.

The third paper investigates the key factors that influence people's tendency to purchase and use personal AVs after collecting data from the 2019 California Vehicle Survey. Results from the Structural Equation Model (SEM) indicate that working-age adults, children, household income, per capita income, and educational attainment are positively associated with AV purchase intention. Similarly, psychological factors (e.g., perceived enjoyment, usefulness, and safety), prior knowledge of AVs, and experience with emerging technologies significantly influence people's BI to purchase AVs. This study finds that family structure and psychological factors are the most influential factors in AV purchase intention of households than the built environment, other socioeconomic, and transportation factors.

The fourth paper investigates the key elements of a household's intentions to use pooled SAVs using the SEM framework. Collecting data from the 2019 California Vehicle survey, this study finds that higher educational attainment, income, labor force participation, Asian population, and urban living are negatively associated with SAVs. In contrast, young and working-age adults are positively associated with SAVs. Study results also show that people who prefer public transportation, car-sharing, ride-hailing, and ride-sharing services are likely to use SAVs. The perceived usefulness, enjoyment, safety associated with AVs, and prior knowledge of AVs significantly influence people to use SAVs. The study concludes that people's travel behaviors, positive attitudes to shared mobility, and psychological features are the key determinants of SAVs.

The fifth paper studies the potential impacts of AVs on the spatial distribution of household and employment locations using the existing Swindon model of the TRANUS urban simulation platform. Results show that the adoption of AVs encourages people to live outside of the city center by increasing convenience and reducing travel costs. On the other hand, AVs would increase employment opportunities in the city center by inducing more economic activities. This study finds that AVs would allow densification of the existing city center by releasing extra space from parking land areas along with peripheral new development over time.

With the same TRANUS simulation platform, the sixth paper aims to assess the potential impacts of AVs on people's travel behaviors such as trip generation, travel distance, travel time, and travel costs. Results indicate that AVs would intensify people's overall travel demand by increasing accessibility. On the other hand, AVs are likely to reduce vehicle ownership, travel distance, travel time, travel costs, and vehicle hours traveled by reducing solo driving and by inducing shared mobility. AVs also have the potential to reduce public and active transportation.

This study makes significant contributions by unraveling critical issues of AVs and their short-, medium-, and long-term impacts. The findings will be helpful for policymakers and professionals to implement appropriate policies to manage travel demand and urban growth, and to urban and transportation scholars in the understanding of the complex mutual relationships between transportation, mobility, and the conditions of urban environments.

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DEDICATION

To my parents and to all freedom fighters who fought for the independence of Bangladesh in 1971.

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LIST OF ABBREVIATIONS

ACC = Adaptive Cruise Control

ACS = American Community Survey

ADDS = Advanced Driver Assistance Systems

AFVs = Alternative Fuel Vehicles

ANOVA = Analysis of Variance

ATT = Attitude Towards Technology

AVs = Autonomous Vehicles

BEV = Battery Electric Vehicle

BI = Behavioral Intention

BLM = Binary Logit Model

CAV = Connected and Autonomous Vehicle

CBD = Central Business District

CBG = Census Block Group

CFA = Confirmatory Factor Analysis

CFI = Comparative Fit Index

CLM = Conditional Logit Model

CACC = Cooperative Adaptive Cruise Control

CSAC = California State Association of Counties

CV = Connected Vehicle

CVS = 2019 California Vehicle Survey

DMV = Department of Motor Vehicles

DS = Descriptive Statistics

EPA = Environmental Protection Agency

EV = Electric Vehicle

FA = Factor Analysis

GHG = Greenhouse Emission

GPS = Global Positioning System

HLM = Hierarchical Linear Model

HMI = Human-machine Interface

HOVs = High-Occupancy Vehicles

ICEs = Internal Combustion Engines

ITAM = Integrated Technology Acceptance Model

ITS = Intelligent Transportation Systems

LKM = Logit Kernel Model

LLM = Log-Linear Regression

LRM = Logistic Regression Model

LUTI = Land Use Transport Interaction

MDCP = Multiple Discrete–Continuous Probit

MLR = Multiple Linear Regression

MNL = Multinomial Logit

MNP = Multinomial Probit Model

MIP = Mixed-Integer Programming

MLM = Mixed Logit Model

NHTSA = National Highway Traffic Safety Administration

OLR = Ordered Logistic Regression

OPM = Ordered Probit Model

PBC = Perceived Behavioral Control

PC = Pearson Correlation

PCE = Passenger Car Equivalent

PHEV = Plug-in Hybrid Electric Vehicle

PFCEV = Plug-in Fuel Cell Electric Vehicle

PEU = Perceived Ease of Use

PKT = Passenger-Km Traveled

PM = Probit Model

PRPLM = Parametric Random Parameter Logit Model

PR = Perceived Risk

P&R = Park-and-Ride

PS = Price Sensitivity

PT = Perceived Trust

PU = Perceived Usefulness

RMSEA = Root Mean Square Error of Approximation

ROD = Robocar-Oriented Development

SAE = Society of Automotive Engineers

SAVs = Shared Autonomous Vehicles

SAEVs = Shared Autonomous Electric Vehicles

SEM = Structural Equation Model

SI = Social Influence

SOVs = Single-Occupancy Vehicles

SRPLM = Semiparametric Random Parameter Logit Mode

SUM = Seemingly Unrelated Model

SWOT = Strength, Weakness, Opportunity, and Threat

TA = Technology Anxiety

TDM = Travel Demand Management

TOD = Transit-Oriented Development

TLI = Tucker Lewis Index

TAM = Technology Acceptance Model

TNCs = Transport Network Companies

TPB = Theory of Planned Behavior

TRA = Theory of Reasoned Action

TS = Traffic Safety

UK = United Kingdom

US = United States

USDOT = United States Department of Transportation

VAD = Vehicle Awareness Devices

VMT = Vehicle Miles Traveled

VHT = Vehicle Hours Traveled

VOT = Value of Travel Time

V2I = Vehicle to Infrastructure Communication

V2X = Vehicle-to-Everything Communication

V2V = Vehicle to Vehicle Communication

WMNL = Weighted Multinomial Logit Model

LIST OF PAPERS

CHAPTER 1: INTRODUCTION

1. Research Motivation

Autonomous Vehicles (AVs) are imminent. Now, the burning questions researchers and policymakers are interested in include how quickly they will arrive, when they will be matured, how they will share the roadway space with conventional vehicles, and what would cause uncertainty in the development and market penetration of AVs (Heineke et al., 2021; Stein, 2020). Additionally, researchers and policymakers are eager to get insights on whether people would adopt them, how fast and how large would the adoption be, how would people adjust their travel patterns, how will the AVs influence people's destination choices, and how the institutional settings will be changed.

Inspired by these salient questions, researchers are studying people's current level of knowledge on AVs and the key determinants of AVs. Although many studies have investigated people's perceptions and opinions, and key factors of AVs, public attitudes towards AVs are changing rapidly with the pace this novel technology is developing. Researchers also investigating the anticipated impacts of AVs on urban transportation and the built environment. Previous studies primarily focused on the short- and medium-term impacts of AVs on transportation, human travel patterns, and the environment. However, there is a knowledge gap in the literature on the long-term effects of AVs on urban land-use patterns. Considering the profound effects of AVs, this study is conducted to enhance understanding of the matters of AVs that are still uncertain and yet to be experienced by the world.

The main objectives of the study are to investigate the factors that influence people's Behavioral Intention (BI) to adopt AVs and Shared AVs (SAVs). Besides, this study is intended to investigate the potential impacts of AVs on the spatial distribution of households and employment locations and people's travel behaviors. The following research questions have been envisioned which founded the basis of this dissertation:

1) How would people's socioeconomic and demographic characteristics influence people's BI to adopt and use AVs and SAVs?
2) How would factors of the built environment, transportation, and technology influence people to adopt and use AVs and SAVs?
3) What are the impacts of AVs on the spatial distribution of household and employment locations?
4) What are the potential impacts of AVs on a household's travel patterns such as trip generation, travel distance, travel time, and costs?

2. Research design

The major steps of this study are illustrated in Figure 1.1. As presented in this figure, this study was conceptualized after conducting a preliminary literature review to identify research gaps in the extant literature. Consequently, four main research questions were formulated. An extensive literature review was conducted to understand people's perceptions and opinions, and the key determinants that influence people's BI to adopt AVs and SAVs. Additionally, the impacts of AVs on urban transportation and the built environment were investigated by critically reviewing the extant literature. To investigate the key determinants of AV purchase intention of people and use of SAV, data were collected from the 2019 California Vehicle Survey (Transportation Secure Data Center, 2019). Additionally, to investigate the effects of AVs on the spatial distribution of household and employment locations, the existing Swindon model developed in the TRANUS framework was selected (Tomás de la Barra et al., 2011).

A Structural Equation Model (SEM) framework was used to calibrate models to assess people's BI to purchase AVs and use SAVs. In the TRANUS platform, land-use and transportation modes were developed to understand the spatial distribution of household and employment locations and people's travel patterns due to the adoption of AVs. Finally, results from the literature review and model building were analyzed and discussed.

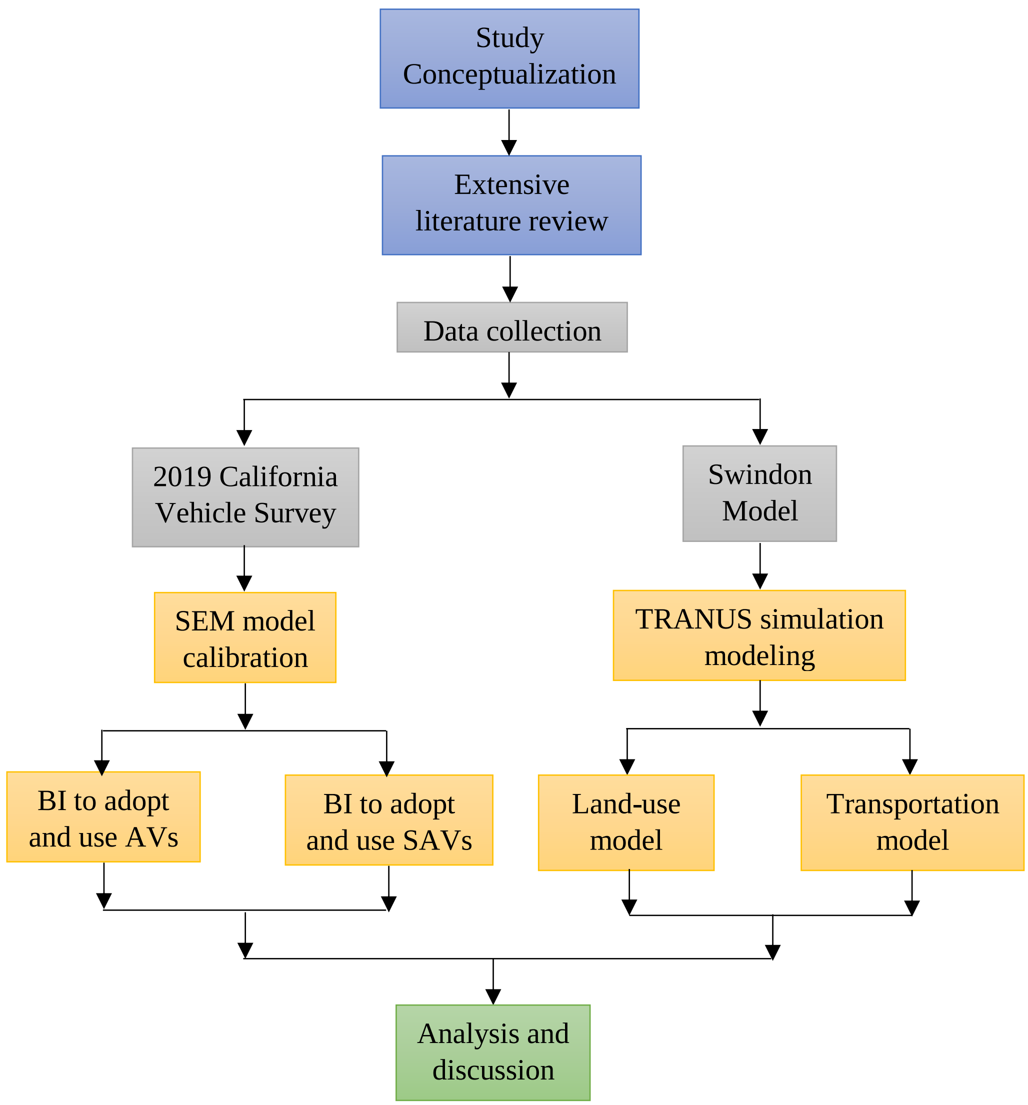

Figure 1.1: Flowchart showing different stages of this dissertation

3. Research impacts and outcomes

AVs are yet to be a regular transport mode and little is known about them. At present, people have very limited knowledge about AVs. This study has a significant contribution by revealing the facts about the willingness of people to adopt and use AVs which is considered a major challenge to increasing the market share of AVs. The impacts of AV adoption are still evolving and unclear. Hence, this study would have significant contributions to the literature by unraveling critical issues of AVs and their short-, medium-, and long-term impacts. The findings would be helpful for policymakers and professionals involved in transportation and city planning to implement appropriate policies to manage travel demand and urban growth by anticipating the change in human travel patterns, transportation systems, and land uses.

This research deals with a scientific paradigm which is evolutionary in nature by discovering new knowledge database. The broader impacts of this study include the production of high-quality research outcomes. The scientific community will be benefited from this research. The research outcomes will be disseminated to the scientific community through academic publications, which will facilitate further research and enhance the existing body of literature.

4. Organization of the dissertation

The rest of the dissertation is structured as follows. Chapter 2 presents a literature review to find out the drives that influence people’s willingness to adopt AVs. The potential impacts of AVs on transportation and human mobility, the urban built environment, energy and environment, and people’s safety and security, and convenience are discussed in Chapter 3 by performing a comprehensive literature review. Chapter 4 empirically investigates the determinants of household purchase intention of AVs taking California as a case study. The key determinants of SAVs in California are evaluated in Chapter 5. The potential impacts of AVs on people's travel behaviors and travel demand are discussed in Chapter 6. Chapter 7 simulates the potential impacts of AVs on the spatial distribution of household and employment locations. Lastly, Chapter 8 outlines the concluding remarks.

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CHAPTER 2: WHAT DRIVES THE WILLINGNESS TO ADOPT AUTONOMOUS VEHICLES? A REVIEW OF PEOPLE PERCEPTIONS AND OPINIONS

Abstract

This article presents a state-of-the-art literature review to understand people's perceptions and opinions of Autonomous Vehicles (AVs) and the factors that influence AV adoption. A strategic literature search was conducted to select articles for this review. Most of the articles were published within the last five years and they used a household questionnaire survey to collect data. Mostly they used statistical and econometric methods to evaluate the factors that affect people's intentions to adopt AVs. The results show that the socioeconomic profile of individuals and their household, their psychological factors (e.g., usefulness, ease of use, trust, risk), and knowledge and familiarity with AV technologies would affect AV adoption tendency. User attributes also indirectly affect AV adoption by influencing the psychological factors of users. Moreover, I identified some opportunities (e.g., safety and security, low congestion, energy use, and emission) and challenges (e.g., system failure, privacy breach, and legal issues) that would significantly influence people's tendency to adopt AVs. Urban form (e.g., urban/rural, density, land use diversity), transportation factors (e.g., travel mode, distance, and time), affinity to new technology, and the institutional regulations would also influence AV adoption rate. Finally, I have identified some limitations of previous studies and provided some directions for future research.

Keywords: Autonomous vehicle, self-driving car, driverless vehicle, transportation, public perceptions, willingness to use/pay, users, review

1. Introduction

In this age of motorization, high vehicle ownership, travel cost, traffic accident, congestion, energy use, and carbon emission motivate business and civic leaders to develop alternative mobility options. Recent innovations and services such as Electric Vehicles (EV), Connected Vehicles (CV), Autonomous Vehicles (AV), and shared mobility are the most significant advances in transportation; they are expected to transform overall transportation systems in the coming years (Bansal & Kockelman, 2018; Castritius et al., 2020; Gruel & Stanford, 2016; Piao et al., 2016). These technological breakthroughs may bring fundamental changes in vehicle ownership, travel patterns, parking demand, infrastructure supply, energy use, and emissions (Compostella et al., 2020; Daziano et al., 2017). However, as some of them remain to be deployed broadly, such as in the case of AVs, the extent of the impacts put forth on people's mobility, on vehicular movement, and on urban development patterns is still quite uncertain and often evaluated with computer simulations only (Cyganski et al., 2018). While it is envisioned that people will interact with AVs actively as passengers or passively as road users (Castritius et al., 2020), an assessment of their willingness to accept this new technology is crucial to predict the market penetration of AVs (Penmetsa et al., 2019) and to plan for ensuing degrees of departure from business as usual trends in urban and territorial organization. Thus, this study is intended to understand people's perceptions and opinions on AVs and the factors that influence their willingness to adopt them.

AVs (also known as self-driving, driverless, and robotic cars) are vehicles that can drive and navigate themselves without human control by using sensing technologies (e.g., radar, Global Positioning System (GPS), and computer vision) and control systems (i.e., sensors) (Daziano et al., 2017; Howard & Dai, 2014; Van den Berg & Verhoef, 2016). According to the National Highway Traffic Safety Administration (NHTSA), AVs are those vehicles in which at least one of the critical safety control functions (e.g., steering, acceleration/deceleration, or braking) are performed without human input (Kopelias et al., 2020). AVs have some level of automation to assist drivers or replace drivers to take full control of the vehicle (Narayanan et al., 2020). The Society of Automotive Engineers (SAE) differentiates between 5 levels[1] of vehicle autonomy ranges, from Level 0 (No autonomy) to Level 5 (Full autonomy) (SAE International, 2018).

An increasing number of studies are exploring people's perception and opinions about AVs and investigating the possible impacts of AVs on transportation and mobility, the environment, and urban development. Researchers have echoed the expectation that AVs would offer a wide range of social, economic, and environmental benefits to city dwellers, despite some concerns about system security and data privacy (Schoettle & Sivak, 2014b). They projected a reduction in traffic crashes, congestion, vehicle ownership, parking demand, energy consumption and emissions, and an increase in human mobility and convenience (Soteropoulos et al., 2019; Sparrow & Howard, 2017; Tafidis et al., 2021). Additionally, Shared AVs (SAVs) have the potentials to reduce overall travel distance and time by reducing empty Vehicle Miles Traveled (VMT). Considering the enormous possibilities of AVs as a new mobility option, governments and manufacturers around the

[1] Level 0 indicates no automation and the vehicle is fully controlled by a human driver. In Level 1 of autonomy, the vehicle has some driver assistance system for either steering or acceleration/deceleration. Partial autonomy is ascribed in Level 2, where the vehicle has driver assistance systems for both steering and acceleration/deceleration. In Level 3, the vehicle has a specific performance by the automated driving system with the expectation that the driver will respond. Level 4 indicates higher automation of the vehicle, which has a specific performance by an automated driving system, even if a driver does not respond. Level 5 indicates the full automation of the vehicle and the vehicle is operated by an automated driving system without human interventions.

world are showing a growing interest in formulating AV policies, in adopting AV technology elements (e.g., adaptive cruise control, automatic parking, lane changing, and braking), and in on-road vehicle testing (Cohen & Cavoli, 2019; Hess, 2020). Most of the automobile companies have retrofitted existing vehicles by incorporating some extent of autonomy and some companies (e.g., Mercedes-Benz, Tesla, Google, Apple, Uber, Lyft) have already developed and tested full AVs (Talebian & Mishra, 2018). Thus, AVs are not a fantasy anymore and it is expected that very soon (i.e., Level 2 vehicle by 2025, Level 3 by 2040, and Level 4 or 5 by 2050) they would be used by millions of people for their daily travels.

At present, most commercially operated AVs include Level 1 ~ Level 3 autonomy (e.g., emergency braking, blind-spot detection, lane-keeping) only due to limited progress in technology and to the high cost of sensors (Van Brummelen et al., 2018). Researchers have argued that a higher level of vehicle autonomy would induce people to raise their outlook on adoption (Schoettle & Sivak, 2014b). Although many studies have investigated the level of human acceptance of AVs, they often do so inadequately, particularly as far as the pace this new technology would be accepted and adopted is concerned (Gurumurthy & Kockelman, 2020; Hilgarter & Granig, 2020; Van Brummelen et al., 2018). It is also postulated that intricate regulations, technical difficulties, public perceptions, and safety concerns would restrain the broad base adoption of AVs (Clark et al., 2019). However, public perceptions of AVs are rather fluid, evolving rapidly with increasing access to vehicles and more widespread discourse on this mobility technology (Gurumurthy & Kockelman, 2020). Assessing public perceptions on AVs and identifying the factors that influence public perception are essential for estimating and understanding the likelihood of AV adoption by the public at large, and for the successful integration of AVs with existing traffic management systems and practices (Hilgarter & Granig, 2020). Therefore, in this review, I will:

1) Evaluate the perceptions and opinions of people on AVs in different study contexts;
2) Identify the factors (e.g., social, economic, psychological, environmental, technological) that influence people's perceptions towards AVs; and
3) Specify research gaps in the existing literature that require further investigation.

The main contributions of this review paper are five-fold:

1) Assessing people's perceptions, opinions, knowledge, and willingness to adopt and use AVs.
2) Investigating the socio-economic, psychological, institutional, transportation, built environmental and technological factors that influence behavioral intentions of people towards adopting AVs.
3) Developing a conceptual framework that articulates the complex relationships between people's socio-economic features, psychological factors, urban form, transportation factors, institutional settings, opportunities and challenges regarding AVs, on the one hand, and people's behavioral intentions to adopt AVs, on the other hand.
4) Identifying key concepts discussed in the previous studies, data used and methods applied for addressing their research questions.

5) Proposing future research directions, considering the limitations of the prior studies and issues on this new transportation option that have so far not been fully addressed.

The rest of the paper is outlined as follows. The second section introduces search strategies and different attributes of reviewed articles and reports. A synthesis of the results from previous studies is presented in the third section. Finally, research problems and directions for future study are drawn in section four.

2. Methods and materials

2.1 Study approach

This state-of-the-art literature review has been conducted to identify, evaluate, and critically analyze relevant scholarship to understand people's perceptions and opinions about AVs and to identify the factors that influence AV adoption. The overall study approach is illustrated in Figure 2.1. The literature search was conducted to select published articles and reports to be included in the review process. Some keywords (e.g., autonomous vehicle, connected and autonomous vehicle, self-driving car, driverless car, public perceptions, opinions, willingness, attitude, opportunities, and challenges) were used as the search terms to identify related articles. Widely used databases such as ScienceDirect, Scopus, SAGE Journals, SpringerLink, Taylor & Francis, and Web of Science, Google Scholar, and the website of different organizations, are the main platforms to identify articles and reports suitable for inclusion in the review process. Items were selected based on the following criteria:

1) Whether the article/report is written in English;
2) Whether the study was conducted within the last five years; and

3) Whether the study has evaluated perceptions and opinions on AVs.

A few studies conducted before 2015 are included in this review for a more comprehensive scan of scenarios and technological developments related to AVs and Connected and Autonomous Vehicles (CAVs). The search identified more than 100 articles and reports. However, after closer examination, 50 were deemed pertinent to the objectives of the study and are included in this state-of-the-art review study. Of these items, 62% have been published in just two periodicals, namely Transportation Research Part C: Emerging Technologies (32%) and Transportation Research Part F: Traffic Psychology and Behaviour (30%). About 90% of the selected items were published between 2015 and 2020, while only 10% were published before 2015. During the selection process of published works, the researchers were careful to select them from different study contexts to get a comprehensive review. Finally, these research items were critically analyzed to understand people's perceptions and opinions about AVs and identify the factors that influence AV adoption.

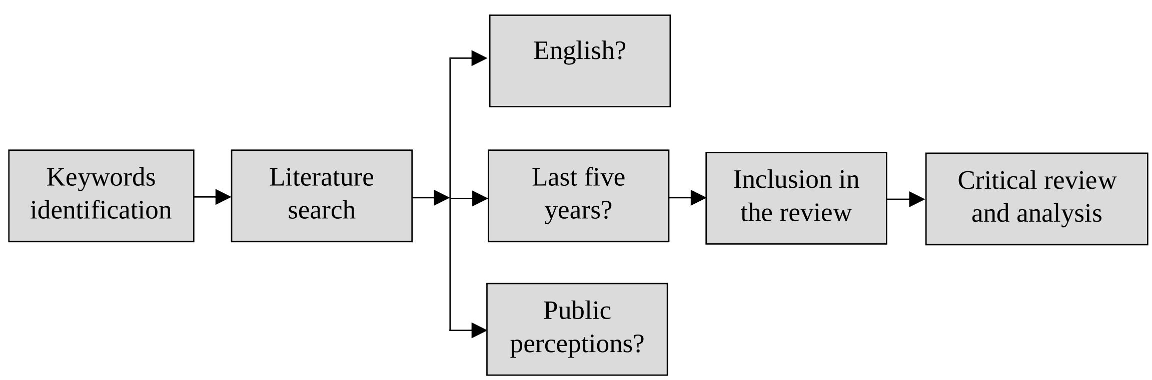

Figure 2.1: Selection procedures of scholarly work and study approach

2.2 Attributes of reviewed articles and reports

Different attributes (e.g., authors, study contexts, data sources, sample size, and methods) of articles and reports reviewed for this review study are reported in Table 2.1.

The table indicates that 32.31%, 27.69%, and 26.15% of articles/reports have been conducted in North American, European countries, and Asian countries, respectively; also, 13.85% of studies are about the Australian context. Most of the studies (80%) conducted web-based or face-to-face household questionnaire surveys to collect information on people's perceptions and opinions on AVs. However, a handful of studies (14%) performed experiments and collected data from the participants of driving simulators. There is high variability in sample sizes in the various studies. The smallest sample (i.e., 19) is used in Hilgarter and Granig (2020), while Shin et al. (2019) collected data from 246,642 individuals, which adequately represent the population of the study area. Table 2.1 also indicates that studies have used a variety of statistical and econometric models to conceptualize people's perceptions of AVs and associated factors.

Table 2.1: Characteristics of reviewed articles and reports

Author	Study area	Data source	Sample size	Methodology
(Panagiotopoulos & Dimitrakopoulos, 2018)	Athens, Greece	Online survey	483	SEM, FA
(Xu et al., 2018)	Xi'an, China	Participants in a field test	300	SEM, FA, MLR
(Rahman et al., 2017)	Boston, MA	Participants in driving simulator, online survey	430	SEM, FA, MLR
(Bansal et al., 2016)	Austin, USA	Online survey	347	OPM, SUM
(Kyriakidis et al., 2015)	109 countries	Online survey	4886	DS
(Schoettle & Sivak, 2014b)	US, UK, and Australia	Online survey	1533	DS, ANOVA
(Schoettle & Sivak, 2014a)	China, India, and Japan	Online survey	1722	DS, ANOVA
(Underwood & Firmin, 2014)	Expert around the world	Expert opinion from AV Symposium, 2014	217	DS
(Howard & Dai, 2014)	Berkeley, California	Opinion of museum visitors	107	MNL, LLM
(Begg, 2014)	London, UK	Survey of transport professionals	3500	DS
(Bazilinskyy et al., 2015)	112 countries of the world	Online survey	8862	DS
(Piao et al., 2016)	La Rochelle, France	Online and telephone survey	425	DS

(Salonen, 2018)	Vantaa, Finland	Participants with experience of driverless shuttle	197	DS, ANOVA
(Shin et al., 2015)	Six cities in South Korea	Stated preference survey	633	MDCP, MNP
(Krueger et al., 2016)	Adelaide, Brisbane, Melbourne, Perth, Sydney	Stated preference survey	435	MLM
(Haboucha et al., 2017)	Israel and North America	Stated preference survey	721	LKM, FA
(Daziano et al., 2017)	USA	Online survey	1260	CLM, PRPLM, SRPLM
(König & Neumayr, 2017)	33 countries	Online survey	489	DS
(Nazari et al., 2018)	Washington, USA	Travel survey	2726	OPM, SEM
(Zhang et al., 2018)	Atlanta, USA	Travel survey	10278	LRM, MIP
(Talebian & Mishra, 2018)	Memphis, USA	Questionnaire survey	327	DS
(Kapser & Abdelrahman, 2020)	Germany	Online survey	501	SEM
(Zhang et al., 2020)	China	Questionnaire survey	647	SEM
(Gurumurthy & Kockelman, 2020)	USA	Online survey	2588	MNL
(Shin et al., 2019)	Japan	Online survey	246642	MLR, OLR
(Wadud & Huda, 2019)	Bangladesh	Online survey	621	MLR
(Laidlaw et al., 2018b)	Toronto and Hamilton Area, Canada	Online survey	3201	PM
(Bansal & Kockelman, 2017)	USA	Online survey	2167	BLM, WMNL
(Webb et al., 2019)	Brisbane, Australia	Household survey	447	MNL
(Bansal & Kockelman, 2018)	Texas, USA	Online survey	1088	OPM
(Kaur & Rampersad, 2018)	Adelaide, Australia	Online survey	101	FA
(Hulse et al., 2018)	UK	Online survey	916	MNL
(Kaye et al., 2020)	Australia	Online survey	505	MLR
(Xu & Fan, 2019)	China	Online survey	1164	DS, ANOVA
(Clark et al., 2019)	UK	Experimental study	30	ANOVA, PC
(Faas et al., 2020)	Germany	Experimental study	59	ANOVA, HLM
(Rahimi et al., 2020)	US	Stated preference survey	1390	SEM
(Hilgarter & Granig, 2020)	Austria	Face-to-face interviews	19	DS, qualitative analysis
(Castritius et al., 2020)	Germany and California	Online survey	536	FA, SEM, LRM
(Penmetsa et al., 2019)	Pennsylvania, USA	General public survey	798	DS
(Nordhoff et al., 2020)	Eight European countries	Online survey	9118	FA, SEM
(Hagl & Kouabenan, 2020)	Germany	Experimental study	101	DS, FA, ANOVA

(Ha et al., 2020)	Korea	Experimental study	48	DS, FA, ANOVA, MLR
(X. Wang et al., 2020)	Singapore	Face-to-face interviews	353	FA, SEM
(Zhu et al., 2020)	Beijing, China	Face-to-face interviews	355	FA, SEM
(S. Wang et al., 2020)	USA	Online survey	721	FA, MNL
(Chen, 2019)	Taiwan	Face-to-face interviews	700	FA, SEM, ANOVA
(Yuen et al., 2020)	Seoul, Republic of Korea	Online survey	526	FA, SEM
(Feys et al., 2020)	Brussels, Belgium	Online survey	529	DS, HLM
(Zmud & Sener, 2017)	Austin, TX, USA	Online survey	556	DS

DS = Descriptive Statistics, ANOVA = Analysis of Variance, PC = Pearson Correlation, SEM = Structural Equation Model, FA = Factor Analysis, MLR = Multiple Linear Regression, BLM = Binary Logit Model, MNL = Multinomial Logit, WMNL = Weighted Multinomial Logit Model, PM = Probit Model, OPM = Ordered Probit Model, OLR = Ordered Logistic Regression, SUM = Seemingly Unrelated Model, MDCP = Multiple Discrete–Continuous Probit, MNP = Multinomial Probit Model, MLM = Mixed Logit Model, LKM = Logit Kernel Model, CLM = Conditional Logit Model, PRPLM = Parametric Random Parameter Logit Model, SRPLM = Semiparametric Random Parameter Logit Model, LLM = Log-Linear Regression, LRM = Logistic Regression Model, MIP = Mixed-Integer Programming, HLM = Hierarchical Linear Model

The key concepts discussed in the reviewed papers are identified in Figure 2.2. The majority of studies (80%) collected socioeconomic information on the respondents and investigated their effects on the decision-making process to adopt AVs. A considerable number of studies explored people's knowledge of AVs (42%) and opportunities and challenges (40%) towards the increase of AV market share. A nearly equal number of studies (34% and 32%) investigated the influence of psychological and transportation factors on AVs adoption, respectively. About 24% of studies discussed people's inclination to adopt and use AVs. The influence of urban form (20%) and technology savviness (14%) on AVs adoption was mentioned in a relatively small number of studies. The condition and effects of institutional settings were described by only 4% of studies. Considering the significant implications of psychological and socioeconomic attributes, transportation factors, urban form, technological innovation, and institutional regulations and guidelines in motivating people towards AVs, their detailed discussion in different study contexts with a diverse background of customers is crucial.

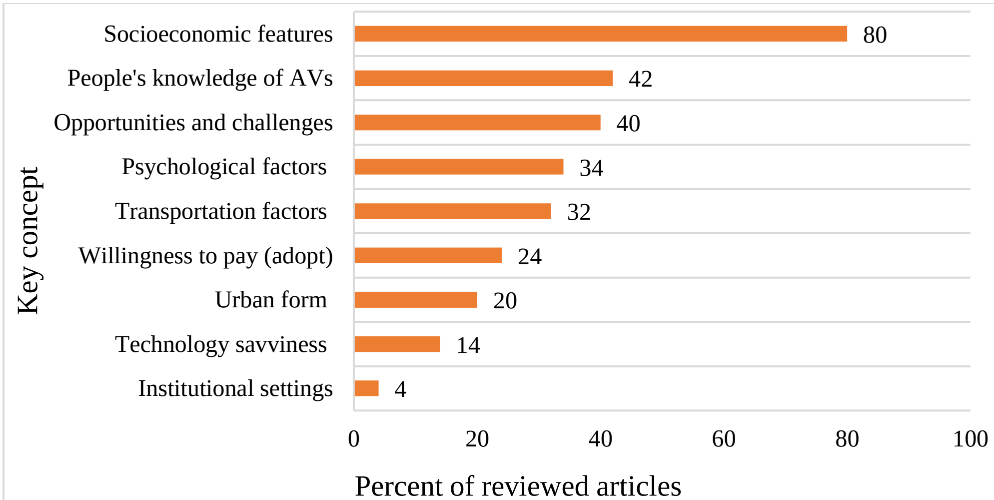

Figure 2.2: Key concepts discussed in the reviewed articles

3. Synopsis of previous literature

3.1 Contextualization of the factors of AV adoption

A conceptual framework is proposed to cohesively articulate the factors that influence people towards adoption and use of AVs. Figure 2.3 shows the factors that fit this framework, and the interactions between them; this review espouses the structure conveyed by this framework. The framework is centered on the individual person and/or household positioning themselves with respect to the AV mobility option in terms of espousing adoption and use of AVs or against it. Some factors are internal and pertain to the psychology and cognition of technological change, and innovation, risk aversion, trust, sense of usefulness. Affinity to new technologies also influences individuals towards AVs. For example, people are interested to adopt and use vehicles if the vehicles are equipped with cutting-edge technologies (e.g., automated speed control, braking and parking, collision warning, blind-spot detection, lane-changing warning). Increasing trust in AVs to reduce accidents induces people to use AVs. Thus, these factors significantly affect the decision-making process of consumers to adopt and use AVs.

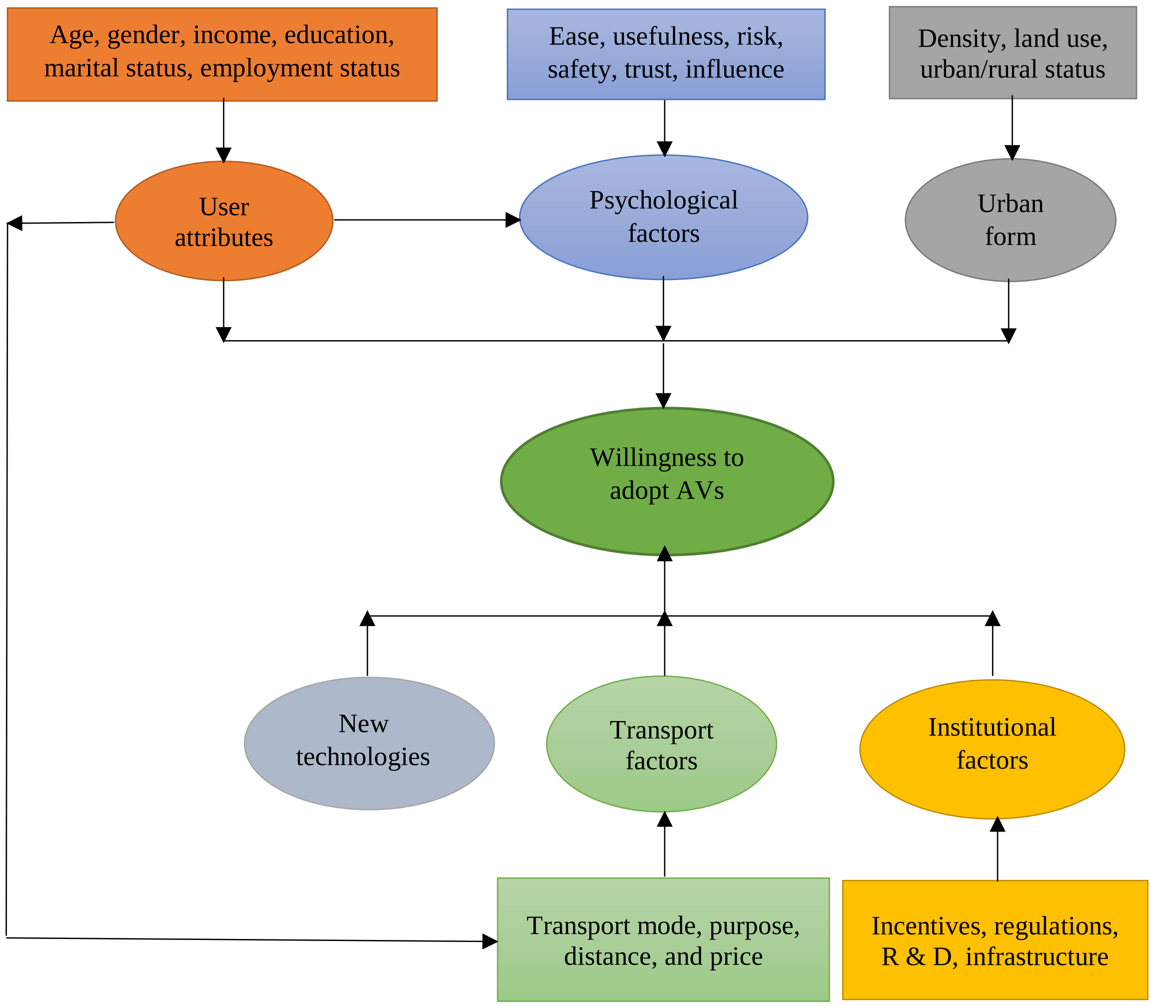

Figure 2.3: Contextualization of the factors that influence AV adoption and use

Other internal factors include various user attributes (i.e., socioeconomic features) that condition attitudes and willingness to adopt. For example, people with higher income and educational attainment are more willing to adopt and use AVs. User attributes also affect AV adoption and use indirectly, by influencing psychological factors of potential users regarding AVs.

Other factors are exogeneous, such as factors of urban form (e.g., urban/rural, density, land use diversity), which may also influence AV adoption outcomes by shaping people's preferences. For example, urban residents are more interested to adopt and use AVs compared to rural people.

Exogeneous factors also encompass transportation factors (e.g., travel mode, distance, and time) and the institutional context of policies and politics. For example, people who mostly use public transportation are interested to use SAVs, while people who drive to destinations are more interested in owning their personal AVs. The ambient technologies and attitudes towards them form a socio-technical context that may evolve over time. Increasing trust in AVs to enhance traffic safety may induce more people to use AVs.

3.2 People's willingness to use AVs and their associated factors

Investigating the willingness of people to adopt and use AVs, most studies observed that people are unwilling to spend more money to adopt and use personal AVs or add AV technologies to their vehicles (Bansal & Kockelman, 2017; König & Neumayr, 2017; Nazari et al., 2018). Rather, they are more interested to ride an AV than owing or leasing an AV (König & Neumayr, 2017). Despite higher price, close to half the respondents (48.72%) in Washington State showed an interest in personal AVs for commuting purposes due to convenience associated with AVs (Nazari et al., 2018). Surveying in the US, Bansal and Kockelman (2017) also found that about 45.8 to 50.7% of respondents showed a certain interest in AV technologies.

As indicated in Table 2.2, studies have also shown that the most important factors that control people's willingness to use AVs include several socio-economic traits (e.g., higher household income, presence of children in the household), personal attitudes like being tech savvy, mobility conditions (car ownership, driving alone, travel assistance for disadvantaged people, better connectivity, driving scope on freeways and inner-city roads, and technological advancements (higher traffic safety and burden of driving) (Bansal et al., 2016; Shin et al., 2015; Shin et al., 2019). In contrast, the most prominent factors that dampen people's willingness to use AVs include socio-economic traits (holding a driver's license), personal attitudes (security, ride sharing attitudes), mobility aspects (driver's license, driving on local roads only), costs (vehicle purchase and maintenance cost), and technological advancements (cybersecurity) (Bansal et al., 2016; Gurumurthy & Kockelman, 2020; Shin et al., 2019). Reduction in purchase and operating costs could increase the willingness of the people to use AVs. For example, reducing travel costs from \$1/mile to \$3/mile can increase people's interest from 3% to 41% to use AVs in the US (Bansal et al., 2016). Thus, overall ownership and maintenance costs could significantly determine people's willingness to adopt and use AVs.

Table 2.2: Factors influencing people's willingness to use AVs

Study	Positive factors	Negative factors
(Bansal et al., 2016)	Social acceptance, reliability, high income, tech savvy, presence of children, driving alone, urban living, higher VMT, long commute.	Holding license, living in job-dense areas, elderly, familiarity with carsharing and ridesharing.
(Bansal & Kockelman, 2018)	Familiarity with Google car, supportive of government intervention, high income, higher VMT, experienced fatal crashes, connectivity.	Holding license, elderly, living in dense area, living far away from transit stations, familiarity with ride-sourcing services.
(Kyriakidis et al., 2015)	Higher VMT, experience with automatic cruise control feature, male, higher income.	-
(Shin et al., 2015)	Cutting edge AV features.	High purchase price, concerned about safety.
(Gurumurthy & Kockelman, 2020)	Long-distance business travel, high income, college educated, employment density.	Higher travel time, elderly, presence of a worker in household, holding driver's license, population density.

(Shin et al., 2019)	Male, travel assistance for elderly, high income, children in household, car ownership, AV features.	Higher purchase and maintenance cost, information leakage to third parties, long travel time, driving on local roads, driver license.
(Laidlaw et al., 2018b)	High income, male, possession of a smartphone, employment density, familiarity with and user of shared mobility.	Unaware of Google car.
(Webb et al., 2019)	High income, environmentally aware, open to public transport and ride-sharing options.	-
(Bansal & Kockelman, 2017)	Long travel distance, experienced with automated features.	-

Some studies have investigated people's attitudes (i.e., positive, negative) towards AVs. Using user opinion surveys, it is often found that most people have a positive intention to adopt and use AVs due to the improved accessibility they afford for all, to various amenities, cutting-edge technologies, and potentiality to enhance traffic safety (Feys et al., 2020; Howard & Dai, 2014; S. Wang et al., 2020). Surveys in multiple countries point that 52.2 to 61.9% of respondents in Australia, the US, and the UK (Schoettle & Sivak, 2014b) and 43 to 87.4% of respondents in China, India, and Japan (Schoettle & Sivak, 2014a) have a positive impression of vehicle automation. Also, only 11.3 to 16.4% of respondents have some negative impression in Australia, the US, and the UK, due in large part to legal liabilities, privacy concerns, and safety issues (Schoettle & Sivak, 2014b).

Investigating positive and negative attitudes towards automated driving in 112 countries, Bazilinskyy et al. (2015) found that 39% of respondents showed a positive attitude and 23% showed a negative attitude to AVs. Researchers in Athens, Greece (Panagiotopoulos & Dimitrakopoulos, 2018) found that 58% and 12% of respondents have positive and negative perceptions about AVs, respectively. Piao et al. (2016) observed that 66.67% of respondents in the city of La Rochelle, France, would like to experience automated buses, even if there are human-operated buses on the street. These studies demonstrate that more people have positive perception of AVs and they are interested to use AVs in the near future as it seems safe, comfortable, fun, and easy to navigate, despite some uncertainties (e.g., emergency reactions, technical failure, and cyber-attack) (Feys et al., 2020).

Surveying in the US, S. Wang et al. (2020) found that 36.7% of respondents have a positive outlook on AVs and 21.8% have a negative outlook. This study also found that the people who own smart devices and are familiar with AVs are more inclined to own and use AVs. Over 40% of respondents in Berkeley, California (Howard & Dai, 2014) and about 30.2% of respondents in California (Castritius et al., 2020) are positive to purchase AVs or retrofit their current vehicles with such technologies. About 24% and 57% of respondents in Austin, TX would like to add Level 3 and Level 4 automation in their next vehicles (Bansal et al., 2016). In the same study context, researchers in (Zmud & Sener, 2017) found that 59% of respondents are interested to own an AV and 41% would like to share AVs. Surveying vulnerable road users (e.g., pedestrians, cyclists) in Pittsburgh, PA, Penmetsa et al. (2019) found that many respondents (nearly 70%) approve AVs on the street because they did not find any difference between AVs and human-operated vehicles and did not experience any negative interaction with AVs (i.e., unexpected movement of AVs). However, some researchers (Bansal & Kockelman, 2018; S. Wang et al., 2020) argued that many Americans are not yet confident and ready to use AVs for work and non-work trips due to associated legal and safety uncertainties, but would be major consumers of AVs compared to people from other parts of the world.

Investigating perceptions and attitudes of populations, researchers reported that many people would be interested to adopt this novel technology. These studies applied various existing theories such as the Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Technology Acceptance Model (Ajzen, 1985; Davis, 1985; Fisbein & Ajzen, 1975) to conceptualize and understand the factors that influence the Behavioral Intention (BI) of people to adopt AVs. According to these theories, human BI to actual AV use is directly influenced by behavioral control factors (e.g., socioeconomic and travel factors), objective factors (i.e., urban form), and psychological factors (i.e., perceived usefulness and perceived ease of use). Additionally, the model indicates that the actual use of AVs also depends on the availability of novel technology (e.g., EV, solar panel) and people's affinity towards new technologies. Socioeconomic factors also indirectly affect AV use by influencing objective factors, psychological factors, and the affinity of the people towards a technology.

3.3 Opportunities and challenges to adopt autonomous vehicles

A considerable number of studies have investigated people's opinions and perceptions on the opportunities and challenges to adopt and use AVs. As reported in Table 2.3, there are many social, economic, transportation, environmental, technical, legal, and institutional opportunities and challenges for the successful implementation of AVs.

Table 2.3: Respondents opinion on opportunities and challenges to adopt AVs

Author	Opportunities (%)	Challenges (%)
(Panagiotopoulos & Dimitrakopoulos, 2018)	Solution to many problems (88%), easy to operate (64%), clear and understandable interaction (69%), easy to become skillful (66%), useful to meet driving needs (46%), safe travel (44%), interesting travel (38.3%), low crashes (55.3%)	Safety concern (55%), waste of time (65.6%), make life more complicated (58.8%), do not increase social status (33%)
(Bansal et al., 2016)	Reduction in crash (63%), talk or text to other (75%), surf the internet 36%), email while driving (45.2%)	Interactions with conventional vehicles (48%), affordability

		(38%), equipment or system failure (50%)
(Schoettle & Sivak, 2014b)	Fuel economy (72%), travel time saving (43%), few crashes (70.4%), reduced severity of crash (71.4%), improved emergency response (66.9%), low emission (66.3%), low insurance cost (55.5%), less traffic congestion (51.8%)	System failure (80.7%), legal liability (74.1%), system security (68.7%), vehicle security (67.8%), data privacy (63.7%), interacting with conventional vehicles (69.7%), interacting with pedestrians/bicyclists (69.8%), learning to use AV (53.5%), system performance in poor weather (62.8%), unexpected situation (75.7%), no driver control (54.3%)
(Schoettle & Sivak, 2014a)	China: Few crashes (85.7%), reduced severity of crash (85.1%), improved emergency response to crash (88.8%), shorter travel time (78.3%), low insurance cost (78.5%). India: less traffic congestion (72.3%), better fuel economy (85.9%)	China: system failure (68.0%), legal liability (55.1%), interacting with pedestrians and bicyclists (42.6%), system performance in poor weather (59.6%), AVs confused by unexpected situations (56.1%) India: system security (54.6%), Vehicle security (57.3%), data privacy (50.9%), learning to use AVs (43.6%)
(Howard & Dai, 2014)	Safe (75%), convenience (61%), amenities (e.g. ability to text message or multitask while driving) (53%)	Liability (70%), cost (60%), lack of control (53%)
(Piao et al., 2016)	Increased mobility (58%), reduced fuel consumption and emission (56%), low bus fares (64%), low insurance rates (53%), low parking costs (49%), safer driving (36%), reduced taxi fares (36%), allows to do other things (20%), improved safety (80% for automated bus, 89% for automated car)	Equipment/system failures (66%), legal liability (56%), vehicle security (54%)
(Gurumurthy & Kockelman, 2020)	Comfortable with data sharing for policy purpose (48%)	Privacy concern (89%), unwilling to pay to anonymize location (39.8%), oppose data sharing for advertising purposes (50%)
(Shin et al., 2019)	Reduced traffic crashes and improved comfort and convenience (37.3%), no need for driver's license (12%), reduced mobility and crashes related problems of elderly persons (50%)	Technological dependability (43.48%), vehicle safety (31.43%) of FAV, cost of new and not-yet-available technology (25.26%)
(Bansal & Kockelman, 2017)	Enjoyable (75.7%), Advance technology (54.4%), comfortable (19.5%), reliable (49%), Omnipresent in future (41.4%), comfortable to transmit information to other vehicles (50.4%), to vehicle manufacturers (42.9%), to insurance companies (36.4%) and to toll operators (33.3%), trust technology companies (62.3%) and luxury vehicle manufacturers (49.5%), willing to use for everyday trips (40%)	Fear of technology (58.4%), not realistic (44%), unwilling to use for short distance (42.5%) and long-distance (40%) trips

(Bansal & Kockelman, 2018)	Talking to others (59.5%), looking out the window (59.4%), fuel economy (53.9%), crash reduction (53.1%), emergency notification (71.5%), vehicle health reporting (68.5%), use of AVs for all trips (33.9%) and social or recreational trips (24.7%)	Congested streets (36.1%)
(Rahimi et al., 2020)	Improved safety (43.3%), reduced driving stress (40.6%), better technology (30.8%), collision avoidance (52.9%), improved fuel efficiency (46.5%), lane-keep assistance (26.5%).	Data privacy (58.4%), trust issue (46.6%), reliability (48.7%), higher travel time (64.8%)
(Kaye et al., 2020)	Reduction of human error in crashes (35.64%), multi-tasking (30%), reduction of risk-taking behaviors (29.3%)	High cost (59.21%), lack of trust (32.1%), no control of vehicle (37.22%), technology malfunction (34.26%), safety for self and others (20%), safety of vehicle (21.39%), loss of driving skill (14.1%)
(Castritius et al., 2020)		Reliability (California: 30.1%, Germany: 25.0%), problems when entering/exiting the highway (Cal: 23.9%, Ger 25.4%), issues with cut-in vehicles (Cal: 15.3%, Ger: 18.7%)
(Hilgarter & Granig, 2020)	Feel safe (84.2%)	Lack of confidence in technology (10.5%)
(Zmud & Sener, 2017)		Lack of trust in technology (41%), safety (24%), cost (22%), Concern about using internet and internet enabled technologies (51%), privacy concerns (71%)
(Nordhoff et al., 2020)	Easy to use (71.06%), easy to become skillful to use AV (60.35%), use of travel time for secondary activities (41.85%), fun to drive (53.21%), enjoyable (52.54%), use for everyday trips (53.45%), meet daily mobility needs (53.27%), entertaining (51.04%), reach destination safely (48.67%)	
(Penmetsa et al., 2019)	Improved road safety (62%), safe to share with other modes of transportation (43%), reduced traffic fatalities and injuries (67%)	Set regulation for AV testing (70%)
(Xu & Fan, 2019)	Trust (51.32%), lower insurance rates (45.28%), willing to pay more (69.24%)	Increased risk (43.86%)
(Nazari et al., 2018)	Reduced congestion (22.96%)	
(Chen, 2019)	Novelty technology (75.7%), low pollution (18.4%), integration with public transportation (3.7%)	

Traffic safety and security from crashes, reliability and confidence in technology, system failure due to poor internet connection and virus attach, and losing control of car are regarded as people’s prime concerns (Bansal & Kockelman, 2018; Kaur & Rampersad, 2018; Talebian & Mishra, 2018). Nazari et al. (2018) have found safety concerns to have the highest marginal effect on AV adoption (i.e., a one-unit decrease in safety concern may reduce the probability of people’s willingness to adopt AVs by over 100%). Unattended drop-offs and pick-ups of children and the anticipated increased number of pedestrian traffic crashes may make AV adoption more challenging (Kaur & Rampersad, 2018). Thus, it is imperative to increase the perceived safety and security of people to boost AV adoption. Similar to traffic safety concern, the lack of personal data privacy from hackers (i.e., location tracking, surveillance) poses a major threat to adopt and use AVs (Haboucha et al., 2017; Hilgarter & Granig, 2020; Rahimi et al., 2020). Thus, the protection of personal privacy is critical to encourage the public to use AVs.

A considerable number of studies have mentioned that the current immature development of AV technologies, insufficient institutional infrastructure, and absence of integration with the existing traffic environment would cause major legal challenges for vehicle owners, manufacturers, and insurance companies (Castritius et al., 2020; Howard & Dai, 2014; König & Neumayr, 2017). The inadequate legal resolutions and institutional setup are leading causes of lagging development of AV technologies and of the lower level of acceptance in the public (Hilgarter & Granig, 2020). However, people who are passengers of a vehicle have less legal concern compared to the drivers of the vehicles due to the legal liability for the drivers and owners of the vehicles (Schoettle & Sivak, 2014b).

Besides, the high initial cost of AVs and high maintenance cost would restrict people particularly from low- and medium-income groups to purchase and use AVs (Hilgarter & Granig, 2020; Howard & Dai, 2014; Talebian & Mishra, 2018). Thus, affordability among certain socio-economic groups could be another major challenge for increasing market share of AVs (Bansal & Kockelman, 2018).

Researchers also mentioned that people who value fuel economy (Howard & Dai, 2014) and greener transportation (Haboucha et al., 2017; Talebian & Mishra, 2018) are more interested in adopting and using AVs compared to their counterparts. Similarly, mobility for disadvantaged people (e.g., elderly, disabled) (König & Neumayr, 2017; Talebian & Mishra, 2018) and improved amenities and services (Howard & Dai, 2014; Rahimi et al., 2020) motivate people to use AVs. Moreover, the possibility afforded by AVs to reduce traffic congestion and travel time, and people's engagement in other activities, and social recognition induce them to adopt and use AVs (König & Neumayr, 2017; Nazari et al., 2018; Rahimi et al., 2020).

The extant literature shows that the potentiality of AVs to reduce accidents and congestion, better amenities to engage in other activities, and proper integration with public transportation could motivate people to use AVs. On the other hand, high costs, security issues, system failure, and violation of personal privacy discourage people to adopt AVs. In conclusion, these opportunities need to be nurtured and ensured and challenges should be minimized to increase public acceptance of AVs.

3.4 Psychological factors of AV adoption

Most studies have investigated the influence of psychological factors on the behavioral intentions of people to adopt and use AVs. Taking Behavioral Intention (BI) to adopt and use as the dependent variable, these studies have estimated the impacts of Perceived Usefulness (PU), Perceived Trust (PT), Perceived Ease to Use (PEU), Social Influence (SI), and Traffic Safety (TS) on AV adoption and use. These studies have mentioned that different psychological factors significantly influence the adoption and use of AVs. Compared to other factors (e.g., socioeconomic and demographic, built environment), psychological factors solely explain 43.7% (Panagiotopoulos & Dimitrakopoulos, 2018), 67.8% (Kaye et al., 2020), 69% (Yuen et al., 2020), 71% (Rahman et al., 2017), and 76% (Kapser & Abdelrahman, 2020) variation in the BI of the people to adopt and use AVs. Table 2.4 shows the impacts of different psychological factors on the BI of people to adopt and use AVs, as expressed by the standardized coefficients of the factors on BI.

Table 2.4: Impacts (standardized coefficient) of psychological factors on BI to adopt AVs

Authors	PU	PT	PEU	SI	TS	PR	PBC	TA	PS
(Panagiotopoulos & Dimitrakopoulos, 2018)	0.52	0.15	0.13	0.14					
(Xu et al., 2018)	0.43	0.12	0.19		0.14				
(Rahman et al., 2017)	0.80		0.13	0.10					
(Zhang et al., 2020)	0.13	0.37	0.14	0.10					
(Kapser & Abdelrahman, 2020)	0.23		-0.05	0.17		-0.17			-0.28
(Castritius et al., 2020)	0.49		0.29						
(Nordhoff et al., 2020)	0.14		0.05	0.40					
(Zhu et al., 2020)	0.42					-0.11			
(Chen, 2019)	0.35	0.04							
(Yuen et al., 2020)	0.45	0.45							
(Kaye et al., 2020)	0.64			0.30			-0.05		
(Rahman et al., 2017)	0.29			0.05			-0.05		
(Chen, 2019)	0.22	0.13	0.43						
(Zhang et al., 2020)		0.20		0.10					
(Hulse et al., 2018)						-0.24			
(X. Wang et al., 2020)								-0.11	
(Zhu et al., 2020)	0.42			0.09		-0.11			

BI = Behavioral Intention, PU = Perceived Usefulness, PT = Perceived Trust, PEU = Perceived Ease of Use, SI = Social Influence, TS = Traffic Safety, PR = Perceived Risk, PBC = Perceived Behavioral Control, TA = Technology Anxiety, PS = Price Sensitivity.

Table 2.4 indicates that PU has the strongest impact on BI compared to other factors. A sense of usefulness by adding autonomous features to vehicles such as Adaptive Cruise Control (ACC), self-parking assistance, and vocal interactions positively influences people's BI to use AVs (Clark et al., 2019; Nordhoff et al., 2020; Shin et al., 2015).

Usefulness also increases when people can engage in other activities (e.g., talking on the phone, reading) while traveling in AVs (Wadud & Huda, 2019). Additionally, PEU of AV has a significantly positive effect on PU of AVs (Chen, 2019). However, familiarity with smart phone and smart vehicle technologies, prior knowledge, and experience of AVs could increase the impacts of PU and PEU on BI and correlations among themselves (Clark et al., 2019; Nordhoff et al., 2020). Performing a study considering before and after AV experience, Xu et al. (2018) mentioned that prior AV experience increases PU by 0.08 unit, PEU by 0.12 unit, , and BI by 0.02 unit. This study also estimated that sociodemographic factors (e.g., age, gender, income, and driving experience) have a very limited influence on BI to AV adoption compared to psychological factors, which is also supported by other studies (Kapser & Abdelrahman, 2020; Zhang et al., 2020).

Researchers have considered PT on technology as one of the most important psychological factors that induce people to adopt AVs (Table 2.4). Vehicles equipped with ADAS increase the trust of the users by reducing the probability of crashes and increasing the controllability of risky driving compared to vehicles without ADAS technology (Castritius et al., 2020; Ha et al., 2020; Hagl & Kouabenan, 2020). Moreover, an external human-machine interface that displays information could increase BI towards AVs by increasing safety, trust, intelligence, and transparency (Faas et al., 2020). Trust increases when AVs become predictable and understandable, complete tasks accurately and correctly, and allow users to get control of the vehicle when they desired (Haboucha et al., 2017; Yuen et al., 2020). Researchers (Zhang et al., 2020) mentioned that personality traits have a significant influence on the trust of individuals in AVs. For example, open-mindedness and sensation seeking have a positive effect on trust, while neuroticism (i.e., frequently changing mode) and agreeableness have negative effect on trust. Thus, it is imperative to build trust of users by promoting AVs rather than only focusing on usefulness and ease of use to increase acceptance of AVs.

Some studies have reported that PR affects the BI of people (Table 2.4). Fear of crashes, cyber-attack, operating speed, inclement weather, and sharing AVs with unknown persons could be the main causes of perceived risk. People perceive a higher risk when AVs are operated at a slow speed on a clear day, whereas people perceive a lower risk when AVs are operated at a slow speed on a snowy night (Ha et al., 2020). Self-identity concern (i.e., AV is a threat to their personal identity as a driver) adversely influences users' willingness to use AV technologies (X. Wang et al., 2020). Thus, people show negative attitudes to AVs and are unwilling to share AVs with unknown persons to avoid risk (S. Wang et al., 2020).

Many studies have reported that social norm and conformity (i.e., influence from relatives, friends, and neighbors) influence BI to use AV (Table 2.4). Bansal and Kockelman (2018) found that about 47% of Texans are willing to adopt AVs when their friends also do so. Similarly, Bansal et al. (2016) reported that about half of the respondents would adopt AVs after the adoption of AVs by their relatives, friends, and neighbors which confirms that people's willingness to use AVs is partly influenced by social norms and status symbol. Social influence positively affects PU, PEU, and PT, consequently determine whether people would use AVs or not (Zhang et al., 2020).

The higher price of the vehicle and travel costs could negatively affect BI to use AVs. Kapser and Abdelrahman (2020) reported that price sensitivity (i.e., how demand changes with changing price of a product) is the strongest factor to influence BI to use AVs compared to performance expectancy, hedonic motivation, perceived risk, social influence, and facilitating conditions.

Some studies have mentioned that confidence and self-efficacy (i.e., capabilities) of users, relative advantages, observability, compatibility, trialability, and pro-AV attitudes directly drive people's intentions to adopt and use AVs (Chen, 2019; Yuen et al., 2020; Zhu et al., 2020). Similarly, extant studies observed that enjoyment, comfort and convenience, and hedonic motivation (i.e., fun, enjoyable, entertaining) positively influence people’s BI to use AVs (Chen, 2019; Feys et al., 2020; Kapser & Abdelrahman, 2020). People’s willingness to adopt and use AVs also increases because of perceived value (i.e., offer superior benefits, more utility) and performance of AVs (Rahman et al., 2017; Yuen et al., 2020). Perceived value also indirectly increases people’s BI by increasing trust and reducing risks through addressing individual's expectations, offering more incentives, increasing safety and reliability. In contrast, losing control of vehicles, obsession for luxury, image and prestige, and complexity reduce people’s intentions to use AVs (Howard & Dai, 2014; Sparrow & Howard, 2017).

This discussion based on previous studies underscores that PU, PT PEU, SI, and TS motivate people to use AVs. On the other hand, PR, TA, and high price reduce intentions of people to adopt AVs. Thus, psychological factors have significant contributions to define people’s BI to adopt and use AVs.

3.5 People’s knowledge and experience of AVs

Prior knowledge about AVs is considered as one of the main factors that can influence people towards AVs. Recent studies have reported that most participants are unfamiliar with AVs and are unaware of automated cars that are already plying the streets of a number of cities (Bansal & Kockelman, 2018; Laidlaw et al., 2018b). Additionally, the vast majority of people (i.e., 99%) have never had any experience of an AV in their life (Kaur & Rampersad, 2018; Rahman et al., 2017). There is strong evidence that awareness and information on the perceived benefits of AVs may motivate AV adoption and willingness to pay for AV services (Daziano et al., 2017; Feys et al., 2020; Hilgarter & Granig, 2020). Thus, there is an imperative need to better inform the general population about AVs to level the plane field and increase their market share.

Table 2.5 shows the status of prior knowledge of people on AVs across various studies. Although the table shows that many people (from 49 to 98.80% in various studies) have heard of AVs, in reality, most of them have very limited idea about AVs and have seldom experienced AV rides. Many people consider anti-lock braking systems, which are very basic in the strata of vehicle autonomy as a form of automation (Bansal et al., 2016). Thus, most people have scant knowledge of AVs and their level of autonomy (i.e., partial human control to no control) due to limited availability of AVs for private use. People mainly receive generic information on AVs from mass media and social media, which indicates that AVs are still not a tangible reality that people can well relate to (Zhu et al., 2020).

Table 2.5: Knowledge of respondents on AVs

Author	Heard of AVs (%)
(Panagiotopoulos & Dimitrakopoulos, 2018)	71.4%
(Xu et al., 2018)	94.3%
(Rahman et al., 2017)	63%
(Bansal et al., 2016)	80% (Google car), 47% (CAV)
(Kyriakidis et al., 2015)	52.2%
(Schoettle & Sivak, 2014b)	66% overall (70.9% in USA, 66% in UK and 61% in Australia)
(Schoettle & Sivak, 2014a)	87% (China), 73.8% (India), 57.4% (Japan)
(Piao et al., 2016)	87%
(König & Neumayr, 2017)	Over 95%

(Zhang et al., 2020)	98.8%
(Kapser & Abdelrahman, 2020)	49%
(Wadud & Huda, 2019)	90%
(Bansal & Kockelman, 2018)	59%
(Xu & Fan, 2019)	94.67%
(Kaye et al., 2020)	78.4%

Conducting a survey in eight European countries, Nordhoff et al. (2020) investigated the experience of drivers with different features of Advanced Driver Assistance Systems (ADDS) (Figure 2.4). The figure shows that a considerable number of drivers have parking assistance (37.83%) and ACC (30.39%) in their vehicles. However, most of the drivers do not have any advanced driving assistance system. During the survey, 47-64% of respondents expected to have them in the vehicles and use them in the future. Although many of the respondents do not have advanced system in their cars, they have showed their interests to experience ADDS features, which confirms their affinity towards advanced technology to make travel safer and enjoyable.

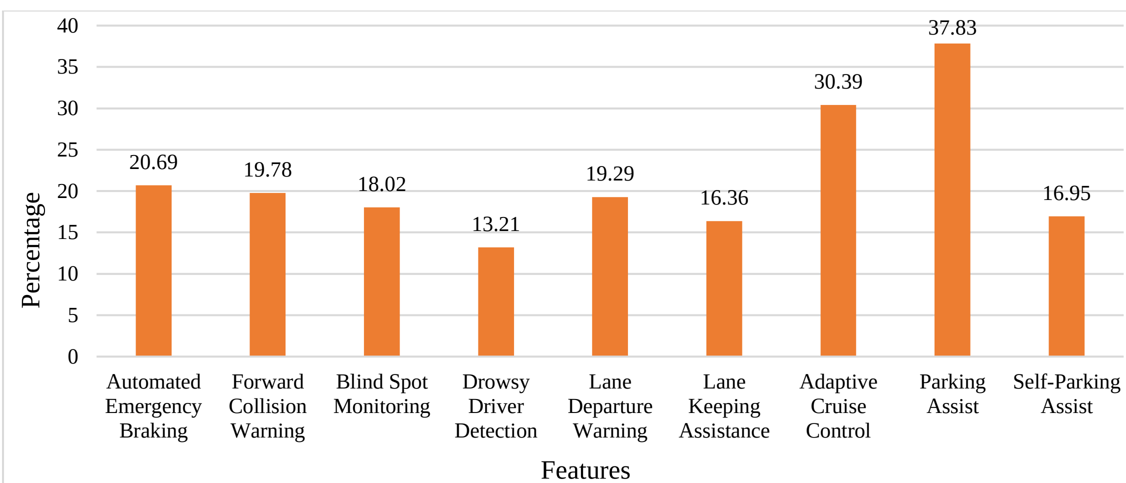

Figure 2.4: Experience with ADDS, adopted from (Nordhoff et al., 2020)

3.6 Socio-economic features of respondents and their influence on AV adoption

People’s socio-economic characteristics are considerations that tend to predispose them towards AVs. Thus, many studies have explored diverse socio-economic features of people and their impact on AV adoption. The following subsections discuss in turn the impacts of various socio-economic features on the AV adoption tendency.

3.6.1 Age of the respondents

Most studies have reported that young people are more interested in using AVs, compared to the elderly (Nordhoff et al., 2020; Rahimi et al., 2020; S. Wang et al., 2020; Webb et al., 2019). Panagiotopoulos and Dimitrakopoulos (2018) reported that respondents in the 18-40 age cohort (60.1%) are more likely to adopt and use AVs compared to the people who are over 40 years old (55.5%). Researchers in (Piao et al., 2016) found that 56% of respondents aged over 65 would use automated cars compared to 62% aged 18 to 34 and 61% aged between 35-64. They also reported that 52% of respondents aged 18-34 would own an AV compared to 39% aged 34-65, and 43% aged over 65. Thus, young adults and people with multimodal travel behaviors are more interested to adopt and use personal AVs and SAVs than the elderly (Haboucha et al., 2017; Krueger et al., 2016; Nazari et al., 2018).

At variance with the above studies, Shin et al. (2015) reported that younger people are less likely to adopt technologically advanced vehicles (e.g., EVs) due to the high purchase price, low driving range, and accessibility to charging stations. Also, a few studies have mentioned no significant associations between age and public acceptance of AV (Salonen, 2018; Wadud & Huda, 2019). Zmud and Sener (2017) observed almost a similar trend of AV adoption among the younger (less than 30 years) and elderly (65+) persons (i.e., 53% of 30-45 years, 55% of 45-65 years). Researchers argued that elderly people are pragmatists (positive), while the youngers are either conservatives (negative and skeptical) and enthusiasts (positive) (Hilgarter & Granig, 2020). Thus, the acceptance and rejection of AVs comprise a balanced distribution of elderly and young people.

3.6.2 Gender of the respondents

Studies have investigated the discrepancies in AV adoption and use between males and females. Gender analysis shows that men are more likely to adopt and use personal AVs and SAVs compared to women due to better economic condition, affinity to technology, and the perceived safety and security of AVs (Howard & Dai, 2014; Nazari et al., 2018; Nordhoff et al., 2020). For example, Piao et al. (2016) found that 64% and 49% of males would use and own AVs compared to 55% and 39% of females, respectively. Additionally, many females hold the view that most of the expected benefits from AVs are unlikely to materialize (Schoettle & Sivak, 2014b). However, researchers have argued that the likelihood to use AVs by females depends on the perceived safety, in-vehicle security, and emergency management systems (Salonen, 2018; Webb et al., 2019). Thus, it is crucial to improve AVs' safety and security and their perception in the public to overcome female apprehension towards the use of AVs.

3.6.3 Marital status

Studies have observed that married couples are more likely to adopt and use AVs and SAVs compared to singles due to improved safety measures, amenities such as multi-tasking opportunity, and scopes to share AVs within the household, which could reduce overall travel costs (Howard & Dai, 2014; Nazari et al., 2018; Webb et al., 2019). Moreover, married people are usually economically better off than single and non-married people, which conditions their greater affinity to personal AVs (Howard & Dai, 2014). On the other hand, Gurumurthy and Kockelman (2020) reported that single persons are more likely to use AVs and SAVs with dynamic ride sharing services, which have the potential to reduce travel costs. Thus, splitting travel costs by sharing mobility with ride companions may induce single individuals to use AVs and SAVs.

In addition, families holding conservative views are less likely to use AVs until it becomes more mainstream and people gain experience of it (Daziano et al., 2017). Thus, besides the marital status of the respondents, some other factors (e.g., progressive attitudes, technology) also determine AV adoption and use tendency of a family.

3.6.4 Educational attainment

The level of education significantly regulates people's willingness to adopt AVs and SAVs. Many studies have assessed the impacts of educational attainment on AV adoption rate. The level of education is seen to be positively associated with people's intention to adopt and use AVs and SAVs for personal travel purposes because they may already know about AVs and are more receptive to new ideas (e.g., shared mobility) and technologies (Daziano et al., 2017; Gurumurthy & Kockelman, 2020; Nazari et al., 2018). For example, Piao et al. (2016) reported that 71% of respondents with higher education (bachelor's and above) are interested to use AVs compared to 52% of respondents with lower education (below bachelor's degree). Moreover, 28% of respondents with higher education would consider using SAVs (e.g., car-sharing/car-pooling/taxis) compared to 8% of their counterparts. Thus, people with educational attainment of bachelor and above are more likely to use AVs compared to people with primary school, secondary school, and some college education.

People with higher education perceive that AVs would reduce the number and severity of traffic crashes, congestion, travel times, and operational cost (e.g., insurance cost, driver salary) (Schoettle & Sivak, 2014b). The perceived benefits of AVs are relatively greater among the highly educated persons and users of on-demand mobility services compared to less educated persons and users of conventional Internal Combustion Engine (ICE) vehicles (Krueger et al., 2019; Yuen et al., 2020). Thus, it can be argued that the level of education has a significant impact on the AV market share, as demonstrated by a large number of studies.

3.6.5 Household income

Among the socioeconomic covariates, employment status and household income are the critical factors to determine AV ownership. Many studies have found that household income is positively associated with AV adoption and use because high-income people have the capacity to afford AVs and they are more likely to pay extra money for improved facilities in cars (Bansal et al., 2016; Rahimi et al., 2020; Yuen et al., 2020). Zmud and Sener (2017) found that 56% of people with income under $25K are unwilling to use AVs and 54% of people with income $25k-$50k are more likely to use AVs. However, people with higher income are less interested to share AVs with other and unknown persons (S. Wang et al., 2020). In contrast, low-income people, unemployed, homemakers, and retired persons are less likely to adopt and use AVs compared to ICE vehicles (Daziano et al., 2017; Nazari et al., 2018; Shin et al., 2015).

Some studies also mentioned that full-time employment is positively associated with AV ownership and use due to their higher ability to pay (Gurumurthy & Kockelman, 2020; Nazari et al., 2018; Schoettle & Sivak, 2014b). Employed people are more likely to own and use AVs compared to the unemployed, student, and retired persons due to higher purchase prices and operating costs of AVs. Also, single-member earning households are less interested to own and use AVs (Gurumurthy & Kockelman, 2020). Thus, employment status with a higher household income is crucial to the adoption and use of AVs.

3.6.6 Household size and composition

Some studies also investigated the size, composition, and type of households on AV adoption. These studies reported that households with children and disabled persons have a positive attitude to adopt and use AVs due to better safety measures and driverless services (Daziano et al., 2017; Laidlaw et al., 2018a; S. Wang et al., 2020). Moreover, people in larger households, and those from Hispanic and Asian communities are more interested in AVs and highly appreciate the technology to improve mobility of the disadvantaged segments of society (Howard & Dai, 2014). However, some large households with more than 4 members are less likely to adopt and use AVs and SAVs due to safety and security reasons (Gurumurthy & Kockelman, 2020; Rahimi et al., 2020). Along the same line, households with children are very cautious to use AVs and SAVs due to perceived safety risks among the parents (Wadud & Huda, 2019; Webb et al., 2019; Zmud & Sener, 2017). Thus, household size and composition of the household have a significant influence on the behavioral intention towards using AVs and SAVs.

3.6.7 Vehicle ownership and holding of a driver’s license

Household vehicle ownership and driver’s license possession could influence AV use and vehicle sharing tendency. A considerable number of studies have evaluated the impacts of vehicle ownership and possession of a valid driving license. Some of these studies have argued that vehicle ownership and number, and driving preference are positively associated with AVs and SAVs due to availed benefits of cars and familiarity with AVs (Daziano et al., 2017; Wadud & Huda, 2019; S. Wang et al., 2020). Moreover, people with a strong inclination to regular ride-sourcing services are more interested in vehicle automation and connectivity (Rahimi et al., 2020). Researchers in (Shin et al., 2015) mentioned that drivers are more interested in alternative fuel vehicles (e.g., hybrid, and electric) than non-drivers due to their familiarity with alternative fuel vehicles and proven track record of driving. Consequently, it is assumed that people who drive regularly have strong preferences for AVs and other alternative fuel vehicles, compared to people who infrequently drive a car (König & Neumayr, 2017; Zmud & Sener, 2017). Moreover, current vehicles equipped with automated features strongly influence people to be enthusiastic about AVs (Zmud & Sener, 2017).

Some studies also observed that SOV drivers are less likely to adopt and use AVs compared to others, considering their preference for driving, and losing the excitement and pleasure of driving (Bansal et al., 2016; Howard & Dai, 2014; Webb et al., 2019). Researchers also found a slightly higher tendency to use AVs among the people who walk and carpool (57%) compared to drivers (52%) (Zmud & Sener, 2017). Thus, vehicle ownership and holding of a driving license could influence the adoption and use of AVs.

3.7 Transportation factors and their impacts on AV adoption

Many studies have investigated the impacts of various travel factors on AV adoption and use. Krueger et al. (2016) found that people professing an interest and preference for public transportation, car sharing, and walking are also favorably disposed towards SAV and AV technologies due to pro-environmental and multi-modality attitudes. Moreover, drivers of cars, motorcycles, and scooters are very interested to use SAVs for their travel purposes because of their interests in ride-sourcing shared mobility. Researchers in (Nazari et al., 2018) found that people passionate about green travel (e.g., walking, public transport) are very interested in AV ownership and rental. Thus, preference for particular transportation modes may be critical determinants for AV and SAV adoption and use.

Gurumurthy and Kockelman (2020) reported a positive association of travel distance with SAVs usage. In contrast, some researchers have found that people who travel more (i.e., total daily VMT) are not favorably disposed towards AV technology for daily use (Nazari et al., 2018). Thus, people would prefer personal AVs for short-distance commuting trips and SAVs for long-distance business and recreation trips. Some studies have found that travel time is positively associated with AV use. For example, Rahimi et al. (2020) observed that long travel times (above 30 min) have positive effects on AVs use due to low travel costs and the multi-tasking features of AV riding. Similarly, Nazari et al. (2018) and Haboucha et al. (2017) reported that travel time has a positive association with preference for personal AVs and SAVs. Although a low in and outside vehicle waiting time (around 5 minutes) has insignificant influence on SAV use (Krueger et al., 2016), researchers elsewhere found that the extra time added to travel time when SAV is used reduces people's interest in AVs (Gurumurthy & Kockelman, 2020). Thus, smooth travel with minimum travel and waiting time would encourage people to use SAV for their daily travel purposes.

Researchers have reported that high purchase, operation and maintenance costs dissuade people to travel by AVs and SAVs (Daziano et al., 2017; Haboucha et al., 2017; Krueger et al., 2016). In contrast, providing free parking space at the workplace may increase the use of AVs and SAVs (Nazari et al., 2018). However, people are more interested to use SAVs than private AVs to reduce overall travel costs (Daziano et al., 2017; Haboucha et al., 2017). Some studies have also found that shopping, medical, business, and recreation trips are negatively associated with AVs with dynamic ride sharing option (Gurumurthy & Kockelman, 2020; Krueger et al., 2016). People mostly use existing personal gasoline vehicles for work and groceries and public transport for traveling to large cities, and bicycle for free time relaxation trips (Hilgarter & Granig, 2020). Still, many respondents consider AV as an alternative mode of transportation. However, the respondents envisioned a greater potentiality of AVs for tourism, healthcare, and passenger transportation for public transportation.

In summary, the extant literature shows that different travel factors (e.g., mode, purposes, distance, time, and costs) are likely to condition people's intentions to use AVs and SAVs. Yet, people are less likely to adopt AVs as their primary household's means of transportation. AV would be used for business and recreation travel purposes with increasing amenities and reducing technological uncertainties.

3.8 Impacts of the built environment on AV adoption

Many studies have evaluated whether the built environment and its properties may be associated with AV adoption and use. Researchers have observed that people who live in urban areas are more likely to adopt and use AVs and SAVs compared to people who live in suburban and rural areas because these new mobility options reduce parking costs and searching time, and because of people's openness to accept promising alternatives that can reduce travel externalities (e.g., accidents, congestions) (Bansal et al., 2016; König & Neumayr, 2017; Nazari et al., 2018). Recent evidence shows that people who live in areas with high population and employment density (e.g., Central Business District (CBD)) and mixed land-uses are inclined towards AV adoption and use (Gurumurthy & Kockelman, 2020; Laidlaw et al., 2018a; Webb et al., 2019). Researchers also found that people who live in urban areas may have a negative attitude towards SAV due to their unwillingness to share vehicle with others (S. Wang et al., 2020). However, affluent urban residents have the capability to own a personal AV due to their better socioeconomic condition compared to households live in rural areas. People living outside of urban areas may embrace the availability of SAVs due to absence of public and nonmotorized transportation (Hilgarter & Granig, 2020). Thus, the built environment provides a context that may be quite influential in shaping behavioral intentions to adopt AVs and SAVs.

3.9 Impacts of technology savviness on AV adoption and use

The extant literature suggests that people's pro-technology attitude is positively associated with AVs and SAVs (Rahimi et al., 2020; Shin et al., 2015; S. Wang et al., 2020). The enhanced services (e.g., convenience, less travel time and cost, high driving range) and improved safety features due to cutting-edge technology motivate people to be positively disposed towards AVs (Daziano et al., 2017; Rahimi et al., 2020). However, a different scenario is observed in the US despite being the largest manufacturer of high-technology products (National Science Foundation, 2018; Zmud & Sener, 2017). Conducting an on-line based survey, Zmud and Sener (2017) found that about 66% of respondents identified themselves as late adopters of AV technologies and about 13% are outright laggards who would adopt at the very last moment, considering the uncertainties associated with AVs. In contrast, only 21% considered themselves as early adopters (i.e., first to adopt). Thus, it would appear that most people would wait and observe the trend of AV adoption before banding the wagon. However, it is believed that Americans would ultimately be the first adopters of AVs when these vehicles will be available on the road for public use, considering their greater affinity to new technologies.

3.10 Impacts of institutional factors on AV adoption

Recent literature has reported that an effective infrastructure and institutional framework (e.g., regulations, incentives, research, and development) could positively affect AV adoption(Howard & Dai, 2014). Conducting an online survey in the US, S. Wang et al. (2020) reported that people who support rigid traffic regulations have a positive attitude towards adopting and using AVs. Thus, city authority should implement efficient institutional regulations to manage transportation system and provide adequate infrastructure to support the increase in the market share of AVs.

4. Discussion and conclusions

4.1 Summary

Considering the higher social, economic, and environmental costs of conventional vehicles to individuals, decision-makers are thinking of the possible introduction of AVs and this alternative mode of transportation would be a reality shortly. Considering the critical role of the users, this study investigated the perceptions and opinions of people and identified the factors that influence people to use and adopt AVs through the review of the extant literature. A strategic literature search was conducted to select articles and reports for this review. Most of the articles were published within the last five years and used a household questionnaire survey to collect data. Mostly they used statistical and econometric methods to evaluate the factors that affect people's intention to adopt AVs.

The review results show that various user socioeconomic features, knowledge and familiarity with AV technologies and psychological factors (e.g., usefulness, ease of use, trust, risk) would affect AV adoption tendency. User attributes also indirectly affect AV adoption by influencing the psychological factors of users regarding AVs. The study also identified some opportunities (e.g., safety and security, low congestion, energy use, and emission) and challenges (e.g., system failure, privacy breach, and legal issues) that would significantly influence people's tendency to adopt AVs. Urban form (e.g., urban/rural, density, land use diversity), transportation factors (e.g., travel mode, distance, and time) affinity to new technology, and the institutional settings would also influence AV adoption rates.

4.2 Study limitations and directions for future research

Analyzing the findings and methodologies of previous studies, I have identified some limitations, which require further attention. Future research could address the following aspects to realize people's perceptions and opinions on AVs and the related factors:

1) Some studies selected samples from a specific stratum (e.g., higher educated people, experts, tech-savvy, visitors of pilot vehicles) ignoring the majority population, which may reflect a self-selection bias and non-response bias under a controlled environment (Faas et al., 2020; Kaur & Rampersad, 2018; Zhu et al., 2020). Thus, a large, diverse, and representative segment of people should be included in the sample to obtain unbiased, true, and insightful results (Haboucha et al., 2017; X. Wang et al., 2020; Xu et al., 2018).
2) Psychological factors are often inadequately measured in studies (Ha et al., 2020; Hagl & Kouabenan, 2020; Xu & Fan, 2019), failing to capture their complete effects on the behavioral intentions to adopt and use AVs. Thus, it is recommended to include all factors of human psychology to understand fully their effects on AVs adoption. Moreover, researchers suggested to survey the same panel of respondents repeatedly over time to be in a position to trace changes in

attitudes and perceptions based on their understanding from peers, relatives, and social and electric media, real-life experience of AVs, availability of cutting-edge technology, sense of personal risks, and changes in household locations (i.e., rural versus urban) (S. Wang et al., 2020). This would also enable a more direct assessment of causal pathways.

3) By keeping the questionnaire short and simple, many important questions were excluded from the survey (also reflected in Figure 2.2) that could significantly influence people's perceptions. Thus, the effects of willingness to pay and use should be investigated considering different costs, urban form, traffic scenarios, technological advancement and uncertainty in technology, and institutional settings (Feys et al., 2020; Hagl & Kouabenan, 2020; Zhu et al., 2020). Moreover, productivity, efficiency, and all types of impacts of AVs should be considered to estimate consumer's psychology and intentions to adopt AVs (Sparrow & Howard, 2017; Zhu et al., 2020).

4) As AVs are not yet available to people, most studies collected data based on the imaginary of travelers, assuming hypothetical driving and urban setting (i.e., a typical road segment, same speed, homogeneous traffic scenario), and educating respondents about AVs beforehand, which may be at variance from the real-world scenario and could influence perceptions of people (Clark et al., 2019; Gurumurthy & Kockelman, 2020; Yuen et al., 2020). Moreover, some studies also generated synthetic data using driving simulators where participants just sit behind the wheel without doing any direct maneuver, which does not capture a real representation of the population (Ha et al., 2020; Xu et al., 2018; Zhang et

al., 2018). Thus, further studies should consider mixed methods and relevant user-behavior data reflecting real-world urban environment and traffic scenarios (e.g., mixed traffic) which can provide a higher level of accuracy in assessing perceptions and opinions of people on AVs (Faas et al., 2020; Salonen, 2018).

5) Despite numerous limitations and unfavorable circumstances, the extant literature has attempted to understand a topic and situation which would be materialized in the future and provided significant insights that would be helpful for policymakers (König & Neumayr, 2017). However, limited existing knowledge of AVs, constant progress in vehicle and communication technologies, and inadequate evidence on AVs' ability to avoid potential crashes call for new initiatives that can focus on changes in people's perceptions and mobility preferences with the advent of new technologies and travel options (Chen, 2019; Kaye et al., 2020; König & Neumayr, 2017).

6) Given the number of existing studies on AVs, a systematic econometric meta-analysis could be conducted to estimate the effects of different factors on AV adoption and generalize the results of individual studies.

7) Considering the effects of recent health crises due to the COVID-19 pandemic on human mobility (Bhouri et al., 2021; Chan et al., 2020; Hu et al., 2021; Rahman et al., 2020; Rahman et al., 2021), future research should investigate how this pandemic could change perceptions and opinions of people to share AVs with others amidst the fear of disease transmission and how a more resilient transportation and mobility system can be fostered.

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CHAPTER 3: IMPACTS OF CONNECTED AND AUTONOMOUS VEHICLES ON URBAN TRANSPORTATION AND ENVIRONMENT: A COMPREHENSIVE REVIEW

Abstract

Technological innovation (e.g., electric vehicle, automation) has significant effects on urban transportation and environment. Some of the early review papers systematically evaluated the short and medium-term effects of Autonomous Vehicles (AVs) disregarding long-term effects on the urban built environment. Thus, this systematic review study discusses the short, medium, and long-term effects of AVs by reviewing 130 published papers. These papers were collected from multiple sources using some keywords. This review study critically analyzes previous papers and summarizes the key findings based on a SWOT (Strength, Weakness, Opportunity, and Threat) analysis. First, AV would influence urban transportation and human mobility by reducing vehicle ownership, public and active travel, Vehicle Miles Traveled (VMT), traffic delay and congestion, travel costs, and increasing accessibility, mobility, and revenue generation for commercial operators. Second, AVs would have long term effects by encouraging dispersed urban development, reducing parking demand, and enhancing network capacity. Third, AVs would reduce energy consumption and protect the environment by reducing Greenhouse Emission (GHG) emissions. Fourth, most people are very concerned about personal safety, security, and privacy from cyberattacks, maliciously controlled vehicles, and software hacks. However, AVs would reduce traffic crashes involving human errors and increase the convenience and productivity of passengers by providing amenities for multitasking opportunities. Finally, the study identified research gaps in the existing literature and proposed some directions for further research.

Keywords: Autonomous vehicle, connected vehicle, transportation, urban, impact, review

1. Introduction

People have used automobiles to travel within and between urban areas since the mid-twentieth century (Howard & Dai, 2014). Nowadays, it has become an integral part of urban life. Technological advancements such as the introduction of Internal Combustion Engines (ICEs), transmission systems, electric motors, steering and cruise control, and emission control technologies are easing people's life and reorganizing city structure (Kim, 2018). While providing benefits to populations, automobiles are also adversely affecting human societies and their environment. The massive use of Single-Occupancy Vehicles (SOVs) is associated with travel delays, traffic congestion, traffic crashes, energy consumption, air pollution, and urban sprawl. Mutation of the transportation system by shifting from ICEs to Electric Vehicles (EVs), and by introducing Intelligent Transportation Systems (ITS), ride-sharing, on-demand services, and Travel Demand Management (TDM) measures has shown evidence to reduce energy use and carbon emission, traffic crashes and congestion (Bansal & Kockelman, 2017; Howard & Dai, 2014). However, a combination of these strategies has the potential to bring dramatic changes to the transportation system, to urban mobility in terms of where people live, where they work, shop and recreate individually and collectively, and hence to the spatial structure of urban environments. This study investigates the impacts of Connected and Autonomous Vehicles (CAVs) on urban transportation and on the geography of urban environments by conducting a state-of-the-art review of the literature.

Many high tech and more traditional automobile companies have been working relentlessly to develop Automated Vehicles (AVs), which can arguably be seen as a new mobility option, to reduce traffic accidents (Moorthy et al., 2017; Narayanan et al., 2020). Google’s self-driving cars have already been driven more than 20 million miles on public roads in 25 cities of the United States as of January 6, 2020. It has been reported that Audi has intended to introduce AVs by 2023, Ford by 2025, GM by 2022, Nissan by 2022, Hyundai and Kia by 2023, BMW by 2024, Toyota by 2022, Tesla by 2023, Jaguar and Land-Rover by 2024, Volkswagen by 2025, and Daimler Benz by 2025 (Day, 2021; Kim, 2018). Despite they all have promised, AVs remain heavily limited at this stage (Day, 2021). However, it is worth mentioning that automated vehicles were first demonstrated by the Houdina Radio Control Company in New York and the Achen Motor Company in Milwaukee in 1926, which laid the foundation of the automated enterprise (Howard & Dai, 2014; Murthy, 2017).

Thus, it is anticipated that AVs would be a reality in the foreseeable future and that it could deeply influence human mobility, the built environment, the socio-economic fabric of cities, and city planning and governance (Fayyaz et al., 2022; Grindsted et al., 2022; Lee et al., 2022). In parallel, decision makers and city planners should prepare policies and plans accommodating issues related to AVs. Many researchers have already conducted studies to understand the potential impacts of AVs on people’s travel behaviors and the urban built environment to facilitate the process (Fagnant & Kockelman, 2015; Fraedrich et al., 2019; Kapser & Abdelrahman, 2020; Meyer et al., 2017). Considering the greater role of people’s safety and security in shaping their travel patterns, previous studies have also explored the urban futures with AVs from the perspectives of personal safety, privacy, and security. These studies have serious drawbacks include a heavy reliance on assumptions, simulations, hypothetical driving settings, etc., which may deviate from the real-world situations. Nonetheless, they are significantly contributing to the current body of literature aimed at unraveling the possible responses to AV adoption in human travel patterns and in the urban built environment. Thus, it is essential to have a comprehensive overview of the current literature and synthesize the existing knowledge domain.

Some of the early review papers systematically evaluated the short and medium-term effects of AVs and disregarded long-term effects on the urban built environment such as people's household and employment location decisions and parking demand (Bahamonde-Birke et al., 2018; Kopelias et al., 2020; Tafidis et al., 2021). To the best of our knowledge, no previous review study explored the current status of AV adoption and future evolution. Thus, this review study has significant contributions to the literature by consolidating existing bodies of literature. The main contributions of this updated comprehensive review paper are threefold. First, the paper critically reviews the state-of the-art literature on the short, medium, and long-term effects of AVs on urban transportation and mobility. Second, it looks at the possible longer-term adjustments to the geography of the built and natural environments of urban regions in the wake of shifts towards more AVs as future markets for AVs become more grounded. Finally, the paper identifies key concepts and provides a foundation for future research by pinpointing research gaps in the existing literature. In this study, I aim to understand current scenarios and potential benefits and costs of AVs after reviewing relevant published scholarship.

The rest of the paper is structured as follows. Our study approach is presented in Section Two. The third section discusses the definition, concept, evolution, and adoption of AVs in different countries across the globe. The potential impacts of AVs are presented in the fourth section. Under Section Four, Subsection 4.1 outlines the impacts of AVs on transportation and human mobility, Subsection 4.2 discusses the impacts of AVs on the urban built environment, Subsection 4.3 summarizes the impacts of AVs on energy and environment, and Subsection 4.4 explains the impacts of AVs on people's safety and security, and convenience. Finally, research problems and directions for future study are discussed in the last section.

2. Study approach

This systematic literature review is conducted to identify, evaluate, and critically analyze relevant scholarship to understand the current status and impacts of AVs. A systematic review can efficiently integrate, compare, and synthesize existing insurmountable information and provide a foundation for rational decision-making.

To this end, a literature search is conducted to select published articles and reports to be included in the review process. The articles and reports are selected based on (1) whether the article/report was written in English, (2) whether the study was conducted within the last five years, and (3) whether the study has investigated the impacts of AVs, Shared Autonomous Vehicles (SAVs), and CAVs, on transportation and mobility, environment, and urban form. However, a few studies that were conducted before 2015 are included in this systematic review to provide a comprehensive overview of possible scenarios and technological developments related to AVs, SAVs, and CAVs. ScienceDirect, Scopus, SAGE Journals, SpringerLink, Taylor & Francis, and Web of Science, the website of different organizations, and Google Scholar are the primary sources to search for suitable articles and reports.

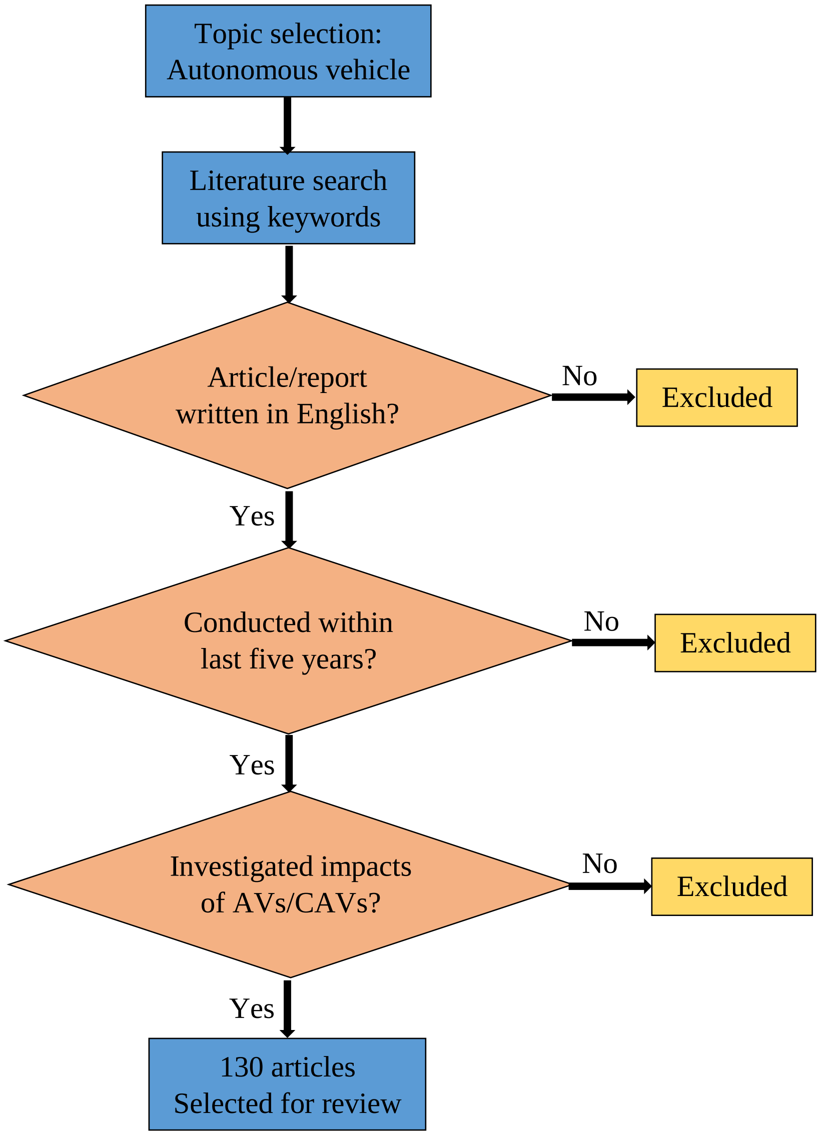

Figure 3.1: Selection procedures of articles and reports

Some keywords are used as the search terms, namely “autonomous vehicle”, “connected and autonomous vehicle”, “self-driving car”, “driverless car”, “urban form”, “urban development”, “parking”, “congestion”, “safety”, “accident”, “energy consumption”, “emission”, “vehicle ownership”. The following search strings are used to retrieve relevant articles from each of the database: “autonomous vehicle” OR “connected and autonomous vehicle” OR “self-driving car” OR “driverless car”) AND (“urban form” OR “urban development” OR “parking” OR “congestion” OR “safety”, “accident” OR "energy consumption" OR "emission" OR "vehicle ownership") AND English. The selection procedures of the studied articles and reports are illustrated in Figure 3.1.

The search identified 360 articles and reports. However, after careful assessment of each item, only 130 items were deemed directly pertinent to the search terms and objectives of the study. They form the basis of this systematic review. Of these items, 18.84%, 7.25%, and 4.35% of the articles have been published in the following three periodicals, respectively: Transportation Research Part C: Emerging Technologies, Transportation Research Part A: Policy and Practice, and Transportation Research Record. About 87% of the articles and reports were published from 2015 to 2020. Also, 46.27% and 18.66% of articles/reports pertained to North American and European countries, respectively. In addition, 8.21% and 3.73% of studies have been conducted in Asian countries and Australia, respectively. Moreover, about 11.94% of them are review studies and 11.19% have been conducted in multiple countries. During the selection process of articles/reports, the researchers were careful to select them from different study contexts to get a comprehensive review. These research items are critically analyzed to understand the current and future implementation of AVs and its impacts on transportation and mobility, environment, and urban form.

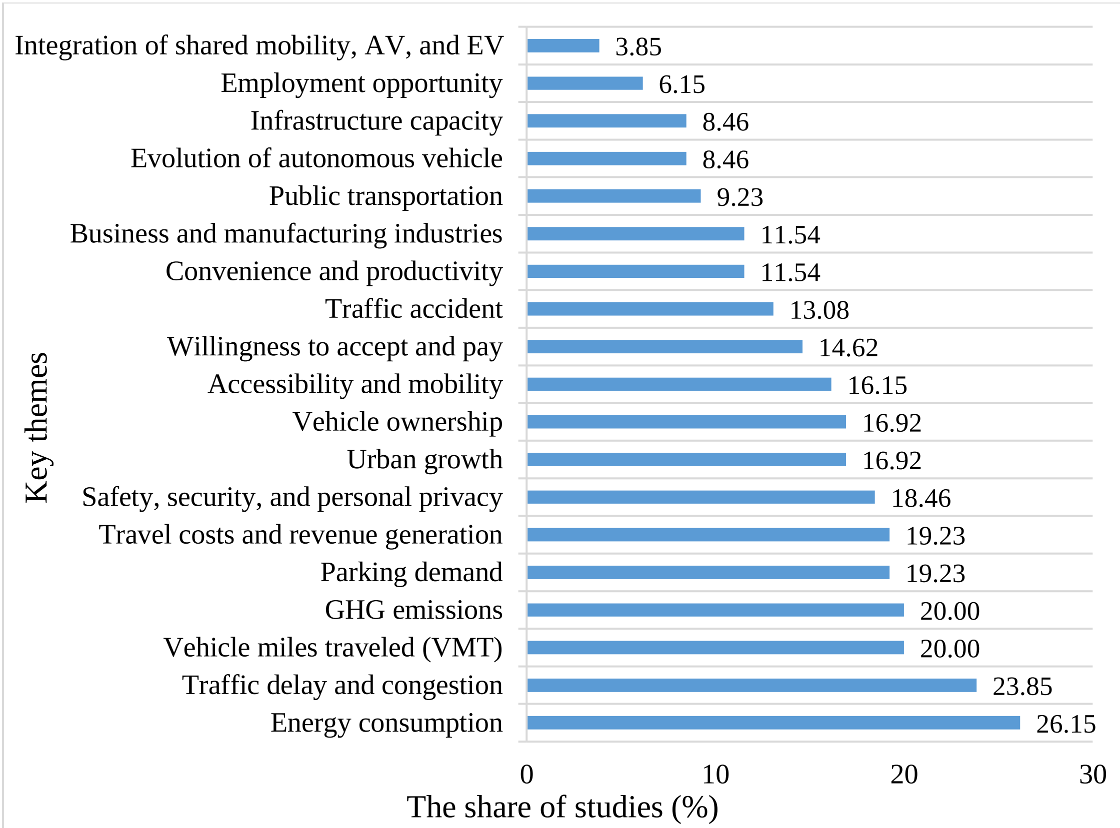

Figure 3.2: Key concepts discussed in the reviewed papers

The key concepts and themes discussed in the extant literature are presented in Figure 3.2. Many previous studies focused on the impacts of AVs on energy consumption (26.15%) and traffic delay and congestion (23.85%) followed by Vehicle Miles Traveled (VMT) (20%) and Greenhouse Emission (GHG) emission (20%). Also, a considerable number of studies have explored the effects of AVs on parking demand (19.23%), travel costs and revenue generation (19.23%), safety, security, and personal privacy (18.46%). In contrast, a few studies discussed the possible integration of shared mobility, AV, and EV (3.85%), impacts of AVs on employment opportunity (6.15%), infrastructure capacity (8.46%), and public transportation (9.23%).

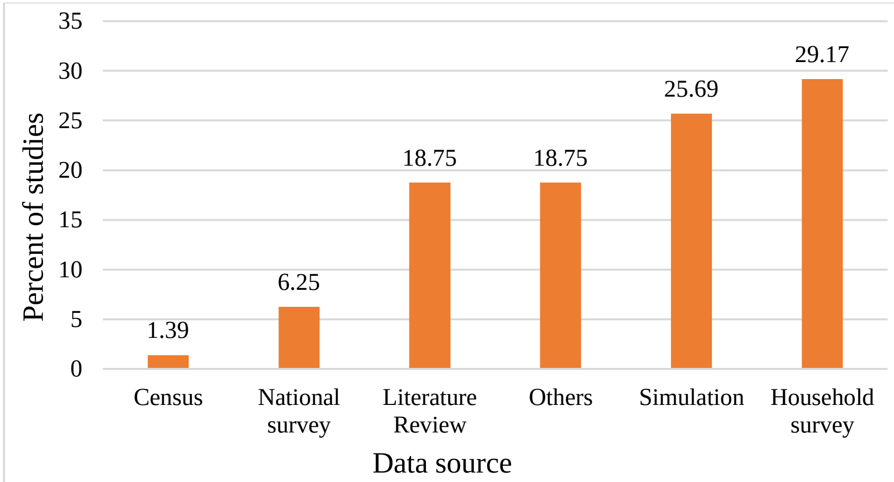

Figure 3.3: Data source of the selected articles/reports

Figure 3.3 shows the data sources of the reviewed articles/reports. The results indicate that 29.17 and 25.69% of studies conducted web-based household surveys and simulations (e.g., field test, experimental driving), respectively, to collect data. In contrast, only 1.39 and 6.25% of studies used data from census and national surveys, respectively. Most of these studies used data from census and national surveys to generate synthetic data under different assumptions to simulate AV scenarios. Thus, the studies using these data may not estimate the actual impacts of AVs on transportation and the urban environment. Additionally, an equal number of studies (about 18.75% each) collected information from published literature (e.g., articles, reports) and other sources (e.g. private, public organizations, national labs).

Of the published literature surveyed (Figure 3.4), 34.85% of studies used simulation techniques (e.g., agent-based simulation) to understand the impacts of AVs, and 20.45% used regression techniques (e.g., discrete choice models, structural equation models). Of the balance, 4.55% used probabilistic techniques, while the rest (40.15%) relied on other statistical methods (e.g., descriptive statistics, tests of hypotheses).

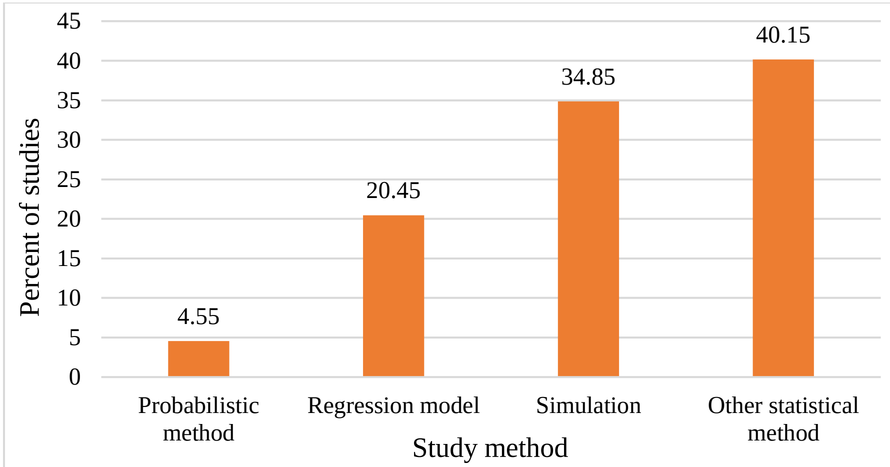

Figure 3.4: Methods used in the selected articles/reports

3. The concept and evolution of autonomous vehicle

AV (also known as a self-driving car, driverless car, robotic car) is able to drive and navigate without direct human inputs by using sensing technology (e.g., radar, Global Positioning System (GPS), and computer vision) and advanced control system (i.e., sensor) (Howard & Dai, 2014; Narayanan et al., 2020). Many cars are already equipped with cameras and sensors to avoid potential crashes (Kim, 2018; Van Brummelen et al., 2018). These automated vehicles will bring revolutionary changes in people's mobility, transportation systems, and land-use patterns (Brown et al., 2014; Meyer et al., 2017). As a distinctive feature, AVs have some level of automation to assist drivers or replace drivers to take full control of the vehicle (Narayanan et al., 2020). According to the Society of Automotive Engineers (SAE) (SAE International, 2018), the level of vehicle autonomy ranges from Level 0 (i.e., no autonomy) to Level 5 (i.e., full vehicle autonomy) (Figure 3.5).

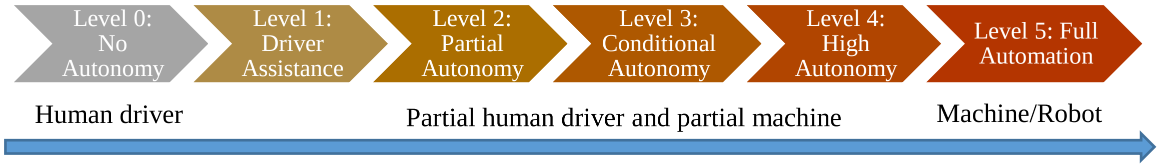

Figure 3.5: Level of vehicle autonomy

The National Highway Traffic Safety Administration (NHTSA) of the United States Department of Transportation (USDOT) proposed a safety rule in 2016 that all vehicles produced after 2020 would be equipped with Vehicle to Vehicle (V2V) communication technology to send and receive safety messages (Administration, 2016b). Although NHTSA has yet to mandate any V2V safety measures, it is expected that vehicles would gradually be equipped with safety equipment (i.e., short-rage communication, safety messages) to protect lives. Moreover, NHTSA has adopted the standard of vehicle automation prescribed by SAE (Administration, 2016a, 2017). These interventions from a top-tier transportation safety agency demonstrate their seriousness towards vehicle automation for curbing traffic crashes.

It is anticipated that on-demand mobility services and vehicle automation will grow rapidly in the coming decades (Jones & Leibowicz, 2019). The annual global sales of AVs would grow to $173.15 billion by 2030, with a 65.31% contribution from shared mobility (Sullivan, 2018). Thus, AV is a reality now and it is expected that it would become a daily travel mode for many people shortly (i.e., 10-30 years) (Stocker & Shaheen, 2018; Zakharenko, 2016).

Despite enormous efforts by different companies and agencies, AVs are yet to be a regular transportation mode. Some studies investigated the current implementation status of AVs and their future evolution across the world (Bansal & Kockelman, 2017; Nieuwenhuijsen et al., 2018). For example, Zhang and Wang (2020) estimated that the market share of AVs may vary from 20% to 90% by 2040 in Atlanta, the United States (US). Conducting a web-based survey of 246,642 Japanese residents between November and December 2015, Shin et al. (2019) reported that 53% of respondents expect AVs to be on the market in 15 years, whereas 40% expect a 6 to 10 years timeframe. Considering 2030 as the year of level 4 and 5 AVs introduction, Trommer et al. (2018) calculated that the market share of AVs (level 4 and 5) would be 17% in Germany and 11% in the US, by 2035. Another study predicted that the market share of AVs would be about 80% in Korea in 2060 (Kim et al., 2015). Litman (2017) commented that level 5 AVs would be able to operate commercially and legally in the 2020s with limited jurisdiction and performance. However, most benefits of AVs will be prominent and significant in the 2050s to 2060s when AVs would be common and affordable.

Based on this discussion, an expected timeline from planning to full implementation of AVs is portrayed in Figure 3.6. The figure illustrates that AVs will be available for people's regular use incrementally over the coming decades. Literature shows that countries around the world are resolute to test and employ AVs. At the same time, city planners are making strategies to adjust to a new reality. However, most urban policymakers are yet to start formulating plans for AV adoption due to a lack of real-world experience (González-González et al., 2019). Thus, it is necessary to understand the merits and demerits of AVs through their impacts on people, communities, and cities for informed decision-making.

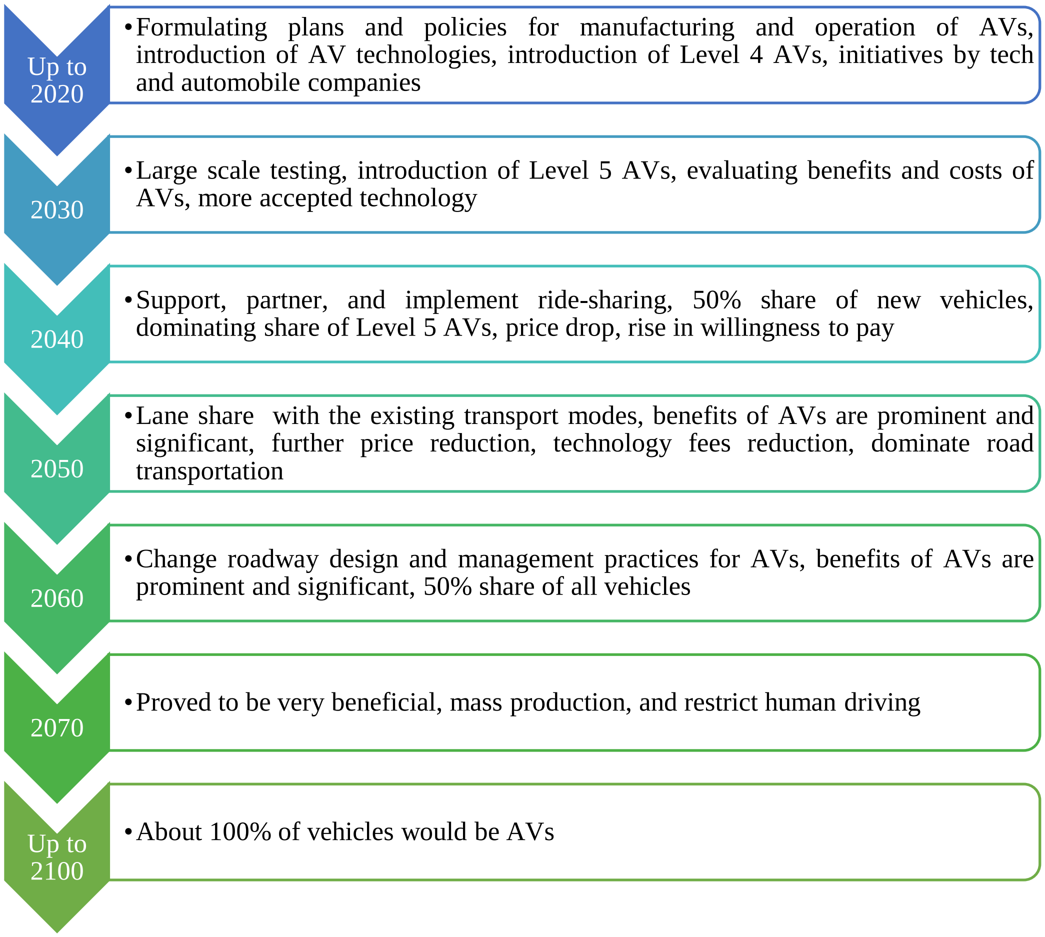

Figure 3.6: Expected timeline of AV's planning to implementation

4. The potential impacts of AVs

AVs would have both positive and negative effects on people and society. To better understand the potential impacts of AVs and their associated advantages and disadvantages, a SWOT (Strength, Weakness, Opportunity, and Threat) analysis is performed after reviewing the existing literature, inspired by (Litman, 2017; University of Kentucky, 2020). As illustrated in Figure 3.7, Strengths and Weaknesses indicate the advantages and disadvantages of AVs, respectively, for the users. On the other hand, Opportunities and Threats illustrate the advantages and disadvantages of AVs for other people and surrounding environments. With the underpinning provided by Figure 3.7, the potential positive and negative effects of AVs on people's travel pattern, environment, and urban built environment are discussed below. Firstly, Subsection 4.1 explains the impacts of AVs on transportation and human mobility. Secondly, the impacts of AVs on the urban built environment are illustrates in Subsection 4.2. Thirdly, Subsection 4.3 outlines the impacts of AVs on energy and environment. Finally, Subsection 4.4 summarizes the impacts on people's safety and security, and convenience.

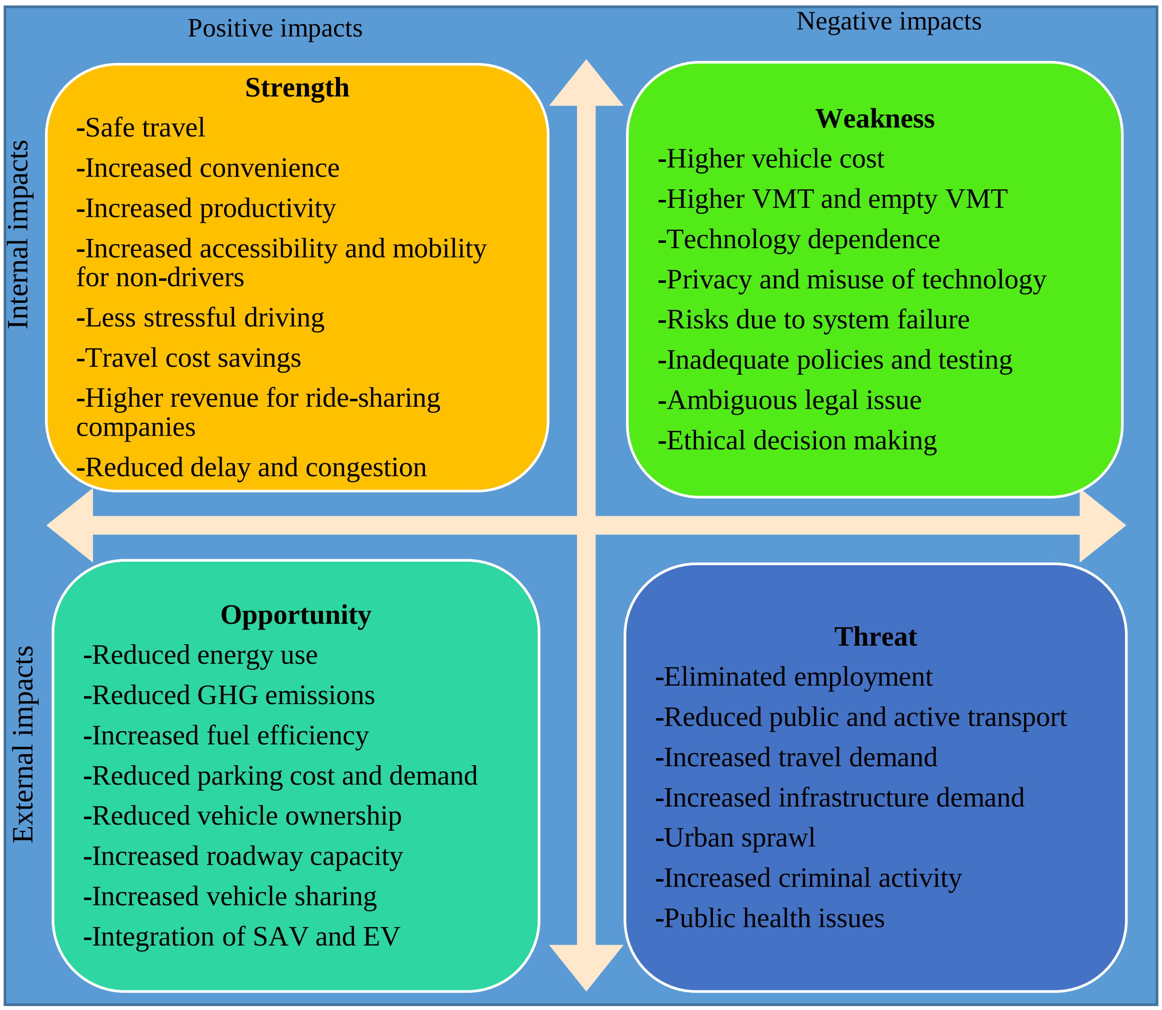

Figure 3.7: SWOT analysis of AVs

4.1 Impacts on transportation and human mobility

As presented in Figure 3.7, the main strengths associated with AVs include delay and congestion reduction, increased accessibility and mobility, travel cost savings, and revenue generation for ride-sharing companies. The opportunities afforded by AVs include reduction in vehicle ownership and integration of SAV and EV. On the other hand, the main weaknesses of AVs are higher vehicle purchase costs and higher VMT, while critical threats would consist in an increase in travel demand and a reduction in public and active transportation. Based on the findings from the extant literature articulated in Figure 3.7, this section discusses the potential impacts of AVs on transportation and human mobility. The transportation aspects discuss here include public transportation, traffic delay and congestion. The aspects related to human mobility encompass vehicle ownership, VMT, and accessibility and mobility.

4.1.1 Vehicle ownership

The introduction and adoption of commercial AVs are likely to reduce the need for households to own cars by way of an increase in ride-sharing services (e.g., SAVs) (Clements & Kockelman, 2017; Krueger et al., 2016; Tirachini et al., 2020). Fagnant and Kockelman (2014) reported that each SAV can serve 31-41 passengers per day and therefore can reduce vehicle ownership. More private vehicles could be reduced at a higher rate of SAVs adoption in areas with low household density and a high number of long-distance trips (Fagnant & Kockelman, 2018). Even privately owned AVs could be rented out to generate income when they are not driven by the owners and could further reduce vehicle ownership (Sparrow & Howard, 2017). Arbib and Seba (2017) forecasted that the number of vehicles would drop from 247 million in 2020 to 44 million in 2030 in the US due to the expected popularity of AVs among Americans. Consequently, citizens may experience a 70% reduction in the supply of cars and trucks. Using the 2011 Atlanta travel survey data, Zhang et al. (2018) found a reduction in vehicle ownership among over 18% of households. Each of these households can reduce about 1.1 vehicles and maintain their current travel pattern. Thus, as reported in Table 3.1, AVs and SAVs have the potential to reduce vehicle ownership without changing people's existing travel demand.

Table 3.1: Impact of AV on vehicle ownership

Study	Car ownership reduction
(Kim, 2018)	44% reduction in ownership per household
(Zhang et al., 2018)	9.5% reduction in private vehicles
(Fagnant & Kockelman, 2014)	10-fold reduction in private vehicles
(Arbib & Seba, 2017)	80% reduction in vehicles
(Fagnant & Kockelman, 2018)	10-fold reduction in private vehicles
(Levin et al., 2017)	-One SAV could replace 3.6 private vehicles -Each SAV can carry up to 4 people with 1000 SAVs and serve 31.4-person trips with 2000 SAVs in the system
(Fagnant & Kockelman, 2015)	10% penetration reduces vehicles by 4.7% (23.7% in 50% and 42.6% in 90% penetration)
(Zhang et al., 2018)	Private vehicle ownership reduced from 9.5% (no delay) to 12.3% (15 min delay).
(Narayanan et al., 2020)	Occupancy increases from 1.2 to 3, 10 vehicles are replaced by 1.18 vehicles.
(Loeb & Kockelman, 2019)	Low-range and slow charge Shared Autonomous Electric Vehicles (SAEVs) replace 3.75 vehicles, long-range and fast charge SAEVs replace 8-11.5 vehicles
(Milakis et al., 2017)	67% to over 90% reduction
(Frey, 2017)	-30,000 AVs will displace 50% peak commuters for 2 million people in the US. -4 million AVs will replace 50% of all commuter traffic
(Ma et al., 2017)	Each SAV replaces over 13 private vehicles or traditional taxis.
(Chehri & Mouftah, 2019)	30% reduction in vehicle number
(Cyganski et al., 2018)	35% reduction in personal car use and 11.6% to 8.6% reduction in car drive with a reduced fleet size in 2030 than 2010
(Chen et al., 2016)	-an 80-mile and a 200-mile range Level 2 SAEVs could replace 3.7 and 5.5 private cars, respectively -Level 3 fast charger can replace 5.4 vehicles for 80-mile and 6.8 vehicles for 200-mile

Research has shown that dynamic ride-sharing (i.e., serving multiple travelers with similar origins, destinations, and departure times) can significantly reduce the number of vehicles. For example, Levin et al. (2017) found that dynamic ride-sharing may reduce vehicle ownership, provide low-cost service, and attract more people by combing multiple trips with the same travel route and destination (e.g., business district). Thus, researchers have recommended mode sharing in larger vehicles (e.g., vans) and promoting public transportation with enhanced quality of services to reduce vehicle ownership (Tirachini et al., 2020). Additionally, accepting some flexible activity schedule can reduce vehicle ownership (i.e., up to 15-minute delays in arrival at the destination can reduce private AVs ownership by 18.3% to 24.1%) (Zhang et al., 2018).

4.1.2 Public transportation

It has been argued that AVs are the most disruptive technologies in the transport sector, having the potential to diminish public transit trips (Hess, 2020; Kapser & Abdelrahman, 2020; Meyer et al., 2017). The availability of shared vehicles and use of SAVs may further reduce public and active transportation (Clements & Kockelman, 2017; Cyganski et al., 2018; Narayanan et al., 2020). Thus, AVs may be regarded as a major existential threat to present and future transit systems (Handsfield, 2011).

However, when seen as a shared mobility option, AVs could be integrated with an efficient public transport system to ensure the sustainability of urban transportation systems (Narayanan et al., 2020; Sparrow & Howard, 2017). Public transport carries a high number of passengers from one station to another, but some other transport option is needed to transfer people from home and workplace to stations. AVs can solve this last-mile problem and attract passengers from private vehicles to public transit (Moorthy et al., 2017; Sparrow

& Howard, 2017). Thus, AVs should be mobilized as such they do not disrupt the current transport system but increase its efficiency and cost-effectiveness.

Similar to Transit-Oriented Development (TOD), Robocar-Oriented Development (ROD) (Templeton, n.d.) could be promoted in areas surrounding transit stations. ROD would be a high residential density and mixed-use development with minimal auto facilities. People would mainly use SAVs to travel to transit stations as a short-distance shuttle service would. There would be convenient drop-off and pick-up zones very close to the entrance of the stations. Multilevel drop-off or pick-up zones also could be built to optimize space utilization where land value is comparatively higher. There would be a vehicle-waiting zone from where personal and shared AVs would drop and pick up riders. Thus, through strategically using AVs, public transport would be popular among the people and a sustainable transportation system could be achieved.

4.1.3 Vehicle miles traveled

Thanks to better accessibility and mobility, empty-vehicle travel, and relocation of parking outside of the city center, AVs would increase per capita travel distance and VMT (Trommer et al., 2018; Wadud et al., 2016; Zhang & Wang, 2020). People would choose to live further away from their workplace due to lower transportation costs and to the drop in the value of travel time by multitasking, which leads to additional VMT (Childress et al., 2015; Gelauff et al., 2019). Thus, AVs are likely to increase travel distance and VMT, as summarized in Table 3.2.

Table 3.2: Impact on travel distance and VMT

Study	Impact on travel distance/VMT
(Narayanan et al., 2020)	Trip length: -15% to +14%, VMT: -45% to +89%
(Gelauff et al., 2019)	5 - 25% increase in VMT
(Fagnant & Kockelman, 2014)	Up to 10% increase in travel distance

(Fagnant & Kockelman, 2015)	2 - 9% increase in VMT
(Zhang et al., 2015)	15.3 - 62.3% increase in daily VMT
(Zhang et al., 2018)	Median VMT increase of 26.5 miles per household, total VMT increase of 13.3%
(Loeb & Kockelman, 2019)	6.05 - 14.2% increase in empty VMT per SAV
(Wadud et al., 2016)	2 - 10% increase in VMT
(Tirachini et al., 2020)	VKT increase of SAV: 7 to 10 km/passenger, VKT increase of buses: 0.4 to 1.1 km/passenger
(Childress et al., 2015)	11 - 20% more empty VMT by SAVs
(Loeb et al., 2018)	SAEV on average generate 19.6 – 31.5% more vacant VMT
(Levin et al., 2017)	Personal AV has a 2.5% lower VMT than a personal conventional vehicle
(Harper et al., 2016)	2 – 14% increase in annual VMT
(Ma et al., 2017)	15% increase in VMT
(Carrese et al., 2019)	100% penetration of ride-sharing reduces VMT up to 19%
(Auld et al., 2018)	42% increase in travel distance
(Alam & Habib, 2018)	15% (20%) share of SAV increases VKT by 1.73% (14%)
(Hörl, 2017)	28.01% and 30.57% empty VMT in Taxi and taxi pool, respectively for 1000 AVs on the fleet.
(Zhang & Guhathakurta, 2017)	5-14% VMT increase
(Arbib & Seba, 2017)	VMT increased by 50% in 2030 over 2015

Some studies have mentioned that the average travel distance by AVs is not significantly higher than a conventional car or taxi (Ma et al., 2017; Moorthy et al., 2017). They argued that increased VMT can be compensated by reducing the total number of vehicles required for passenger transport and by optimizing trip chaining (Ma et al., 2017). VMT could also be reduced by increasing dynamic ride-sharing (Fagnant & Kockelman, 2018; Milakis et al., 2017). Fagnant and Kockelman (2018) observed that a 20% to 30 % increase in trip share would reduce VMT by 4.4 miles per shared-trip (i.e., a 4.2 % reduction). Thus, increasing SAVs, particularly within a high-density area, may reduce empty VMT (Fagnant & Kockelman, 2014; Levin et al., 2017). Furthermore, the implementation of a flexible work schedule could reduce the average VMT per traveler (Greenblatt & Saxena, 2015; Kyriakidis et al., 2015). A flexible work schedule will allow workers to work at variable work rosters and SAV drop-offs and pick-ups can be coordinated to reduce empty VMT.

4.1.4 Traffic delay and congestion

AVs have the potential to reduce traffic delay and congestion by promoting ride-sharing options, and by smoothing traffic flows using Adaptive Cruise Control (ACC) measures and traffic monitoring systems (Alam & Habib, 2018; Daziano et al., 2017; Krueger et al., 2016). A higher rate of automation, dedicated lanes for AVs/CAVs, and dynamic control of the fleet size could significantly reduce travel time and delay by increasing roadway capacity and throughput of vehicles and by reducing empty trips (Amirgholy et al., 2020; Levin et al., 2017; Zhang et al., 2015). Under a 100% AV scenario in 2060, Kim et al. (2015) calculated that about 3 million vehicle hours will be saved in the Seoul Metropolitan Area (SMA) which is equivalent to saving one hour for each trip to the SMA in 2013. Thus, SAVs in a dynamic ride-sharing situation could be an effective policy option to reduce traffic delay and congestion, as also reported in Table 3.3.

Table 3.3: Impact on traffic delay and congestion

Study	Impact on delay/congestion/speed
(Fagnant & Kockelman, 2015)	Drop of 15% in freeway congestion delay at 10% AV penetration
(Carrese et al., 2019)	At 100% penetration of SAV, travel time reduction of 10 - 19%
(Levin et al., 2017)	-Personal AV (PAVs) can reduce average travel time by 73% over personal car -160% increase in SAVs reduces travel time by 70%
(Amirgholy et al., 2020)	A higher market share and optimal lane management strategy reduce delay up to 78%, limit increase of travel time to 5%, and reduce delay cost by 66%
(Atiyeh, 2012)	35 - 39% less congestion and 8-13% higher traffic speeds at 50% penetration
(Zhang et al., 2015)	Average waiting time reduced by 98.4% with a 45.45% increase in SAVs
(Zhang et al., 2018)	-V/C ratio increased by 6.79 - 8.44% due to increased travel demand

	-V/C ratio increased by 4.99% and 4.39% on expressways and minor arterials
(Papadoulis et al., 2019)	-Travel time increased by 20% in a 100% penetration rate
(Auld et al., 2018)	30%-50% reduction in the value of travel time
(Qi et al., 2018)	-10.7% time saving due to driving assistance via HMI (human-machine interface) -Increase of time by 3.2% due to partially automated driving
(Chehri & Mouftah, 2019)	Urban travel time reduction of 30%
(Martinez & Viegas, 2017)	30% congestion reduction with full adoption of SAVs
(Kockelman et al., 2017)	78% reduction in travel time at a 100% AVs penetration
(Wellik & Kockelman, 2020)	3.4 to 8.1% increase in travel time to work at 100% AV scenario

Researchers also reported that an heterogeneous traffic situation (i.e., a mixture of PAVs and SAVs) could increase delay and congestion by reducing the average speed of the network (Narayanan et al., 2020). Carrese et al. (2019) reported that SAVs could yield a positive impact for intra-urban trips but suburban commuters may experience extra traffic congestion due to the huge relocation of residents to suburbs. Some people also believe that AVs are unlikely to reduce congestion and travel time in suburban, exurban, rural areas and urban commercial facilities due to higher travel demand in these particular areas (Piao et al., 2016; Schoettle & Sivak, 2014b; Van Brummelen et al., 2018). Considering the potential for congestion reduction by AVs, policymakers should implement appropriate policy measures to achieve a higher rate of AV penetration and vehicle ride sharing.

4.1.5 Accessibility and mobility

As indicated in the literature, AVs are expected to increase the accessibility and mobility of all people, including persons with need for special assistance (i.e., disabled, elderly, children) and without driving licenses (Daziano et al., 2017; Martinez & Viegas, 2017; Trommer et al., 2018). Researchers found a 2–10% (Wadud et al., 2016), 1.4-10.3% (Narayanan et al., 2020), and 14% (Milakis et al., 2017) increase in overall travel demand due to improved accessibility by AVs. People choose AVs as a useful tool to mitigate mobility and accident-related problems (Shin et al., 2019). AVs would enhance social justice and welfare for all people and provide scope to achieve a sustainable transportation system (Hess, 2020; Milakis et al., 2017). However, increased travel demands may well exceed roadway capacity and may lead to worsening traffic congestion (Meyer et al., 2017). In such situations, a large SAV (e.g., van, bus) could be implemented to reduce traffic congestion by transferring groups of passengers simultaneously.

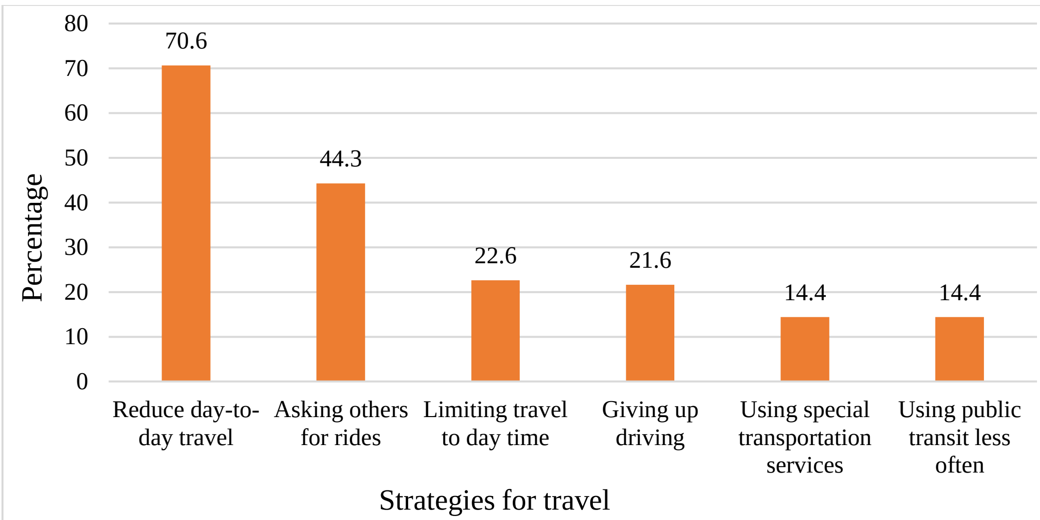

Figure 3.8: Travel strategies of US people (age 18-64) with disabilities (FHWA, 2018)

According to the Bureau of Transportation Statistics of the USDOT, about 25.5 million Americans have travel limitations due to disabilities (Brumbaugh, 2018). Among them, about 3.6 million do not leave their homes due to low vehicle ownership, driver's license possession, and unemployment. They mostly depend on other family members and friends for travel purposes. Information on the travel strategies of US people with disabilities (ages 18-64) is collected from the 2017 National Household Travel Survey (NHTS) and presented in Figure 3.8. It is estimated that 70.6% of them reduced day-to-day travel, whereas 44.3% depend on others for travel. About 21.6% and 14.4% of them are giving up driving and using less public transport, respectively. Moreover, about 14.4% of them are using special transportation facilities (i.e., dial-a-ride or reduced-fare taxi). However, improving shared mobility could increase their mobility. AV technologies could further increase the mobility of people with disabilities substantially who are unable to drive and travel otherwise (Brumbaugh, 2018).

4.1.6 Travel costs and revenue generation

Many researchers have reported that the automation of vehicles may reduce travel costs to people by reducing vehicle operation and maintenance costs (e.g., fuel, insurance fees) (Kopelias et al., 2020; Nunes & Hernandez, 2020; Zakharenko, 2016) (Table 3.4). SAVs could further reduce travel costs by avoiding parking fees and reducing fleet size (Loeb et al., 2018). Ride-sourcing AVs by Transport Network Companies (TNCs) are much cheaper than solo driving due to no cost of driver, depreciation, and insurance (Compostella et al., 2020). Although the initial price is high, total lifetime costs remain minor when paying back for 400,000 miles of service life. AVs also could reduce the value of travel time as people can spend time in other activities (e.g., reading, talking with friends, e-work) while riding in a vehicle (Van den Berg & Verhoef, 2016). On the other hand, some studies also reported that AVs would increase third-party liability coverage (Xu & Fan, 2019). Additionally, policymakers are yet to decide whether travelers or manufacturers would pay insurance premium for AVs due to newly perceived cyber risks bedsides risks of traffic accidents (Yeomans, 2014). Thus, there is uncertainty in reducing overall cost of AV ownership and use considering diverse insurance such as third-party insurance, comprehensive vehicle insurance, public liability insurance, product liability insurance, self-insurance etc. (Abu Bakar et al., 2022).

Table 3.4: Impacts of AVs on travel costs and revenue generation

Study	Impacts on travel costs and revenue generation
(Fagnant & Kockelman, 2014)	SAVs reduce average trip costs by 30 to 85%
(Van den Berg & Verhoef, 2016)	2 to 40% reduction in total travel costs by AVs compared to no-AV condition
(Milakis et al., 2017)	Social benefits/AV/year could reach $3900 at 90% AV adoption
(Wadud, 2017)	At least a 15% reduction in the total cost of ownership from full automation
(Moorthy et al., 2017)	Travel cost of AV ($13.71) is less than personal vehicle ($14.01), higher reduction of travel time in AV ($18.20) than personal vehicle ($15.9)
(Fagnant & Kockelman, 2018)	Fleet operator paying $70,000/SAV could earn 19 %/year while offering services at $1.00/mile for a non-shared trip (i.e., 33% less from traditional taxi fare)
(Greenblatt & Saxena, 2015)	-Cost/mile is lower for SAV (30-50 US¢/mile) than private vehicles (80 US¢/mile) -AV would add 3-4 (shared) to 11 (private) US¢/mile to the total cost
(Gelauff et al., 2019)	Up to 10% of welfare benefits due to population relocation and land-use changes
(Narayanan et al., 2020)	-Value of travel time reduced from 10 to 31%, household savings per year increased by $5600, and revenue generation increased by 19%
(Fagnant & Kockelman, 2015)	$2000 to $4000/year/AV benefits from crash savings, travel time reduction, fuel efficiency, and parking benefits -Parking saving $3.2, $250 savings per AV, 756 million hours travel time saving, 102 million gallons fuel saving
(Compostella et al., 2020)	-Cost reduced by 4-10%/year after commercial introduction -50% decrease in maintenance and insurance costs reduce $0.04 per VMT -Decreasing AV cost to $3333 per vehicle lowers cost by $0.06 per mile -A $2.75 congestion charge increases the short trip cost by 140% and long trip by 28%
(Nunes & Hernandez, 2020)	Revenue increased by 30% with increasing occupancy from 1.67 to 2.2 and 75% with increasing occupancy from 1.67 to 2.92, whereas single AV lowered profits by 37%.
(Chehri & Mouftah, 2019)	Reduce travel costs by 50%
(Martinez & Viegas, 2017)	SAV reduce travel cost by 45%/km than public transport
(Clements & Kockelman, 2017)	A higher share of CAV saves $3800/American/year by reducing costs related to insurance, accidents, vehicle repair, personal travel, legal service, etc.
(Kockelman et al., 2017)	75% reduction of crash costs, $1357 per year cost savings per driver

The adoption of AVs would increase the welfare benefits of citizens and revenue generation of commercial transportation operators (Narayanan et al., 2020). On average, AVs could yield up to 5 billion euros in savings per year in the Netherlands under full automation by reducing generalized transport costs and modal split (Gelauff et al., 2019). Fagnant and Kockelman (2015) found a total of $196 billion economic benefits with 90% AV market share in the US due to cost reduction for congestion, crash, travel time, fuel use, and parking fees. These benefits, although small compared to commercial taxi operation, will be enjoyed by households in the wealthiest percentile under full automation in personal cars (Wadud, 2017).

The extant literature shows that AVs and SAVs are likely to reduce transportation costs and increase revenue generation for commercial fleet operators. Thus, researchers have suggested to expand funding for R&D and formulating guidelines for AVs to increase AV use (Fagnant & Kockelman, 2015).

4.1.7 Integration of shared mobility, AV, and EV

SAVs would be more popular than other vehicles operated by TNCs due to cheaper, safer, and more efficient transport options. Researchers indicated that SAVs can further influence people's travel behaviors by embracing cutting-edge EV technologies (Loeb & Kockelman, 2019; Offer, 2015; Zhang et al., 2020). Hence, SAEVs will be efficient (e.g., low travel costs, energy use, empty VMT) and reliable. However, Chen et al. (2016) mentioned that long-range and fast-charger SAEVs can serve 96-98% of trip requests with an average wait time of 7-10 minutes per trip. In contrast, short-range and slow-charger SAEVs would be unable to serve 55% and a further 5.4% of trips due to poor response time and trip length, respectively (Loeb & Kockelman, 2019). Thus, long-range and fast charger SAEVs are more efficient compared to short range and slow charger SAEVs. Simulating a similar scenario for Austin, Chen et al. (2016) found that empty VMT could drop to 3–4%, average wait times could shrink to 2-4 minutes per trip, and 5-9 private vehicle could be replaced by each SAEV. Thus, SAEVs have the potential to reduce vehicle ownership, empty VMT, response time, and wait time.

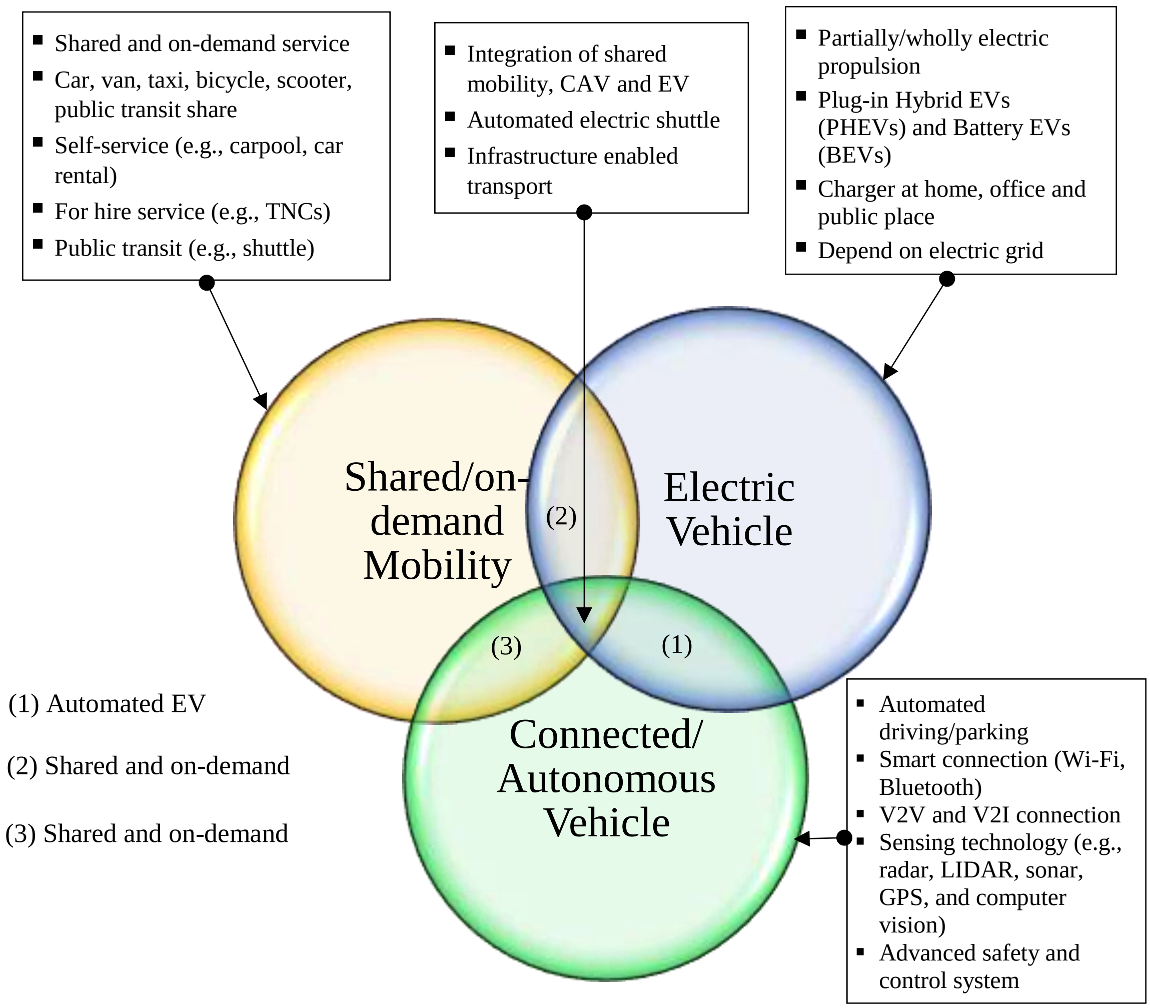

Figure 3.9: Future of transportation system, modified from (Dennis et al., 2017; Shaheen, 2015)

SAVs also can provide environment-friendly transport options by coupling with a renewable power source. An SAEV can reduce energy use by 90-100% compared to ICEs due to efficient travel and electrification of vehicles (Milakis et al., 2017). Conducting agent-based modeling, researchers in (Zhang et al., 2020) found that each SAEV can reduce carbon emission by 75% in California. They also observed that SAEVs are likely to reduce travel costs by reducing vehicle operation costs. Thus, the integration of AVs and EV technologies with adequate vehicles has a synergistic effect on reducing VMT, vehicle ownership, travel cost, and GHG emissions (Offer, 2015). Researchers have mentioned that future transportation would consist of shared and on-demand mobility, CAVs, and EVs to provide improved transportation services to population. Figure 3.9 illustrates the paradigm shift of the transportation system with the advent of technologies where a proper integration of SAEVs will provide reliable transportation for people.

4.2 Impacts of AVs on the urban built environment

Figure 3.7 indicates that AVs would have the opportunity to reduce parking demand and cost, but would also increase roadway capacity. However, the main threats AVs may cause include increased demand for transport infrastructure and urban expansion. Based on the existing literature this subsection explains the potential impacts of AVs on the urban built environment.

4.2.1 Patterns of urban growth

Many studies have mentioned that the advent of AVs would influence the layout of urban areas (González-González et al., 2019; Meyer et al., 2017; Van den Berg & Verhoef, 2016). By reducing travel costs, they possibly influence residential and work locations, and intensify urban sprawl and inefficient use of land (Fraedrich et al., 2019; Krueger et al., 2019; Zakharenko, 2016). An agent-based simulation study in Korea found new and scattered growth throughout the region and also around urban centers due to households' preference for urban amenities in a scenario where 100% of vehicles are assumed to be AVs compared to the business as usual scenario over the next five decades (Kim et al., 2015). The adoption of AVs may increase city radius by 3.5%, land area by 7.1%, and residential area by 7.6% (Zakharenko, 2016). Under current policies and conditions (i.e., high initial purchase cost and low performance, reduction in travel time and costs, personal AVs), AVs can increase urban expansion by 10-30% (Litman, 2017). Thus, policymakers should understand the potential impacts of AVs on spatial distribution of land uses to facilitate the emergence of AVs without hampering urban living and development.

Conducting a web-based survey, Carrese et al. (2019) found that about 40% of respondents would move to the suburbs under the AV regime in Rome, Italy. Similarly, Wellik and Kockelman (2020) reported a 5.3 to 5.5% reduction in the number of households living in the metropolitan regions of Austin, TX at a 100% AV scenario compared to a 0% AV scenario over a 27-year timespan (2013-2040). They also mentioned a 5.8 to 6.2% growth in the number of households living in the non-metropolitan regions of Austin. Thus, AV would influence people's residential locations by increasing accessibility, mobility, and convenience and reducing the value of travel time.

Experts confirmed that, in conjunction with developing new peripheral centers, AVs would also densify the existing development by allocating more spaces for residential, economic, and leisure activities (González-González et al., 2019; Milakis et al., 2018). Space released from on and off-street parking could be used for building wider sidewalks, bicycle paths, delivery bays, and new public facilities (Clements & Kockelman, 2017; Martinez & Viegas, 2017). Thus, AVs are likely to change the urban landscape by densifying existing development.

A majority of the literature points that AVs would lead to dispersed urban development by enhancing the mobility of the people and reducing travel costs. Polycentric development may be seen surrounding the urban areas due to new development induced by AVs. Consequently, it is likely that city land area and residential and commercial land use would increase. At the same time, a densification would be observed in the city core by allocating space released from parking spaces for new residential, commercial and recreational development.

4.2.2 Parking demand

Besides influencing the physical extent of urban areas, AVs could influence urban form by reducing the demand for parking in the urban center (Clements & Kockelman, 2017; Kopelias et al., 2020; Van den Berg & Verhoef, 2016). As indicated in Table 3.5, AVs would reduce overall parking demand quite drastically. As a case in point, a recent simulation study estimated 10%, 42%, and 75% reductions in parking land area by 2020, 2030, and 2040, respectively in the Atlanta core after introducing SAVs (Zhang & Wang, 2020). Conducting a study in Los Angeles County, researchers in (Chester et al., 2015) observed that about 14% of county area are used for parking. However, this parking area could be reclaimed, particularly in the city center, and repurposed for building high-quality and attractive spaces for economic activities to increase land productivity (González-González et al., 2019; Zakharenko, 2016). Wellik and Kockelman (2020) reported a 19.4% to 62.9% increase in developable land in Austin at a 100% AVs scenario over a 0% AVs scenario due to reduction in parking demand.

Table 3.5: Impact of AV on parking demand

Study	Impact on parking space
(Fagnant & Kockelman, 2014)	Average 11 parking space reduction per SAV
(Narayanan et al., 2020)	48% to 90% reduction in parking land area
(Milakis et al., 2017)	Up to 90% reduction in parking land area
(Zhang et al., 2015)	Up to 90% reduction in parking land area at a 2% SAV penetration and about 8.6% reduction in parking land area per SAV
(Kondor et al., 2018)	50% reduction of parking land area by SAVs
(Kim, 2018)	40% reduction of parking lots

(Chehri & Mouftah, 2019)	40% reduction in overall parking land area and 44% reduction in required parking spots
(Zhang & Guhathakurta, 2017)	4.5% reduction in parking land area at a 5% SAV adoption and over 20 parking spots reduction per SAV

In contrast, some studies have also mentioned an increase in parking demand due to increase in people's travel demand and lack of ride-sharing services (Zakharenko, 2016; Zhang & Wang, 2020). However, people's willingness to share vehicles, the availability of AV ride-sharing services, and higher penetration rates of SAVs can significantly reduce parking demand (Milakis et al., 2017; Zhang et al., 2015). Thus, researchers (Narayanan et al., 2020) have suggested to take policy actions to augment the use of SAVs and thereby reduce overall vehicle parking demand.

Most of the previous studies have argued that higher penetration of AVs and SAVs may lower parking demand in residential areas and city centers by reducing car ownership and increasing ride-sharing. Moreover, AVs may self-park in less expensive areas outside of city centers and reduce parking demand in the city core (Fagnant & Kockelman, 2015). Consequently, space released from vehicle parking would be used for other purposes, such as developing activity centers and high-quality recreation spaces. Since AVs can reduce car ownership, it is likely that less space will be used for building streets, parking, garages, and possibly allow high density and mixed uses development (Dennis et al., 2017; KPMG International, 2019). If someone choses to own an AV, living in the outskirts of the city may be preferred, with parking provision just immediately outside of the city center to reduce traffic volume in the city. A multi-storied parking complex could be built at the edge of the city center to accommodate commuting traffic to reduce space utilization at the centers. However, convenient drop-off and pick-up locations could be provided near residences and workplaces for the convenience of travelers.

4.2.3 Infrastructure capacity

The extant literature reveals that vehicle automation can increase road and intersection capacity by vehicle platooning, using Cooperative Adaptive Cruise Control (CACC), and exchanging information between them (Kopelias et al., 2020; Meyer et al., 2017; Zhang et al., 2018). The results in Table 3.6 show that AVs are likely to increase roadway capacity by using existing facilities more efficiently without adding any lanes (Fernandes & Nunes, 2012). Thus, the necessity of roadway expansion could be avoided. However, capacity could be affected by the presence of heterogeneous traffic which could disrupt communication among vehicles (Milakis et al., 2017).

Table 3.6: Impact of AV on roadway capacity

Study	Capacity increase
(Fernandes & Nunes, 2012)	367%
(Van den Berg & Verhoef, 2016)	7 - 200%
(Narayanan et al., 2020)	43% to 273% on highway, 40% on urban roads, 9.39% to 39.21% with 100% penetration, 215% at 100% penetration with connectivity and 9.38% without connectivity
(Milakis et al., 2017)	40% (100%) penetration of AVs increases capacity by over 10% (200%).
(Shladover et al., 2012)	-10%, 50%, and 90% penetration of CACC increase 1%, 21% and 80%, respectively. -20%, 30%, and 50% to 60% penetration of vehicles with Vehicle Awareness Devices (VAD) increase capacity by 7%, over 10%, and 15%, compared with cases without VADs.
(Tientrakool et al., 2011)	About 43% to 273% capacity increase by CAVs due to sensors and communication technologies -34.85% to 83.5% reduction in gaps between vehicles due to communication technologies and sensor
(Shladover et al., 2012)	A 100% increase in capacity by each vehicle equipped with short-range communication radios (e.g., CACC, VAD)

CAVs could increase roadway capacity substantially by reducing the average distance between vehicles with the help of sensors and communication technologies (Tientrakool et al., 2011). Roadway capacity also increases if all vehicles have CACC and

Vehicle Awareness Devices (VAD) (Shladover et al., 2012). Thus, AVs with appropriate sensing and communication technologies may have a greater influence on increasing roadway capacity. Greater capacity benefits could be achieved even at a lower penetration of AVs if the non-ACC vehicle populations are equipped with VADs which can serve as the lead vehicles for the CACC vehicles (Shladover et al., 2012). In contrast, Narayanan et al. (2020) mentioned that AVs should be more than 20% of the vehicle population to achieve an increase in roadway capacity. Thus, a large enough number of CAV is essential in the market to increase communication between them and thereby to increase roadway capacity over a mixed traffic situation (i.e., non-, semi-, full AV).

4.3 Impacts of AVs on energy and environment

AVs have the opportunities to protect the natural environment by reducing transport energy use and GHG emissions and by increasing vehicle fuel efficiency. This subsection illustrates the potential impacts of AVs on energy and environment critically reviewing the existing literature.

4.3.1 Transport energy consumption

As presented in Table 3.7, AVs could reduce energy use by decreasing vehicle ownership and weight, and operating vehicles efficiently by limiting acceleration and deceleration using ACC with lane assist systems and Vehicle-to-Everything (V2X) communication (Haboucha et al., 2017; Loeb et al., 2018; Mersky & Samaras, 2016). A coordinated flow of CAVs could also increase the energy efficiency of gasoline vehicles in mixed traffic situations by establishing a harmonized relationship with the surrounding traffic even at a lower level of CAVs penetration (Vahidi & Sciarretta, 2018). Energy use could be further reduced by implementing the ride-sharing services of AVs particularly in the urban areas where most of the travel demand is higher (Greenblatt & Saxena, 2015; Ross & Guhathakurta, 2017). Thus, prior knowledge on roadway environment (e.g., speed limit, grade, curve), avoiding frequent starts and stops, efficient lane change, coordinated and smooth flow, proper signal phasing and timing, vehicle weight reduction and right-sizing, and vehicle sharing, could reduce transport energy consumption significantly (Vahidi & Sciarretta, 2018; Wadud et al., 2016).

Table 3.7: Impact on transport energy use

Study	Impacts on energy use
(Fagnant & Kockelman, 2014)	Each SAV will reduce energy use by 12%
(Kopelias et al., 2020)	CAVs reduce fuel use by 30-90%
(Qi et al., 2018)	12 - 22% energy savings from driving assistance via HMI and partially automation
(Atiyeh, 2012)	Increase fuel economy by 23–39% for all vehicles in freeway travel stream
(Chen et al., 2018)	As high as a 90% improvement in fuel economy by each automated vehicle
(Narayanan et al., 2020)	Energy consumption reduced by 37% to 80% by SAVs
(Moorthy et al., 2017)	Public transit with last-mile AV would save energy up to 37% than personal vehicle
(Arbib & Seba, 2017)	About 30% reduction in 2030 compared to 2020, the price will fall to $25 per barrel
(Kim, 2018)	About 56% reduction in 2030 compared to 2016
(Manzie et al., 2007)	Only 7s traffic look-ahead ability to improve fuel economy by 33%
(Greenblatt & Saxena, 2015)	A 10% decrease in single-occupancy VMT reduces energy use by about 3%.
(Bullis, 2011)	4-m inter-track spacing reduce fuel consumption by 10-15%
(Milakis et al., 2017)	-Up to 45% fuel savings by control algorithms and optimization systems -About 90-100% of energy saving by battery SAEVs
(Vahidi & Sciarretta, 2018)	2 - 50% energy gain due to advanced knowledge of road grade, proper signal phasing and timing, cooperative car following and lane selection
(Wadud et al., 2016)	0 - 45% reduction due to congestion mitigation, platooning, eco-driving, light-weighting, right sizing, reduced infrastructure and 0 - 60% increase due to higher speed, increased features and travel demand
(Brown et al., 2014)	AVs could reduce energy use by over 90%. However, under rise in service demand and speed of AVs, energy use could increase to 173%

(Chehri & Mouftah, 2019)	ACC, eco-driving, and inter-vehicle communication reduce fuel use by 2-4%
(Liu et al., 2017)	11 to 55% reduction by CAV
(Ross & Guhathakurta, 2017)	Over 50% of energy savings by ride-sharing of full AVs

In contrast, some researchers also found that AVs and ride-sharing schemes could potentially increase energy consumption because of increased travel demand, VMT, and traffic speed, and in case automobile-oriented developments are encouraged (González-González et al., 2019; Ross & Guhathakurta, 2017). Vehicle automation can also generate longer and more energy-intensive commutes, replace energy-efficient public transportation, induce urban sprawl, and thus increase energy use (Hess, 2020). Additionally, reduction in the Value of Travel Time (VOT) can increase fuel use substantially by increasing long-distance trips (Auld et al., 2018). Thus, the net effect of AVs on transport energy use is uncertain, which warrants further investigation (Milakis et al., 2017).

Although automation would reduce overall energy use, oil demand for electricity generation will increase to charge AVs. Kim (2018) estimated that to charge 44 million AVs with a battery of 70kWh, the industry would require 3080 GWh per day extra energy by 2030 in the US, assuming each AV charge once a day. About 33 more nuclear power plants of equal size to Palo Verde nuclear power plant in Arizona would be required with 24 hours of operation each day to generate that amount of electricity. Thus, the policymakers should take appropriate actions to manage additional energy demand considering the anticipated impacts on the electrical grids.

4.3.2 Transport GHG emissions

Researchers found that AV technologies can significantly reduce NOx and COx emissions (Duan et al., 2020; González-González et al., 2019; Haboucha et al., 2017).

CAVs, SAVs, and on-demand mobility options can further reduce emissions by lowering the number of engine start, energy consumption, and vehicle ownership (Coulombel et al., 2019; Wadud & Anable, 2016). Jones and Leibowicz (2019) found that the adoption of SAVs could be more impactful for controlling vehicle emissions than a carbon tax policy despite higher VMT. The estimations of emission reduction by different types of AVs are presented in Table 3.8. Overall, AVs show the potential to reduce emissions and improve air quality. However, a lower share of AVs (i.e., 30%) could increase emission due to a slight rise in traffic demand, traffic flow, and aggressive acceleration after a stop to cruise control the vehicle speed (Rafael et al., 2020). Shared and battery AVs have a greater potential to reduce emissions significantly.

Table 3.8: Emission reduction by AVs

Study	Emission reduction
(Milakis et al., 2017)	Up to 94% reduction in GHG emission
(Greenblatt & Saxena, 2015)	87-94% reduction in GHG emissions per mile
(Kopelias et al., 2020)	CAVs reduce GHG emission by 5 to 94%
(Wadud et al., 2016)	20% reduction in carbon emission
(Rafael et al., 2020)	30% reduction of both NOx and CO2 emissions
(Fagnant & Kockelman, 2014)	5.6 to 49% reduction in GHG, 34% CO, 19% SO2, 18% NOx, 49% VOC, and 6.5% PM10 emission reduction by each SAV
(Narayanan et al., 2020)	10 to 94% emission reduction by SAVs
(Greenblatt & Shaheen, 2015)	63 - 82% GHG reduction per mile compared to private gasoline vehicles
(Vahidi & Sciarretta, 2018)	1 - 18% emission reduction due to cooperative control
(Igliński & Babiak, 2017)	40 - 60% reduction in GHG emission
(Chehri & Mouftah, 2019)	66% GHG emission reduction
(Martinez & Viegas, 2017)	40% reduction in carbon emission
(Liu et al., 2017)	3 to 19.09% reduction in emission
(Eilbert et al., 2017)	Up to 215% reduction in emission

AVs operated as shuttle services (6 kg CO2-equivalent per passenger) emits lower carbon in the whole life than the AVs operated as a personal vehicle (10 kg CO2-equivalent per passenger) (Moorthy et al., 2017). However, the net effect of AVs on GHG emissions remains ambiguous (Milakis et al., 2017). Travel demand reduction due to shared mobility is canceled out by the increased travel distance and empty running (Wadud et al., 2016). Thus, further research is more likely necessary to determine the actual effect of AVs on emission reduction (Rafael et al., 2020).

4.4 Impacts on people's safety and security, and convenience

The key strengths of AVs include people's safe travel, increased convenience, and productivity, and reduced driving stress, as indicated in Figure 3.7. The prominent weaknesses people would encounter include breach of personal privacy, misuse of technology, and system failure due to the adoption of AVs. On the other hand, one of the main threats people would experience is increased criminal activities. This subsection describes the potential impacts of AVs on the safety and security, and convenience of people.

4.4.1 Safety, security, and personal privacy

The extant literature indicates that AVs would increase the safety and security of passengers (Duan et al., 2020; Trommer et al., 2018; Vahidi & Sciarretta, 2018). Vehicles equipped with ADDS, higher levels of automation (i.e., level 3 or higher), and a higher rate of AV adoption would increase people's safety and security (Milakis et al., 2017). The opinions expressed by potential riders on the safety, security and emergency responses of AVs are presented in Table 3.9. The results show that most people are very concerned about personal safety, security, and privacy. The main sources of concern are cyberattacks, maliciously controlled vehicles, and software hacks (Milakis et al., 2017).

Table 3.9: Opinion of people regarding safety, security, and personal privacy

Study	Opinions
(Piao et al., 2016)	44% and 22% of people very concerned about their security for evening/night-time services and daytime services, respectively

(Salonen, 2018)	-37%, 8%, and 8% of respondents think driverless shuttle bus is much safer, secure, and have better emergency management system than a conventional bus, respectively -36%, 28%, and 38% of respondents think shuttle bus are same to conventional bus in safety, security, and emergency management, respectively -27%, 64%, and 54% of respondents think safety, security, and emergency management of driverless shuttle buses, respectively are much worse or worse than the conventional bus
(Begg, 2014)	36% agreed and 24% strongly agreed that AVs will improve safety and security
(Underwood & Firmin, 2014).	25% of experts agree that AVs will be more than twice as safe as conventional vehicles
(Xu & Fan, 2019)	42.35% of people expected lower risks associated with AV, 16.02% consider AVs would increase the risk substantially
(Hulse et al., 2018)	About 10% of participants directly opposed AVs, 43% of participants expressed acceptance of AVs, 46% of them are uncertain.
(Schoettle & Sivak, 2014a)	50.9%, 54.6%, and 57.3% of people expressed concern on data privacy, system security, and vehicle security from hackers, respectively
(Schoettle & Sivak, 2014b)	System security from hackers (68.7%), vehicle security from hackers (67.8%), and data privacy (63.7%) are leading concerns of people for riding SAVs
(Panagiotopoulos & Dimitrakopoulos, 2018)	31% are concerned about system security and data privacy, 26.7% are somewhat frightened
(Salonen, 2018)	64% of passengers have the worst experience in driverless shuttle buses

Many researchers found that AVs would breach privacy of the passengers by increasing the level of surveillance of mobility patterns, which may threaten people's security and privacy and discourage people to buy and share AVs (González-González et al., 2019; Hess, 2020; Howard & Dai, 2014). They could be easily tracked down by using locational information and knowing what travel destinations are (König & Neumayr, 2017). Consequently, people would be unwilling to use SAVs. For example, Gurumurthy and Kockelman (2020) reported that only 4 to 8% of Americans and 5 to 11.0% of Texans are willing to use SAVs with strangers. Thus, personal privacy is one of the main factors that affect SAVs. Similar to privacy issues, people are concerned about the misuse of technology by unscrupulous individuals (software hackers) (Kyriakidis et al., 2015; Van den Berg & Verhoef, 2016). During the survey, many riders recommended to increase the security and maintain their privacy to increase the use of AVs and SAVs (Salonen, 2018). Thus, appropriate regulations and standards should be implemented to augment the safety, security, and data privacy of the riders, which could positively influence AV adoption (Fagnant & Kockelman, 2015; Kaur & Rampersad, 2018).

4.4.2 Traffic crashes

It is estimated that AVs can avoid more than 90% of all crashes that involve human errors by adding collision avoidance technologies (Chehri & Mouftah, 2019; Daziano et al., 2017; Nunes & Hernandez, 2020). More than 40% of fatal crashes due to human factors can be avoided by using AV technologies (e.g., ACC, lane change warnings, on-board navigation) (Fagnant & Kockelman, 2015). Conducting a simulation study in England, Papadoulis et al. (2019) reported that CAVs would reduce traffic crashes by 12 to 94% with a 25 to 100% penetration rate. The majority of these crashes, particularly at a higher rate of penetration, would be eliminated by designing the control system of vehicles to avoid collisions in the merging and diverging areas due to high variations of speeds and lane change occurrence. Collecting data from police-reported crashes from 2005 to 2008, Najm et al. (2010) estimated that V2V and Vehicle to Infrastructure (V2I) could reduce 72 to 83% of crashes. Thus, vehicle automation and various connectivity technologies are likely to reduce vehicle crashes.

Conducting online surveys, researchers found that 37.30 to 88.80% of respondents would like to adopt AVs due to their capability to reduce the number and severity of crashes, and improve emergency response to crashes (Piao et al., 2016; Schoettle & Sivak, 2014a, 2014b). Although AVs could reduce the number of crashes caused by human errors, they are also prone to accidents themselves due to faulty design (Bansal et al., 2016). These studies mentioned that during the survey many of the respondents (50-96.1%) expressed concerns about system failure of AVs, which may pose threats to public health. Thus, adequate R&D and comprehensive testing of AVs are required to mitigate risks associated with AVs and address public concerns.

4.4.3 Convenience and productivity

Many researchers mentioned that AVs would increase the convenience, efficiency, and productivity of riders while traveling despite paying low transportation costs (Clements & Kockelman, 2017; Hess, 2020; Vahidi & Sciarretta, 2018). People would be involved in a variety of productive activities (e.g., reading, messaging, talking on the phone, sleeping) rather than passing time idling, which makes the journey meaningful and useful (Piao et al., 2016; Schoettle & Sivak, 2014b). Wadud and Huda (2019) reported that car passengers engage in 3.6 different types of activities in each leg of the journey. Talking or texting friends and looking out of the window are the most appealing tasks among people traveling in AVs (Howard & Dai, 2014; Schoettle & Sivak, 2014b). Thus, automated driving can significantly increase the convenience and efficiency of the journey by engaging people in different activities.

AVs can also increase the convenience of passengers by reducing waiting time, particularly during peak hours via dynamic ride-sharing (Fagnant & Kockelman, 2014; Fagnant & Kockelman, 2018). Fagnant and Kockelman (2018) found that total service time (i.e., wait, pick-up/drop-off, and in-vehicle) could be reduced from 15 minutes to 14.7

minutes via dynamic ride-sharing. Fagnant and Kockelman (2014) also found that average wait time could be reduced by 51% when the trip rates are doubled and fleet size is increased to 92%. Thus, a large enough number of SAVs is required to increase the convenience and service quality for passengers by reducing overall wait time.

5. Conclusion and directions for future study

The extant literature shows that AVs have the potential to bring dramatic changes to urban transportation systems, their use by populations and to the spatial structure and conditions of the urban built environment. Previous review papers systematically evaluated the short and medium-term effects of AVs on transportation and human mobility and disregarded long-term effects on the urban built environment. This updated systematic literature review identified, evaluated, and critically analyzed relevant scholarship to understand the current status and impacts of AVs. To better understand the impacts of AVs and their associated advantages and disadvantages, a SWOT analysis was performed. With the underpinning provided by the SWOT analysis (Figure 3.7), the potential positive and negative effects of AVs on people’s travel pattern, environment, and urban built environment are discussed. This study significantly contributes to the literature by investigating the current status of AV research and adoption in different study contexts and the potential short, medium, and long-term impacts of AVs. The study also contributes by identifying the research gaps in the existing literature and proposing the directions for further research.

Investigating the current status of implementation, researchers reported that AVs will be available for people’s regular use incrementally over the coming decades. The findings from the existing literature show that AV would influence urban transportation and human mobility by reducing vehicle ownership, public and active travel, VMT, traffic delay and congestion, travel costs, and increasing accessibility, mobility, and revenue generation for commercial operators. Some studies also mentioned that AVs can further influence people's travel behaviors by embracing cutting-edge EV technologies and providing shared and on-demand mobility services. Investigating the long-term effects, researchers reported that AVs would encourage dispersed urban development, reduce parking demand in city centers and residential areas, and enhance the capacity of the road network. Some studies also observe that AVs have the potential to reduce energy consumption and protect the environment by reducing GHG emissions. Investigating people's safety, security, and privacy, the extant literature reported that most people are very concerned about personal safety, security, and privacy from strangers, cyberattacks, maliciously controlled vehicles, and software hacks. On the other hand, researchers mentioned that AVs are able to reduce traffic crashes involving human errors and increase the convenience and productivity of passengers by providing amenities for multitasking opportunities.

Researchers also believe that SAVs have greater positive impacts on transportation and urban environment compared to private AVs (University of Kentucky, 2020). SAVs in a dynamic ride-sharing situation could be an effective policy option to reduce vehicle ownership, traffic congestion and travel time, and improve overall performance of the transportation system (Loeb et al., 2018; Zhang et al., 2015). Researchers proposed to formulate appropriate funding mechanisms and policies to encourage ride-sharing and on-demand mobility among travelers to increase use of SAVs (Ross & Guhathakurta, 2017). Thus, pertinent policies in transportation (e.g., automation of transit, integration of transit and non-motorized transport, encourage shared and micro mobility), infrastructure (e.g., adjustment, and redesign of existing roads), and urban planning (e.g., update of urban development plans, land-use plans, parking policies and design, green belt) are essential to realize the benefits of AVs. Moreover, law and order situation need to be improved to provide safety and security of the passenger while sharing AVs.

Despite huge contributions to the literature, previous studies have some prominent drawbacks. The limitations of the reviewed papers are discussed below to identify research gaps and provide guidelines for future research.

1) AVs are not currently available for people to use; thus, many simulation studies estimating impacts of AVs is solely based on assumptions (e.g., same vehicle and speed, similar travel behaviors, vehicles shared by household members only), imaginations of riders in simulate urban setting (e.g., grid city, typical city), and limited testing (Compostella et al., 2020; Fagnant & Kockelman, 2015; Zhang et al., 2018). Sometimes, vehicles are operated in a homogeneous traffic environment with a little interaction with neighboring vehicles (Piao et al., 2016). Moreover, lower levels of autonomy (i.e., Level 1, 2 or 3) were used to understand people's perceptions and assess the impacts of fully automated vehicles (Level 4 or 5) (Rahman et al., 2017; Xu et al., 2018). Thus, future studies should investigate the impacts of AVs considering heterogenous traffic environment allowing interactions with other vehicles, inclement weather conditions, and full automation of vehicles (Level 5) to gauge the real-world impacts of AVs.
2) Conducting stated preference surveys, some studies investigated travel patterns of persons with prior knowledge on AVs, and with technological affinity disregarding other sections of people (Haboucha et al., 2017; Kapser & Abdelrahman, 2020;

König & Neumayr, 2017). Some studies consider travel by private AVs or SAVs, which partially represent a large and complex transportation system (Duan et al., 2020; Krueger et al., 2016; Salonen, 2018). Thus, future studies should draw samples from all sections of people and investigate people's travel patterns by AVs and SAVs to understand a holistic overview of the complex system.

3) Some studies only considered part of trips ignoring vehicle operations for fueling and parking to estimate the impact of AVs (Compostella et al., 2020; Ma et al., 2017). Additionally, studies also deal with the last-mile transportation problems (i.e., travel to and from transit station) (Moorthy et al., 2017) and consider a small section of the whole network (e.g. a junction) (Papadoulis et al., 2019). Thus, a study considering the whole transport network of a city is necessary to understand the overall impacts of AVs.
4) Most of the studies considered the costs of ownership to estimate the travel costs by AVs disregarding the vehicle operation and maintenance costs (Wadud, 2017). Some studies only consider fare collection to estimate the revenue generation ignoring the maintenance and refueling costs (Duan et al., 2020; Nunes & Hernandez, 2020). Thus, a comprehensive estimation of travel costs and revenue generation comprising of all factors is necessary to guide customers and commercial operators.
5) Although some researchers mentioned some positive (e.g., densification, economic growth) and negative (e.g., urban expansion, higher trip length) (Gelauff et al., 2019; Kim et al., 2020; Milakis et al., 2018) effects, still it is unclear and there is little evidence on how AVs would effects people's residential and employment location

decisions (Kim et al., 2020; Krueger et al., 2019). Thus, future researchers should investigate the long-term effects of AVs on urban land-use patterns.

6) Door-to-door services provided by AVs would reduce walking and cycling trips, increase physical inactivity and related health problems (González-González et al., 2019). However, to the best of our knowledge, there is no empirical study to investigate the impacts of AVs on public health (Crayton & Meier, 2017; Sohrabi et al., 2020). Thus, it is essential for the researchers to conduct studies and evaluate the possible impacts of AVs on public health considering the change in human travel behaviors and urban built environment, which may affect policy decisions.

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CHAPTER 4: DETERMINANTS OF HOUSEHOLD PURCHASE INTENTION OF AUTONOMOUS VEHICLES: EMPIRICAL EVIDENCE FROM CALIFORNIA

Abstract

This study aims to investigate people's perceptions and opinions on Autonomous Vehicles (AVs) and the key factors that influence people's Behavioral Intention (BI) to purchase and use AVs. Data were sourced from the 2019 California Vehicle Survey to explore the determinants of AV purchase. A Structural Equation Model (SEM) of stated intentions is estimated to validate a theoretical framework drawn on relevant bodies of literature. The descriptive statistics show that many people are already aware of AVs. Many people also think that traveling by AVs is enjoyable, safe, and effective, although some of them would miss the joy of driving and would not entrust a driverless AV to shuttle their children. Results from the SEM indicate that working-age adults, children, household income, per capita income, and educational attainment are positively associated with AV purchase intention. Similarly, psychological factors (e.g., perceived enjoyment, usefulness, and safety), prior knowledge of AVs, and experience of emerging technologies (e.g., electric vehicles) significantly influence BI to purchase AVs. This study found that family structure and psychological factors are the most influential factors of AV purchase intention, and more so than the built environment, other socioeconomic, and transportation factors.

Keywords: Autonomous Vehicle, Public Acceptance, Theory of Planned Behavior, Theory of Reasoned Action, Technology Acceptance Model, Structural Equation Modelling

1. Introduction

Connected and autonomous vehicles will reshape the automobile industry and recast how humans travel in cities in the near future (Acheampong & Cugurullo, 2019; Losada-Rojas & Gkritza, 2021). Many high-tech and automobile companies are determined to bring forth the new mobility option of Autonomous Vehicles (AVs) to modern societies (Kim, 2018; Moorthy et al., 2017). It is estimated that the rapid progress in the research and development of the constellation of technologies that enable AVs will shepherd the rise of their share of the global private vehicle market to 25% by 2040 (Yuen et al., 2020a). However, the impacts of AVs on peoples' travel patterns, transportation systems, and physical and built environments are still largely unknown. Moreover, people's acceptance of this new technology is key for successful distribution of AVs (Mara & Meyer, 2022) and will condition the nature and scale of these impacts. Given the knowledge gap, this study aims to enhance our understanding of the key determinants of people's tendency to purchase and adopt personal AVs, looking at a range of factors, including socioeconomic, demographic, transportation, technology, the built environment, and vehicle-specific (i.e., safety, convenience, usefulness) elements.

AVs are capable of driving and navigating without direct human input by using sensing technologies (e.g., radar, Global Positioning System (GPS), and computer vision) and advanced control systems (i.e., sensor) (Narayanan et al., 2020). According to the Society of Automotive Engineers (SAE) (SAE International, 2018), AVs have six levels of autonomy ranging from Level 0 (No autonomy to assist drivers or replace drivers to control the vehicle) to Level 5 (Full autonomy). Many cars are already equipped with cameras and sensors to avoid potential crashes (Kim, 2018; Van Brummelen et al., 2018). Researchers have predicted that Level 5 AVs would be available commercially in the 2020s to 2030s (Litman, 2017; Trommer et al., 2018). However, most benefits of AVs will become prominent in the 2050s to 2060s when these vehicles would be common and affordable (Litman, 2017). In this study, I will investigate the determinants of Level 5 AVs.

Despite tremendous advancements in research and development, the implementation of this novel technology is still in its infancy and the presence of AVs on public roads is yet to materialize. Consequently, most people have very limited knowledge of AVs, which could curb the introduction and slow the widespread availability of AVs. Findings on the behavioral intention of people to adopt AVs and on associated socioeconomic, urban, and technological factors are far from conclusive at this time and have not fully accounted for the complex interplay between personal preferences and influences from the broader community and socio-spatial environment. Thus, it is timely to study the factors that influence people's intentions to purchase and use AVs. The following research questions frame this study:

1) What are the perceptions, opinions, and expectations of people about AVs?
2) How would people's socioeconomic and demographic characteristics influence Behavioral Intention (BI) to purchase AVs for their travel purposes?
3) How would awareness of AVs, and perception of their convenience, comfort, and safety influence people's BI to purchase and use AVs?
4) How would factors of the built environment, transportation, and technology influence people to purchase and use AVs for meeting their travel demand?

This study uses data from the 2019 California Vehicle Survey (Transportation Secure Data Center, 2019); by design, the sampling scheme of this household survey includes responses from actual users of electric vehicles. This survey comprises data on opinions and perceptions of people about self-driving vehicles through a 12-question survey instrument, which allows to address some of the stated research problems.

The rest of the paper is organized as follows: Section Two discusses findings from the relevant literature, presents the theoretical framework, and outlines the hypotheses of the study. The research design is presented in Section Three. The main results of our analysis are presented in Section Four. Section Five articulates the discussion of these results. Section Six concludes the study by indicating directions for future research.

2. Literature review and theoretical framework

2.1 Synopsis of literature

A considerable number of empirical studies have evaluated the factors that influence people to purchase and use AVs. A summary of the findings from the extant literature is presented in Table 4.1. In substance, the intention of customers to purchase and use AVs is strongly influenced by people's socio-economic and demographic features. For example, working-age adults, elderly and disabled persons, males, married persons, people with bachelor's education, high income, children, and vehicle ownership are more interested to purchase and adopt AVs. Similarly, prior knowledge of AVs positively influences people to purchase and use AVs. In contrast, educational attainment limited to high school, low household income, a household without private vehicles, and possession of a driving license are negatively associated with AV purchase and adoption. Besides a variety of user attributes, psychological and social factors affect AV adoption tendency. For example, people's perception of the usefulness, ease of use, trustworthiness, safety, and social influences increase the willingness of people to purchase and use AVs. On the other hand, perceived risk and technology anxiety negatively affect the tendency of people to purchase and use AVs.

Table 4.1: Concepts describing AV ownership in the literature

Feature		Relationship	References
Age	Median age	Positive	(Bansal & Kockelman, 2017; Hilgarter & Granig, 2020; Hulse et al., 2018)
	Less than 50	Positive	(Panagiotopoulos & Dimitrakopoulos, 2018; Piao et al., 2016; X. Wang et al., 2020)
	50 and above	Negative	
Gender	Male	Positive	(Howard & Dai, 2014; Wadud & Huda, 2019; Zmud & Sener, 2017)
Marital status	Married/ couple	Positive	(Howard & Dai, 2014; Nazari et al., 2018; Webb et al., 2019)
Education	Bachelor/ Master	Positive	(Daziano et al., 2017; Haboucha et al., 2017; Nazari et al., 2018)
	High school/college	Negative	
Income	High income (more than $100,000)	Positive	(Bansal et al., 2016; S. Wang et al., 2020; Webb et al., 2019)
	Low income	Negative	
Household size and composition	Large household (3 and less)	Mixed (Positive and negative)	(Gurumurthy & Kockelman, 2020; Laidlaw et al., 2018a; Nazari et al., 2018)
	Household with children	Mixed (Positive and negative)	
	Elderly, disabled	Positive	
Vehicle ownership	No or 1	Negative	(Daziano et al., 2017; Wadud & Huda, 2019; S. Wang et al., 2020)
	2 and more	Positive	
License	Yes	Negative	(Howard & Dai, 2014; Nazari et al., 2018; Webb et al., 2019; Zmud & Sener, 2017)
AV Knowledge		Positive	(Feys et al., 2020; Hilgarter & Granig, 2020; König & Neumayr, 2017)
Psychological factors	Perceived usefulness	Positive	(Castritius et al., 2020; Nordhoff et al., 2020; Shin et al., 2015)
	Perceived trust	Positive	(Castritius et al., 2020; Chen, 2019; Hagl & Kouabenan, 2020)
	Perceived ease to use	Positive	(Castritius et al., 2020; Nordhoff et al., 2020; Xu et al., 2018)
	Social influence	Positive	Bansal and Kockelman (2018); (Bansal et al., 2016; Nordhoff et al., 2020)
	Traffic safety	Positive	(Xu et al., 2018)
	Perceived risk	Negative	(Ha et al., 2020; Hulse et al., 2018; Zhu et al., 2020)
	Technology anxiety	Negative	(X. Wang et al., 2020)
Built Environment			
Population density		Positive	(Gurumurthy & Kockelman, 2020; Nazari et al., 2018; Webb et al., 2019)
Employment density		Positive	
Mixed land use		Positive	

Travel distance to city center/CBD/Workplace	Positive	(Haboucha et al., 2017; Nazari et al., 2018; Rahimi et al., 2020)
Urban area/Rural	Positive /less likely	(Daziano et al., 2017; König & Neumayr, 2017; Nazari et al., 2018)
Transportation Factors		
Public (e.g., bus, train) and green (e.g., walk, cycle) transport	Positive	(Hilgarter & Granig, 2020; Krueger et al., 2016; Nazari et al., 2018)
Ride-sourcing, car share	Positive	(Krueger et al., 2016; Rahimi et al., 2020)
Work trip	Positive	(Gurumurthy & Kockelman, 2020; Krueger et al., 2016)
Shopping and recreation trips	Negative	
Purchase price of vehicles	Negative	(Daziano et al., 2017; Haboucha et al., 2017; Krueger et al., 2016)
Technology affinity	Positive	(Rahimi et al., 2020; S. Wang et al., 2020)
Institutional Aspects		
Incentive (e.g. price rebate, tax reduction, and subsidy)	Positive	Howard and Dai (2014); (S. Wang et al., 2020)
Traffic regulation	Positive	
Research and Development	Positive	
Separate infrastructure	Positive	

People's preference for adopting and using AVs also depends on the context provided by their built environment (e.g., density, land-use diversity). For example, high population and employment density, mixed land use, and high travel distance to destinations increase people's willingness to use AVs. Additionally, urban people are more interested to purchase and use AVs than rural residents.

The rate of AV adoption is also influenced by different transportation factors (e.g., travel mode, distance, and time) and institutional supports. For example, people who mostly use public and active transportation and ride-sharing services are interested to use shared AVs, and people who drive to work are more interested in owning personal AVs. Affinity to new technologies also influences individuals towards AVs. In this respect, people are interested to purchase and use vehicles if the vehicles are equipped with cutting-edge technologies (e.g., automated speed control, braking and parking, collision warning, blind-spot detection, lane-changing warning). In contrast, people are less likely to use AVs when they make shopping and recreational trips. Similarly, a high vehicle price reduces the willingness to purchase AVs. However, active support from central and local governments (e.g., incentives, research and development, infrastructure) strengthens people's resolve to purchase and use AVs.

Thus, the extant literature indicates that people's socio-economic, demographic, and psychological factors, the built environment, transportation features, and institutional aspects have a greater role in deciding on the AV adoption intention of households.

2.2 Theoretical framework

Various theories have been advanced to describe human behaviors for choosing an alternative. These theories demonstrate that human behavior is influenced by some internal (e.g., personal attitudes, norms) and external (e.g., incentives, institutional constraints, surrounding environment) factors (Adjei & Behrens, 2012). Some popular theories are discussed hereafter.

2.2.1 Theory of Reasoned Action

The Theory of Reasoned Action (TRA) is a widely recognized model in social psychology that intends to explore the core determinants of individual BI towards an action (Ajzen & Fishbein, 1980; Madden et al., 1992). According to TRA, BI for a specific action is jointly determined by attitude (i.e., positive or negative) towards the behavior and by subjective norms (i.e., the influence of other people on behavioral action), as depicted in Figure 4.1. Attitude towards a behavior is determined by the user's salient beliefs or information about the probability that performing a behavior has a consequence and leads to a specific outcome (Davis et al., 1989; Madden et al., 1992). Subjective norms are determined by individual normative beliefs (i.e., perceived expectation of individual or group) and his/her motivation to comply with these expectations.

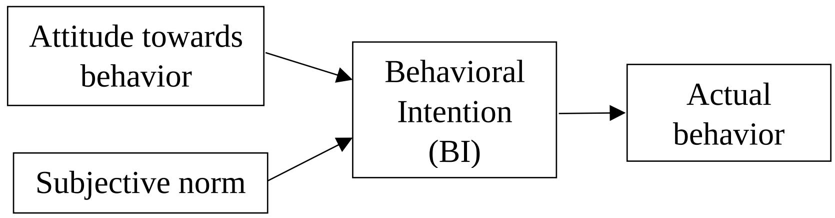

Figure 4.1: Theory of Reasoned Action (TRA)

2.2.2 Theory of Planned Behaviors

Researchers have used the Theory of Planned Behavior (TPB) to investigate the factors that influence people's travel mode choice behaviors (Bamberg, 2006; Bamberg et al., 2003; Conner & Armitage, 1998; Heath & Gifford, 2002). They particularly investigated psychological factors of travel mode choice. However, the surrounding physical environment (i.e., urban form) also influences travel behaviors.

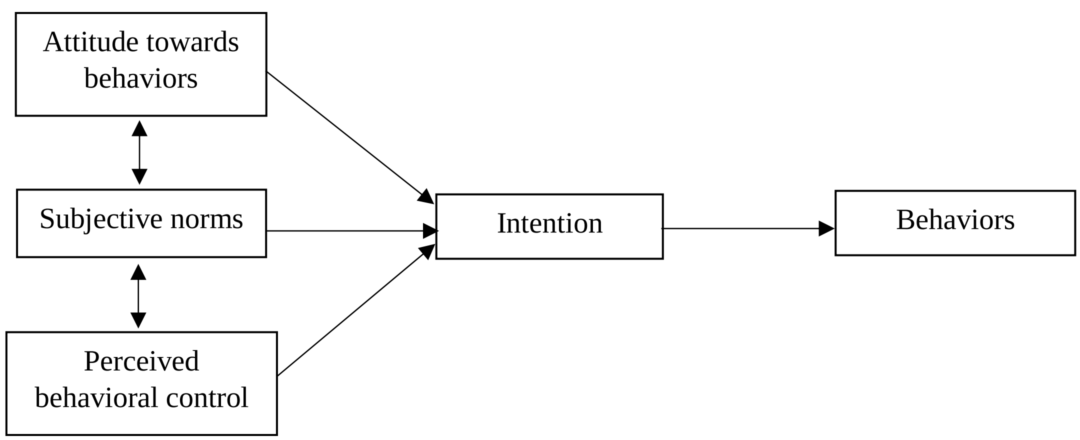

Figure 4.2: Theory of Planned Behavior, adopted from (Ajzen, 1985), (Ajzen, 1991)

Ajzen (1985) first introduced the TPB theory based on TRA to investigate the influence of external factors (i.e. where people have no control) on behavioral actions. According to Figure 4.2, the TPB explains that human behavior is dependent on the intention to behavioral change (Morris et al., 2012). Intentions are influenced by attitudes, subjective norms, and perceived behavioral control measures. Attitude indicates the belief and values of a behavioral outcome. Subjective norms denote the collective perception of other people on the decision faced by the decision makers (i.e., other people suggest the final decision) and social pressure towards the behavioral outcome. Perceived behavioral control represents external factors (e.g., ability, opportunity, resources, skill) to choose an alternative.

2.2.3 Technology Acceptance Model

The Technology Acceptance Model (TAM) is a widely used model to understand how users accept and use a technology (Lee et al., 2003; Zhang et al., 2020). Davis (1985) originally proposed the TAM based on the TRA (Fisbein & Ajzen, 1975). According to the initial version of TAM, users' attitude is the main determinants to understand whether they will accept it or not. As indicated in Figure 4.3, user's Attitude Towards Technology (ATT) depends on two major beliefs: Perceived Usefulness (PU) and Perceived Ease of Use (PEU) (Davis, 1985; Davis et al., 1989). ATT is defined as the positive or negative feelings of an individual about the performance of a technology. PU of technology is defined as the degree to which it can enhance the job performance of the users. On the other hand, PEU is defined as the degree to which it can reduce the physical and mental effort of the users. PEU has a direct causal effect on PU since all are equal. The technology that is easy to use increases the job performance of the users.

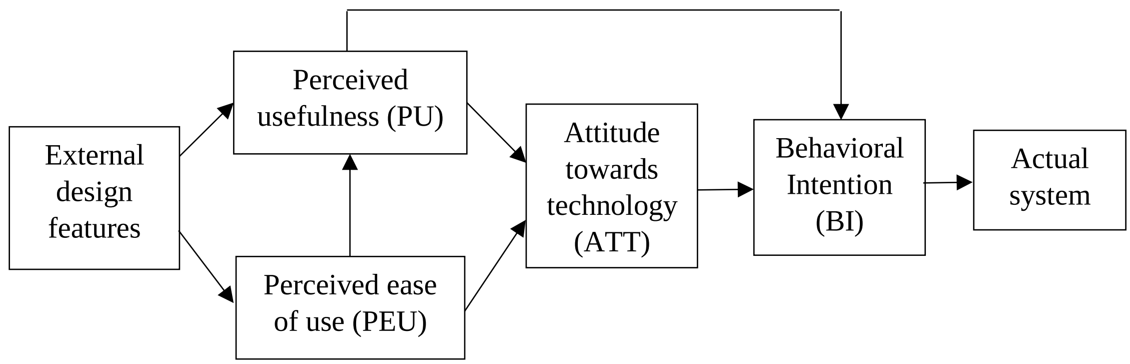

Figure 4.3: TAM (1985)

The model also demonstrated that external features (e.g., socio-economic features, nature of the behavioral outcomes, prior behavior, and persuasive communication) have direct effects on PU and PEU. These external features indirectly influence people's attitude and belief by directly affecting PU and PEU. The model indicates that positive ATT and high PU significantly influence people to use technology. The earlier version of TAM includes core variables of user motivation (i.e., PU, PEU, and ATT) and outcome variables (i.e., BI, actual technology use) along with some external factors (Scherer et al., 2019). However, Davis (1989) proposed another version of TAM (Figure 4.4) where they argued that ATT is not an influencing factor, rather PU and PEU have direct and positive effects on the intentions of individuals toward technology use (Rahman et al., 2017).

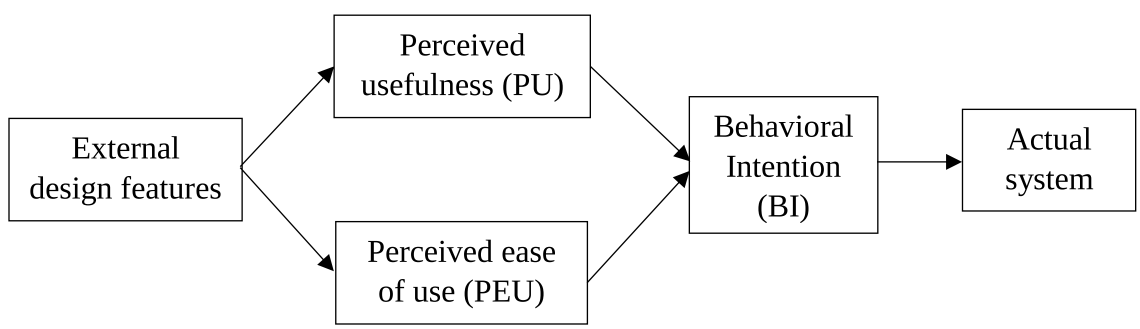

Figure 4.4: TAM (1989)

2.2.4 Theoretical framework to investigate the factors affecting BI to use AV

Based on the findings from the literature and existing theories (e.g., TRA, TPB, and TAM), a theoretical framework dubbed the Integrated Technology Acceptance Model (ITAM) is proposed to investigate the factors that influence people's BI to adopt and use AVs. The new model is more aligned with the updated version of TAM where Davis (1989) argued that PU and PEU have direct effect on BI rather than ATT. Figure 4.5 shows the proposed ITAM featuring the behavioral control factors, objective factors, and people's attitudes towards AVs that influence AV purchase and use intention of the people.

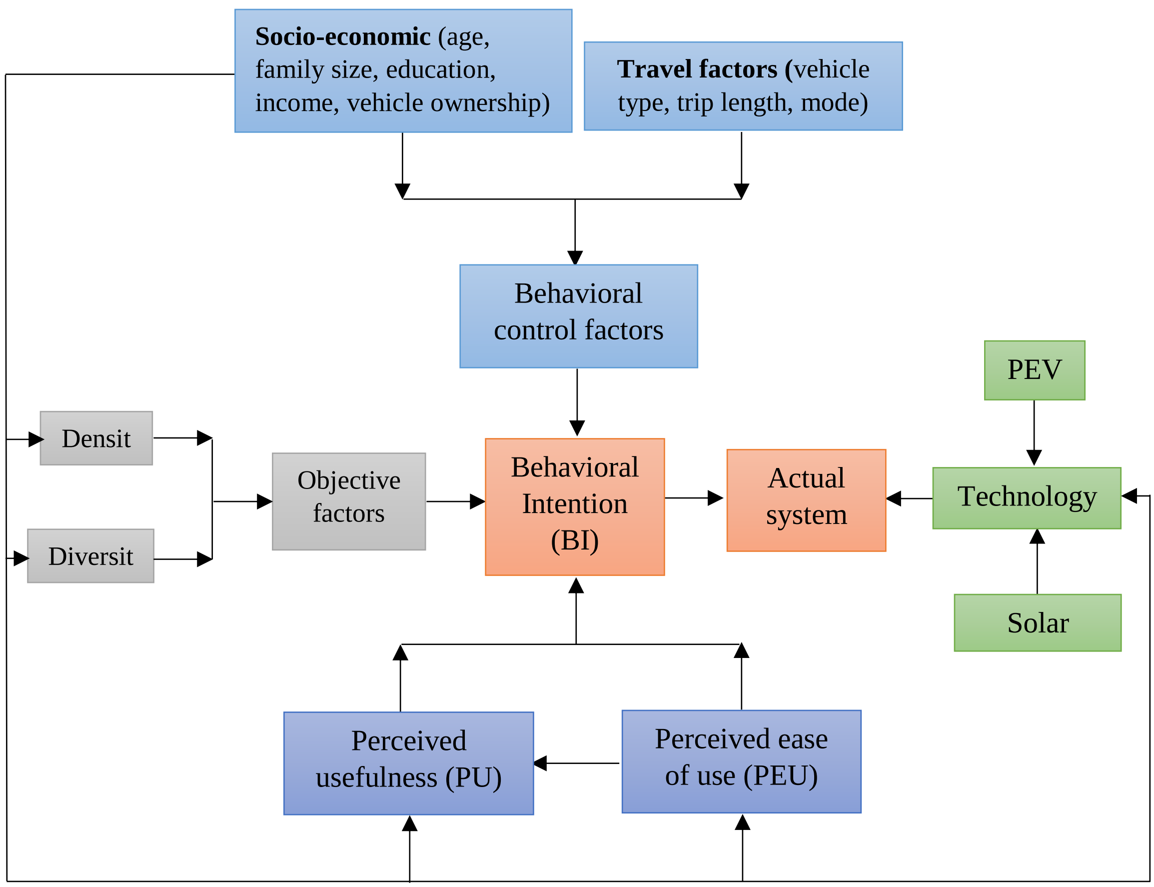

Figure 4.5: Integrated Technology Acceptance Model (ITAM)

According to the ITAM, human BI to actual AV use is directly influenced by behavioral control factors (e.g., socioeconomic and travel factors), objective factors (i.e., urban form), and psychological factors (i.e., PU and PEU). Additionally, the model indicates that the actual use of AVs also depends on the availability of novel technology (e.g., EV, solar panel) and the affinity of the people towards new technologies. Socioeconomic factors also indirectly affect AV use by influencing objective factors, psychological factors, and the affinity of the people towards a technology.

Based on the conceptual framework of ITAM and the review of the literature, a number of research hypotheses are formulated as follows.

a) Socioeconomic and demographic factors

1) Young, working-age adults, and households with children have a positive BI to purchase AVs (Hypothesis 1 (H1)).
2) Education attainment is positively associated with BI to purchase AVs (H2).
3) People with higher household income are more interested to purchase AVs compared to their counterparts (H3).

b) Travel factors

1) Preference for ride-hailing and ride-sharing services are negatively associated with BI to purchase AVs (H4).
2) People who prefer public transport for their daily travel purposes are unwilling to purchase AVs (H5).

c) The built environment

1) High population and employment density and high walkability score are positively associated with BI to purchase AVs (H6).

2) Mixed land uses and short travel distance to workplaces are positively associated with BI to purchase AVs (H7).
3) People who live in neighborhoods with a higher number of democratic supporters are interested to purchase AVs (H8).

d) Psychological factors

1) Perceived usefulness, safety, and effectiveness are positively related to BI to purchase AVs (H9).
2) People having familiarity with advanced automated technologies are likely to purchase AVs (H10).
3) Age, income, and education positively mediate people's psychological attributes to purchase AVs (H11).

e) Technological development

1) Experience with alternative fuel vehicles (e.g., electric vehicles, hybrid electric vehicles, fuel cell vehicles) is positively associated with BI to purchase AV (H12).
2) Households' preference for gasoline vehicles is negatively associated with BI to purchase AV (H13).
3) Working-age adults, high income, and education level mediate people's technological preference to purchase AV (H14).

3. Research design

3.1 Data

To conduct this study, data are sourced from the 2019 California Vehicle Survey conducted by the California Energy Commission (Transportation Secure Data Center, 2019). The survey collected data to assess transportation fuel needs and provide key policy guidelines for transportation planning in California. The survey assessed consumer preferences for light-duty vehicles (i.e., personal and commercial) and Electric Vehicles (EVs). This survey collected economic and demographic data, vehicle information including vehicle and fuel types, vehicle choice information using a stated preference survey. Moreover, charging behavior, electricity rates, and main motivations for purchasing EVs were collected from the EV owners. In addition, a total of 13 questions were articulated to know people's perceptions, opinions, intentions, and motivation towards self-driving cars and ride-sharing facilities. The study analyzes the data collected from residential surveys only. A total of 4,248 individuals including 718 EV owners participated in an online-based residential survey. A stratified random sampling technique was used to collect data from six regions: San Francisco, Sacramento, Central Valley, Los Angeles, San Diego, and the Rest of California. Households were selected randomly by address at the county level and invited to participate in the survey in such a way to ensure that samples are proportional to the population in each county.

Other data sources include the American Community Survey (US Census Bureau, 2018), Environmental Protection Agency (Environmental Protection Agency, 2020), and California State Association of Counties (California State Association of Counties, 2019). The data aggregated at the county level were collected and combined with the 2019 California Vehicle Survey. Finally, the data were processed (i.e., missing value imputation with the median values, creation of new variables from the original data) and analyzed to test the research hypotheses. A detailed description of the variables used in the study is presented in Table 4.2.

Table 4.2: Description of the variables

Variable	Variable Description	Measure	Source
Dependent variable			
AV_HH	Household's intention to purchase AV	1 = Wait and try to avoid ever buying, 2 = eventually buy when they are in common use, 3 = One of the first to buy an AV	CVS
Independent variables			
AGE1	Age of the respondent between 18 and 64 years	1 = Yes, 0 = No	CVS
AGE3	Age of the respondent between 18 and 34 years	1 = Yes, 0 = No	CVS
MEM5	Number of people age 15 or below in the household	#	CVS
EVHE	Experience in owning or leasing an electric or hydrogen cell vehicle (e.g., HEV, PHEV, BEV, and FCV) of the household	1 = Yes, 0 = No	CVS
CHARGE	EV charging spots at the workplace	1 = Yes, 0 = No	CVS
GAS	Willingness to consider gasoline-only vehicle	1 = Yes, 0 = No	CVS
PHEV	Willingness to consider PHEV only vehicle	1 = Yes, 0 = No	CVS
BEV	Willingness to consider BEV only vehicle	1 = Yes, 0 = No	CVS
PFCEV	Willingness to consider PFCEV only vehicle	1 = Yes, 0 = No	CVS
PUB2	Use of public transportation (e.g., bus, light rail/tram/subway, and commuter train) for trips in the local area	1 = Yes, 0 = No	CVS
RH2	Use of ride-hailing services (e.g., Taxi, Uber/Lyft, Uberpool/Lyftline) for trips in the local area	1 = Yes, 0 = No	CVS
RS1	Availability of ride-sharing services (e.g., bikeshare, Car2Go, ZipCar, Jump) for trips in the local area	1 = Yes, 0 = No	CVS
RS2	Use of ride-sharing services for trips in the local area	1 = Yes, 0 = No	CVS
MODE_F3	Frequency to use Light rail/tram/subway (e.g., BART, LA Metro)	1= >1/month, 2 = 1-3 times/month, 3 = 1-2 times/week, and 4 = ≥ 3 times/week	CVS
AV_AW	Familiarity of the respondent with AVs	1 = Never heard, 2 = Heard but not familiar, 3 = heard and somewhat familiar, and 4 = heard and very familiar	CVS
AV1	AVs would enable the respondent to enjoy traveling more (e.g., watch the scenery, rest)	1 = Strongly disagree, 2 = Somewhat disagree, 3 = Somewhat agree, and 4 = Strongly agree	CVS
AV2	People would miss the joy of driving and be in control		CVS
AV3	People would accept longer travel times so the AV could drive at a low speed to prevent unsafe situations for pedestrians and bicyclists		CVS
AV5	People would reduce time at the regular workplace and work more in the AVs		CVS
AV6	People would send an empty AV to pick up/drop off my child		CVS
AV7	People would be able to travel more often even when he is tired, sleepy, or under the influence of alcohol/medications		CVS
HHI3	Annual household income $100K and above	1 = Yes, 0 = No	CVS

POPDEN	Population density aggregated at the county level	People/km^2	ACS
EDU5	Population 25 years and over have bachelor and above degree aggregated at the county level	%	ACS
PCI	Per capita income in the past 12 months aggregated at the county level	$	ACS
EMP	Employment density aggregated at the county level	Jobs/acre	EPA
ENTROPY	Employment and household entropy aggregated at the county level	Index	EPA
WI	Walkability index aggregated at the county level	Index	EPA
VMT	Average daily VMT per worker aggregated at the county level	VMT/day/worker	EPA
EVD	Registered Democrat Voters in 2019 aggregated at the county level	%	CSAC

HEV = Hybrid Electric Vehicle, PHEV = Plug-In Hybrid Electric Vehicle, BEV = Battery Electric Vehicle, FCV = Fuel Cell Vehicle, PFCEV = Plug-In Fuel Cell Electric Vehicle, CVS = 2019 California Vehicle Survey, ACS = American Community Survey, EPA = Environmental Protection Agency, and CSAC = California State Association of Counties.

Some variables require further elaborations. ENTROPY measures the diversity in population count and land-use areas in census block groups (Environmental Protection Agency, 2020). Since a geographic unit of interest is the county and since the county of residence is recorded in the survey, the county median value is used and related back to each survey response. The entropy value ranges from 0 to 1, where 0 indicates the absence of diversity and 1 indicates prefect diversity.

The Walkability Index (WI) indicates the likelihood or feasibility of walking for utilitarian purposes (Environmental Protection Agency, 2020). This composite index is created using four built environment measures, namely the population and land-use entropy measure mentioned earlier, a measure of employment diversity (also using the entropy principle), the street intersection density, and the distance to the nearest transit stop, which are all considered as supporting walking. Similar to ENTROPY measure discussed above, the county median values of WI, EMP, and VMT are used and related back to each survey response.

Tables 4.3 and 4.4 report the descriptive statistics of dependent and independent variables used in model building. Asking the intentions to purchase an AV for households, the survey found that about 53.93% of respondents expressed their interest to purchase AVs (Table 4.4). Suffices it here to comment on the dependent variable. In the sample, 8.97% of respondents self-identify as eager to be among the early customers who would purchase AVs, while 44.96% mentioned that they would wait and buy AV when AVs will be common in use. In addition, 46.07% of respondents would wait longer before purchasing an AV and even try to avoid buying an AV altogether.

Table 4.3: Descriptive statistics of variables (N= 4,248)

Variable	Minimum	Maximum	Mean	Std. Deviation
MEM5	0.00	12.00	0.32	0.77
POPDEN	0.60	7066.04	741.81	1072.17
EDU5	12.05	58.79	34.98	10.06
PCI	17,590.00	69,275.00	36,800.41	9,748.39
EMP	0.00	7.24	1.62	1.11
ENTROPY	0.37	0.65	0.51	0.03
WI	3.58	16.00	12.71	1.89
VMT	11.96	42.49	19.48	4.49
EVD	14.34	49.16	34.60	7.71

Table 4.4: Descriptive statistics on respondents' socioeconomic features and opinions on technology and AVs (N= 4,248)

Variable	Measure	Percent
AGE1	No	34.70
	Yes	65.30
AGE3	No	87.57
	Yes	12.43
HHI3	No	57.84
	Yes	42.16
EVHE	No	88.30
	Yes	11.70
CHARGE	No	86.84
	Yes	13.16
GAS	No	42.37
	Yes	57.63
PHEV	No	53.15
	Yes	46.85
BEV	No	64.83
	Yes	35.17
PFCEV	No	86.42
	Yes	13.58

PUB2	No	64.74
	Yes	35.26
RH2	No	54.24
	Yes	45.76
RS1	No	41.48
	Yes	58.52
RS2	No	92.75
	Yes	7.25
MODE_F3	>1/month	91.41
	1-3 times/month	4.80
	1-2 times/week	1.65
	≥ 3 times/week	2.14
AV_AW	Never heard	4.47
	Heard but was not familiar	38.21
	heard and somewhat familiar	43.06
	heard and very familiar	14.27
AV1	Strongly disagree	22.72
	Somewhat disagree	19.33
	Somewhat agree	39.76
	Strongly agree	18.20
AV2	Strongly disagree	11.80
	Somewhat disagree	19.60
	Somewhat agree	37.30
	Strongly agree	31.40
AV3	Strongly disagree	23.73
	Somewhat disagree	23.07
	Somewhat agree	36.68
	Strongly agree	16.53
AV5	Strongly disagree	46.00
	Somewhat disagree	28.63
	Somewhat agree	19.87
	Strongly agree	5.51
AV6	Strongly disagree	61.06
	Somewhat disagree	19.11
	Somewhat agree	14.67
	Strongly agree	5.16
AV7	Strongly disagree	28.27
	Somewhat disagree	19.35
	Somewhat agree	35.19
	Strongly agree	17.18
AV_HH	One of the first to buy an AV	8.97
	Eventually buy when they are in common use	44.96
	Wait and try to avoid ever buy	46.07

Considering the enormous possibilities, many people are interested to adopt and use AVs in California. The California Department of Motor Vehicles (DMV) has already developed regulations for the manufacturers to follow during testing and before the deployment of AVs to encourage innovation and promote safety (Department of Motor vehicles, 2021). The California DMV first permitted Nuro, a robotics company, to test AVs on public roads in 2017 and they got approval from DMV to deploy AVs for commercial use in the Bay Areas in December 2020 (Klar, 2020). Nuro is already operating AVs in partnership with 7-Eleven to deliver convenience store products (Hawkins, 2021). Currently, more than fifty robotics and auto companies are permitted to test full AVs in California including Waymo and General Motors (Subin & Wayland, 2021). It is expected that AVs would be common in California in a few years and people would use AVs for their daily travel purposes.

3.2 Methods

A Structural Equation Model (SEM) is employed to find the factors that affect people's BI towards AVs using the conceptual framework described in Figure 4.5. SEM is commonly used in psychology, biological sciences, transportation, business, and environment to unveil complex relationships between dependent and independent variables by introducing mediators (Bayard & Jolly, 2007; Irfan et al., 2020; Janggu et al., 2014). As a powerful multivariate modeling technique, SEM combines various statistical tools such as regression, factor analysis, and path analysis (Shen et al., 2016; Wang et al., 2016). The main strengths of SEM include (1) the modeling of intervening indirect effects of explanatory variables on response variables, (2) the estimation of total effects in addition to direct and indirect effects, (3) estimation of the relationship between latent constructs and their manifest factors, and (4) correcting measurement error in all observed variables (Rahman et al., 2021; Van Acker et al., 2007). Moreover, SEM shows existing concepts in a structural model to estimate the relationships.

Based on Exploratory Factor Analysis (EFA) and existing concepts, eight latent constructs are generated based on observed variables. A Confirmatory Factor Analysis (CFA) is used to validate the model grounded on EFA and extant theories. Finally, the relationships between the dependent, mediator, and independent variables is estimated conducting a path analysis after controlling for socioeconomic features. A maximum likelihood estimator is used for estimating coefficients. Several fit indices (e.g., chi-square, RMSEA, SRMR, CFI, TLI) are used to verify the goodness-of-fit of the calibrated model. The model is calibrated with MPlus Version 7.4 (Muthén & Muthén, 2017). The Weighted Least Squares Means and Variance Adjusted Estimators (WLSMV) approach is used to estimate the model given the ordinal nature of the dependent variable.

4. Results

4.1. Calibrated model

The complete structure of the calibrated model based on the CFA and path analysis is given in Figure 4.6. Some non-significant associations between latent constructs and outcome variables were excluded to achieve a robust model. The final specification of the model consists of interactions between explanatory and response variables through some mediators. As indicated in Figure 4.6, the rectangles represent the observed variables and circles indicate latent dimensions. It is worth mentioning that I also included some important factors of the built environment (e.g., activity density, workers per household, percent of high wage workers, jobs within 45 minutes auto travel time), transportation factors travel behavior (e.g., gas price, percentage of workers who choose public transport to work), technological factor (e.g., experience of solar panel), and socioeconomic factors (e.g., per capita gross domestic product, household size) in the base model. However, I dropped these variables during model calibration to achieve the best-fit final model. Several variables (e.g., population and employment density, land-use diversity, VMT, share of registered democrat supporters, per capita income) are long-transformed to linearize the relationships captured in the model.

The overall fit of the calibrated model is assessed on the basis of several fit indices (Table 4.5). All indices are within the acceptable range and thus satisfy the model requirements and confirm the model validity (Hu & Bentler, 1999; MacCallum et al., 1996; Rahman et al., 2020; Rahman et al., 2021).

Table 4.5: Goodness-of-fit indices of the calibrated model

Indices	Recommended value	Value
Chi-Square	Lower values suggest better fit	8181.73
TLI (Tucker Lewis Index)	0 to 1, 1 implies perfect fit	0.80
CFI (Comparative Fit Index)	0 to 1, 1 implies perfect fit	0.82
RMSEA (Root Mean Square Error of Approximation)	<0.05 indicates very good fit (threshold level is 0.10)	0.07
SRMR (Standardized Root Mean Square Residual)	<0.08 is generally considered a good fit	0.07

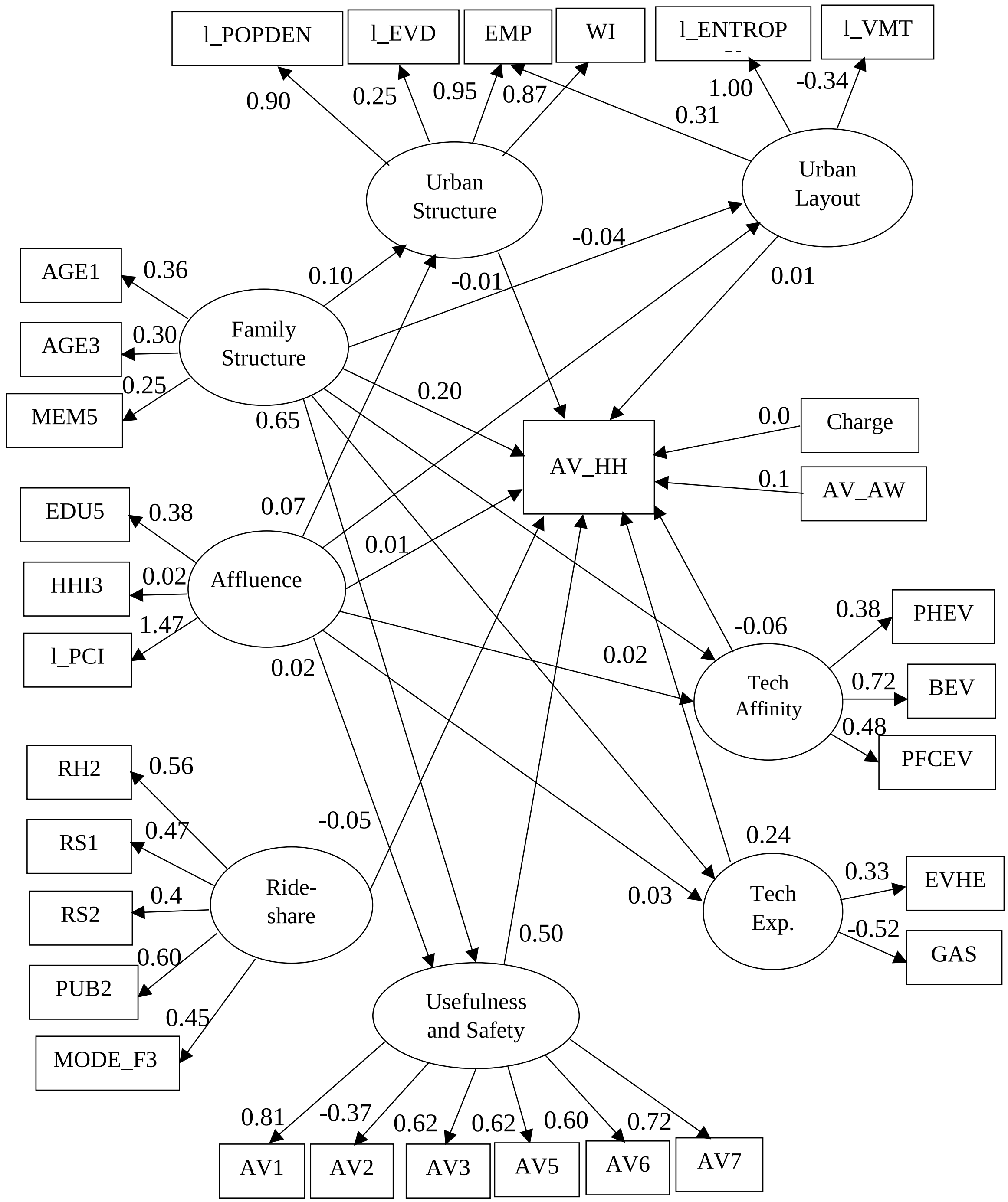

Figure 4.6: Calibrated model with direct standardized effects

4.2 Standardized direct effects on the intention to purchase AVs

The standardized coefficients of the calibrated SEM and the direction of modeled direct effects are given in Table 4.6. These coefficients indicate the direct connections between and among explanatory variables, response variables, and latent dimensions.

Most interactions are significant at the P-value of 0.00, 0.01, or 0.05. However, some of the interactions with a P-value larger than 0.05 are kept to better understand the model and demonstrate a complete relationship.

Table 4.6: Estimated standardized direct effects (N = 4,248)

Relationship between observed/estimated variables and latent factors			Estimate	Z	P
AGE1	←	Family Structure	0.36	16.85	0.00
AGE3	←	Family Structure	0.30	14.51	0.00
MEM5	←	Family Structure	0.25	12.09	0.00
l_POPDEN	←	Urban Structure	0.90	239.03	0.00
l_EVD	←	Urban Structure	0.25	16.77	0.00
EMP	←	Urban Structure	0.95	245.37	0.00
WI	←	Urban Structure	0.87	197.94	0.00
AV1	←	Usefulness and Safety	0.81	108.04	0.00
AV2	←	Usefulness and Safety	-0.37	-25.12	0.00
AV3	←	Usefulness and Safety	0.62	57.56	0.00
AV5	←	Usefulness and Safety	0.62	56.04	0.00
AV6	←	Usefulness and Safety	0.60	52.31	0.00
AV7	←	Usefulness and Safety	0.72	79.68	0.00
EDU5	←	Affluence	0.38	21.89	0.00
HHI3	←	Affluence	0.02	2.19	0.03
l_PCI	←	Affluence	1.47	33.07	0.00
RH2	←	Ride-share	0.56	34.77	0.00
RS1	←	Ride-share	0.47	28.19	0.00
RS2	←	Ride-share	0.42	24.62	0.00
PUB2	←	Ride-share	0.60	36.87	0.00
MODE_F3	←	Ride-share	0.45	25.94	0.00
PHEV	←	Tech Affinity	0.38	21.51	0.00
BEV	←	Tech Affinity	0.72	41.09	0.00
PFCEV	←	Tech Affinity	0.48	28.78	0.00
l_D2A	←	Urban Layout	1.00	207.01	0.00
l_VMT	←	Urban Layout	-0.34	-23.06	0.00
EMP	←	Urban Layout	0.31	44.30	0.00
EVHE	←	Tech Experience	0.33	15.14	0.00
GAS	←	Tech Experience	-0.52	-17.91	0.00
Urban Structure	←	Family Structure	0.10	4.65	0.00
Urban Structure	←	Affluence	0.07	5.44	0.00
Urban Layout	←	Family Structure	-0.04	-2.80	0.01
Urban Layout	←	Affluence	-0.57	-28.19	0.00
Usefulness and Safety	←	Family Structure	0.65	31.18	0.00
Usefulness and Safety	←	Affluence	0.02	1.82	0.07
Tech Affinity	←	Family Structure	0.61	24.47	0.00
Tech Affinity	←	Affluence	0.02	2.09	0.04

Tech Experience	←	Family Structure	0.47	11.03	0.00
Tech Experience	←	Affluence	0.03	2.22	0.03
AV_HH	←	Family Structure	0.20	3.36	0.00
AV_HH	←	Urban Structure	-0.01	-1.12	0.27
AV_HH	←	Usefulness and Safety	0.50	17.02	0.00
AV_HH	←	Affluence	0.01	0.95	0.35
AV_HH	←	Ride-share	-0.05	-2.12	0.03
AV_HH	←	Tech Affinity	-0.06	-1.39	0.16
AV_HH	←	Urban Layout	0.01	1.02	0.31
AV_HH	←	Tech Experience	0.24	5.42	0.00
AV_HH	←	AV_AW	0.11	9.11	0.00
AV_HH	←	CHARGE	0.02	1.79	0.07

Eight latent dimensions are generated based on observed variables:

1) Family Structure: AGE1, AGE3, and MEM5
2) Affluence: EDU5, HHI3, and l_PCI
3) Ride-share: RH2, RS1, RS2, PUB2, and MODE_F3
4) Urban Structure: l_POPDEN, l_EVD, EMP, and WI
5) Urban Layout: l_ENTROPY and l_VMT
6) Perceived Usefulness and Safety: AV_1, AV_2, AV_3, AV_5, AV_6, AV_7
7) Tech Affinity: PHEV, BEV, and PFCEV
8) Tech Experience: EVHE and GAS

I now proceed to discuss the estimated relationships between observed or estimated independent variables and each of the latent dimensions in the model successively.

Family Structure: This exogeneous latent dimension represents the demographic structure of the household and is developed by AGE1, AGE3, and MEM5. As reported in Table 4.6, this latent dimension has a positive association with AV_HH (0.20), after accounting for other factors, which indicates that households with more working-age adults and children are likely to purchase AVs. Their motivations to purchase AVs are grounded in state and federal incentives (e.g. price rebate, tax reduction, and subsidy), research and development, conducive traffic regulations, and infrastructure, in addition to affinity to advanced technologies. The study also finds that family structure is positively associated with the perceived usefulness and safety of AVs, tech affinity, and tech experience. Households with working adults and children lean towards advanced technology and have experience with advanced transportation modes (e.g., EVs), and hence they value the convenience, usefulness, and safety features of AVs (Nordhoff et al., 2020; Piao et al., 2016; Webb et al., 2019).

Affluence: This exogeneous latent factor denotes the prosperity of the household at the study context and is generated from three observed variables: EDU5, HHI3, and l_PCI. It is positively associated with AV_HH (0.01), which indicates that people living in areas with high household and per capita income, and having a higher number of people holding a bachelor's degree or higher education are likely to purchase AVs, which resonates the findings from the previous literature (Bansal et al., 2016; Daziano et al., 2017; Rahimi et al., 2020). However, the relationship is statistically insignificant (P-value: 0.35). Affluence is also positively associated with the perceived usefulness and safety of AVs, tech affinity, and tech experience. Thus, prosperity in the household motivates people to adopt and experience advanced transportation options and thereby value the convenience, usefulness, and safety features of AVs despite high purchasing and operating prices. However, family composition has significant effects on influencing AV purchase intentions of the households compared to their affluence.

Ride-share: This latent dimension represents the availability and use of public transportation and shared mobility options (i.e., ride-hailing and ride-sharing) in the local area. The ride-share latent dimension is developed based on five observed variables: RH2, RS1, RS2, PUB2, and MODE_F3. As indicated in Table 4.6, shared mobility is characterized by the availability and use of public transportation (e.g., bus, light rail/tram/subway, and commuter train), ride-hailing services (e.g., Taxi, Uber/Lyft, Uberpool/Lyftline), and ride-sharing services (e.g., bike-share, Car2Go, ZipCar, Jump). SEM results (Figure 4.6) show that ride-share has a direct significant negative effect on AV_HH (-0.05). Thus, people who have ride-share mobility options in their localities and use them for daily travel purposes are unlikely to purchase personal AVs. The calibrated model explains that a one-unit increase in ride-sharing services significantly reduces people's AV purchase intentions by 0.05 unit, other things being equal. However, they could be interested to use shared AVs (SAVs) motivated by multimodal travel behaviors, by willingness to share vehicles with fellow riders, and by concerns for reducing environmental degradation and transportation costs (Gurumurthy & Kockelman, 2020; Krueger et al., 2016; Nazari et al., 2018).

Urban Structure: This endogenous latent dimension represents the patterns of the built environment in the study context. It is comprised of four calculated variables: l_POPDEN, l_EVD, EMP, and WI. The urban structure in California is characterized by high population and employment density, walkability, and a higher share of democrat supporters (Table 4.6). The calibrated model in Figure 4.6 shows that urban structure has a negative effect on AV_HH (-0.01), which indicates that people who live in urban areas with high population and employment density, walkability, and democrat supporters are unlikely to purchase AVs. The availability of good quality public transportation and ride-sharing services in the urban context discourage people to purchase personal AVs. Moreover, they could adopt SAVs. However, the effect of urban structure on people's intention to purchase personal AVs is minimal and statistically insignificant (P-value: 0.27). Thus, the urban structure has very little effect to determine household's AV purchase intention. AVs would ensure convenience to the riders by providing then multitasking opportunities (i.e., people can work, talk with family and friends, and take a rest). Thus, because they would be in a better position to benefit from the advantages, people who live far from their workplaces would more likely purchase AVs compared to people who live in urban areas. Consequently, AVs have the potential to increase urban sprawl (González-González et al., 2019; Meyer et al., 2017).

Urban Layout: This endogenous latent dimension also represents the built environment of the study context. It is developed based on two calculated variables: l_ENTROPY and l_VMT. SEM estimation shows (Table 4.6) that the urban layout is positively associated with mixed land use and negatively associated with vehicle miles travelled. Thus, urban layout in the study context is distinguished by mixed land uses and low travel distance. Figure 4.6 indicates that urban layout is positively associated with AV_HH (0.01), which indicates that people who live in a neighborhood with a diversity of land uses and low travel distance are likely to purchase AVs, which is in agreement with the extant literature (Laidlaw et al., 2018a; Nazari et al., 2018). However, the association is statistically insignificant with a P-value of 0.31. Thus, this factor of the built environment has little effect to determine people's AV purchase intention.

Perceived Usefulness and Safety: This endogenous factor is developed by AV1, AV2, AV3, AV5, AV6, AV7. This is the only latent dimension that encompasses various features (e.g., convenience, usefulness, safety) of AVs. From the results reported in Table 4.6, I find that people enjoy traveling (i.e., watch scenery), make use of time by doing work or taking a rest, and accept longer travel time to ensure the safety of pedestrians and bicyclists when traveling by AVs. On the other hand, people would miss the joy of driving. Figure 4.6 reveals that perceived usefulness and safety are positively associated with AV_HH (0.50). Thus, perceived enjoyment and usefulness (e.g., work, talking on the phone, reading, taking a rest) significantly influence the BI of people to purchase AVs. Similarly, perceived lower risk for pedestrians, bicyclists, kids, and themselves due to the low speed of AVs influence people to purchase AVs. On the other hand, fear of losing control of vehicles discourages people to purchase AVs. Thus, those who enjoy driving are less likely to purchase an AV. The higher magnitude of the effect of perceived usefulness and safety indicates that this latent dimension has a greater role in deciding people's BI to purchase AVs compared to socioeconomic features, and the factors of transportation and of the built environment. The study findings are also supported by the literature (Kaye et al., 2020; Rahman et al., 2017; Yuen et al., 2020b).

Tech Affinity: This endogenous latent dimension is created based on three observed variables: PHEV, BEV, and PFCEV. As explained in Table 4.6, this latent dimension is positively associated with the willingness of the respondents to consider PHEV, BEV, and PFCEV in their future purchase. Tech affinity is negatively associated with AV_HH (-0.06) which contradicts the extant literature (Rahimi et al., 2020; S. Wang et al., 2020). This finding indicates that despite a higher tendency to use technology, many people would wait and observe the trend of AV adoption before going to purchase this new technology due to risks and uncertainty associated with AVs (Zmud & Sener, 2017). However, the association between tech affinity and AV_HH is not statistically significant (P-value: 0.16).

Tech Experience: This endogenous factor is developed from two EVHE and GAS. It illustrates the previous experience of a household with owning or leasing an electric or hydrogen cell vehicle (e.g., HEV, PHEV, BEV, and FCV) and future intention to purchase gasoline vehicles. Table 4.6 indicates that tech experience is positively associated with AV_HH (0.24). Assuming everything is held equal, a one-unit increase in tech experience increases people's BI to purchase AVs by 0.24 unit. People who have real experience with EVs and vehicles equipped with smart technologies (e.g., automated speed control, braking and parking, collision warning, blind-spot detection, lane changing warning) are more interested to purchase AVs compared to conventional gasoline vehicles (Chen, 2019; Shin et al., 2015). Thus, vehicles equipped with improved services for people and ensuring safety, security, and personal privacy significantly motivate people to adoption and use AVs (Daziano et al., 2017; Rahimi et al., 2020). Figure 4.6 also indicates that people's familiarity with AVs (AV_AW) is positively associated with people's BI to purchase AVs (0.11). The people who have prior knowledge about AVs are more likely to purchase and use AVs compared to the people who have little knowledge or never heard of AVs. In the survey, 57.33% of respondents heard about AVs; hence it is assumed that these people would be the first to purchase and use AVs. Thus, prior knowledge about AVs is considered as one of the main factors that would influence people towards AVs, as mentioned in previous studies (Daziano et al., 2017; Feys et al., 2020; Laidlaw et al., 2018b). Similarly, the EV charging station at the workplace is positively associated with AV_HH (0.02). Thus, people who have access to an EV charging station at their work place are more likely to purchase and use AVs compared to their counterparts.

4.3 Standardized total effects on the intention to purchase AVs

For a full account of the reasons, the total effects of latent dimensions on people's AV purchase intentions considering both direct and indirect effects are presented in Table 4.7, which are not explicitly mentioned in Figure 4.6.

Table 4.7: Standardized total (direct and indirect) effects of latent factors on AV purchase

Effects of latent factors on AV purchase			Direct	Indirect	Total
AV_HH	←	Family Structure	0.202	0.401	0.603
AV_HH	←	Affluence	0.006	0.005	0.011

As specified by the calibrated model (Figure 4.6), family structure and affluence are the only two latent factors that have indirect effects on people's intention to purchase AVs by mediating urban structure, urban layout, tech affinity, tech experience, and usefulness and safety of AVs. Considering both direct and indirect effects, family structure has a total effect of 0.603 on people's AV purchase intentions. Households with working adults and children are the first to purchase and use AVs due to their experience and affinity to advanced technologies, convenience, usefulness and improved safety features of AVs, and neighborhood selection. Similarly, affluence has a total effect of 0.011 consisting of direct (0.006) and indirect (0.005) effects. Better economic conditions and higher education attainment in the study context increase the affordability of AV purchase. However, the magnitude of the effect is rather minimal. After accounting for a number of built environment attributes, other socioeconomic features, and transportation factors, the family structure remains the most influential factor of AV purchase intention of households. Thus, the family structure comprising of adults and children is the key consideration in households' intention to purchase AVs.

5. Discussion

The study shows that many people are already aware of AVs and of services provided by AVs, which is vital to increase the market share of AVs. A considerable number of people also think that traveling by AVs is enjoyable, safe, and effective, although some would not send an empty AV to drop-off or pick-up their children due to insecurity and uncertainty. Regardless of personal preference for driving, many people are interested to purchase AVs when they will be available to the public. Additionally, the California state government has already introduced regulations to test and operate AVs. Thus, considering the enormous possibilities and favorable institutional supports, many people would purchase and use AVs in California. However, adequate measures (e.g., easy to operate and navigate, onboard driver, sharing option, incentives, a collaboration between state agency, tech, and automobile companies) need to be taken to motivate people to adopt and use AVs (Bazilinskyy et al., 2015; Feys et al., 2020; S. Wang et al., 2020).

Results from the SEM indicate that households with more working-age adults and children are likely to purchase personal AVs. Similarly, people living in areas with higher household and per capita income, and people with higher educational attainment are positively associated with AVs purchase intention. Considering both direct and indirect effects, family structure and affluence of the study context also influence AV purchase of the household by interceding urban structure, urban layout, tech affinity and experience, and usefulness and safety of AVs. However, the family composition has significant effects on AV purchase intention than affluence. The results also show that the family structure remains the most influential factor after accounting for the built environment, other socioeconomic features, and transportation factors. Thus, the family structure is the key consideration in households' intention to purchase AVs. Overall, the study supports the hypotheses that younger people, working-age adults, households with children, education attainment, and high household income are positively associated with BI to purchase AVs (Hypotheses 1, 2, and 3).

I also observed that people who are interested in public transportation, ride-hailing, and ride-sharing services and use them for daily travel purposes are unlikely to purchase AVs, which supports our hypotheses 4 and 5. However, these people demonstrate an interest in adopting SAVs for their daily commuting. Thus, appropriate initiatives should be implemented by transit agencies and other transport providers (i.e., Transport network companies) to provide SAVs for people who are driven to protect the environment and to ensure sustainable urban form and transportation compared to private AVs (Narayanan et al., 2020; Sparrow & Howard, 2017). SAVs integrating with public transit could solve the last-mile problem and increase transit ridership and reduce transportation costs (Moorthy et al., 2017; Sparrow & Howard, 2017). Thus, SAVs should be introduced at large to realize the benefits of AVs and eventually encourage people to have an AV which will be shared by all household members.

Similarly, people who live in urban areas with high population and employment density, walkability, and democrat supporters are unlikely to purchase personal AVs due to better access to public and shared transportation and consciousness to reduce emissions. However, mixed land use and vehicle travel distance encourage private AVs purchase. These findings lend support to hypothesis 7 but not to hypotheses 6 and 8. However, the convenience features of AVs (e.g., take rest, sleep, enjoy the scenery) may encourage people to live far from their workplaces. Thus, private AVs have the potentials to increase urban sprawl (González-González et al., 2019; Meyer et al., 2017). Thus, it is essential for the policymakers to understand the potential effects of private AVs and formulate policies to protect the urban living and the environment.

Different psychological factors such as perceived enjoyment, usefulness, and safety significantly influence people's BI to purchase AVs. In contrast, people who enjoy driving are less likely to purchase an AV by fear of losing control of the vehicle. Overall, the latent dimension representing people's psychological understanding have the greatest direct effect on AV purchase intention compared to socioeconomic features, and the factors of transportation and the built environment. The study also observes that the people who have prior knowledge about AVs would be the first to purchase and use AVs compared to the people who have little knowledge or never heard of AVs. These findings support hypotheses 9, 10, and 11.

The study demonstrates that in spite of a higher affinity to technology, many people would wait and observe the trend of AV adoption before going to purchase this novel technology. However, according to many scholars Americans would be the first adopters of AVs when they will be available on the road for person use. The study also observes that people who have experience with EVs, FCEVs, and advanced safety equipment (e.g., emergency braking, parking assistance, collision warning, blind-spot detection) are more interested to purchase AVs, which supports hypotheses 12 and 13. Moreover, the structure and affluence of the family affect the tech affinity and experience of the household, which conforms with hypothesis 14.

6. Conclusions and future research agenda

This study significantly contributes to the literature by empirically investigating public perceptions and opinions on AVs and the salient determinants of households' AV purchase intentions. The study findings can advise transportation agencies, professionals, stakeholders, and AV developers to formulate pertinent policy guidelines for designing and implementing AVs (Zou et al., 2022). Since many people are already aware of the usefulness and convenience of AVs, some effective measures could further increase people's willingness to use AVs. For example, the availability of adequate low-cost SAVs can provide hands-on experience to the people to assess anticipated benefits of AVs and consequently motivate people to adopt and use AVs (Bansal et al., 2016; Nazari et al., 2018). Different ride-hailing and ride-sharing companies could be the pioneer to launch SAVs and let the people gain real-world experience of this efficient and novel transportation mode.

Despite this, the strengths of this study are shattered by some cautionary limitations. These limitations are the results of the unavailability of AVs in the real-world, the lack of consistent results in previous studies, flawed study design and methodologies, and inadequate data collection, which have the potential to affect the findings of this study. However, careful considerations are undertaken to minimize the effects of the study limitations. The following research constraints are encountered in this study and pertinent research agenda are proposed:

1) It is perceived that there is a lack of consistency in study results concerning people's perceptions and opinions and the key determinants of AVs. Thus, comparing our results with previous studies to validate the study findings could be biased and

unsalable. Future study should select sample population from different states of the US to check consistency in the model results.

2) Despite a considerable large sample size (i.e., 4,248 people), the views from the respondents are confined within the Californian geographic regions which could vary in other geographic regions (e.g., other states, countries). Moreover, California as a place for international migrants hosts a large number of respondents from diverse cultural and socioeconomic backgrounds. Thus, transferability and generalization of the study findings to other study regions is challenging and limited. However, researchers could replicate this study in other states and compare the results to check robustness of the model.
3) To estimate the effects of urban form on AV purchase and use, I used data aggregated at the county level which is a coarse geographic unit. Thus, a finer granularity in the geographic unit should be used in future studies to get additional insights.
4) The dependent variable of the study represents household's intention to purchase AV and does not reflect responses of the individual family members. Thus, it is yet to fully capture the personal preference within the household to purchase and use AVs (Wali et al., 2021).
5) This study primarily investigates the factors affecting household intention to purchase personal AVs. However, considering people's use of public transportation and interest in shared mobility options (e.g., carshare, bikeshare, ride-sourcing), a study should be conducted to find out the factors that influence the AV share tendency of people.

6) Impacts of different opportunities (e.g., low congestion, emission) and challenges (e.g., legal aspect, breach of privacy, system failure) related to AVs, and institutional arrangement (e.g., incentives, regulations) are not evaluated, which requires further investigation.

7) It is documented that AVs would increase the mobility of the elderly, children, and disabled persons. However, a study investigating AV adoption disparities among different income and racial groups is necessary to ensure justice and equity in transportation.

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CHAPTER 5: DETERMINANTS OF SHARED AUTONOMOUS VEHICLES: EMPIRICAL EVIDENCE FROM CALIFORNIA

Abstract

The study investigates people's perceptions of Shared Autonomous Vehicles (SAVs) and the key determinants of household intentions to use SAVs using a structural equation modeling framework. Data were sourced from the 2019 California Vehicle survey to estimate the complex association between dependent and independent variables via mediators. Results indicate that higher educational attainment, income, labor force participation, Asian population origin, and urban living are negatively associated with SAVs. In contrast, young and working-age adults are positively associated with SAVs. Study results also show that people who prefer public transportation, car-sharing, ride-hailing, and ride-sharing services are more likely to use SAVs. The perceived usefulness, enjoyment, safety associated with Autonomous Vehicles (AVs) and prior knowledge of AVs significantly influence people to use SAVs, while the enjoyment of driving and the fear of losing control of vehicles are dissuasive factors. The study concludes that people's travel behaviors, positive attitude to shared mobility, and psychological features of AVs are the key determinants of SAVs.

Keywords: Shared Autonomous Vehicle, Public Acceptance, Theory of Planned Behavior, Theory of Reasoned Action, Technology Acceptance Model, Structural Equation Modelling

1. Introduction

The emergence of smartphones and the social, economic, and environmental impacts of automobiles motivate people to use shared mobility options. New shared mobility options, such as car-sharing, ride-sourcing, and certain micro-mobility services, allow people to rent vehicles for the short-term and enjoy mobility as a service (Hu & Creutzig, 2022; Machado et al., 2018). It has been argued that shared mobility would efficiently manage people's travel demand by increasing the occupancy of vehicles and thereby reduce traffic congestion, energy use, and emissions (Chan & Shaheen, 2012; Hu & Creutzig, 2022). The usefulness of shared mobility can be further enhanced by integrating Autonomous Vehicles (AV) technologies and developing Shared AVs (SAVs) services. This new business model would provide low-cost driverless and on-demand mobility services, increase vehicle efficiency, reduce congestion and emissions, facilitate multimodality, and ensure clean and sustainable transportation (Fagnant & Kockelman, 2018; Golbabaei et al., 2021).

SAVs can be seen as disruptive as they may transform people's lifestyle and travel patterns, transportation systems, and natural and built environments. Given the evolving socio-technical system of SAVs, how people would respond remains unsettled, while transport professionals and local public authorities are working at scoping adjustments to regulatory frameworks and infrastructures for SAVs (McKenzie, 2020). To the best of our knowledge, only a few studies have investigated public attitudes towards SAVs and the factors that may lead people to use SAVs. These studies tend to fall short, however, owing to a variety of reasons, including their use of hypothetical stated choice experiments and low sample sizes (Krueger et al., 2016). Nonetheless, people's willingness to accept this new technology is key to higher use of SAVs and to having them realize their potential benefits (Mara & Meyer, 2022; Paddeu et al., 2020). Realizing the importance of public perceptions and advancing the extant literature, this study investigates the key determinants of people's Behavioral Intentions (BI) to use SAVs for daily travel purposes. To this end, the following research questions are used:

1) How would people's socioeconomic and demographic characteristics influence them to use SAVs for their travel purposes?
2) How would awareness, perceived convenience, comfort, and safety influence the tendency of people to use SAVs?
3) How would factors of the built environment, transportation, and technology influence people to use SAVs for meeting their travel demands?

The rest of the paper is organized as follows: Section Two summarizes the relevant literature, introduces research hypotheses, and explains the theoretical framework of the study. The research design is outlined in Section Three. The main results of the study are reported in Section Four. Section Five articulates the discussion of these empirical results. Conclusions are drawn in Section Six.

2. Literature review and theoretical framework

2.1 Findings from past studies

SAVs are the convergence of shared mobility, AV technologies, smartphone services, and electrification; they are considered one of the most disruptive innovations of modern technological advances (Golbabaei et al., 2021; Stocker & Shaheen, 2018). SAVs can be shared exclusively by a travel party or simultaneously by multiple travel parties (Paddeu et al., 2020). Although shared mobility has been extensively studied, understanding the characteristics of potential SAV users and identifying the potential opportunities and challenges of SAV adoption have drawn attention recently only. These studies have mainly investigated consumer preferences for SAVs, operational mechanisms, and the effect of SAVs on vehicle ownership and last-mile travel (Maeng & Cho, 2022; Menon et al., 2018; Moorthy et al., 2017).

Extant research has found that male, young and working-age individuals, students and part-time workers, higher educational attainment, and black individuals are positively disposed towards SAVs (Barbour et al., 2019; Cartenì, 2020; Zhou et al., 2020). In contrast, the elderly, people with high income, households with children and a higher number of workers, single individuals, and full-time employees would be less likely to use SAVs (Hao et al., 2019; Krueger et al., 2016; Lavieri & Bhat, 2019). Although high income people and single individuals are unwilling to use SAVs, they are more inclined to use private SAVs (Gurumurthy & Kockelman, 2020; Lavieri & Bhat, 2019; Wang et al., 2020). Additionally, the elderly who aspire to engage in more social activities and have limited capability to travel are more interested to use SAVs (Hao et al., 2019). Thus, travelers' socioeconomic and demographic factors significantly influence their behavioral intentions to use SAV for travel purposes.

Researchers have found that individuals with inclination towards transit and multimodal travel, and with carsharing tendencies, those traveling by car as a passenger, and without a driver's license are more likely to use SAVs due to their pro-environment quality, their innovation content, convenience, and scopes for social interactions (Asgari et al., 2018; Lavieri & Bhat, 2019; Zhou et al., 2020). In contrast, the tendency to travel alone and higher vehicle ownership are negatively associated with SAVs (Hao et al., 2019; Lavieri et al., 2017). Previous studies also found that people are more likely to use SAVs for long distance business trips (Gurumurthy & Kockelman, 2020) and less likely to use them for recreational/leisure trips (Lavieri & Bhat, 2019). Therefore, people's previous and current travel behaviors could describe their intentions to use SAVs.

Breach of privacy, personal safety concerns, legal issues, insurance liabilities, and additional travel time for servicing other passengers could be major barriers to use SAVs (Asgari et al., 2018; Cartenì, 2020; Merfeld et al., 2019). Despite open-minded attitudes to accept AVs, many people are still reluctant to use AVs without a driver or share AVs with strangers (Wang et al., 2020). However, productive use of travel time and prior criminal background check could overcome this barrier. Researchers also found that perceived performance (i.e., the capacity of services, on time service, time saving, low congestion and emission), perceived ease of use, compatibility with novel technology, cost-effectiveness, hedonic motivation (i.e., fun, enjoyable, and pleasant), perceived norm (i.e., the influence of friends, availability on roads), and perceived behavioral control (i.e., knowledge, skill, time, money, preference) positively influence people's behavioral intentions to use SAVs (Hao et al., 2019; Merfeld et al., 2019; Wang et al., 2020). Tech-savviness, prior knowledge and use of advanced technology (e.g., automated braking, lane and parking assistance), higher level of vehicle autonomy, enabling mobility for physically impaired individuals, and appropriate legal clarity (i.e., accident liability lies with service providers) could increase people's tendency to use SAVs (Cartenì, 2020; Lavieri et al., 2017; Maeng & Cho, 2022). Additionally, prior involvement in traffic crashes increases people's willingness to use SAVs (Barbour et al., 2019). So, psychological factors have major roles to motivate people to use SAVs. However, researchers also reported that people who use SAVs are less concerned about safety, security, privacy, reliability, travel time, and costs (Barbour et al., 2019).

Research has found that social acceptability is the key to increasing SAV use (Paddeu et al., 2020). In this respect, critical components include improved mobility, accessibility and safety, reduction in environmental impacts, and ensuring social equity with regards to race, ethnicity, age, and disability status. Thus, given that the public rollout of SAV services are still in the design and planning stage, they may be well positioned to overcome the deficiencies of other travel modes.

People who live in urban areas are more likely to use SAVs compared to people who live in rural and less urban settings (Lavieri & Bhat, 2019; Merfeld et al., 2019). Researchers have also mentioned that demand for SAVs would be higher in megacities where facilities for vehicle parking are limited (Merfeld et al., 2019). Thus, considering the context of urbanization, privately owned AVs are more feasible in rural or suburban areas and SAVs are practical in urban areas (Merfeld et al., 2019). Although Wang et al. (2020) observed no significant impact of geographic location, they indicated that the availability of parking space at home or near residence significantly influences the propensity to share or own an AV. Barbour et al. (2019) noticed higher use of SAVs among the individuals who live close to grocery stores. Etminani-Ghasrodashti et al. (2021) explained that a supportive built environment (i.e., access to sidewalks, ramps, and curb cuts in pick-up and drop-off points) increases SAV use by the people with disabilities. The extant literature explains that, besides socioeconomic, transportation, psychological and social aspects, the factors of the built environment have a significant role to determine people's BI to use SAVs.

2.2 Theoretical framework

Adjei and Behrens (2012) have categorized the existing theories of human behavior for choosing among discrete alternatives based on the following questions:

- How choices are made from different alternatives (e.g., rational choice theory)?
- What factors affect the choice for an alternative (e.g., theory of planned behavior)?
- When does behavior change occur (e.g., cognitive theory)? and
- How do decision makers respond to behavioral change interventions (e.g., self-perception theory)?

These theories explain that people's behaviors respond to both internal factors --such as attitudes and norms-- and other external factors --such as incentives, institutional constraints (Adjei & Behrens, 2012). Among them, the Theory of Reasoned Action (TRA) is widely recognized in social psychology to explore the core determinants of people's BI towards an action (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1977; Madden et al., 1992). The central concept of the TRA is that people's BI for a specific action is jointly determined by individual's positive or negative attitudes and by subjective norms that indicate the influence of other people on behavioral action.

Some studies have used the Theory of Planned Behavior (TPB) to investigate the psychological factors that influence people's travel mode choices (Bamberg, 2006; Bamberg et al., 2003; Heath & Gifford, 2002). However, the surrounding built environment also influences travel behaviors. Consequently, Ajzen (1985) first introduced the TPB theory based on TRA to investigate the influence of external factors on behavioral actions.

The TPB explains that human behavior depends on the person's intention to take some action (Morris et al., 2012; The World Bank, 2007). Their intentions are influenced by attitudes, subjective norms, and perceived behavioral control measures (i.e., ability, opportunity, resources, skill).

The Technology Acceptance Model (TAM) is a widely used framework to understand how users accept and use a technology (Lee et al., 2003; Zhang et al., 2020). Davis (1985) initially proposed the TAM based on the TRA (Fisbein & Ajzen, 1975). According to the early TAM, users' attitude is the main factors to understand people's BI to accept or reject. However, Perceived Usefulness (PU) and Perceived Ease of Use (PEU) define user's Attitude Towards Technology (ATT) (Davis, 1985; Davis et al., 1989). ATT denotes the positive or negative feelings about the performance of a technology. PU is defined as the degree to which a technology can enhance the job performance of the users. In contrast, PEU is defined as the degree to which it can reduce overall, physical and mental effort of the users. The model also demonstrates that the external features indirectly influence the attitude and beliefs of the users by directly affecting PU and PEU. Although, the earlier version of TAM indicates that ATT is the main factor (Scherer et al., 2019), Davis (1989) argued that ATT is not an influencing factor, but rather PU and PEU have direct and positive effects on the intentions of individuals toward technology use (Rahman et al., 2017).

2.2.4 Theoretical framework of the BI to use SAVs

Based on the extant literature and core concepts of behavioral theories, a theoretical framework – Integrated Technology Acceptance Model (ITAM) – is developed to investigate the factors of people's BI to use SAVs. The proposed ITAM (Figure 5.1) features the behavioral control factors, objective factors, and people's attitudes towards AVs that influence the SAV use intention. It is aligned with the updated TAM.

According to the ITAM, human BI towards actual SAV use is directly influenced by behavioral control factors, objective factors, and psychological factors. Additionally, the model posits that the actual use of SAVs also depends on the availability of novel technology such as EV, solar panel and people's affinity towards new technologies. Besides direct effects, socioeconomic factors also have indirect effect on SAV use by moderating objective factors, psychological factors, and the affinity of the people towards a technology.

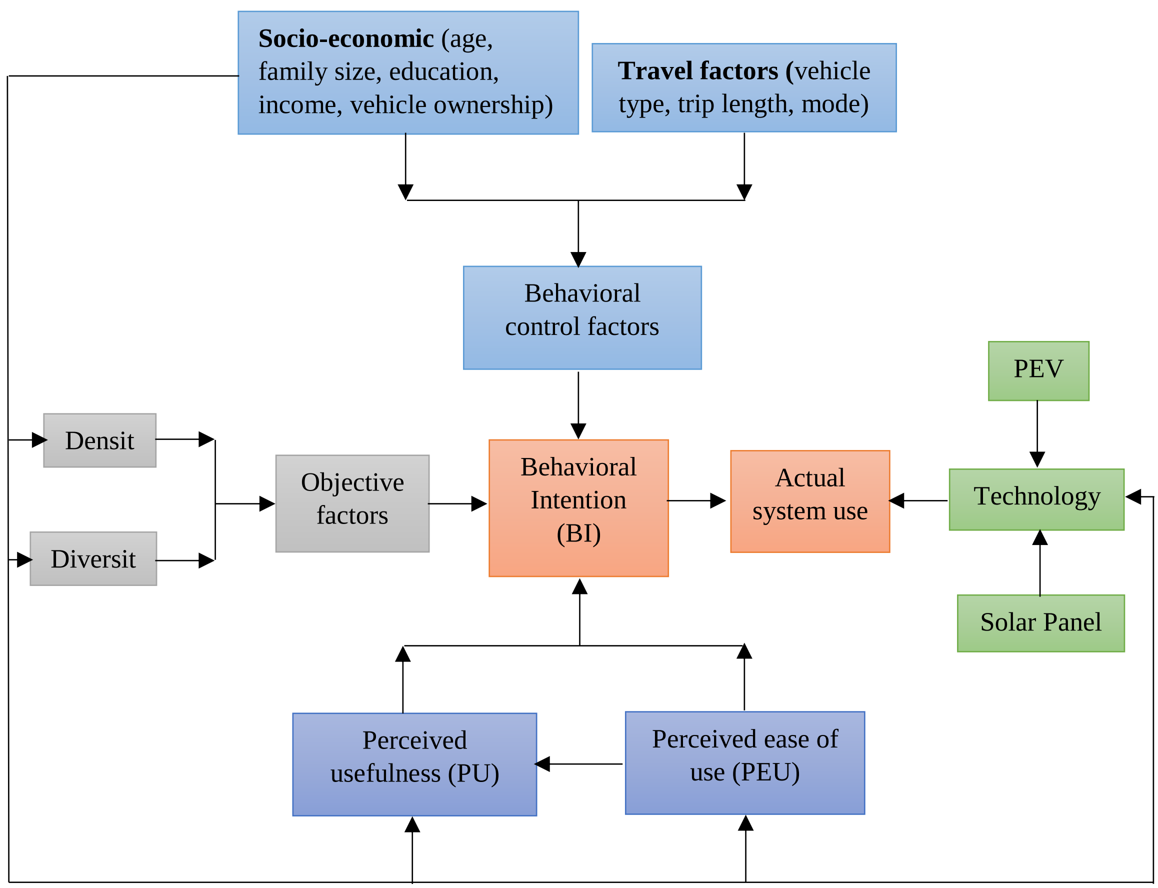

Figure 5.1: Integrated Technology Acceptance Model (ITAM)

The following hypotheses are formulated to address the research questions based on the extant literature and the conceptual framework of ITAM.

a) Socioeconomic and demographic factors

1) Young and working-age adults are positively associated with BI to use SAVs (Hypothesis 1).
2) Family households are negatively associated with BI to use SAVs (Hypothesis 2).
3) Education attainment is positively associated with BI to adopt SAVs (Hypothesis 3).
4) People with employment status and higher household income are less interested to use SAVs compared to their counterparts (Hypothesis 4).

b) The built environment

1) High population and employment density are positively associated with BI to use SAVs (Hypothesis 5).
2) Mixed land uses are positively associated with BI to use SAVs (Hypothesis 6).
3) Neighborhoods with a higher share of zero-vehicle households are more conducive to SAV use (Hypothesis 7).

c) Travel factors

1) People who drive alone to work are less likely to use SAVs (Hypothesis 8).
2) Preference for ride-hailing and ride-sharing services is positively associated with BI to adopt SAVs (Hypothesis 9).
3) People who prefer public transport for their daily travel purposes are more likely to use SAVs (Hypothesis 10).

d) Psychological factors associated with SAVs

1) Perceived usefulness, safety, and effectiveness are positively related to BI to use SAVs (Hypothesis 11).
2) People having familiarity with advanced automated technologies are more likely to use SAVs (Hypothesis 12).
3) Employment status, income, and education positively influence the psychological attributes of people to use SAVs (Hypothesis 13).

e) Technological development

1) Experience with alternative fuel vehicles (e.g., electric vehicles, hybrid electric vehicles, fuel cell vehicles) is positively associated with BI to use SAVs (Hypothesis 14).
2) Employment status, high income, and education level are positively related to the technological preference of people to adopt SAV (Hypothesis 15).

3. Research design

3.1 Data

To understand the factors that influence people's inclination to adopt SAVs as a transportation mode, this study uses data from the 2019 California Vehicle Survey conducted by the California Energy Commission (California Energy Commission, 2022; Transportation Secure Data Center, 2019). The main purposes of the survey were to assess transportation fuel needs and provide key policy guidelines for transportation planning in California. The survey assessed consumer preferences for light-duty vehicles (both personal and commercial) in the context of expanding autonomous and electric vehicle technologies. It collected economic and demographic data, vehicle information including vehicle and fuel types, and vehicle choice information using a stated preference approach. Moreover, charging behavior, electricity rates, and main motivations for purchasing EVs were collected from the EV owners. The survey instrument includes questions pertaining to perceptions, opinions, intentions, and motivations of people toward self-driving cars and ride-sharing facilities.

This study uses only the online-based residential survey portion of the data. It includes a total of 4,248 responses, which encompass 718 responses by EV owners. A stratified random sampling technique was used to collect data from six regions across the state: San Francisco, Sacramento, Central Valley, Los Angeles, San Diego, and the rest of the state. Households were selected randomly by address at the county level and invited to participate in the survey in such a way to ensure that samples are proportional to the population of each county.

Some data were also collected from the American Community Survey (US Census Bureau, 2018), Environmental Protection Agency (Environmental Protection Agency, 2020), and California State Association of Counties (California State Association of Counties, 2019). These county-level data were then combined with the 2019 California Vehicle Survey as measures of the socioeconomic and demographic environment of each respondent and of their built environment. Finally, the data were processed (i.e., missing value imputation with the median values, creation of new variables from the original data) and analyzed to test the research hypotheses. Detailed description of the variables used in the study is given in Table 5.1.

Table 5.1: Description of the variables

Variable	Variable Description	Measure	Source
Dependent variable			
AV_POOL	Unlikely to use shared driverless services with strangers	1 = Strongly agree, 2 = Somewhat agree, 3 = Somewhat disagree, and 4 = Strongly disagree	CVS
Independent variables			
AGE1	Age of the respondent between 18 and 64 years	1 = Yes, 0 = No	CVS
PHEV	Willingness to consider PHEV only vehicle	1 = Yes, 0 = No	CVS
BEV	Willingness to consider BEV only vehicle	1 = Yes, 0 = No	CVS
PFCEV	Willingness to consider PFCEV only vehicle	1 = Yes, 0 = No	CVS
PUB2	Use of public transportation (e.g., bus, light rail/tram/subway, and commuter train) for trips in the local area	1 = Yes, 0 = No	CVS
RH2	Use of ride-hailing services (e.g., Taxi, Uber/Lyft, Uberpool/Lyftline) for trips in the local area	1 = Yes, 0 = No	CVS
RS2	Use of ride-sharing services for trips in the local area	1 = Yes, 0 = No	CVS
AV_AW	Familiarity of the respondent with AVs	1 = Never heard, 2 = Heard but not familiar, 3 = heard and somewhat familiar, and 4 = heard and very familiar	CVS
AV1	AVs would enable the respondent to enjoy traveling more (e.g., watch the scenery, rest)	1 = Strongly disagree, 2 = Somewhat disagree, 3 = Somewhat agree, and 4 = Strongly agree	CVS
AV2	People would miss the joy of driving and be in control		CVS
AV3	People would accept longer travel times so the AV could drive at a low speed to prevent unsafe situations for pedestrians and bicyclists		CVS
AV5	People would reduce time at the regular workplace and work more in the AVs		CVS
AV6	People would send an empty AV to pick up/drop off their child		CVS
AV7	People would be able to travel more often even when they are tired, sleepy, or under the influence of alcohol/medications		CVS
RACE3	Asian population in the county	%	ACS
HHI2	Households with $25,000 to $49,999 income in past 12 months in the county	%	ACS
HHI5	Households with $100,000 and more income in past 12 months in the county	%	ACS
POPDEN	Population density in the county	People/km2	ACS
EDU5	Population 25 years and over with bachelor’s or above degree in the county	%	ACS
PCI	Per capita income in the past 12 months in the county	$	ACS
LF	Population 16 years and over in the labor force in the county	%	ACS
MHV	Median value of the occupied housing units in the county	$	ACS
MY	Median year of housing units in the county	Year	ACS
BR1	Housing units with no bedroom in the county	%	ACS
BR2	Housing units with 1 bedroom in the county	%	ACS
FHH	Family households in the county	%	ACS

HHS4	Family households of 5 and more persons in the county	%	ACS
MTW1	Workers 16 years and over who drive alone to work in the county	%	ACS
MTW2	Workers 16 years and over who choose to carpool to commute in the county	%	ACS
D1D	Gross activity density (employment + HUs) in the county	(emp.+HUs)/acre	EPA
R_PCT	Low wage workers in a CBG (home location) in 2017 in the county	%	EPA
PCT	Zero-car households in CBG in 2018 in the county	%	EPA
EVR	Registered Republican Voters in 2019 in the county	%	CSAC
GDP	Gross Domestic Product per capita in 2018 in the county	$/per capita	CSAC

PHEV = Plug-in Hybrid Electric Vehicle, BEV = Battery Electric vehicle, PFCEV = Plug-in Fuel Cell Electric Vehicle, CVS = 2019 California Vehicle Survey, ACS = American Community Survey, EPA = Environmental Protection Agency, and CSAC = California State Association of Counties.

Tables 5.2 and 5.3 report the characteristics of the respondents, households, and counties in California by outlying the descriptive statistics of dependent and independent variables used in model building. Asking their intentions to use SAVs, the survey found that about 34.40% and 32.60% of respondents are strongly unlikely and somewhat unlikely, respectively, to use SAVs for their daily travel. In contrast, about 10.50% and 22.60% of respondents are strongly and somewhat interested to use SAVs for their daily travel.

Table 5.2: Descriptive statistics of the variables (N= 4,248)

Variable	Minimum	Maximum	Mean	Std. Deviation
EDU5	12.05	58.79	34.98	10.06
RACE3	0.00	35.85	15.34	9.14
HHI2	11.57	28.83	18.22	3.66
HHI5	13.20	56.38	37.06	9.69
PCI	17,590.00	69,275.00	36,800.41	9,748.39
LF	35.12	73.08	63.85	3.50
MHV	133,300.00	1,009,500.00	551,136.55	199,935.60
MY	1942.00	1991.00	1973.10	9.08
FHH	47.87	79.90	68.62	4.92
BR1	0.90	14.92	4.15	2.47
BR2	5.47	25.81	13.67	4.47
HHS4	5.83	30.51	19.17	3.94
MTW1	32.94	81.81	73.59	7.81
MTW3	0.00	34.22	5.11	5.78
GDP	36,309.27	210,532.00	80,843.83	36,843.50
EVR	4.87	41.69	18.65	6.57
PCT	0.00	22.00	4.08	2.99
R_PCT	15.00	36.00	20.92	2.88

D1D	0.01	27.12	6.94	3.92
POPDEN	0.60	7066.04	741.81	1072.17

Table 5.3: People's socioeconomic features and opinions on technology and AVs (N= 4,248)

Variable	Measure	Percent
AGE1	No	34.70
	Yes	65.30
PHEV	No	53.15
	Yes	46.85
BEV	No	64.83
	Yes	35.17
PFCEV	No	86.42
	Yes	13.58
PUB2	No	64.74
	Yes	35.26
RH2	No	54.24
	Yes	45.76
RS2	No	92.75
	Yes	7.25
AV_AW	Never heard	4.47
	Heard but was not familiar	38.21
	Heard and somewhat familiar	43.06
	Heard and very familiar	14.27
AV1	Strongly disagree	22.72
	Somewhat disagree	19.33
	Somewhat agree	39.76
	Strongly agree	18.20
AV2	Strongly disagree	11.80
	Somewhat disagree	19.60
	Somewhat agree	37.30
	Strongly agree	31.40
AV3	Strongly disagree	23.73
	Somewhat disagree	23.07
	Somewhat agree	36.68
	Strongly agree	16.53
AV5	Strongly disagree	46.00
	Somewhat disagree	28.63
	Somewhat agree	19.87
	Strongly agree	5.51
AV6	Strongly disagree	61.06
	Somewhat disagree	19.11
	Somewhat agree	14.67
	Strongly agree	5.16
AV7	Strongly disagree	28.27
	Somewhat disagree	19.35
	Somewhat agree	35.19
	Strongly agree	17.18
AV_POOL	Strongly disagree	10.50

	Somewhat disagree	22.60
	Somewhat agree	32.60
	Strongly agree	34.40

Thus, the survey reveals that about one-third of the respondents are interested to adopt and use SAVs in California. The California Department of Motor Vehicles (DMV) has already developed regulations for the manufacturers to follow during testing and before the deployment of AVs on the roads to encourage innovation and promote safety (Department of Motor vehicles, 2021). The California DMV first permitted Nuro, a robotics company, to test AVs on public roads in 2017 and they got approval from DMV to deploy AVs for commercial use on some streets in the Bay Area in December 2020 (Klar, 2020). Consequently, Nuro is already operating AVs in partnership with 7-Eleven to deliver convenience store products (Hawkins, 2021). Currently, more than fifty robotics and auto companies are permitted to test full AVs in California including Waymo and General Motors (Subin & Wayland, 2021). It is expected that AVs would be common on the streets of California in a few years and people would use AVs for their daily travel purposes. Thus, a study investigating people's perceptions, and the factors that influence people to adopt and use AVs is appropriate and timely.

3.2 Methods

A Structural Equation Model (SEM) is employed to find the factors that affect peoples' BI toward AVs using the theoretical and conceptual framework described in Figure 5.1. SEM is popularly used by researchers in psychology and biological sciences, transportation, business, and environmental studies to unveil complex relationships between dependent and independent variables by introducing mediators (Bayard & Jolly, 2007; Irfan et al., 2020; Janggu et al., 2014; Scherer et al., 2019). As a powerful multivariate modeling approach, SEM combines several statistical tools such as regression, factor analysis, and path analysis, to study causal relationships between dependent and independent variables (Shen et al., 2016; Wang et al., 2016). The main strengths of SEM include (1) calculating interceding indirect effects of predictors on outcome variables, (2) estimating total effects through direct and indirect effects, and (3) estimation of the relationship between latent constructs and their manifest factors (Van Acker et al., 2007; Wang et al., 2016). Moreover, SEM shows existing theories in a structural model wherein all the relationships are explicitly specified and estimated (Rahman et al., 2021; Wang et al., 2016).

Eight latent constructs are generated based on Exploratory Factor Analysis (EFA) and extant theories. The constructed model is verified with a Confirmatory Factor Analysis (CFA). Lastly, a path analysis is performed to evaluate the relationships between outcome variable, mediator, and predictors accounting for socioeconomic features. Several fit measures (e.g., chi-square, RMSEA, CFI, TLI) are employed to verify the robustness of the model. The model is calibrated with MPlus Version 7.4 (Muthén & Muthén, 2017). To estimate the model with a categorical (ordinal) dependent variable, this study uses the Weighted Least Squares Means and Variance Adjusted (WLSMV) estimation approach.

4. Results

4.1. Calibrated model

The overall calibrated model is shown in Figure 5.2. Several non-significant relations are omitted to attain a robust model. The final estimated model includes interactions between predictors and outcome variable through mediators. In Figure 5.2, the observed variables are denoted by rectangles and circles indicate latent dimensions. It is worth mentioning that several factors fitting our conceptual model were dropped from the final model after testing to achieve the best-fit final model. These include factors of the built environment (e.g., activity density, workers per household, percent of high wage workers, jobs within 45 minutes of auto travel time), transportation and travel behavior factors (e.g., gas price, percentage of workers who choose public transport to work), technological factor (e.g., the experience of solar panel), and socioeconomic factors (e.g., per capita gross domestic product, household size). Several variables (e.g., population and employment density, land-use diversity, VMT, the share of registered democrat supporters, per capita income) are long-transformed to linearize the relationships captured in the model.

The overall fit of the estimated model is assessed based on several goodness-of-fit indices (Table 5.4). All fit indices are within the acceptable range and thus satisfy the model requirements and confirm the model validity (Hu & Bentler, 1999; MacCallum et al., 1996; Rahman et al., 2020).

Table 5.4: Goodness-of-fit indices of the calibrated model

Indices	Recommended value	Value
Chi-Square	Lower values indicate a better fit	29,348.32
TLI (Tucker Lewis Index)	0 to 1, 1 suggests a perfect fit	0.57
CFI (Comparative Fit Index)	0 to 1, 1 suggests a perfect fit	0.52
RMSEA (Root Mean Square Error of Approximation)	<0.05 indicates a very good fit (threshold level is 0.10)	0.11

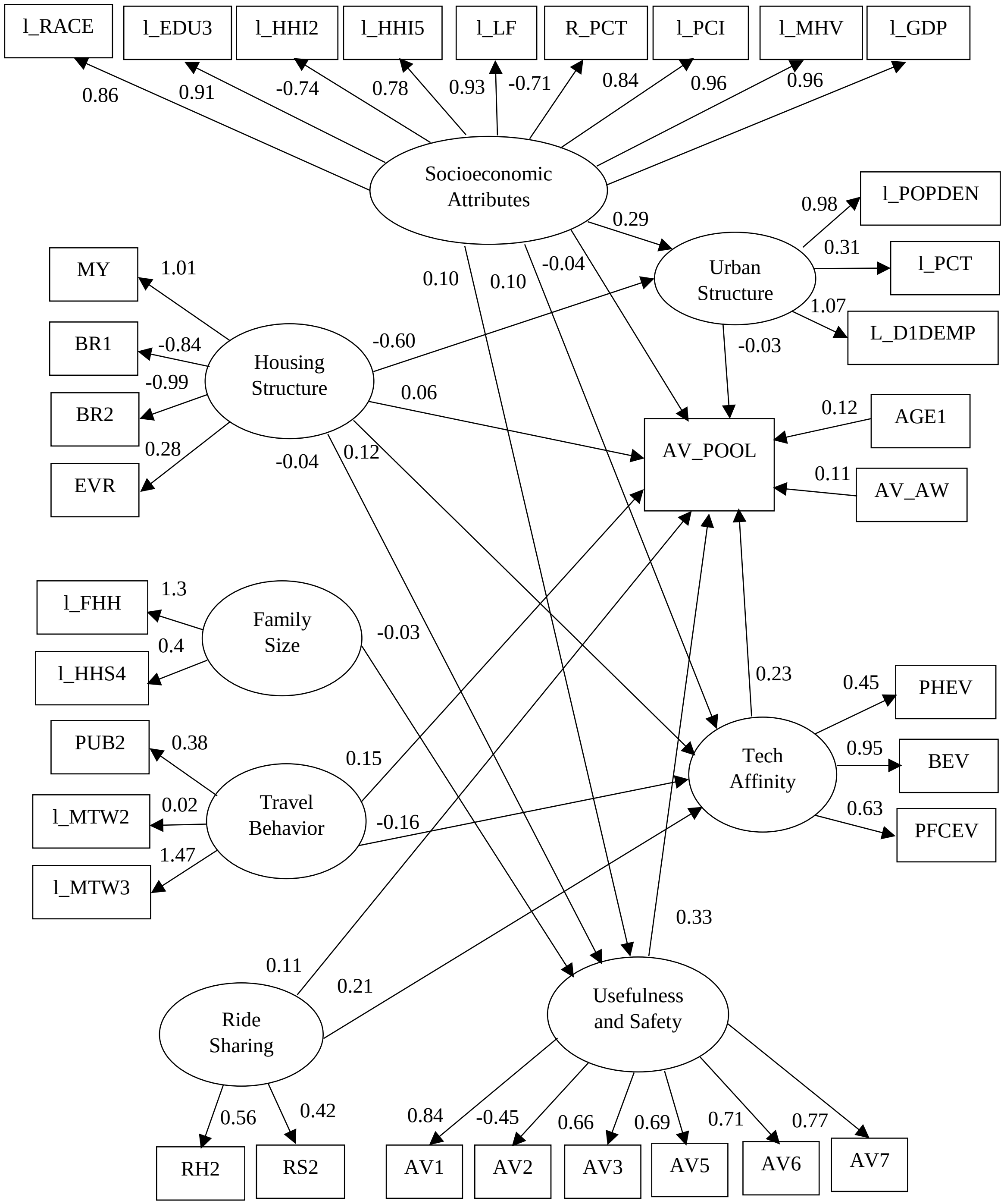

Figure 5.2: Calibrated model with direct standardized effects

4.2 Standardized direct effects on the intention to use SAVs

The standardized coefficients of the calibrated SEM and the direction of modeled direct effects are given in Table 5.5. These coefficients indicate the direct associations between and among predictors, outcome variables, and latent dimensions. It indicates that most of the associations are statistically significant at the 0.00, 0.01, or 0.05 levels. However, some of the interactions with a P-value above 0.05 are kept to better understand the model and demonstrate a complete relationship.

Table 5.5: Estimated standardized direct effects (N= 4,248)

Relationship between observe/estimated variables and latent factors			Estimate	Z	P
l_RACE3	←	Socioeconomic Attributes	0.86	152.99	0.00
l_EDU5	←	Socioeconomic Attributes	0.91	300.46	0.00
l_HHI2	←	Socioeconomic Attributes	-0.74	-150.96	0.00
l_HHI5	←	Socioeconomic Attributes	0.78	151.43	0.00
l_LF	←	Socioeconomic Attributes	0.93	203.73	0.00
R_PCT	←	Socioeconomic Attributes	-0.71	-147.47	0.00
l_PCI	←	Socioeconomic Attributes	0.84	213.68	0.00
l_MHV	←	Socioeconomic Attributes	0.96	344.64	0.00
l_GDP	←	Socioeconomic Attributes	0.96	261.27	0.00
MY	←	Housing Structure	1.01	245.74	0.00
BR1	←	Housing Structure	-0.84	-188.47	0.00
BR2	←	Housing Structure	-0.99	-230.33	0.00
EVR	←	Housing Structure	0.89	152.44	0.00
l_FHH	←	Family Size	1.32	54.43	0.00
l_HHS4	←	Family Size	0.43	34.58	0.00
l_POPDEN	←	Urban Structure	0.98	166.76	0.00
l_PCT	←	Urban Structure	0.31	34.98	0.00
l_D1D	←	Urban Structure	1.07	237.68	0.00
AV1	←	Usefulness and Safety	0.84	96.05	0.00
AV2	←	Usefulness and Safety	-0.45	-29.58	0.00
AV3	←	Usefulness and Safety	0.66	57.79	0.00
AV5	←	Usefulness and Safety	0.69	60.05	0.00
AV6	←	Usefulness and Safety	0.71	57.05	0.00
AV7	←	Usefulness and Safety	0.77	77.90	0.00
PUB2	←	Travel Behavior	0.45	26.42	0.00
l_MTW1	←	Travel Behavior	-0.76	-177.50	0.00
l_MTW2	←	Travel Behavior	0.96	272.56	0.00
RH2	←	Ride Sharing	1.10	12.70	0.00
RS2	←	Ride Sharing	0.51	11.69	0.00
PHEV	←	Tech Affinity	0.45	12.23	0.00
BEV	←	Tech Affinity	0.95	17.22	0.00
PFCEV	←	Tech Affinity	0.63	15.95	0.00
Urban Structure	←	Socioeconomic Attributes	0.29	49.68	0.00
Urban Structure	←	Housing Structure	-0.60	-113.80	0.00
Tech Affinity	←	Socioeconomic Attributes	0.09	2.67	0.01
Tech Affinity	←	Housing Structure	0.12	2.85	0.00
Tech Affinity	←	Travel Behavior	0.16	2.99	0.00

Tech Affinity	←	Ride Sharing	0.21	6.61	0.00
Usefulness and Safety	←	Socioeconomic Attributes	0.09	4.83	0.00
Usefulness and Safety	←	Housing Structure	-0.04	-2.16	0.03
Usefulness and Safety	←	Family Size	-0.03	-2.02	0.04
AV_POOL	←	Socioeconomic Attributes	-0.04	-1.52	0.13
AV_POOL	←	Housing Structure	0.06	1.95	0.05
AV_POOL	←	Urban Structure	-0.03	-1.38	0.17
AV_POOL	←	Usefulness and Safety	0.33	21.56	0.00
AV_POOL	←	Travel Behavior	0.15	3.97	0.00
AV_POOL	←	Ride Sharing	0.11	4.90	0.00
AV_POOL	←	Tech Affinity	0.23	9.94	0.00
AV_POOL	←	AV_AW	0.11	7.03	0.00
AV_POOL	←	AGE1	0.12	7.69	0.00

Eight latent dimensions are created based on observed and calculated variables.

1) Socioeconomic Attributes: l_RACE3, l_EDU5, l_HHI2, l_HHI5, l_LF, R_PCT, l_PCI, l_MHV, and l_GDP
2) Housing Structure: MY, BR1, BR2, EVR
3) Family Size: l_FHH and l_HHS4
4) Travel Behavior: PUB2, l_MTW1, and l_MTW2
5) Ride-sharing: RH2 and RS2
6) Urban Structure: l_POPDEN, l_PCT, and l_D1D
7) Perceived Usefulness and Safety: AV_1, AV_2, AV_3, AV_5, AV_6, AV_7
8) Tech Affinity: PHEV, BEV, and PFCEV

I now proceed to examine the estimated relationships between observed or estimated independent variables and each of the latent dimensions in the model successively in the context of the hypotheses laid out in Section 2.2.4.

Socioeconomic Attributes: This exogenous latent dimension represents the socioeconomic status of the people in the study area. As indicated in Table 5.5, this latent dimension is negatively associated with AV_POOL, which indicates that people living in areas with a higher number of highly educated individuals, household income, labor force participation, and Asian identity are less interested in using SAVs. However, the relationship is of marginal statistical significance (P-value of 0.13). Also, I find that this latent dimension is positively associated with the latent dimensions of tech affinity and perceived usefulness and safety of AVs. Thus, people in the higher socioeconomic strata have a greater affinity for Alternative Fuel Vehicles (AFVs) (i.e., EVs) and consider AVs as useful and safe.

Housing Structure: This exogenous latent dimension represents the physical features of the housing units in the study context. As indicated in Table 5.5, it is positively associated with AV_POOL, which indicates that people living in housing units with more than one bedroom and built after the 1970s, and located in an area with a higher share of republican voters are interested in using SAVs, after controlling for other factors.

Family Size: This exogenous latent dimension is positively associated with l_FHH and l_HHS4 (Table 5.5). The table also indicates that family size is negatively associated with the perceived usefulness and safety of AVs. Thus, people living in areas with a higher share of family household are concerned about the usefulness, convenience, and safety features of AVs due to the uncertainty and insecurity of family members associated with AVs, but no direct effect on the intention to use SAVs is found.

Urban Structure: This endogenous latent dimension represents the patterns of the built environment. It is positively associated with l_POPDEN, l_PCT, and l_D1D (Table 5.5). The calibrated model in Figure 5.2 indicates that urban structure has a negative direct effect on AV_POOL, which indicates that people who live in urban areas with high population and activity density and where car ownership is lower are less likely to use

SAVs. The possible explanation lies in the fact that high quality public transportation services in the urban areas could dissuade people from using SAVs. Moreover, people living in such communities would prefer to walk or use bicycles in the urban areas where activities are in closer proximity and reachable in a short travel time. Thus, people in these urban environments are less likely to use SAVs despite the enormous convenience and usefulness of AVs.

Travel Behavior: This exogenous latent dimension denotes people's travel pattern and is created from PUB2, l_MTW1, and l_MTW2. It has a positive association with PUB2 and l_MTW2 and negatively associated with l_MTW1 (Table 5.5). It is also noticed that travel behavior is positively associated with AV_POOL. Thus, the people who use public transportation for local travel and carpool to work would also likely use SAVs. On the other hand, the people who drive alone to work are less likely to use SAVs.

Ride Sharing: This exogenous latent dimension denotes people's ride sharing status. As it is positively associated with both of the observed variables (RH2 and RS2), the study finds that shared mobility is characterized by the use of different ride-hailing (e.g., Taxi, Uber/Lyft, Uberpool/Lyftline) and ride-sharing services (e.g., bike-share, Car2Go, ZipCar, Jump) for trips in the local area. Table 5.5 denotes that ride sharing is positively associated with AV_POOL (0.11). All other things held constant, a one-unit increase in ride-sharing services increases people's intentions to use SAVs by 0.11 units. Thus, people's tendency to use ride-sharing services with family and friends significantly increases their willingness to use SAVs.

Perceived Usefulness and Safety: This endogenous latent factor is the only latent dimension that represents convenience, usefulness, and safety features of AVs. As indicated in Table 5.5, people enjoy traveling (i.e., watching scenery) by AVs, do multitasking while traveling by AVs, and accept longer travel time by AVs to ensure the safety of pedestrians and bicyclists. On the other hand, people would miss the joy of driving. Figure 5.2 reveals that perceived usefulness and safety are positively associated with AV_POOL (0.33). Other things being constant, a one-unit increase in perceived usefulness and safety increases people's willingness to use SAVs by 0.33 units. Thus, perceived enjoyment and usefulness and perceived lower risk for pedestrians, bicyclists, kids, and themselves have a greater role in motivating people to use SAVs. In contrast, fear and apprehension of losing control of the vehicle they ride in would dissuade people to use SAVs. A higher magnitude of the effect indicates that this latent dimension has a greater role in influencing the intention of people to use SAVs. Thus, psychological factors associated with AVs have a much greater power to influence the willingness of people to share AVs compared to socioeconomic features, and the factors of transportation and of the built environment.

Tech Affinity: This endogenous latent dimension explains people's tech affinity and their willingness to consider AFVs as their travel mode. It encompasses three observed variables (PHEV, BEV, and PFCEV) and is positively associated with the willingness of the respondents to consider PHEV, BEV, and PFCEV in their future purchases (Table 5.5). The calibrated model in Figure 5.2 shows that tech affinity has a significant direct positive impact on AV_POOL (0.23). All other things held identical, a one-unit increase in people's tech affinity increases their willingness to use SAVs by 0.23 units. Thus, people who have prior experience of EVs and who are interested in advanced AV technologies have a much higher tendency to use SAVs (Chen, 2019; Shin et al., 2015).

The calibrated model in Figure 5.2 also indicates that people's familiarity with AVs (AV_AW) is positively associated with their intention to use SAVs (0.11). Thus, a one-unit increase in people's familiarity with AVs increases their willingness to use SAVs by 0.11 units, all other things being held equal. The people who have prior knowledge of AVs are more likely to use SAVs with strangers compared to the people who have little knowledge of AVs or have never heard of them. The California vehicle survey indicates that about 57.33% of respondents have heard about AVs; hence it is assumed that these people would be willing to use SAVs. Thus, prior knowledge about AVs is considered one of the main factors that would influence people toward AVs, as mentioned in previous studies (Hilgarter & Granig, 2020; Laidlaw et al., 2018; Webb et al., 2019). Similarly, the model also explains that working-age people (aged between 18 and 64 years) are positively associated with AV_POOL (0.12). A one-unit increase in the working-age population increases SAV use with strangers by 0.12 units, all other things being held equal. Thus, the working-age people are more interested to use SAV due to their interest in public transportation and shared mobility. Perceived usefulness of AVs further induces working-age people to use SAVs.

4.3 Standardized total effects on the intention to use SAVs

A number of latent factors have both direct and indirect effects on the use of SAVs. For a full account of the reasons for SAV adoption, the total effects of these latent factors can readily be calculated from the SEM estimates. They are presented in Table 5.6, taking into account direct and indirect effects which are not explicitly mentioned in Figure 5.2.

Table 5.6: Standardized total (direct and indirect) effects of latent factors on AV purchase

Effects of latent factors on AV purchase			Direct	Indirect	Total
AV_POOL	←	Socioeconomic Attributes	-0.04	0.04	0.01
AV_POOL	←	Travel Behavior	0.15	0.04	0.18
AV_POOL	←	Ride Sharing	0.11	0.05	0.16
AV_POOL	←	Family Size	--	-0.01	-0.01
AV_POOL	←	Housing Structure	0.06	0.03	0.09

As specified in Table 5.6, socioeconomic attributes have direct and indirect effects on people's willingness to use SAVs by mediating urban structure, tech affinity, and perceived usefulness and safety of AVs. Considering both direct and indirect effects, the socioeconomic attributes have a total effect of 0.01 on sharing AVs with strangers. People living in areas with high socioeconomic status of households are interested to use SAVs due to their affinity to advanced technologies, improved AV amenities, and neighborhood selection in the areas with high population and activity density. However, the magnitude of this total effect is minimal and insignificant. Similarly, the housing structure has a total effect of 0.09 including direct and indirect effects through urban structure, tech affinity, and perceived usefulness and safety of AVs. On the other hand, family size only has an indirect effect of -0.01, mediating the perceived usefulness and safety of AVs. The magnitude of this effect is minimal. Table 5.6 also indicates that housing structure has greater effects on SAV use compared to socioeconomic attributes and family structure.

Travel behavior has a total effect of 0.18 consisting of direct and indirect effects by mediating people's tech affinity. Similarly, considering direct and indirect effects through tech affinity, ride sharing has a total effect of 0.16 on sharing AVs with strangers. Thus, people's tendency to use public transportation, carpool, ride-hailing, and ride-sharing services significantly increase their intention to use SAVs with family, friends, and even strangers. People's travel mode choice behaviors remain the most influential factor in deciding SAV use after accounting for the built environment attributes, the physical structure of housing units, and socioeconomic features. Thus, people's preference for public transportation and other ride-sharing services are the key factors to increase SAV adoption.

5. Discussion

The study found that many people are already aware of AVs and services provided by AVs in California. People consider that riding AVs is enjoyable, safe, and effective, although some of them would not send empty AVs to drop off or pick up their children due to insecurity and uncertainty. Nevertheless, many people are interested in using SAVs due to their prior experience with EVs and higher tendency to use public transportation and shared mobility options. Also, the California state government has already introduced regulations to test and operate AVs. Consequently, many people would be interested to use SAVs. However, appropriate strategies (e.g., onboard driver, incentives, collaboration with transport network companies, conducive built environment, and institutional framework) should be implemented to encourage people to use SAVs (Etminani-Ghasrodashti et al., 2021; Feys et al., 2020).

Results from the SEM indicate that people residing in areas with a higher share of highly educated individuals, household income, labor force participation, and Asian identity are less interested to use SAVs, which supports hypothesis 4 runs contrary to hypothesis 3. Accounting for indirect effects, it is also observed that people living in areas with high socioeconomic status have an interest in AVs due to their tech affinity and perceived usefulness and safety of AVs. Thus, it could be argued that although people with high education and income are less interested in SAVs, they are more interested to use private AVs which echoed the findings of previous studies (Lavieri & Bhat, 2019; Wang et al., 2020). The results also indicate that young and working-age adults would be favorably inclined to use SAVs due to their interest in cutting-edge technologies and shared mobility, and financial ability, which supports hypothesis 1.

Similarly, people living in areas with larger and newer housing units are more interested to use SAVs. The possible explanation lies in the fact that people living in larger and new housing have a greater consumption capability and are willing to use private SAVs, considering the convenience and usefulness associated with AVs. Although family size has no direct effect on SAVs, the indirect effect indicates that people living in the context with a higher share of family households are less interested to use SAVs due to uncertainty, breach of privacy, and safety issues associated with AVs which conforms with previous studies (Hao et al., 2019; Krueger et al., 2016) and supports hypothesis 2. Overall, socioeconomic attributes, housing structure, and family size illustrating the study context have limited influence on the BI of people to use SAVs.

The study also estimated that people who live in urban areas with a higher population and activity density and a higher share of household with no car are less likely to use SAVs, which contradicts hypotheses 5, 6, and 7. The results challenge the findings from previous studies where researchers demonstrated that urban people would be more interested to use SAVs (Barbour et al., 2019; Lavieri & Bhat, 2019; Merfeld et al., 2019). The possible explanation lies in the fact that people in urban areas where activities are closely located would prefer to walk or use bicycles instead of using SAVs. Another possible explanation is that people who live in urban areas have higher household income. Therefore, considering better services offered by AVs, they could use private AVs compared to SAVs which indicates the multifarious effect of household income. Moreover, a supportive built environment (e.g., ramp, appropriate pick-up and drop-off points) could further motivate people to use SAVs including the people with mobility challenges (Etminani-Ghasrodashti et al., 2021). Overall, the factors of the built environment have little power to govern people's BI to use SAVs.

Study results also showed that people who prefer public transportation, car-sharing, ride-hailing, and ride-sharing services for daily travel purposes are more likely to use SAVs. In contrast, people who drive alone to work are less likely to use SAVs. The findings agree with hypotheses 8, 9, and 10 and support previous studies (Asgari et al., 2018; Lavieri & Bhat, 2019; Zhou et al., 2020). Also, people's travel behaviors and ride-sharing attitudes are the most influential factor to influence BI to use SAVs after accounting for socioeconomic features, family structure, the built environment, and transportation and psychological factors associated with AVs. Thus, people's perceptions of shared mobility are one of the key factors in households' intention to use SAVs. Integration of SAVs with existing on-demand ride-sharing services and identifying concerns, preferences, and expectations of potential users could be practical strategies to motivate people to use SAVs (Etminani-Ghasrodashti et al., 2021).

The study also found that perceived enjoyment, usefulness, and safety significantly influence people to use SAVs. On the other hand, people who enjoy driving are less likely to use SAVs due to fear of losing control of vehicles. Thus, psychological features of AVs significantly influence people's BI to use SAVs compared to socioeconomic features, housing structure, transportation factors, and the built environment. The study also observes that the people who have prior knowledge about AVs are more likely to use SAVs compared to the people who have little knowledge of them or have never heard of AVs and never used an EVs. Additionally, people with high affordability and education are positive about the usefulness and convenience of AVs. These findings sustain hypotheses 11, 12, and 13 and align well with the conclusions from previous studies (Hao et al., 2019; Merfeld et al., 2019; Yuen et al., 2020). The study also found that people's prior experience of using alternative fuel vehicles (e.g., electric vehicles, hybrid electric vehicles, fuel cell vehicles) significantly motivates people to use SAVs (accept hypothesis 14). Moreover, people with high income and education level have a greater affinity for advanced technology, which further motivates them to use SAVs (accept hypothesis 15).

6. Conclusions and future research agenda

This study significantly contributes to the literature by empirically investigating the prominent determinants of people's intentions to use SAVs. The study findings can be helpful for transportation agencies, professionals, stakeholders, and AV developers to formulate relevant policies for designing and implementing SAVs. Since many people are already aware of AVs, some effective measures could increase the willingness of people to use SAVs. Appropriate initiatives should be implemented by transit agencies and other transport providers (i.e., transport network companies, bike-sharing companies) to facilitate SAVs, which are environmentally friendly and ensure multimodal transportation (Cohen et al., 2017; Narayanan et al., 2020; Sparrow & Howard, 2017). The ride-hailing and ride-sharing companies could pioneer the launch of SAVs and let the people have the real-world experience of this efficient and novel transportation mode.

Through coordination with public transit agencies, SAVs can be implemented to solve the last-mile problem and thereby increase transit ridership and reduce transportation costs (Moorthy et al., 2017; Sparrow & Howard, 2017). Planning agencies could implement several policy actions such as designated lanes for SAVs, priority curb space for SAVs in urban areas, and a higher posted speed of SAVs to ensure equity and motivate people to use SAVs (Cohen et al., 2017). Since many people already have their cars, they would be less interested to use SAVs. However, implementing some strategies such as playing music or movie of people's choice, recommending some driving routes based on users' travel history, and customized interior lighting and design could be implemented to develop psychological ownership to induce them to use SAVs (Lee et al., 2019).

Despite insightful findings, the strengths of this study are shattered by some cautionary limitations. I identify hereunder some priority extensions of the present work:

1) This research should be replicated in other states to establish the robustness of the model and compare possible variability under different cultural, socioeconomic, and political contexts.
2) To understand the effects of the built environment, data related to the built environment aggregated at a finer granularity in the geographic unit (e.g., block group, census tract) should be used in future studies.
3) As the technology context change quickly, and given the strong dependence of intentions formulation on knowledge and experience of AVs technologies, a longitudinal analysis would be invaluable to more cogently articulate the criticality of certain decision points in the shaping of opinions and better estimate when societal acceptability may become pervasive.
4) The impacts of different opportunities (e.g., low congestion, emission) and challenges (e.g., legal aspect, breach of privacy, system failure) related to AVs, and

institutional arrangement (e.g., incentives, regulations) are not evaluated in this study, which requires further investigation.

5) Future studies should investigate the equity aspects of SAV among different income and racial groups to ensure justice in transportation.

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CHAPTER 6: SIMULATING THE POTENTIAL IMPACTS OF AUTONOMOUS VEHICLES ON TRAVEL BEHAVIORS AND TRAVEL DEMAND

Abstract

This study aims to assess the potential impacts of Autonomous Vehicles (AVs) on people's travel behaviors such as trip generation, travel distance, travel time, and travel costs. Several hypotheses are formulated to address the research questions under a simulated environment using the TRANUS simulation framework. To estimate the possible effects of AVs, a transportation model is developed and calibrated for the city of Swindon, the United Kingdom (UK). Three hypothetical scenarios (i.e., baseline scenario, AVs adopted on local roads, and AVs adopted throughout the entire transportation network) are created to estimate the effects of AVs. Additionally, sensitivity analysis is performed by increasing the occupancy, speed, and wait time of AVs to check the robustness of the calibrated models. The results indicate that AVs would intensify people's overall travel demand by increasing accessibility. On the other hand, AVs are likely to reduce vehicle ownership, travel distance, travel time, travel costs, and vehicle hours traveled by reducing solo driving and inducing shared mobility. AVs also have the potential to reduce public and active transportation. The study links the gap in the literature and sheds light on policy implications for informed policy-making considering the expected change in transportation systems by AVs.

Keywords: Shared Mobility, Shared Autonomous Vehicle, Travel Behaviors, Trips, Travel Distance, Travel Time, Travel Costs, Simulation

1. Introduction

Although sharing mobility among users via public transportation and taxis is familiar, recently cities are experiencing the rapid growth of new shared mobility services such as carsharing, ride-hailing, bike-sharing, etc. (Jiao et al., 2020). Researchers predicted numerous benefits of shared mobility such as lower car use, Vehicle Miles Traveled (VMT), congestion, energy use, and costs (Heineke et al., 2021; Jiao et al., 2020; Khan & Shaheen, 2021). Additionally, shared mobility provides transport services to all and ensures transportation safety, comfort, and convenience to people. Considering these anticipated potentials, this study aims to investigate the impacts of Autonomous Vehicles (AVs) shared by all household members on travel behaviors by conducting a simulation using the TRANUS framework.

AVs could navigate automatically and facilitate people to share the same ride (Zhang et al., 2015). AVs could provide a similar level of convenience and flexibility as a personal car, which allows users to take a rest or engage in productive activities (Krueger et al., 2016). Recently, AVs have received enormous attention from public and private organizations (Loeb et al., 2018). Nonetheless, the adoption and use of AVs are uncertain due to a lack of evidence on the potential impacts of AVs on people's travel behaviors.

Previously, most discussions on AVs were focused on the technology (Soteropoulos et al., 2018). A decent number of studies investigated the perceptions and key determinants of AVs (Hulse et al., 2018; Kim et al., 2022; Rahimi et al., 2020; Wang et al., 2020). Investigating the potential impacts of AVs on travel behaviors and transportation systems has received recent attention (Soteropoulos et al., 2018). On the other hand, very little is known about the potential impacts of Shared AVs (SAVs) on people's travel behaviors. To address this issue, this study estimates the potential impacts of AVs on travel behaviors (e.g., trips, travel distance, time) and bridges the gap in the literature. The following research questions are formulated to explore the impacts of AVs.

1) What are the impacts of AVs on a household's daily total number of trips?
2) What are the impacts of AVs on Passenger-Km Traveled (PKT) and Vehicle-Km Traveled (VKT)?
3) What are the impacts of AVs on the Vehicle-Hour Traveled (VHT)?
4) What are the impacts of AVs on a household's travel time and costs?

The rest of the paper is organized as follows. Section Two discusses relevant past studies to understand the impacts of AVs and SAVs on travel behaviors, research hypotheses, and the theoretical framework for model building in TRANUS. Section Three outlines the overall research design. The detailed analysis of the results is presented in Section Four. Section Five discusses the results. Finally, Section Six draws the concluding remarks and provides guidance for future research.

2. Literature review and theoretical framework

2.1 Summary of past studies

The ecosystem of urban transportation would change with the advent of AVs. It is expected that this new mobility choice would influence trip generation and distribution. A good understanding of how AVs would affect people's travel decisions and transportation systems is essential. This review is intended to conceptualize the impacts of AVs on people's trip generation, travel distance, vehicle ownership, travel costs, and time.

Investigating the impacts of AVs on people's travel demand, the researcher found that AVs could upsurge overall household travel demand by providing transport services to all people including the disabled, elderly, children, and people without driving licenses (Martinez & Viegas, 2017; Narayanan et al., 2020). Similar to AVs (Harper et al., 2016; Trommer et al., 2018; Zakharenko, 2016), SAVs could also increase VMT by increasing empty VMT and relocating parking outside of the city center (Childress et al., 2015; Liu et al., 2017; Soteropoulos et al., 2018). However, additional VMT could be reduced by implementing dynamic ride-sharing services (i.e., serving multiple travelers with similar origins, destinations, and departure times) (Fagnant & Kockelman, 2018; Lokhandwala & Cai, 2018). Additionally, an increase in the number of SAVs particularly within a concentrated area (i.e., urban core), and people's willingness to rideshare may reduce VMT (Bischoff et al., 2017; Fagnant & Kockelman, 2014; Levin et al., 2017). Thus, SAVs have the potential to reduce overall vehicular and passenger travel distance by adopting dynamic ride-sharing services. However, SAVs could increase long-distance travel by reducing travel costs and increasing multitasking (Gelauff et al., 2019; Heilig et al., 2017).

Researchers have mentioned that AVs are likely to reduce car ownership by encouraging ride-sharing (Clements & Kockelman, 2017; Ma et al., 2017; Tirachini et al., 2020). Even, privately owned AVs could be rented out when they are not used and further could reduce vehicle ownership (Sparrow & Howard, 2017). Thus, AVs have the potential to reduce vehicle ownership by increasing dynamic ridesharing (Fagnant & Kockelman, 2018; Levin et al., 2017; Lokhandwala & Cai, 2018), despite an increase in travel demand (Fagnant & Kockelman, 2014).

The extant research has reported that AVs are likely to reduce transit and active travel (Booth et al., 2019; Kapser & Abdelrahman, 2020; Meyer et al., 2017). The availability of SAVs may further contract public and active transportation (Clements & Kockelman, 2017; Cyganski et al., 2018) by disrupting the existing transportation operations and inducing a modal shift from public transport (Narayanan et al., 2020). Thus, AVs and SAVs may affect the existing and future transit systems (Handsfield, 2011). However, proper integration of AVs and SAVs with an efficient public transport system can increase transit use (Narayanan et al., 2020; Sparrow & Howard, 2017).

Researchers mentioned that a higher share of AVs with dynamic ride-sharing could reduce travel time by reducing empty trips and eliminating searching time for parking (Levin et al., 2017; Loeb et al., 2018; Zhang et al., 2015). Additionally, SAVs can significantly reduce traffic delay and congestion by promoting ride-sharing options, smoothing traffic flows by minimizing acceleration and braking and traffic monitoring systems, and increasing the capacity of the roadway (Alam & Habib, 2018; Fagnant & Kockelman, 2015; Kopelias et al., 2020). Thus, SAVs in a dynamic ride-sharing situation could be an effective policy option to reduce traffic congestion and overall travel time.

AVs could reduce the value of travel time by providing people with multitasking opportunities (e.g., reading, and talking with friends) (Van den Berg & Verhoef, 2016). Consequently, AVs have the potential to increase VHT (Childress et al., 2015; K. Kim et al., 2015; Soteropoulos et al., 2018). Unlike AVs, SAVs could reduce VHT if there is no possibility of using personal vehicles and the value of travel time is increased (Childress et al., 2015; Soteropoulos et al., 2018). Since SAVs would provide a lower level of convenience and flexibility compared to private AVs, people would spend less time in SAVs, and thereby overall VHT would reduce.

Automation of vehicles is likely to reduce people's travel costs by moderating vehicle operation and maintenance costs (Duan et al., 2020; Nunes & Hernandez, 2020; Piao et al., 2016). SAVs could further reduce travel costs by avoiding parking fees and reducing the fleet size (Compostella et al., 2020; Loeb et al., 2018; Martinez & Viegas, 2017). Ride-sharing AVs are much cheaper than solo driving due to low costs for drivers, depreciation, and insurance (Compostella et al., 2020). Thus, AVs and SAVs have the potential to reduce households' overall vehicle operation and maintenance costs.

Based on the literature review, the following hypotheses have been formulated to address the research questions of the study after reviewing relevant literature.

1) AVs would increase people's overall travel demand (i.e., trips) by providing transport services to all people, particularly children, the elderly, and mobility-challenged people (H1).
2) Overall, the personal car usage would be reduced since one AV would be sufficient for a family of four members to meet their travel demands (H2).
3) AVs could decline the use of public transportation (e.g., bus, train) and active travel (e.g., walking and cycling) of people (H3).
4) AVs would reduce PKT and VKT by increasing people's vehicle sharing tendency and reducing empty VKT (H4).
5) AVs would reduce the overall VHT and increase the performance of the transportation system (H5).

6) Adoption of AVs would reduce overall travel time and traffic delays by promoting ride-sharing and avoiding empty trips and vehicle parking (H6).
7) Adoption of AVs would reduce overall travel costs by reducing vehicle operation and maintenance costs (H7).

2.2 Theoretical framework

This subsection discusses the theoretical aspects to simulate the impacts of AVs on people's travel behaviors using Land Use and Transportation Interaction (LUTI) models after introducing AVs within the transportation system.

2.2.1 A brief overview of land use and transport interaction models

Literature suggests that changes in transportation systems influence urban development patterns (Cervero & Kockelman, 1997; Rahman, Hossain, et al., 2021; Zondag et al., 2015). Concurrently, changes in development patterns influence transportation activities. Thus, transportation and land use have a mutual but complex relationship (Holz-Rau & Scheiner, 2019; Soria-Lara et al., 2016; Wegener & Fürst, 2004). The complex two-way interactions can be easily conceptualized by the "land use transport feedback cycle" presented in Figure 6.1 (Acheampong & Silva, 2015; Wegener, 2004; Wegener & Fürst, 2004). According to the feedback cycle, the distribution of land uses determines the locations of human activities. Through the transportation system, human activities fulfill spatial interaction or trips and travel from one destination to another. Transport infrastructure and facilities create opportunities for spatial interaction of human activities.

Many studies over the past 60-70 years have investigated the impacts of transportation policies on travel patterns and destination location choices (Acheampong &

Silva, 2015; Chang, 2006; Wegener & Fürst, 2004). They used various types of LUTI models, including the TIGRIS XL model (Zondag et al., 2015), UrbanSim (Joshi et al., 2006; Waddell, 2002; Waddell et al., 2003), agent-based model (K.-H. Kim et al., 2015; Zhang et al., 2020; Zhang et al., 2015). Some studies also used TRANUS to develop land use and transport interaction models (Bujanda et al., 2011; Capelle et al., 2019; Pupier, 2013; Vichiensan et al., 2005). Since this study has used TRANUS, the theoretical discussion focuses on the theories related to land use and transport interaction models developed in TRANUS.

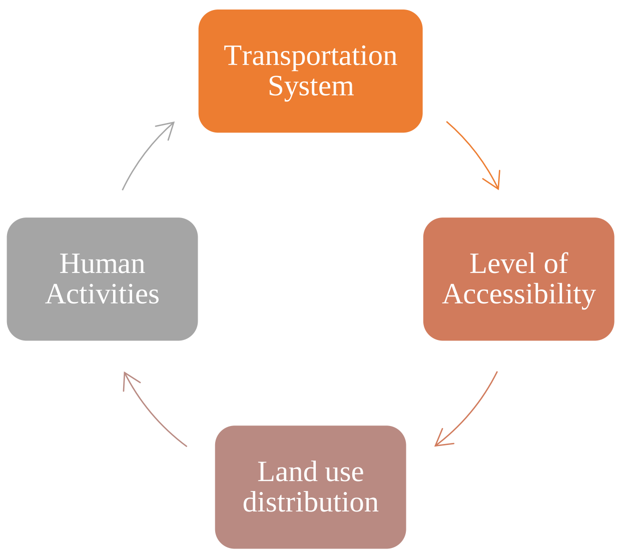


Figure 6.1: Land use transport feedback cycle

TRANUS is used for simulating the effects of transport policies adopted at urban, regional, and national levels. Originally conceptualized by De la Barra and Rickaby (1982) and Thompson (1990), developed at the Central University of Venezuela (Brown et al., 1998), and maintained by Modelistica (2005), TRANUS is a free and well-documented software package (Capelle et al., 2019; Dutta et al., 2012; Morton et al., 2008).

2.2.2 Theoretical basis of land use and transport interactions in TRANUS

The theoretical basis of LUTI models in TRANUS system is based on the concept of spatial microeconomics theories, gravity-based theories, input-output model, discrete choice model, and Dijkstra transportation model (Hansen, 1959; Lowry, 1964; Modelistica, 2005). The spatial microeconomics theories indicate that landowners rent properties at the maximum price and renters try to maximize their revenue by renting the property at a lower price and reducing transportation costs. Gravity-based models explain that interaction between two zones is proportional to the number facilities in each zone and inversely proportional to the distance friction. Input-output model illustrates the intersectoral flows. The discrete choice model shows that people logically choose an option which provides maximum benefit or utility. Lastly, the TRANUS family tree also includes traditional transportation models proposed by Dijkstra in the 1950s (Modelistica, 2005; Zhang et al., 2016).

2.2.3 Main components of the TRANUS model

As shown in Figure 6.2, the two main subsystems of the LUTI model in the TRANUS are the activities subsystem and the transport subsystem (Modelistica, 2005). There are demand and supply elements in each subsystem that interact to achieve an equilibrium state. Location and interaction between activities (e.g., households, industries) indicate demand-side elements and real estate supply (i.e., land, floor space) indicates the supply-side elements of the activities subsystem. In the transportation subsystem, travel demand for transferring people and goods from the origin to destinations represents demand-side elements and physical infrastructure and transport operators represent the supply-side elements. The components of activities and transport subsystems are fully interrelated and mutually dependent. The interaction between activities causes travel demand and in response transportation supply affects the location and interaction of activities and land supply in the real estate market.

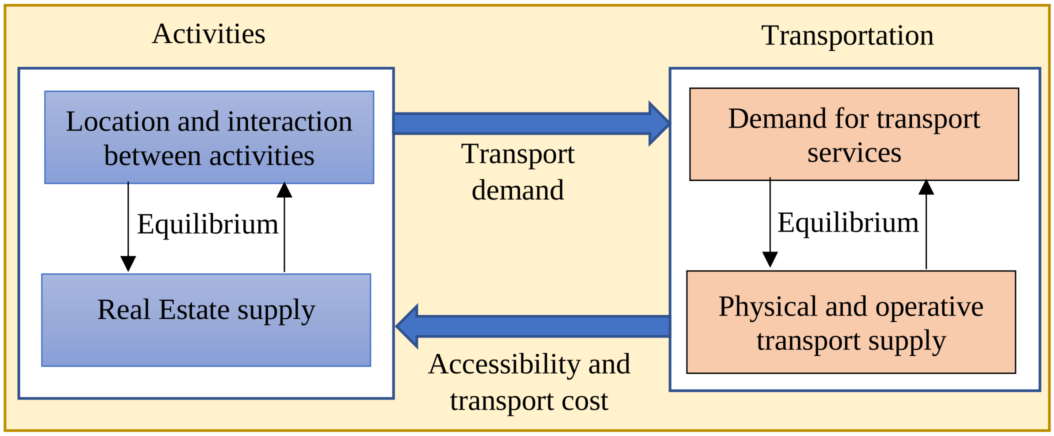


Figure 6.2: Main elements of a LUTI model in

2.2.4 Dynamic relationship between land use and transportation

The two main components of the LUTI model are dynamically related to each other via time (Modelistica, 2005). The dynamic relationship between land use and transportation systems is presented in Figure 6.3. As indicated in Figure 6.3, the interaction between transportation and land use is dynamic through time t1, t2, t3, and so on. The interaction between activities in space generates functional flows of jobs or households from one sector to another, which create travel demand. The travel demand is assigned to the transport system in the same period. However, the state of equilibrium in transport demand and supply determines the accessibility between locations and influences economic flows and provides feedback for the next period. Thus, accessibility in time t1 affects functional flows in time2 and so on.

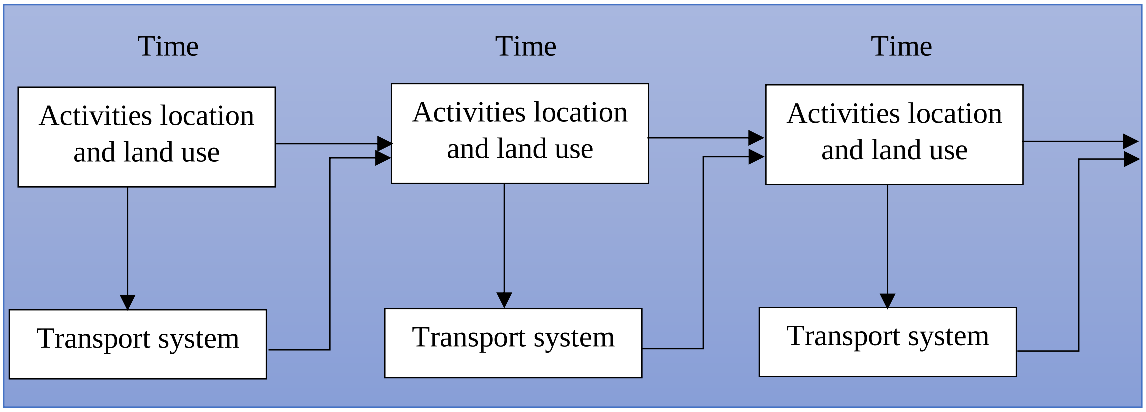


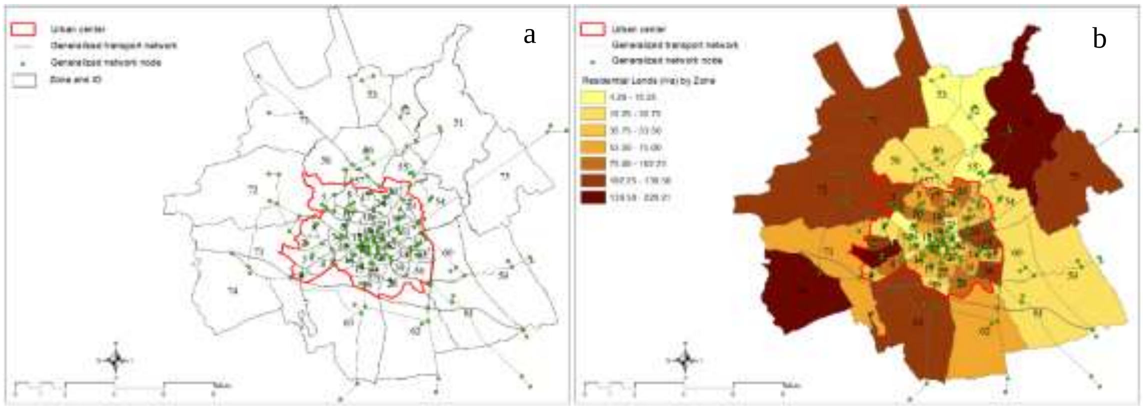
Figure 6.3: Dynamic relationship between land use and transportation

3. Research design

TRANUS simulates the location of activities (e.g., residential, employment) and transportation systems as they are closely related. Space and activities interact with each other and demand transportation systems (e.g., roads, modes). The LUTI model in the TRANUS system has two main components: the land-use component and the transportation component. In this study, the transportation model is developed to estimate the effects of AVs on people's travel behaviors after heavily customizing TRANUS to handle AVs.

3.1 Study context

In this study, the concept of land use and transportation interaction model integrated with the TRANUS system has been applied to the city of Swindon, the United Kingdom (UK) (Tomás de la Barra et al., 2011). Figure 6.4a indicates the boundary of the city including contiguous rural hinterland and villages, highlighting the urban core of the city. There are 56 internal and 9 external zones in Swindon. The external zones were created to estimate the effect of external trips. Since, the land use and transportation interaction models are complex with many economic sectors, floor space, land types, and transportation systems, taking a small study area with few zones to develop the models is convenient and faster in the current computer configurations. Figures 6.4b represents the spatial distribution of residential land types and 6.4c illustrates the distribution of employment land types in Swindon.



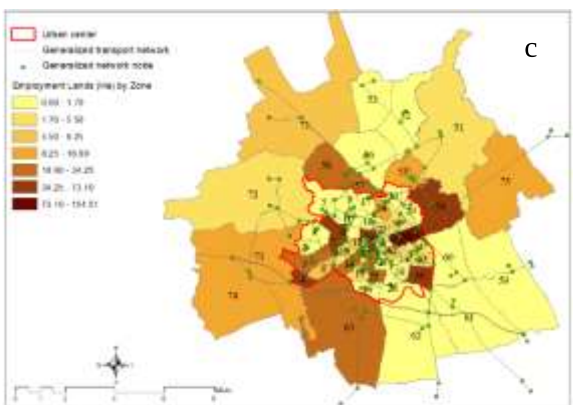


Figure 6.4: (a) Subdivision of study area into zones, (b) distribution of residential land types, and (c) distribution of employment land types.

Swindon is a small English city with relatively few zones, about half-way between Bristol and Oxford. The city had 490,000 population in 2020, with a density of 222 persons/km^2 (UK Census, 2020). Swindon's economy are thriving due to strong financial services and advanced manufacturing and engineering activities (Swindon Borough Council, 2022). The main purposes to consider Swindon as the study area are as follows:

a) I am evaluating the theories associated with AVs, thus, it is convenient to use the existing model with significant modifications to account for AV use.

b) Using an existing model could provide a baseline to compare the results. Given that, there is little scope to authenticate the results due to the unavailability of AVs, thus using an existing model provides scope for validating and checking the results on how people would travel after adopting AVs.

c) The Swindon model is equipped with data, thus using this model as a reference would reduce data collection, cleaning, and organizing time significantly.

d) Researchers usually use parameter values from existing models and previous studies. Thus, using the Swindon model for investigating the potential impacts of AVs is suitable and falls within the common practices of the researchers.

e) The development, adoption, and evaluation of AVs are still in the preliminary phases. Many stakeholders are undertaking pilot projects to test AVs, review regulations, assess the infrastructural requirements, evaluate the effectiveness of AVs, and allow users to experience AVs. Currently, the implementation of AVs is limited to a small and controlled environment (e.g., university area, parks) to gauge their effectiveness. As such, it is likely that AVs would be implemented in small cities first before adopting them in large urban areas. Thus, it is appropriate to take Swindon as a case to understand the effects of AVs.

3.2 Land use model

The land use model is the first component of the integrated LUTI model in the TRANUS system. In this study, I developed land use model to quantitatively estimates the effects of AVs on the spatial distribution of land uses (Acheampong & Silva, 2015). As shown in Figure 6.5, a land-use model development includes the delineation of the study area, division of study area into zones, the definition of activity sectors, distribution of floor space and land for different activity types, and the generation of functional flows.

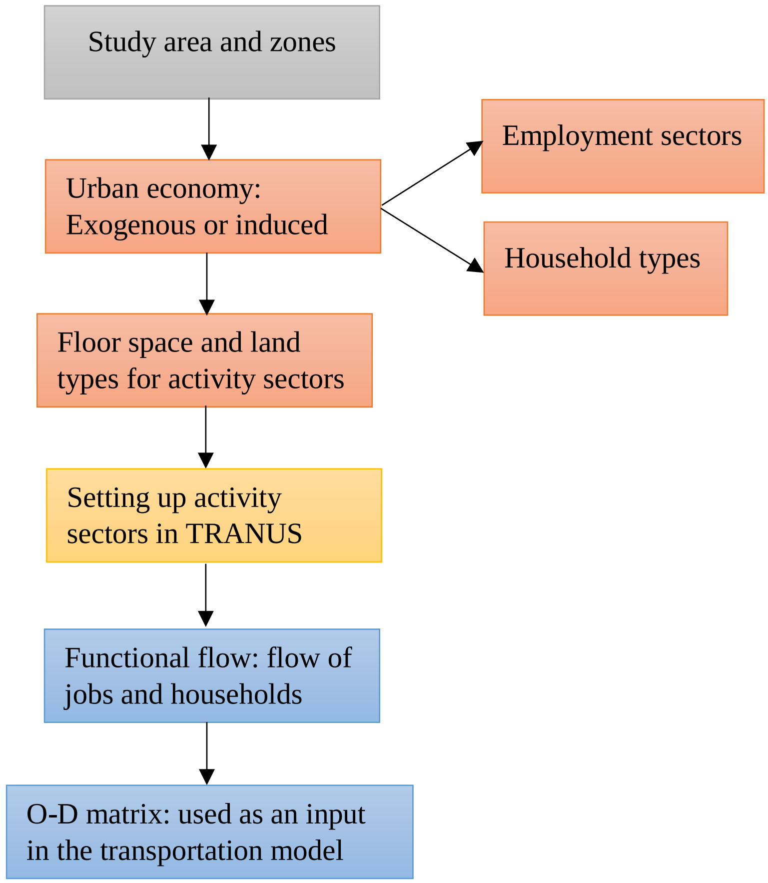


Figure 6.5: Different steps of land use model in TRANUS

The city of Swindon is subdivided into internal and external zones. The entire urban economy is divided into exogenous (i.e., depend on external forces) and induced (i.e., generated within the zones by other activities) sectors to define activity sectors in Swindon. The sectors include employment (e.g., industry, agriculture, government, retail, office, education, health) and household (e.g., low-, medium-, and high-income) sectors. Floor space (e.g., sheds, terraces and flats, detached and semi-detached houses) and land types (e.g., industrial, business park, mixed land, residential) are assigned for different activity sectors using a multinomial logit model. These activity sectors generate intersectoral functional flows of jobs and households. Low-, medium-, and high-income households generate trips to work and trips attracted by retail and warehousing, office, education, and health activity sectors are defined as trips to services. The outputs are arranged in Origin-Destination (O-D) matrix to use it in the transportation model. A detailed description of the land use model in TRANUS is provided in Chapter 7.

To generate trip matrices, it is assumed that all flows are commuter trips to work and trips to services and indicated as 1. Trips are calculated for one day and expansion factors are used to estimate the trips for a month. A factor of 1 is considered for trips to work and services. Finally, I assumed that trips are unidirectional (i.e., people typically go to work from home and come back home again after work) and a factor of 1 is used for both trips to production and consumption.

3.3 Transportation model

The transportation model is the second component of the integrated LUTI model in the TRANUS system. In the study, this component investigates people's travel patterns due to adoption of AVs considering the existing demand and supply of transport infrastructure and transport operators. Outputs of the land use model are used to simulate travel patterns in this model. Since the output is in matrix form, there is no need for trip distribution in the transportation model in TRANUS. Modal split and traffic assignment are integrated with the procedures of the transport model. Thus, separate models for modal split and traffic assignment are not required. Developing a transportation model in TRANUS mainly includes defining different components of transport demand and supply categories (Tomás de la Barra et al., 2011).

3.2.1. Demand categories

The demand component in transportation model indicates the functional flows of jobs and households generated from activity sectors in O-D matrix to simulate travel patterns. The parameter details of transport modes (e.g., occupancy, travel time, waiting time, vehicle availability) are defined in TRANUS to complete those travel demands.

3.2.2. Supply categories

In the TRANUS transportation model, supply categories are divided into physical supply and operative supply (Tomás de la Barra et al., 2011). The physical elements include roads, cycles way, railways, busways, stations, and so on and are presented as a transport network comprising links and nodes. Each link is categorized based on its length, capacity, speed, cost, etc. Table A1 in the Appendix describes the link types adopted in the model with assigned speeds.

On the other hand, operative elements (e.g., modes, operators, and routes) use the physical infrastructure to provide transport services to customers. In TRANUS, a single-mode approach (e.g., passenger) is used and an integrated multimodal transport network is used. Travelers are free to select a combination of transport operators to travel from origin to destination with some restrictions in selecting the combinations, as indicated in Table A2 in Appendices.

In the Swindon model, the operators are defined as normal (i.e., move freely around the network), transit (i.e., move freely around the network but charge fares and have a waiting time, such as a taxi), transit with routes (i.e., use specific route), and non-motorized (e.g., walking and cycling) (Table 6.1) (Tomás de la Barra et al., 2011). There are two types of cars such as Single-Occupancy Vehicle (SOV) and High-Occupancy Vehicle (HOV) (i.e., more than two occupants). In this study, I assumed that AVs would be shared by household members similar to HOV which is reflected in occupancy setting in TRANUS. Additionally, AVs would be operated by battery. Buses are classified into regular and express buses based on their services, speed, and tariff structure along with other public transportation (e.g., minibus, train, and rural bus). The park-and-ride operator provides access from one operator to another.

Table 6.1: Types of transport operators

Operator	**Type**
Single-Occupancy Vehicle (SOV)	Normal
High-Occupancy Vehicle (HOV)	Normal
Autonomous Vehicle (AV)	Normal
Regular and express Bus	Transit with routes
Rural bus, all type	Transit with routes
Minibus	Transit with routes
Passenger rail	Transit with routes
Walk	Non-motorized
Bicycle	Non-motorized
Park-and-Ride (P&R)	Normal

Table 6.2 demonstrates basic parameters associated with different operators in the model. I followed the recommendation model parametrization for the city of Swindon with adjustments to allow for AVs. The occupancy of an operator indicates that the model can assign passengers to this capacity. The time factor indicates how long an operator can operate within 24 hours. Waiting time indicates how long a passenger will have to wait to get that operator. Speed in km/hour indicates the maximum speed an operator can achieve on the defined network. Operators with no speed mean either they have a specified network (e.g., rail) or they cannot travel (e.g., park-and-ride). Passenger Car Equivalent (PCE) is used to calculate an equivalent number of vehicles compared to a car by multiplying the total number of vehicles. A higher value of overlap factor indicates that the program will

try to avoid that path during the path search. Distance indicates the travel cost of the operator per unit distance.

Table 6.2: Parameter associated with each operator

Operator	**Occupancy**	**Time factor (hour)**	**Waiting time (hour)**	**Target occupancy (%)**	**Speed (km/hour)**	**PCE**	**Distance**	**Overlap factor**	**Penalize**
SOV	1	24	0		68	1	0.17	4	1.1
HOV	2.3	24	0		64	1.05	0.17	4	1.1
AV	2.3	24	0		64	1.05	0.17	4	1.1
Bus	61	16	0.08	50	50	2.5	0.55	1.4	1
Rural bus	53	16	0.08	50	50	2.5	0.55	1.4	1
Minibus	35	16	0.08	50	55	2	0.35	1.4	1
Rail	350	18	0.1	50				1	1
Walk	1	24	0		5			1.4	1
Bicycle	1	24	0		12	0.2		2	1
Park-and-ride	1	24	0.05					1	1

Figure 6.6 shows the steps of the transportation model in TRANUS. The development of the transportation model includes taking travel demand data from the land use model, importing the transport network, assigning link type, administrator, and parameters to the network, assigning operator type, combination type, and parameters to the operators, and assigning operators to the network. TRANUS uses probabilistic multinomial logit models for assigning household trips to transport operators based on their utilities. TRANUS uses the same logit model to assign operators to transport network based on their properties.

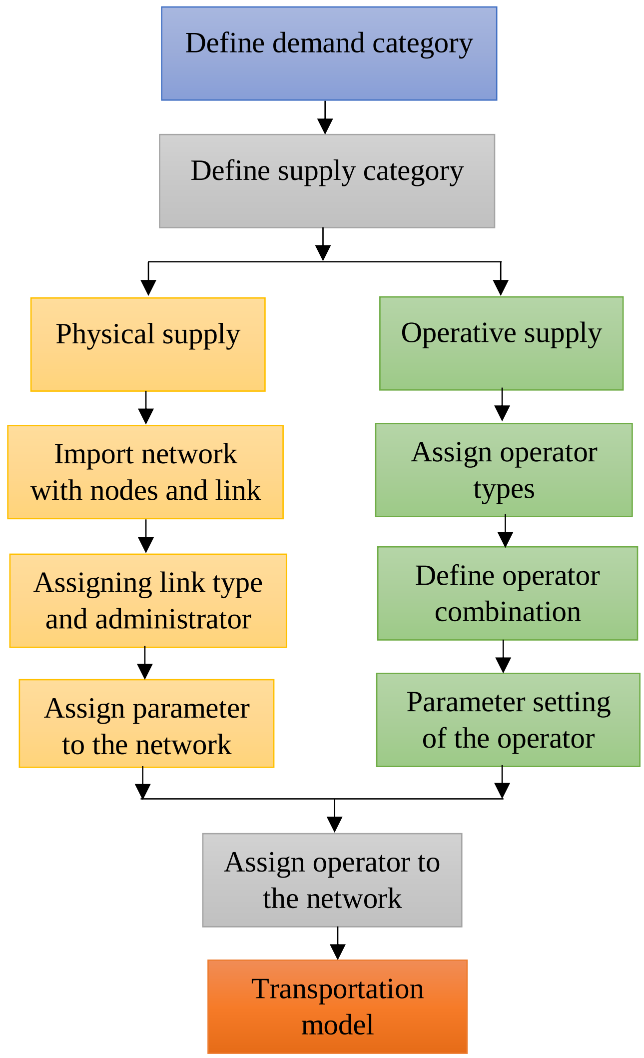


Figure 6.6: Different steps in the transportation model in TRANUS

3.3 Hypothetical scenarios to estimate the effects of AVs

To investigate the potential impacts of AVs, a set of hypothetical scenarios are envisioned. Parameters and information/data on transportation links and nodes (e.g., types, capacity, speed), and types, capacity, waiting time, and speed of different operators presented in Tables 6.1 and 6.2 are used to calculate outputs of scenario in transportation models. Data on types and elasticity of activity sectors, floor space and land types, trip categories discussed in Chapter 7 are used for developing a land use model are used to calculate the outputs of the scenarios. Additionally, the land use model is set for up to 200 iterations with a convergence factor of 0.0001. On the other hand, the transportation model is set for up to 18 iterations with a convergence factor of 0.001. In both cases, a smoothing factor of one is assigned, which indicates that the values of each iteration are averaged with the values from the previous iteration with an equal proportion.

1) Baseline scenario

   Initially, a baseline scenario (B) is developed by considering the existing land use and transportation attributes of the Swindon model. Values of the parameters of transportation links, nodes, and operators presented in Tables 6.1 and 6.2 and information on activity sectors, floor space, and land types discussed in Chapter 7 are used to estimate people's travel patterns under the current policy framework and without the adoption of AVs.

2) Scenario 1: Introduction of AVs on the local roads only

   Scenario 1 (S1) is developed to explore the potential impacts of AVs on people's travel behaviors under the condition that AVs would be operated on local roads only. Access road, central narrow and wide, peripheral narrow and broad link types mentioned in Table A1 are selected for adopting AVs and examined the impacts of this policy option on people's travel behaviors. Similar to the baseline scenario, the above-mentioned data and parameters are used to develop this model.

3) Scenario 2: Introduction of AVs to the entire transportation network.

   Scenario 2 (S2) investigates the impacts of AVs when AVs would be allowed to navigate throughout the entire transportation network of the city. However, some mode-specific routes such as bus-only routes and lanes, railway, and cycle lanes are free from any AV operation. Scenario 2 also considers the above-mentioned parameters and information.

Sensitivity analyses are performed to check the robustness of the simulation results by changing model assumptions and values of the parameters. Table 6.3 indicates different criteria to assess the sensitivity of the model. Increasing AV occupancy and speed, and wait time, and allowing growth in jobs, sensitivity analyses are conducted to explore the change in the travel patterns.

Table 6.3: Criteria for sensitivity analysis

Parameter	Base scenario	Changes in parameter
Occupancy of AV	S2	10%, 20%, 30, and 40% increase in occupancy
Wait time of AVs	S2	1, 2, 3, 4, 5, and 10 minutes extra wait time
Speed of AVs	S2	5%, 10%, 15%, and 20% increase in speed

Finally, the percent change of trips, travel distance, travel time and costs, and vehicle hours of traveled in different hypothetical scenarios are calculated and compared to understand the potential impacts of AVs.

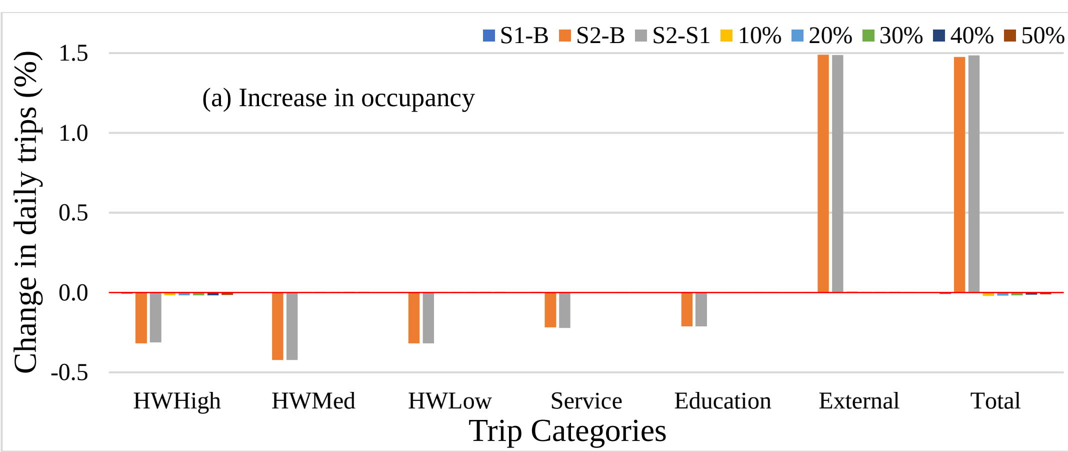
4. Results

This study explores the change in daily trips, travel distance, travel time, and travel costs of high-income (HWHigh), medium-income (HWMed), and low-income (HWLow) households to work and to service centers (i.e., retail and warehouses, offices, healthcare facilities), educational institutions, and external zones (i.e., external). Similarly, this study examines the change in people’s travel patterns by different modes of transportation. The study also checks the sensitivity of simulation results by increasing occupancy, wait time, and speed of AVs.

4.1 The impacts of AVs on daily trips

4.1.1 Impacts on the number of daily trips by trip categories

The potential impacts of AVs on household's daily trip generation are presented in Figure 6.7. The figure indicates that the adoption of AVs in S2 reduces household trips to work, services centers, and education institutions compared to the baseline scenario (-0.42 to -0.21%) and S1 (-0.42 to -0.21%). The overall daily trips made by high, medium, and low-income households are reduced due to sharing of AVs with other household members and fellow riders. In contrast, the total number of external trips increases slightly in S1 (0.003%) and S2 (1.49%) compared to baseline. Similarly, total external trips increase in S2 (1.49%) compared to S1 due to the wide adoption of AVs which allow people from surrounding cities and regions of Swindon to commute daily and thereby increase the total number of trips. The convenience and enjoyment while riding AVs particularly motivate people to make long-distance trips from external zones. Consequently, the total number of trips increased in S2 (1.48% compared to baseline and 1.49% compared to S1) due to the wide adoption of AVs, higher speed of AVs, no waiting time of AVs compared to public transportation, and available amenities for other activities (e.g., sleeping, talking, reading).



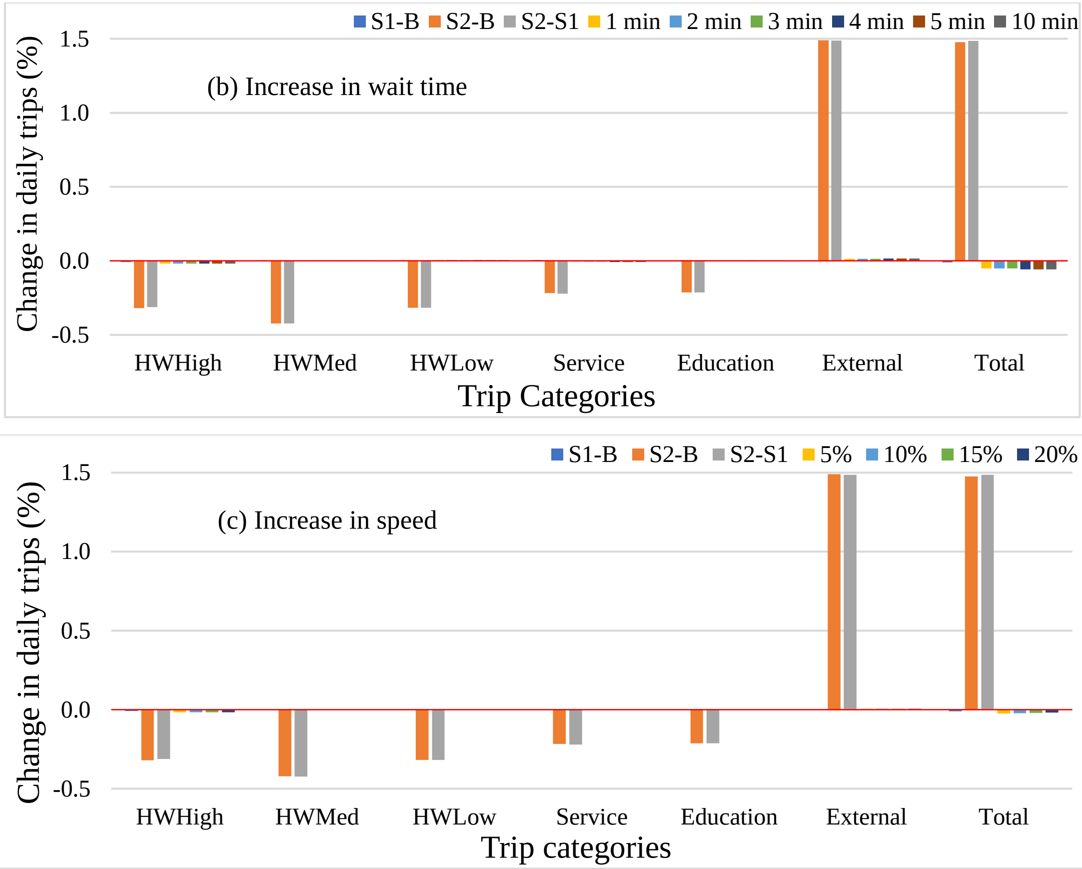
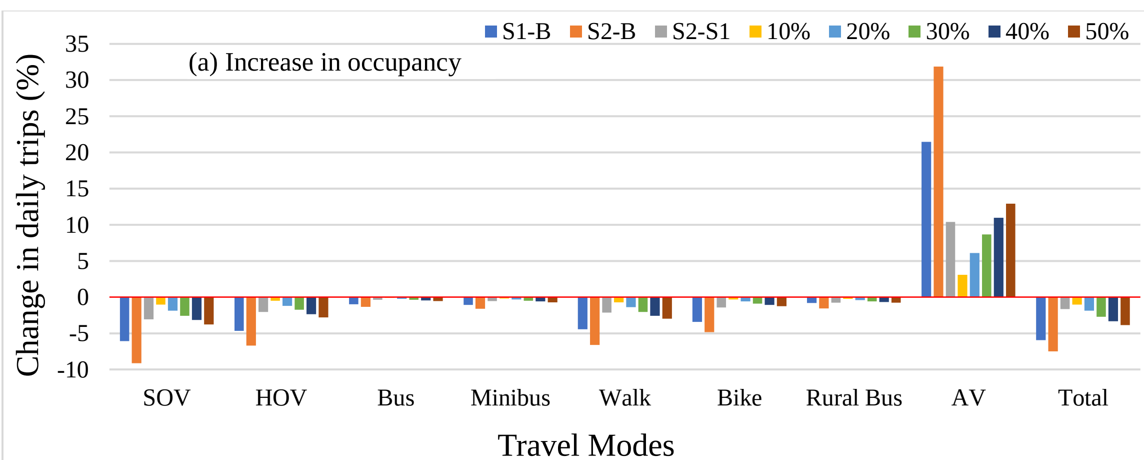


Figure 6.7: Impacts of AVs on the number of daily trips by trip categories

The sensitivity of the model is assessed by changing occupancy, wait time, and speed of AVs to quantify how the change in daily trips is related to the change in model parameters associated with AVs. Increasing occupancy of AVs by 10%, 20%, 30%, 40%, and 50% (Figure 6.7a), the study notices a decreasing trend in daily trip generation particularly for high-income households to work and the total number of trips, albeit the change is very trivial (about -0.02%). Thus, sharing AVs has the potential to reduce the total number of trips compared to private use. Similarly, by increasing the speed of AVs by 5%, 10%, 15%, and 20% (Figure 6.7c), the study finds a lower number of trips by encouraging people to make long-distance trips. Increasing the wait time of AVs by 1, 2, 3, 4, 5, and 10 minutes (Figure 6.7b), the study also observes a 0.05 to 0.06% reduction in people's trip generation. Thus, increasing the wait time for AVs increases their disutility and reduces people's willingness to use AVs. However, the impact of the wait time is greater than the occupancy and speed of AVs.

4.1.2 Impacts on the number of daily trips by travel modes

Results in Figure 6.8 indicate that introduction of AVs in S1 and S2 reduces trips made by SOVs, HOVs, buses, walking, and cycling (-6.07 to -0.82% in S1 and -9.16 to -1.59% in S2 compared to baseline scenario) due to wide AV adoption, no wait time, higher speed compared to public transport. AVs capture these reduced trips and hence the market share of AVs increased by 21.48% in S1 and 31.87% in S2 compared to the baseline scenario. However, the number of AV trips is lower in S2 compared to S1 due to a higher long-distance trip induced by the wide adoption of AVs on major roads (e.g., motorways, dual carriageways). The study also observes that AV adoption reduces the total number of trips by travel modes by 5.95% in S1 and 7.5% in S2 through increasing shared mobility and seamless movement and reducing solo driving. Thus, AVs are very effective to address people's higher travel demand (i.e., increase in total household daily trips).



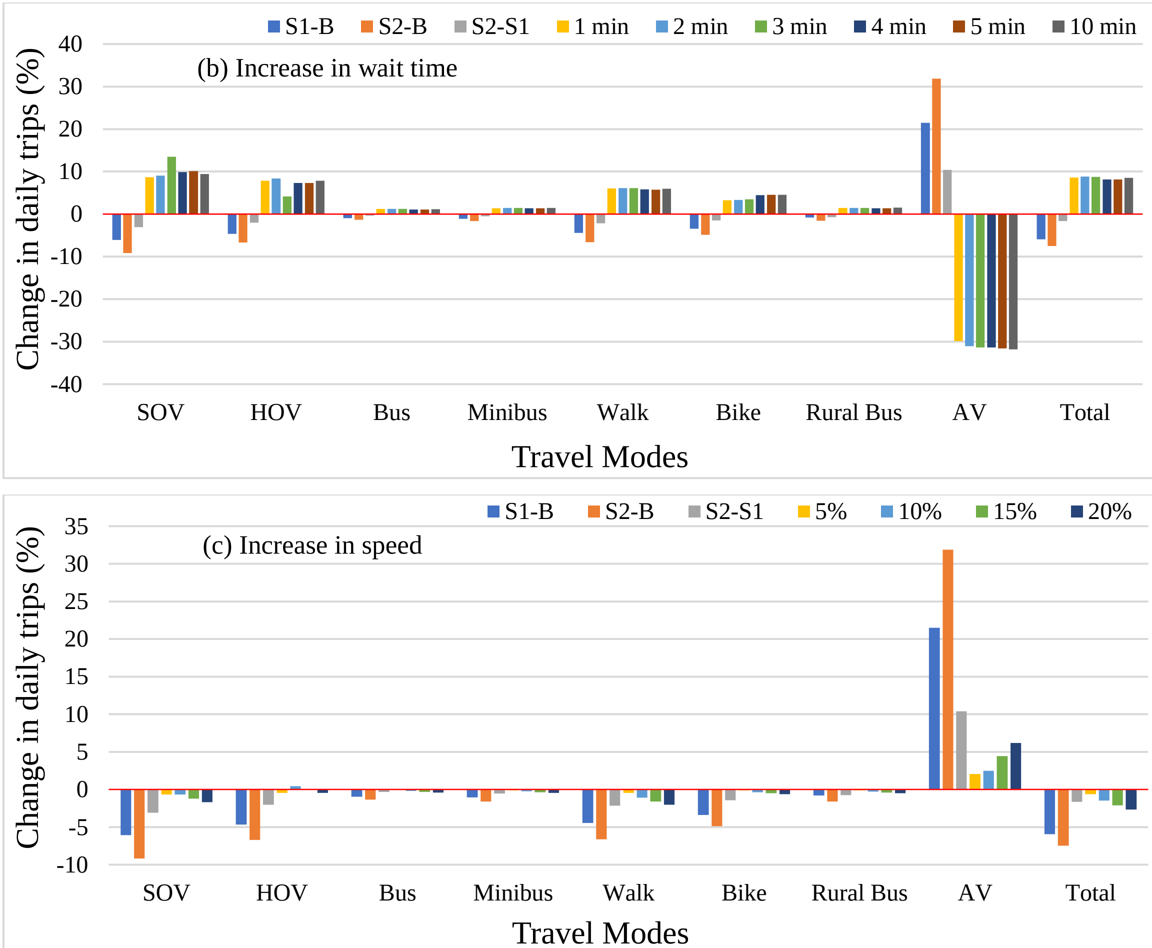


Figure 6.8: Impacts of AVs on the daily trips by travel modes

Increasing occupancy of AVs by 10 to 50% (Figure 6.8a), it is noticed that the market share of AVs increased from 3.10 to 12.91%. However, the total number of trips reduced by 1.02 to 3.86% due to the increased capacity of AVs. Similarly, by escalating the speed of AVs by 5 to 20% (Figure 6.8c), we observe a 2.05 to 6.18% growth in the market share of AVs. Nevertheless, the total number of trips is reduced by 0.64 to 2.66% by increasing the utility of AVs and hence attracting passengers from other modes of transportation. Thus, AVs have the potential to reduce overall trips despite the increasing travel demand of the people. On the other hand, increase in wait time of AVs by 1 to 5 and 10 minutes reduced AV trips by 29.88 to 31.84% (Figure 6.8b). Consequently, the total number of trips increased by 8.11 to 8.80% including a considerable increase in trips by SOVs (8.69 to 13.53%), and HOVs (4.15 to 7.86%), walks (5.76 to 6.11%), and cycle (3.27 to 4.55%). Thus, an increase in the disutility of AVs (i.e., extra wait time), discourages people to use AVs. Consequently, a shift in trips from AVs to traditional vehicles and an increase in the total number of trips are observed. Thus, AVs have the potential to influence the total number of household trips by changing perceptions of people and utilities of AVs.

4.2 The impacts of AVs on travel distance

4.2.1 Impacts on the daily travel distance of different trip categories

Figure 6.9 explains that the adoption of AVs in S1 and S2 reduces household's travel distance to work (-0.22 to -0.01%), services (-0.0 to -0.05%), and education centers (-0.03 to -0.01%) compared to baseline scenario by increasing shared mobility of the people. However, a higher reduction in travel distance of all trips is observed in S2 compared to S1. In contrast, the travel distance of external trips increased by 0.25% in S1 and 0.54% in S2 due to growth in long-distance external trips induced by AV implementation all over the transport network. The adoption of AVs on major roads besides local roads leads to long-distance external trips in S2 compared to S1. Subsequently, total travel distance increased in S2 by 0.93% and 1.30% compared to baseline and S1 scenarios, respectively due to increasing exogenous activities triggered by AVs. However, the adoption of AVs on local roads (S1) have the potential to reduce household total travel distance (-0.36%) compared to the baseline scenario by inducing short distance AV travel to destinations.

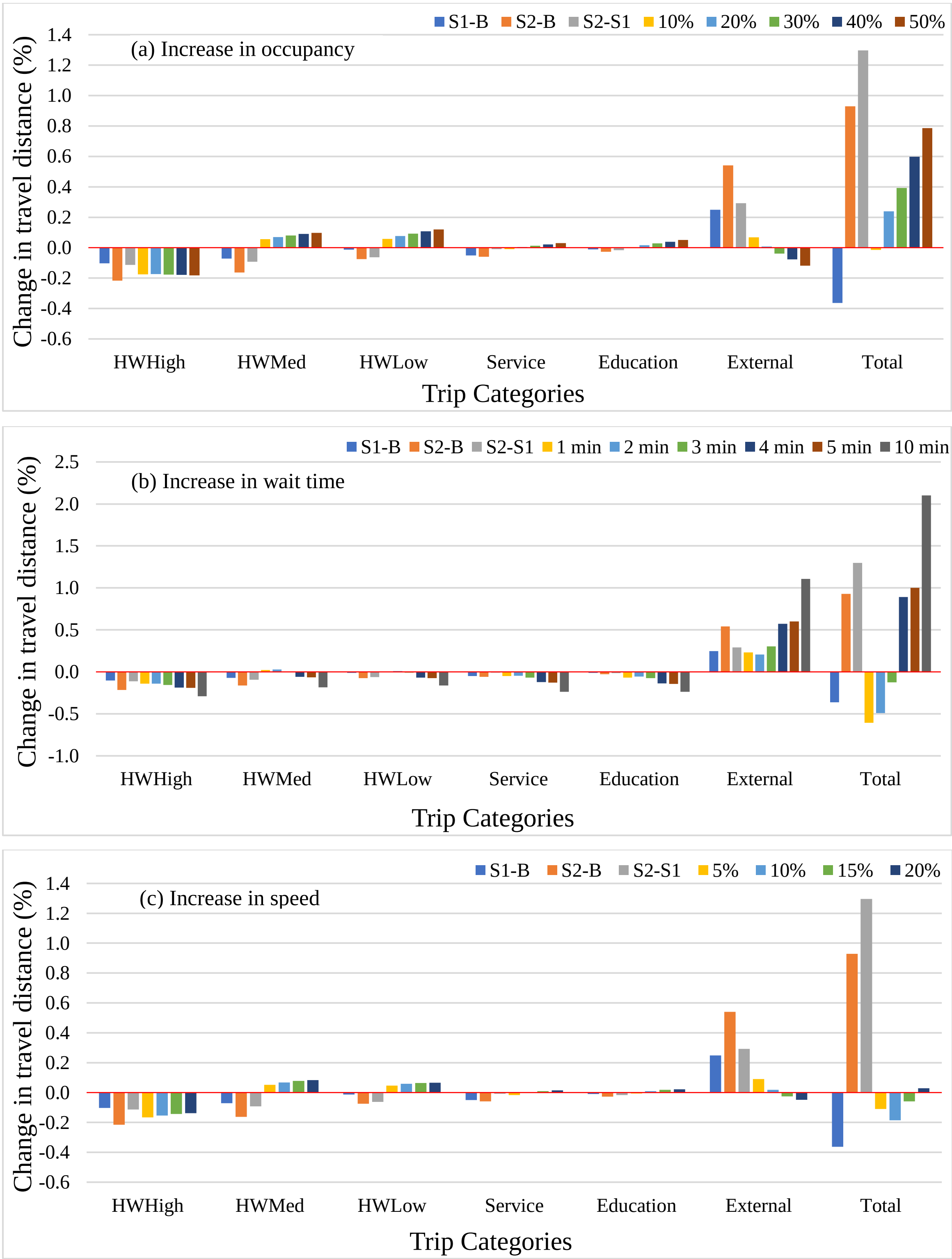


Figure 6.9: Impacts of AVs on the daily travel distance of different trip categories

Increasing occupancy of AVs by 10 to 50% (Figure 6.9a), it is noticed that the travel distance of high-income households to work (about 0.18%) and external trips (-0.12 to -0.04%) reduced compared to S2 who are considered as the potential consumers of AVs. However, total travel distance increased due to the increased travel distance of other trip categories. Similarly, by increasing the speed of AVs by 5 to 20% (Figure 6.9c), a 0.15% reduction in travel distance of high-income households is observed. Thus, increasing occupancy and speed has the potential to increase AV use and thereby reduce people's overall travel distance. On the other hand, increased wait time by 1 to 5, and 10 minutes (Figure 6.9b) also reduces travel distance (-0.29 to -0.14%) particularly of AVs users (i.e., high-income households) by depressing AV use and thereby reduce travel distance. We also observed that wait time has greater effects on AV use compared to occupancy and speed.

4.2.2 Impacts on PKT by travel modes

The adoption of AVs reduces PKT by all travel modes including a higher rate of reduction in SOVs (-4.91% in S1 and -14.84% in S2 than baseline) and HOVs (-3.98% in S1 and -12.23% in S2 than baseline) (Figure 6.10). Similarly, PKT by public transportation and active transportation is also reduced. In contrast, PKT by AVs increased by 12.04% in S1 and 31.87% in S2. Thus, the adoption of AVs induces the shift of passenger travel from other modes of transportation. Similar to the household travel distance, the adoption of AVs on local roads (S1) have the potential to reduce total travel distance by different modes of transportation (-0.36%) compared to the baseline scenario by inducing short-distance AVs travel to destinations. Although total PKT reduced in S1, the overall passenger travel increased in S2 due to the wide adoption of AVs, higher personal travel, and a higher number of long-distance external trips. Thus, the wide adoption of AVs has the potential to increase PKT by increasing long-distance passenger travel to the city center or workplaces from surrounding cities and towns.

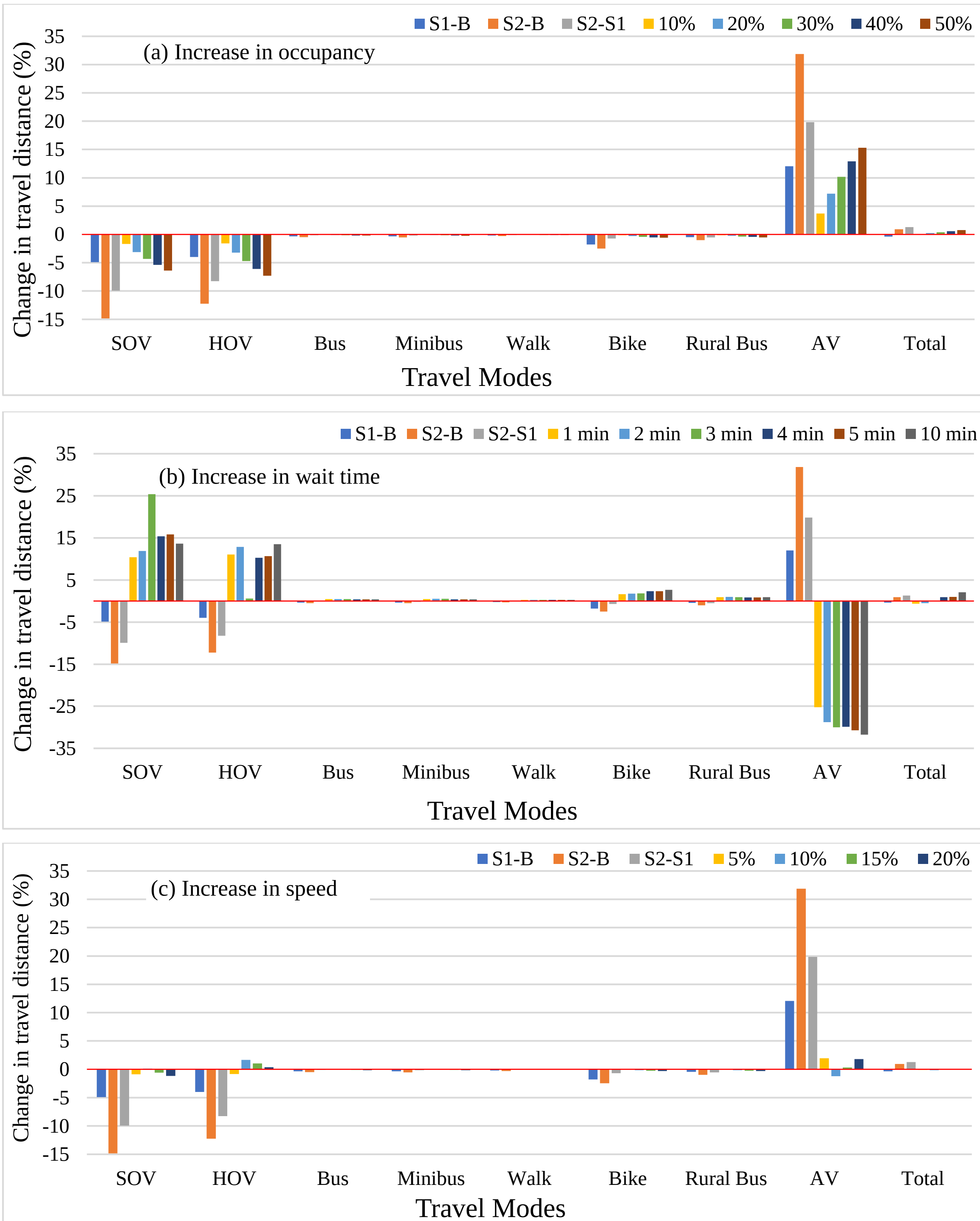


Figure 6.10: Impacts of AVs on PKT by travel modes

Increasing occupancy of AVs (Figure 6.10a), we notice an increase in AV use from 3.70% to 15.30% under 10% to 50% increase in occupancy, respectively. Thus, a higher capacity of AVs draws passenger from other transport modes and generate a higher PKT, although the overall increment is negligible (0.24 to 0.79%). Similarly, a rise in speed (Figure 6.10c) increases AV use by 0.33 to 1.93%. However, overall VKT reduced by 0.06 to 0.19%. Thus, increasing speed is more effective than occupancy to induce people to use AVs and reduce overall PKT. On the other hand, increasing wait time (Figure 6.10b) reduces passenger travel by AVs and increases passenger travel by SOV, HOV, Bus, and active transportation. Thus, the addition of disutility to AVs discourages AV use and thereby increases total PKT by increasing travel using SOVs and HOVs.

4.2.3 Impacts on VKT by travel modes

Figure 6.11 shows that the implementation of AVs reduces overall vehicle travel in both S1 (-2.56%) and S2 (-9.07%) compared to the baseline scenario including a higher reduction in SOVs (-6.39% in S1 and -18.58% in S2) and HOVs (-2.04% in S1 and -5.65% in S2). On the other hand, VKT by AVs increased by 8.42% in S1 and 24.18% in S2 compared to the baseline scenario. Similarly, VKT by bus, minibus, and rural bus increased slightly by 0.01 to 0.02%. and public transportation increased. Thus, unlike PKT, the adoption of AVs has the potential to reduce overall VKT by increasing the use of AVs and public transportation and reducing empty VKT.

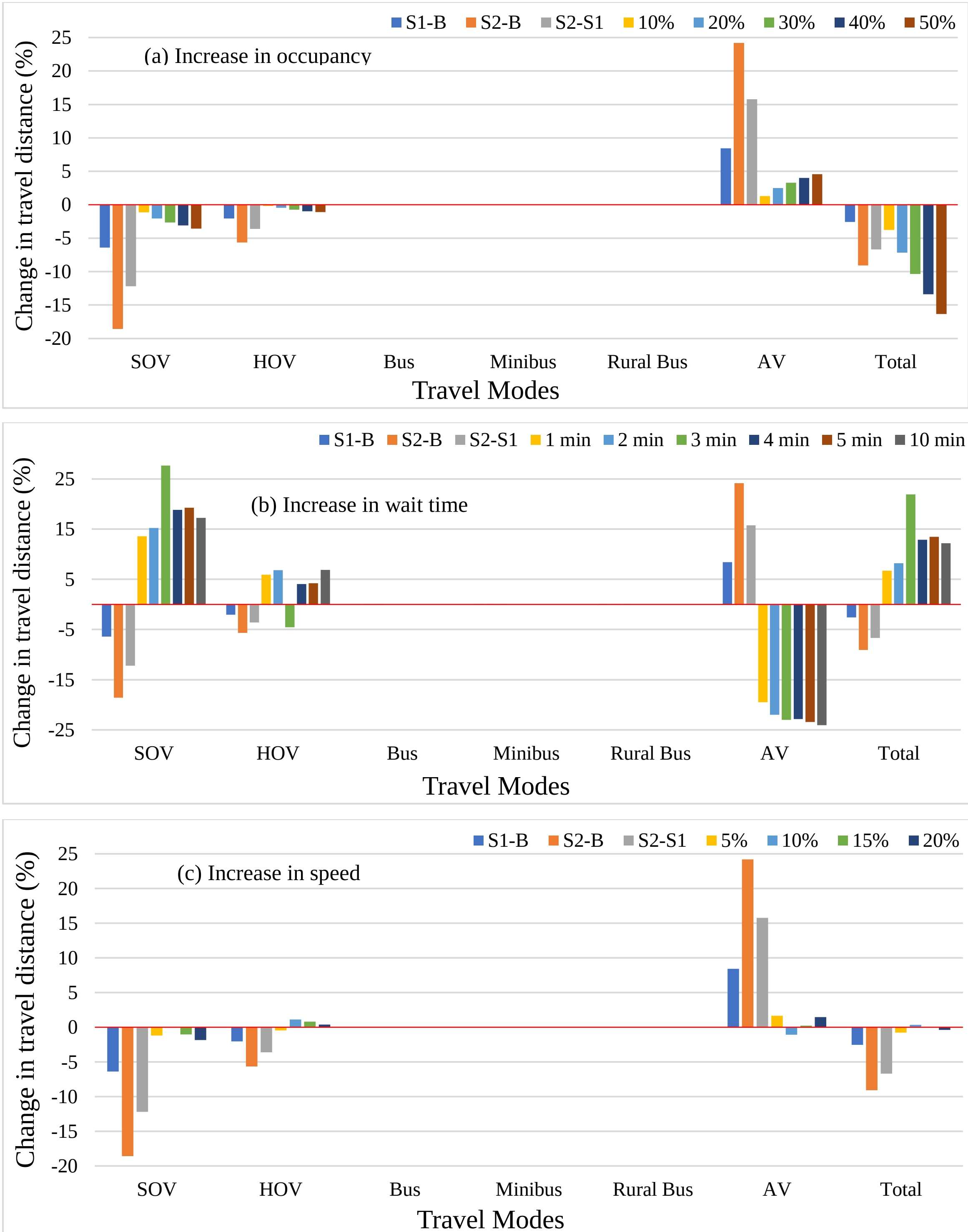


Figure 6.11: Impacts of AVs on VKT by travel modes

Increasing occupancy of AVs (Figure 6.11a), a significant decrease in overall VKT is observed (i.e., VKT decreased by 3.78% under 10% increase in occupancy to 16.32% by 50% increase in occupancy) due to a higher share of AVs (1.31 to 4.56% increase) and public transportation (0.01 to 0.04% increase) and lower share of SOVs (1.15 to 3.58% decrease) and HOVs (0.18 to 1.08% decrease). A similar situation, yet at a lower magnitude, is also observed when we increase the speed of AVs (Figure 6.11c). However, we observe a reduction in VKT of AVs by 19.48% under 1-minute wait time to 24.09% under 10 minutes wait time (Figure 6.11b). We also observe that adding extra wait time increases overall VKT by 6.73% to 13.47% by increasing the VKT of SOVs and HOVs. This sensitivity analysis confirms that a higher utility in AVs would encourage people to use AVs and thereby reduce overall travel distance by vehicles.

4.3 The impacts of AVs on travel time

4.3.1 Impacts on household's travel time

Figure 6.12 shows that the adoption of AVs slightly increases the travel time of high-income households to work and external trips in both S1 (0.18% and 1.5%, respectively) and S2 (0.27% and 0.63%, respectively) due to a higher number of long-distance trips carried out by AVs. In contrast, the travel time of all other trips reduces. Thus, overall household travel time is reduced significantly (4.72% reduction in S1 and 21.79% reduction in S2 compared to the baseline scenario). The figure also demonstrates that the adoption of AVs throughout the transportation network further reduced travel time by 17.92% compared to the adoption of AVs on local roads only. Thus, the wide adoption of AVs ensures seamless transportation services to the people and thereby saves travel time to destinations. The findings confirm that AVs have the potential to reduce the overall travel time of the people.

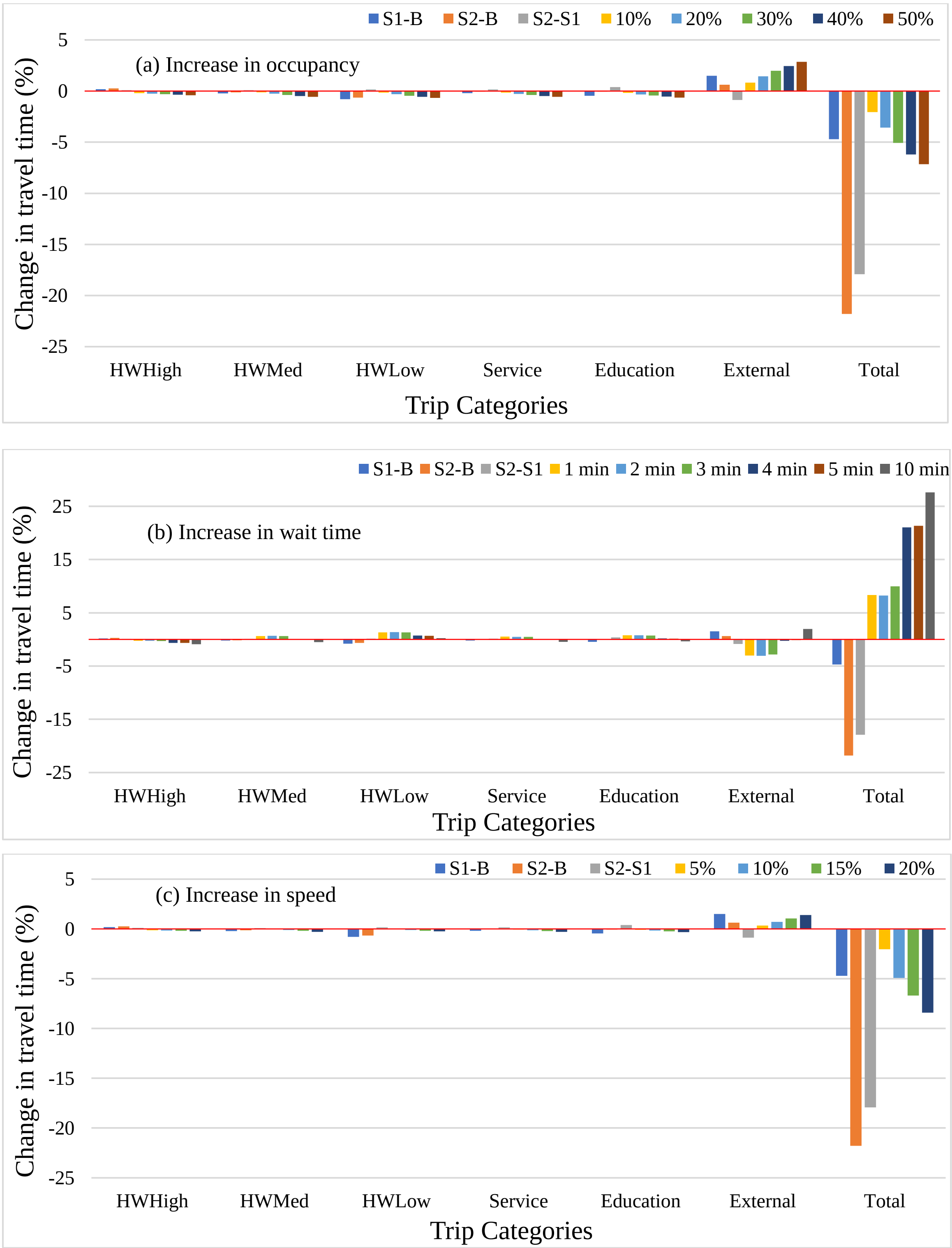
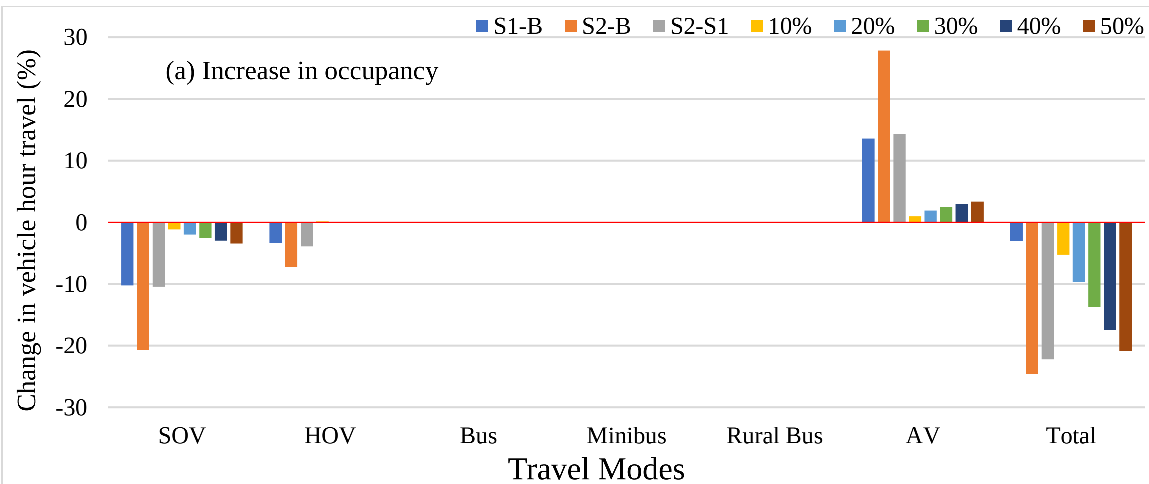


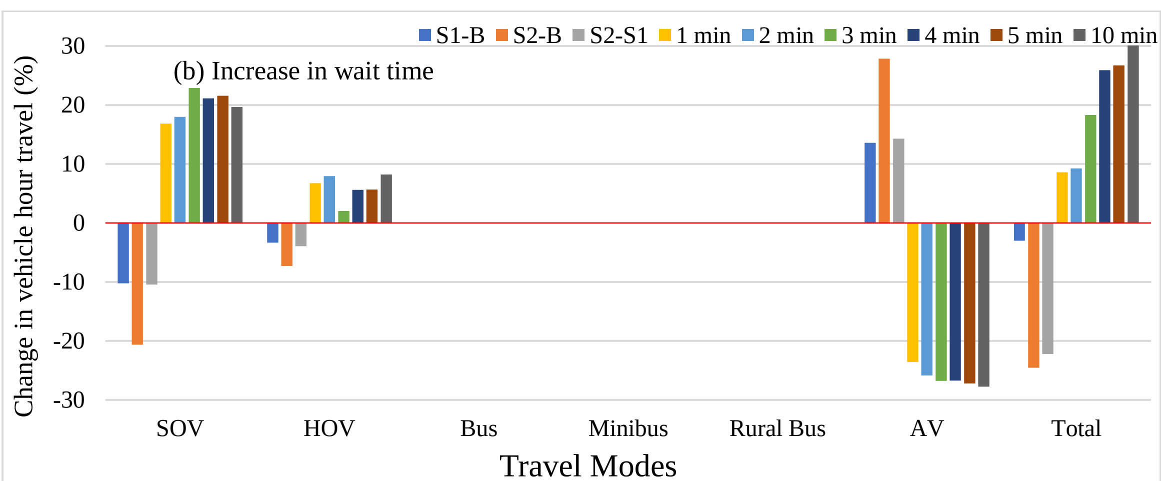
Figure 6.12: Impacts of AVs on household travel time

Increasing occupancy of AVs (Figure 6.12a), a substantial reduction in overall travel time is observed (i.e., 2.06 to 7.16% reduction due to a 10 to 50% increase in occupancy of AVs). Similarly, a reduction in household's travel time to work, service, and education are also seen. However, the travel time of external trips increased slightly by 0.83 to 2.86% due to a 10 to 50% increase in occupancy of AVs. A higher number of trips from outside of the city and additional time for passenger pick-up and drop-off cause this slight increase in travel time. Similarly, by increasing the speed of AVs (Figure 6.12c), we observe a 2.04 to 8.42% reduction in overall travel time due to a 5 to 20% increase in speed including travel time reduction in all other trips. However, travel time for external trips increased by 0.34 to 1.38% under the same rise in speed due to a higher travel demand from external zones. As expected, on the other hand, an extra wait time for AVs (Figure 6.12b), increases overall travel time (8.35 to 27.59% in 1 min to 10 minutes extra time) by reducing AV use which is reflected in trips made by high-income households and external trips. Extra wait time discourages people to use AVs and thus reduces travel time for high-income household trips to work (0.27 to 0.92% reduction) and trips from external zones (0.13 to 3.05% reduction).

4.3.2 Impacts on vehicle hours of traveled

Figure 6.13 illustrates that the adoption of AVs significantly reduces overall VHT (i.e., a 3.03 and 24.6% reduction in S1 and S2, respectively). The VHT by SOVs reduces by 10.22% and 20.65% in S1 and S2, respectively compared to the baseline scenario. A similar reduction in VHT by HOVs is also seen in S1 (-3.35%) and S2 (-7.28%). Conversely, VHT by AVs increases by 13.56% in S1 and 27.85% in S2 due to the wide adoption of AVs. By doing so, AVs induce people to shift from SOVs and HOVs and thereby reduce overall travel time by other vehicles. A higher reduction of VHT (-22.2%) is noticed in S2 compared to S1. Thus, the adoption of AVs throughout the transportation network is effective to attract people to AVs and reduce overall travel time. However, a 0.002%, 0.01%, and 0.01% increase in VHT of bus, minibus, and rural buses, respectively are seen in S1. Similarly, a 0.02%, 0.03%, and 0.04% increase in VHT of bus, minibus, and rural buses, respectively are observed in S2. Thus, AVs have very little influence on the VHT of public transportation.





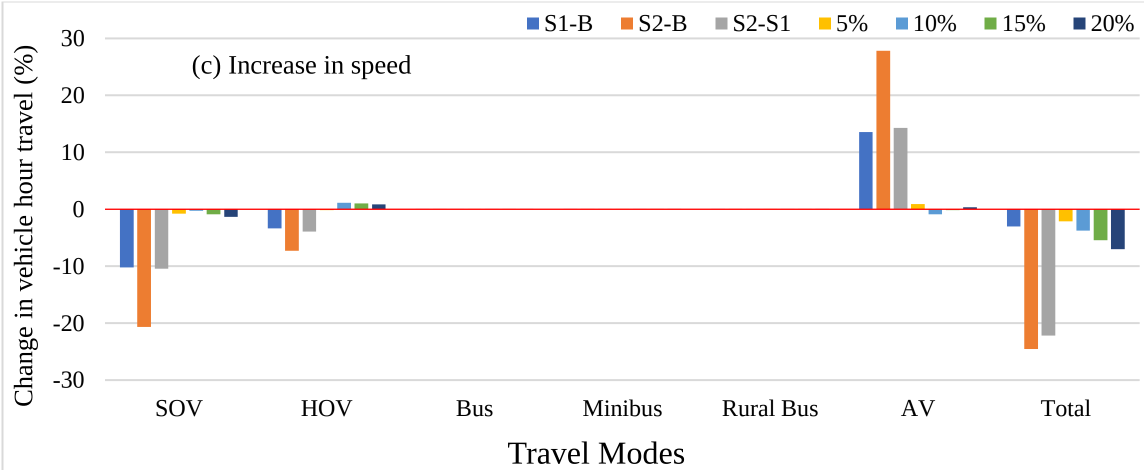


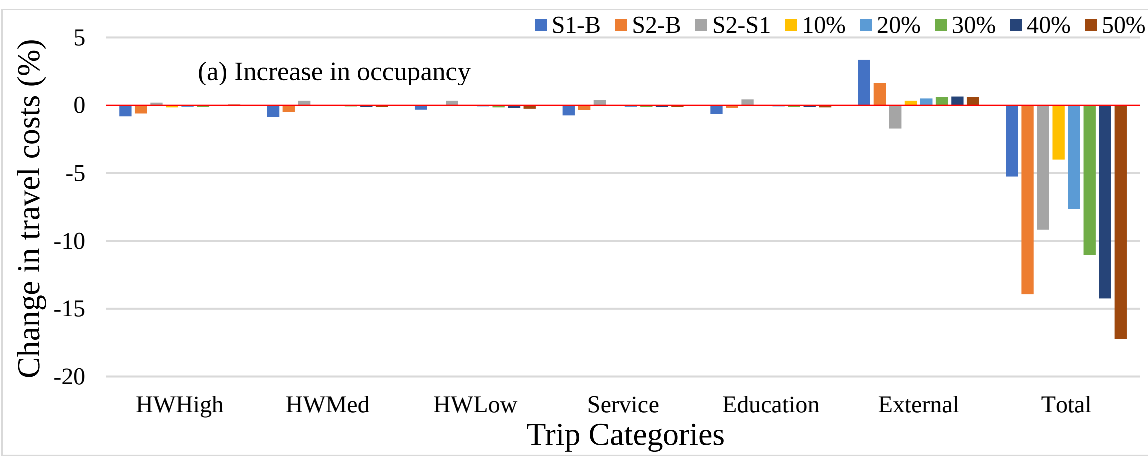
Figure 6.13: Impacts of AVs on vehicle hours of traveled

Increasing occupancy of AVs (Figure 6.13a), a significant reduction in overall VHT is observed (i.e., 5.25 to 20.9% reduction in total VHT due to a 10 to 50% increase in occupancy). Similarly, a 1.16 to 3.43% reduction in VHT of SOV is noticed due to a 10 to 50% increase in occupancy and a 0.04 to 0.10% reduction in VHT of HOVs due to a 30 to 50% increase in occupancy. Thus, higher occupancy of AVs has the potential to attract more passengers and reduce overall VHT. Increasing the speed of AVs (Figure 6.13c), we also observed a decrease in overall VHT (i.e., a 3.03 and 24.6% reduction of VHT in S1 and S2 compared to the baseline scenario). VHT of SOVs and HOVs reduced by 10.22% and 3.35%, respectively in S1 and 20.65% and 7.28% in S2. In contrast, by adding extra 1 to 10 minutes of wait time for AVs (Figure 6.13b) we notice a significant increase in total VHT (i.e., 8.62 to 30.66%). The increasing disutility of AVs by adding extra wait time demotivates people and diverts them to use SOVs and HOVs which is evident in Figure 6.13b (i.e., a higher VHT for SOVs and HOVs due to a higher number of passengers). Thus, AVs have the potential to reduce overall VHT by increasing travel utility (e.g., high occupancy and speed and no wait time).

4.4 The impacts of AVs on travel costs

4.4.1 Impacts on household travel costs

As shown in Figure 6.14, the adoption of AVs in S1 and S2 reduces overall household travel costs (i.e., maintenance and operation) by 5.24% and 13.94%, respectively compared to the baseline scenario due to lower costs for parking, energy use, and cost-sharing among travel companions. Similarly, a reduction in travel costs is seen in household trips to work (-0.86 to -0.32%), education (-0.62 to -0.18%), and service centers (-0.75 to -0.35%) in S1 and S2, respectively compared to the baseline scenario. Although travel costs of external trips increase, the growth is lower in S2 (1.64% compared to baseline) compared to S1 (3.36% compared to baseline) which indicates that the wide adoption of AVs has the potential to reduce overall travel costs.



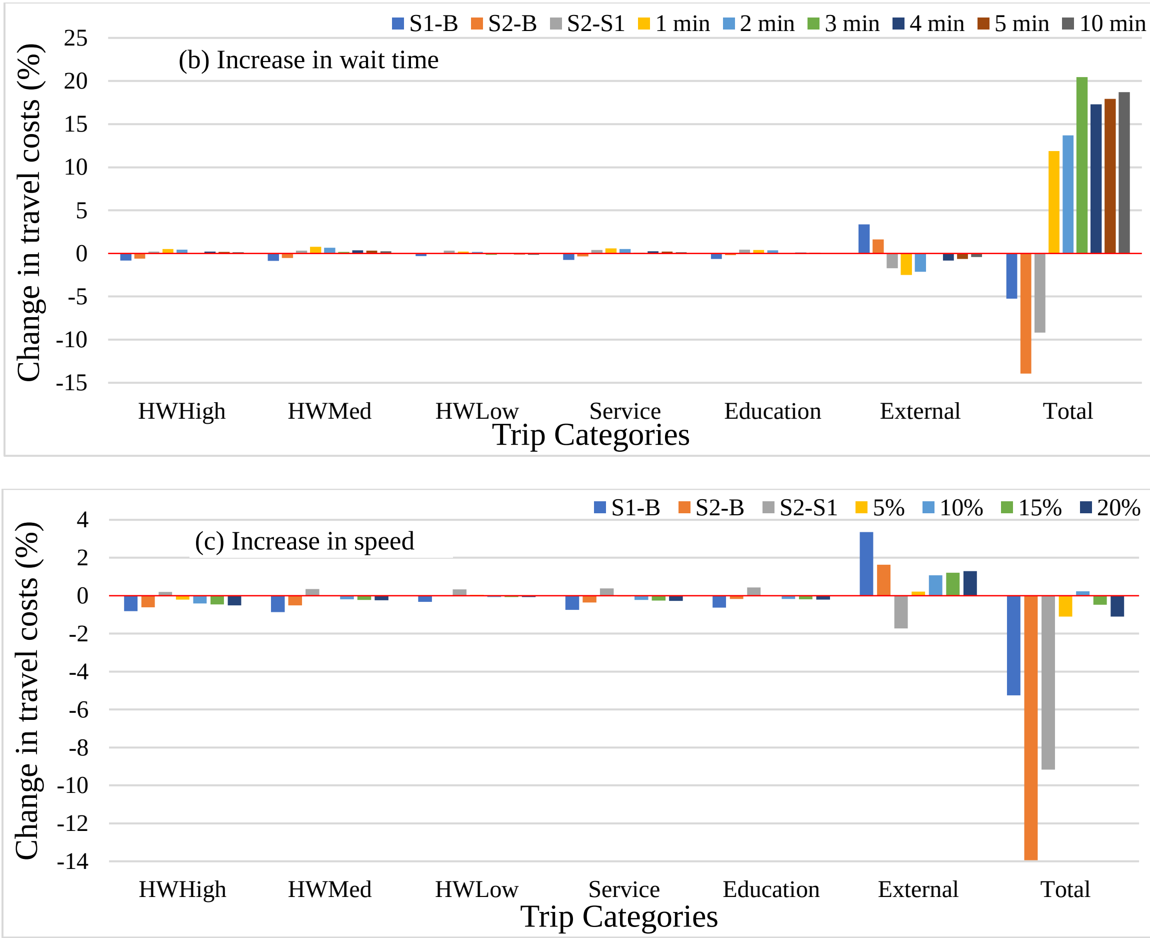


Figure 6.14: Impacts of AVs on household travel costs

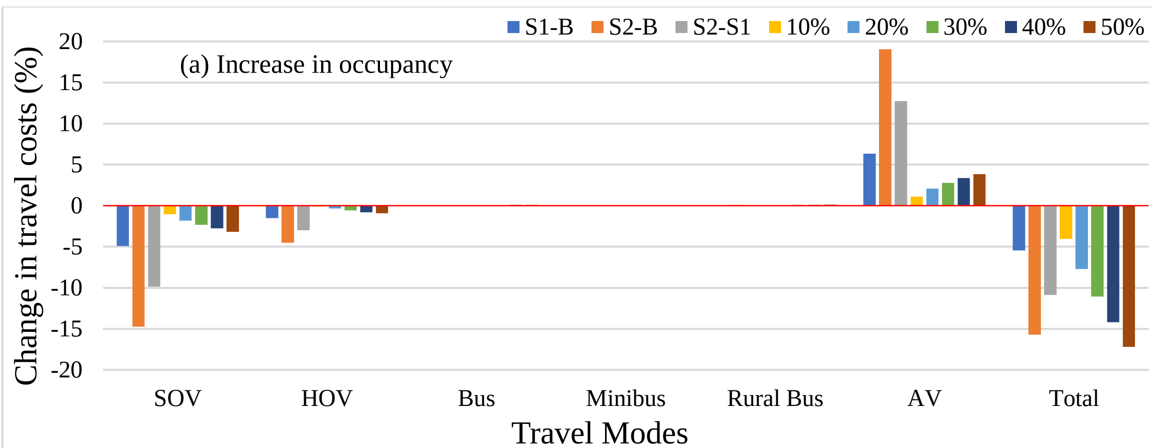
With increasing occupancy of AVs (Figure 6.14a), a substantial reduction in overall household travel costs is noticed (i.e., a 4.01 to 17.24% reduction in travel costs due to a 10 to 50% increase in SAV occupancy). A similar reduction in travel costs is also seen in household trips to work (-0.25 to -0.03%), service centers (-0.15 to -0.07%), and education centers (-0.15 to -0.06%). In contrast, travel costs for external trips increased slightly by 0.34 to 0.64% due to an increase in pick-up or drop-off time for the additional people and a higher number of external trips induced by the convenience and usefulness of AVs. Increasing the speed of AVs by 5 to 20% (Figure 6.14c), we also observed a reduction in overall travel costs (-1.10 to -0.47%) compared to S2. Travel costs of household trips to work (-0.51 to -0.04%), service (-0.28 to 0.04%), and education (-0.20 to -0.02%) centers are also reduced. In contrast, travel costs of external trips increased slightly (0.21 to 1.30%) due to the increase in speed of AVs. However, increased occupancy has a greater influence on reducing travel costs compared to increased speed of AVs.

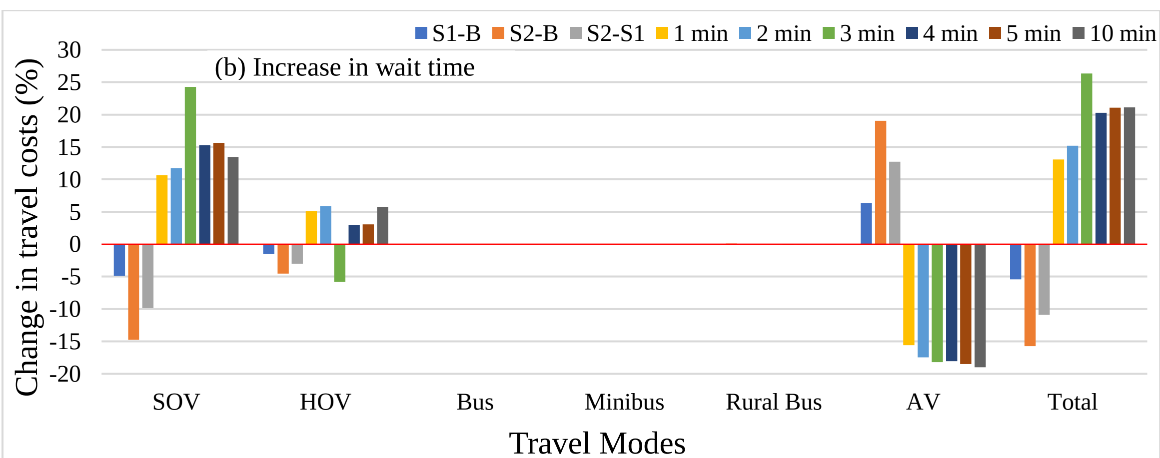
On the other hand, adding extra wait time for AVs (Figure 6.14b), overall travel costs increased by 11.88 to 20.46% due to a reduction in AV use and an increase in the use of gasoline vehicles. Figure 6.14b also demonstrates that household's travel costs to work (0.01 to 0.75%), service (0.07 to 0.60%), and education (0.05 to 0.42%) increased. In contrast, travel costs of external trips reduced by 0.04 to 2.51%. The reason behind travel costs reduction of external trips lies in the fact that the extra wait time of AVs compels people to choose other modes of transportation (e.g., SOVs, HOVs, public transportation). However, overall travel costs increased significantly by increasing operating and maintenance costs of SOVs and HOVs (i.e., costs for parking and energy use). Thus, AVs have the potential to reduce overall household travel costs by increasing utility (e.g., high occupancy and speed, no wait time, stable traffic flow due to automation and connectivity) and thereby attracting trips from other modes of transportation.

4.4.2 Impacts on travel costs of different travel modes

As indicated in Figure 6.15, the adoption of AVs reduces travel costs of SOVs by 4.90% and 14.75% in S1 and S2, respectively, and HOVs by 1.51% and 4.52% in S1 and S2, respectively compared to the baseline scenario. The adoption of AVs alters people's trip generation tendency from SOVs and HOVs to AVs due to greater utility associated with AVs (i.e., high occupancy compared to SOVs, low operation and maintenance costs, energy use compared to SOVs, HOVs, and public transportation). Thus, the adoption of

AVs reduces the overall costs of different travel modes by 5.4% in S1 and 15.7% in S2 compared to the baseline scenario. However, the wide adoption of AVs has a greater influence to reduce travel costs than a limited adoption of AVs (10.9% reduction of travel costs in S2 compared to S1). Thus, AVs have the potential to reduce the overall travel costs of different modes. In contrast, AVs have little to deal with the travel costs of public transportation which indicates that AVs do not discourage people to use public transportation rather it facilitates people to use public transportation.





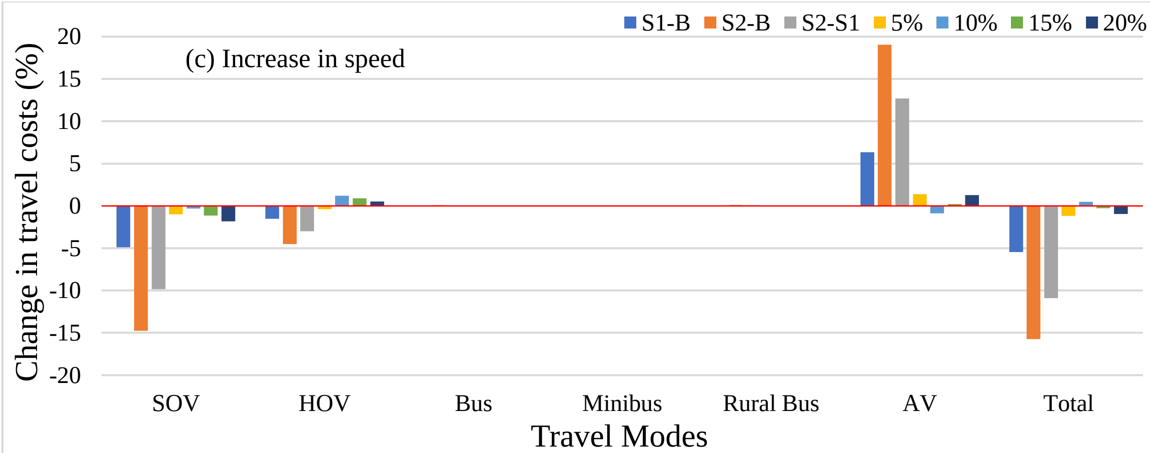


Figure 6.15: Impacts of AVs on travel costs of different travel modes

Increasing occupancy of AVs (Figure 6.15a), it is observed that overall travel costs of different modes of transportation reduced by 4.05 to 17.2% due to a 10 to 50% increase in AV capacity, despite a slight increase in the travel costs by AVs (1.09 to 3.83%). A higher occupancy of AVs attracts more passengers from SOVs and HOVs and thereby reduces people's travel costs of SOVs (-3.19 to -1.04%) and HOVs (-0.92 to -0.11%). Similarly, an increase in the speed of AVs (Figure 6.15c) reduces overall travel costs (-1.2 to -0.94%) by reducing travel costs of SOVs (-1.80 to -0.33%). Although travel costs by HOVs increases slightly (0.53 to 1.2%), travel costs by bus, minibus, and rural bus remain almost unchanged (0.00 to 0.01% increase). On the other hand, an extra wait time (Figure 6.15b) increases total transportation costs significantly (13.1 to 26.37%) by reducing AVs and increasing SOVs use. This is reflected by reducing travel costs of AVs (-18.99 to -15.57%) and public transportation, and increasing travel costs of SOVs (10.64 to 24.26%). Thus, AVs have the potential to influence transportation costs of different travel modes and thereby the total cost of transportation of the people.

5. Discussion

Using the calibrated Swindon model, the study shows that the wide adoption of AVs expands the total household's daily trip generation by providing transport services to all people, which echoes the findings from the extant literature (Martinez & Viegas, 2017; Narayanan et al., 2020) and supports our hypothesis (H1). However, it is also observed that households' trips to work, service, and education centers within the city shrink slightly due to people's vehicle sharing tendency with family members. The overall increase in trip generation lies in the fact that AVs induce people to make long-distance trips from surrounding cities and regions to Swindon by reducing travel costs and providing amenities to perform multitasking (Gelauff et al., 2019; Heilig et al., 2017). Thus, AVs have the potential to reduce households' trips within the city due to people's willingness to share vehicles, despite a small increase in external trips. The sensitivity analysis reiterates that AVs have the potential to reduce overall households' trips by increasing utility (e.g., availability, occupancy, speed) and reducing disutility (e.g., wait time) of AVs.

Analyzing households' trip generation by different modes of transportation, we observe that the wide adoption of AVs reduces the total number of trips by providing seamless travel opportunities. The introduction of AVs in the transportation system captures a significant number of household trips from another mode of transportation induced by the usefulness and convenience associated with AVs. Consequently, household trips by SOVs, HOVs, buses, walking, and cycling are reduced. Thus, AVs would reduce overall vehicle ownership, public transportation, and active travel by encouraging shared mobility and reducing solo driving, yet ensuring flexibility and convenience of travel. The sensitivity analysis also demonstrates that increased capacity and speed of AVs and no extra wait time in AVs reduce overall household trips by increasing AV trips and decreasing trips by conventional vehicles and public and active transportation. The results imitate the past studies where researchers found that AVs would reduce vehicle ownership (Fagnant & Kockelman, 2014; Kim, 2018; Tirachini et al., 2020) and affect public transit trips and active travel (Clements & Kockelman, 2017; Cyganski et al., 2018; Narayanan et al., 2020) by increasing shared mobility. The findings also support our hypotheses (H2 and H3).

Aggregating travel distance at the household level, we notice that AVs would reduce household travel distance to work, services, and education centers by increasing the vehicle sharing propensity of people. In contrast, a slight increase in travel distance of exogenous trips is observed due to growth in trips from external zones induced by AVs implemented all over the transport network. However, the adoption of AVs on local roads has the potential to reduce household total travel distance by inducing short-distance AV travel to destinations. A similar situation is also observed in the case of PKT (i.e., the adoption of AVs on local roads and throughout the transport network reduces PKT by SOVs, HOVs, and public and active transportation). Although adoption of AVs on local roads only reduces total PKT, the adoption of AVs throughout the transport network increases total PKT by increasing travel demand and long-distance external trips. Investigating the impacts on VKT, we perceive that the adoption of AVs on local roads and throughout the transport network reduces overall vehicle travel by encouraging shared travel and discouraging travel alone. The sensitivity analysis confirms that the adoption of AVs on local roads has the potential to reduce household travel distance and PKT by increasing short-distance AV trips. Similarly, the adoption of AVs is likely to reduce VKT by increasing ride-sharing and reducing empty VKT for transferring passengers and searching for parking spots. The study results are consistent with the extant literature (Fagnant & Kockelman, 2014; Levin et al., 2017; Soteropoulos et al., 2018) and support our hypothesis (H4).

Evaluating the potential impacts of AVs on households' travel time, we diagnose that the adoption of AVs significantly reduces household travel time by increasing ride-sharing and reducing travel time for empty trips and searching for parking. The results also indicate that the wide adoption of AVs is more effective to reduce travel time by ensuring seamless connection throughout the city compared to AVs adopted on local roads. Thus, AVs would reduce overall households' travel time, as also pointed out in the previous studies (Levin et al., 2017; Loeb et al., 2018; Zhang et al., 2015). Moreover, AVs reduce travel delay and congestion by promoting sharing travel and smoothing traffic flows (Alam & Habib, 2018; Fagnant & Kockelman, 2014; Krueger et al., 2016). The study also found that the adoption of AVs significantly reduces overall VHT by reducing solo driving and promoting shared travel. Unlike solo driving AVs which have the potential to increase VHT by reducing value of travel time (Van den Berg & Verhoef, 2016), shared AVs would reduce VHT by offering a lower level of flexibility and convenience (Childress et al., 2015; Soteropoulos et al., 2018). Similar to travel time, a wide adoption of AVs which ensure seamless transportation of passenger is more effective to reduce VHT compared to limited adoption. Thus, AVs have the potential to reduce overall travel time, traffic congestion, and VHT which supports our hypothesis (H5 and H6).

This study also estimates that AVs have the potential to reduce overall household transportation costs by moderating vehicle operation and maintenance costs (parking, fuel, insurance, and driver costs), reducing fleet size, and encouraging ride-sharing. The study findings also supported by the extant literature (Compostella et al., 2020; Loeb et al., 2018; Martinez & Viegas, 2017). Thus, it is likely that AVs would reduce overall travel cost of households, which sustenance the study hypothesis (H7).

6. Conclusions and directions for future research

The study links the gap in the literature by investigating the potential impacts of AVs on people's travel behaviors. The study also sheds light on policy implications for informed policy-making by the decision-makers and transport professionals considering the expected change in transportation systems due to the advent of AVs. Since AVs are very effective to address the increasing travel demand of the people, the city authority should promote AVs. They could partner with transport network companies to promote AVs and make them affordable for the people. Since AVs are more likely to reduce traffic delay and congestion, an appropriate measure could be taken by the policymakers to increase in AV use to control traffic congestion, particularly in the city centers. For example, AVs in a dynamic ride-sharing situation could be implemented as an effective policy option to reduce traffic congestion and overall travel time (Fagnant & Kockelman, 2018; Krueger et al., 2016). AVs in the form of public transportation could be implemented as effective congestion mitigation strategies (Rahman, Najaf, et al., 2021). As the results indicated, AVs could suppress public and active transportation. To increase transit use and active travel, and ensure a sustainable transportation system, proper initiatives should be taken by the policymakers to integrate AVs with an efficient public transport system (Narayanan et al., 2020; Sparrow & Howard, 2017).

Despite significant contributions to the literature, the study is shuttered by some cautionary measures. Due to the absence of AVs and lack of data, this study estimated the potential effects based on numerous assumptions and simulations, which may be unreasonable in real-world situations. This study partially estimated the effects of AVs on transportation. A further study is necessary to estimate the effects of AVs on travel speed, energy consumption, carbon emission, traffic safety, the capacity of roads, etc. Moreover, another study is warranted to investigate the potential effects of AVs on the built environments. We have experienced radical changes in people's travel behaviors due to the recent COVID-19 pandemic (Bhouri et al., 2021; Chan et al., 2020; Rahman, Paul, et al., 2021). The current study fails to capture this scenario. Future studies should investigate how a public health crisis could influence the travel pattern of people including the use of AVs and SAVs. There is a lack of evidence of the potential impacts of AVs and SAVs on public health. Future study should focus on public health issues of vehicle automation to protect people from unforeseen fitness tragedies.

Appendix: Supplementary Tables

Table A1: Types of transportation links in the model

Link-type	Description of the link	Assigned speed
Access	Access to zones without parking charges	25 kph
Acc/wpark	Access to zones with parking charges	25 kph
CentNarr	Central street narrow	30 kph
CentWide	Central street wide	38 kph
PerNarr	Peripheral street narrow	45 kph
PerBroad	Peripheral street broad	68 kph
Mtway	Motorway	90 kph
DualCway	Dual carriageway	80 kph
CenNarrB	Central street narrow buses only	30 kph
CenWideB	Central street wide buses only	35 kph
AccessB	Access to zones buses only (pedestrians)	5 kph
Railway	Railway line	30 kph
Station	Railway station (pedestrians)	5 kph
P&R	Park-and-ride	5 kph
External	For external zones	68 kph

PerNarrRC	Peripheral street reduced capacity (parallel to bus lanes)	65 kph
Cycle	Cycle ways	12 kph
BusLink	Bus-only lane	35 kph
CenNarrRC	Central street narrow reduced capacity (parallel to bus lanes)	30 kph
CenBroadRC	Central street broad reduced capacity (parallel to bus lanes)	36 kph

Table A2: Combination between operators

From/To	SOV	HOV	AV	RegBus	ExpBus	LRTBus	Walk	P&R	Metro	LRT
SOV										
HOV										
AV										
RegBus										
ExpBus										
LRTBus										
Walk										
P&R										
Metro										
LRT										

Shaded cell: Combinations are not allowed.

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CHAPTER 7: SIMULATING THE POTENTIAL IMPACTS OF AUTONOMOUS VEHICLES ON THE SPATIAL DISTRIBUTION OF URBAN HOUSEHOLD AND EMPLOYMENT LOCATIONS

Abstract

The potential effects of Autonomous Vehicles (AVs) on land-use distribution in urban regions have received little attention. To bridge this gap, this study focuses on the potential impacts of AVs on the spatial distribution of household and employment locations. Using the existing Swindon model of the TRANUS platform, it estimates the effects of AVs on household and employment locations against a business-as-usual scenario. A sensitivity analysis is also carried out by allowing growth in jobs to check the robustness of the results. The simulation results show that the adoption of AVs would lead to a decrease in the number of households in the city center and an increase in households in the periphery of the city stemming from a reduction of travel time and an increase in accessibility. The wide adoption of AVs would increase employment in the city center and the urban periphery by inducing more economic activities. Sensitivity analysis confirms that AVs would allow densification of the existing city center by releasing extra space from parking land areas along with peripheral new development over time. Finally, the study provides some policy guidelines to control the growth of cities by investigating the long-term effects of AVs.

Keywords: Autonomous vehicles, built environment, land use, travel behaviors, simulation

1. Introduction

The advent of autonomous vehicles (AVs) has captured the attention of individuals including transportation professionals, researchers, technology entrepreneurs, and travelers (Ho, 2019; Soteropoulos et al., 2018). Practitioners and policy makers in transport and urban planning are concerned about the effects that AVs may have on the core domain of city planning, that is the mutual interactions between transportation and land uses (Fraedrich et al., 2019). As of now, the predominant discussion on AVs is focused on cutting-edge technologies, human travel patterns, environmental consequences, private or shared models of deployment, ethics, liabilities, and the willingness of users to use AVs (Ho, 2019; Soteropoulos et al., 2018). However, the potential effects of AVs on land-use distribution in urban regions have received scant attention. To bridge this gap in the literature, this study investigates the potential impacts of AVs on the spatial distribution of household and employment locations.

It is anticipated that AVs would have profound effects on society as a disruptive technology (Tao & Cao, 2022; W. Zhang et al., 2020). A considerable number of studies have reported that AVs would reduce traffic crashes, congestion, costs, and energy use, while increasing transport accessibility, travel demand, the capacity of roads, and convenience to users (Curl et al., 2018; Eluru & Choudhury, 2019; Golbabaei et al., 2021). It has been argued that AVs could also release land in city centers and in residential areas by reducing parking demand and reallocating newly freed space for developing housing, commercial, and urban amenities (Curl et al., 2018). Hence, there is real potential for AVs to change people's residential location and urban land-use patterns by enhancing transport accessibility and reducing transportation costs, which would trigger urban expansion

(Cordera et al., 2021; Gelauff et al., 2019; Heilig et al., 2017). Thus, AVs may trigger changes that fundamentally alter the landscape of the built environment.

Considering the complexity of possible urban futures of cities brought about by the arrival of AVs and preparing for this watershed time, urban researchers and professionals are exploring policies and strategies to manage people's travel demand and control the growth of cities. Although previous studies have investigated the short- and medium-term effects of AVs, evidence on the long-term effects of AVs on urban land-use patterns is still fairly limited. Researchers are interested to know how AVs would influence urban land-use patterns. Are future cities going to be more compact? Are urban landscapes going to be dominated by sprawl? Could polycentricity become a dominant model of urban form? To this end, this study aims to assess the potential impacts of AVs on the spatial distribution of household and employment locations. The analysis is conducted in a mid-size British city using the simulation platform provided by the TRANUS land-use and transportation interaction model. This study significantly contributes to policy formulation by providing insights into matters that are still quite uncertain and yet to be experienced in the real world. The following research questions are projected in this study to estimate the long-term effects of AVs:

1) What are the impacts of AVs on the spatial distribution of household locations?
2) What are the impacts of AVs on the spatial distribution of employment locations?

2. Literature review and theoretical framework

2.1 Synthesis of past studies

Although limited, previous studies provide empirical evidence on how AVs would influence the built environment and people's destination location choices. Very few studies have explored the change in the land-use patterns due to large-scale adoption of AVs. For example, conducting a simulation study, Kang and Kim (2019) estimated the effects of AVs on urban land use in Seoul, Korea. Results show that AVs would reduce agricultural lands and increase residential and commercial areas on the outskirts of cities. Rural and exurban peripheries would be suburbanized due to convenient travel afforded by AVs, low land price, and the availability of green space. On the other hand, the city center would become denser and large commercial centers would see their size increase further. Small and non-intensive commercial areas would be converted to residential use if AVs can be adapted to resupply supermarkets and other retail outlets. Thus, AVs are likely to accentuate urban expansion towards peripheral areas and nearby rural areas owing to increased accessibility and reduced transport costs (Meyer et al., 2017).

Some studies investigated how AVs would influence people's destination choices for living and working (Gelauff et al., 2019; Kim et al., 2020; Meyer et al., 2017). For example, Thakur et al. (2016) explored people's housing location choices in Melbourne, Australia by conducting a simulation study. They reported a 0.25% to 2% reduction in population within 30 km of the Central Business District (CBD) and a 2.47% increase in population beyond 30km from the CBD due to a 50% reduction in vehicle travel time by personal AVs. Conducting a survey, Carrese et al. (2019) mentioned that some households (about 40%) are interested to relocate in the suburbs under the AV regime. Thus, personal AVs are likely to reduce the population in and around city centers and increase the population in the outer suburbs. Since AVs will be able to fetch groceries from supermarkets and collect children from school by themselves, people can live, work, and shop at a greater distance (Kang & Kim, 2019; Milakis et al., 2017; Smith, 2012).As far as the adoption of SAVs is concerned, Thakur et al. (2016) reports effects similar to those of personal AVs. (Meyer et al., 2017; Zhang, 2017) pointed to the same effects.

A considerable number of past studies have investigated the effects of AVs on parking demand in city centers and residential areas (Clements & Kockelman, 2017; Kopelias et al., 2020; Zhang et al., 2015). Some researchers mentioned that AVs are likely to reduce up to 90% of parking demand by decreasing car ownership (Milakis et al., 2017; Narayanan et al., 2020; Zhang et al., 2015). Some other researchers also estimated that AVs would reduce parking land areas by 50% (Kondor et al., 2018) to 40% (Chehri & Mouftah, 2019; Kim, 2018). These studies argued that a higher reduction in parking demand can be achieved by adopting SAVs compared to personal AVs (Milakis et al., 2017; Zhang & Wang, 2020). The space released from vehicle parking and garages could be used for developing activity centers and high-quality recreation spaces (Dennis et al., 2017; KPMG International, 2019).

As indicated in the literature, AVs are likely to intensify urban expansion by reducing travel time, providing transport services to all people, and increasing people’s convenience by allowing multitasking. However, the adoption of SAVs to some extent could control urban sprawl. Indeed, AVs would also reduce parking demand in city centers and residential areas by reducing vehicle ownership. This newly freed space could be redeveloped for residential, economic, and recreational activities. In conclusion, earlier studies suggest that AVs have the potential to influence the urban built environment by influencing land uses, location choice for households and businesses, and parking demand.

The following hypotheses are formulated to investigate the impacts of AVs on destination locations.

1) Since people can work while riding on an AV, AV users may see fewer obstacles to living in the suburban areas and outskirts of city centers (H1).
2) In addition to the densification of existing city centers with various activities, concurrent peripheral development and suburbanization would be experienced by urban residents (H2).
3) The space released from parking demand in city centers and residential areas will be used for residential, economic activities and recreational activities, which will lead to more employment generation (H3).

2.2 Theoretical framework

This subsection discusses the theoretical foundations to simulate the impacts of SAVs on people's travel behaviors via Land Use and Transportation Interaction (LUTI) models after introducing SAVs within the existing transportation system.

2.2.1 A brief overview of land use and transport interaction models

A large number of studies have suggested that changes in transportation systems and associated policy measures influence urban development patterns and location choices of households and employment (Cervero & Kockelman, 1997; Zondag et al., 2015). Concurrently, changes in development patterns and land uses influence transportation activities (e.g., number of trips, travel mode choice, distance, time, and cost). Hence, it is a common understanding that transportation and land use have a mutual but complex interaction, which provides mobility benefits (e.g., access to services and jobs, reduction in VMT) and reduces transportation externalities (e.g., congestion, emissions) (Holz-Rau & Scheiner, 2019; Soria-Lara et al., 2016; Wegener, 2021). Thus, policymakers should use transportation models that integrate land-use models for accurate estimation of the impacts of transportation policy options on urban development patterns and consequent transportation systems (Waddell, 2011; Zondag et al., 2015).

The complex two-way interaction between transportation and land use can be easily conceptualized by the "land use transport feedback cycle" (Acheampong & Silva, 2015; Wegener, 2004) presented in Figure 7.1. According to the feedback cycle, the distribution of land uses (e.g., residential, industrial, commercial, institutional) over the urban space determines the locations of human activities (e.g., living, working, shopping, education, leisure). Through the transportation system, human activities distributed in space fulfill spatial interaction or trips and travel from one destination to another. Infrastructure and facilities (e.g., road network, transit stations, transport modes, schedule) in the transportation systems create opportunities for spatial interaction of human activities which is measured as accessibility. The level of accessibility in space and over time influences location decisions of human activities and thereby affects land use distribution across space.

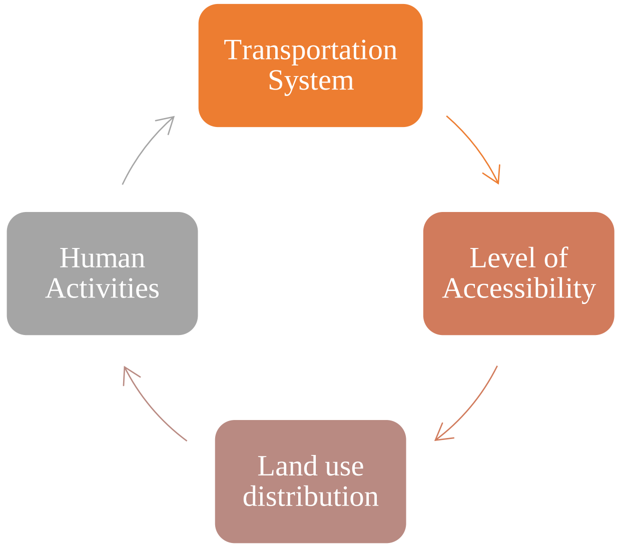


Figure 7.1: Land use transport feedback cycle

A good deal of research over the past 60-70 years have investigated the impacts of transportation policies on travel pattern (e.g., mode and route choice, travel distance and time), destination location choices, accessibility to destination, property values, and public health (Acheampong & Silva, 2015; Chang, 2006; Wegener & Fürst, 2004). Previous studies used various types of LUTI models (Wegener, 2004), including the TIGRIS XL model (Zondag et al., 2015), UrbanSim (Waddell, 2002; Waddell et al., 2003), Agent-based model (H. Zhang et al., 2020; Zhang et al., 2015) to evaluate alternative policy options. Some studies also used TRANUS to develop land use and transport interaction models (Bujanda et al., 2011; Pupier, 2013). Further discussion of the theoretical framework focuses on TRANUS as this modeling environment is used in the research reported later in this article.

TRANUS is a simulation model well suited to assess the effects of transport policies and strategies in the context of an urban region. Originally conceptualized by De la Barra and Rickaby (1982) and Thompson (1990), TRANUS is a free, effective, and well-documented software package and widely accepted model by city planners and transport modelers (Capelle et al., 2019; Dutta et al., 2012; Morton et al., 2008).

2.2.2 Theoretical basis of land use and transport interactions in TRANUS

The theoretical basis of the TRANUS system are grounded in spatial microeconomics theory, gravity based theories, input-output model, random utility theory, and Dijkstra transportation model (Modelistica, 2005). According to the spatial microeconomics theory, landowners rent their properties at the maximum price and the person tries to maximize their revenue by renting a property at a cheaper price and reducing transportation costs by renting the property close to the activity center (e.g., city center, CBD) (Pupier, 2013). Gravity-based models indicate that interaction between two zones is proportional to the number of facilities in each zone and inversely proportional to the friction (e.g., distance, time) imposed by the infrastructure that connects those zones (De la Barra, 1989).

The input-output model represents the urban economy with several zones or sectors and shows transactions between them (Modelistica, 2005). The main concept of random utility theory is that individuals logically choose an option from different alternatives, which provides the maximum level of benefit or utility (De la Barra, 1989). In this study, the logit model is used to choose floor space and land types for location of different activities. Lastly, the main concept of the Dijkstra algorithm is that it finds the shortest possible route from a transportation network for moving people and goods with minimum transfer costs and distance (Zhang et al., 2016).

2.2.3 Main components of the TRANUS model

The two main components of the LUTI model (Figure 7.2) in TRANUS are the activities subsystem and the transport subsystem (Modelistica, 2005). Within each subsystem, there are demand and supply elements that interact to achieve an equilibrium state. In the activities subsystem, location and interaction between activities (e.g., households, industries) indicate demand-side elements, and real estate supply (i.e., land, floor space) indicates the supply-side elements. Activities interact with other activities to perform their function. Real estate developers provide spaces for performing different functions of the activities. When demands of activities for space are higher than the real estate supply in a specific place, land price/rent will increase to reduce demand for spaces to achieve equilibrium. Interaction between these activities generates travel demands.

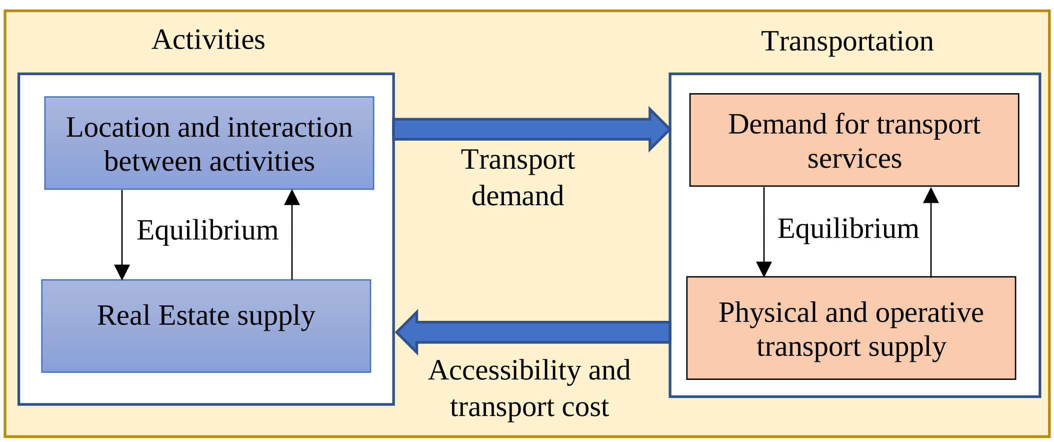


Figure 7.2: Main elements of the LUTI model in TRANUS

Travel demand for transferring people and goods from origins to destinations represents demand-side elements of the transportation subsystem. On the other hand, transport infrastructure and travel modes represent the supply side elements. Travel modes use transport infrastructure to perform their activities. . When travel demand becomes higher than supply, travel cost or time increases to achieve equilibrium. Interactions between demand and supply of the transport subsystem impose friction in terms of accessibility and transport cost that affect the interaction between activities and land price/rent in the real estate market.

2.2.4 Dynamic relationship between land use and transportation

As indicated in Figure 7.3, the interaction between transportation and land use in TRANUS is dynamic through time based on discrete intervals (Modelistica, 2005). The interaction between activities in space generates functional flows (i.e., the flow of jobs or households from one sector to another), which create travel demand. The travel demand is assigned to the transport system in the same period. However, the state of equilibrium in transport demand and supply determines the accessibility between locations and influences economic flows and provides feedback for the next period. Thus, accessibility in time t1 affects functional flows in time2 and so on.

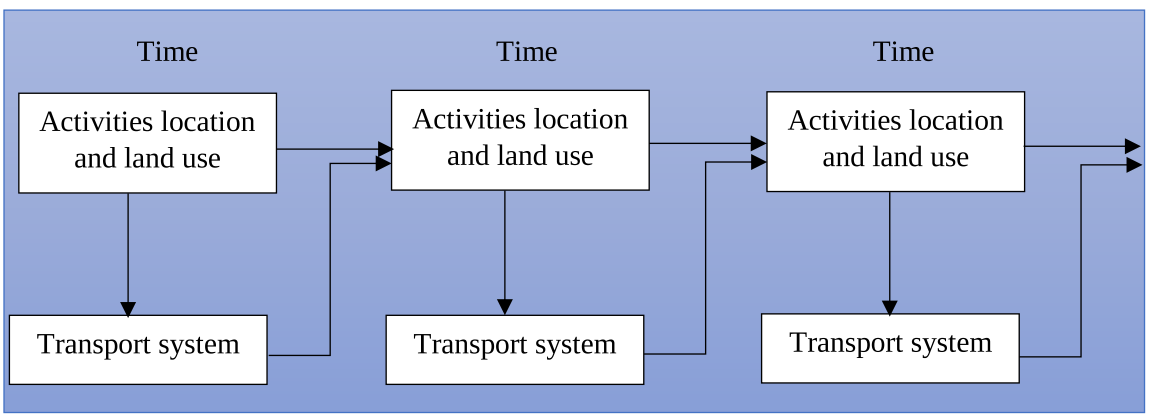


Figure 7.3: Dynamic relationship between land use and transportation

3. Research design

To assess the potential impacts of AVs, a simulation study is performed using the TRANUS simulation environment. The impacts of AVs are investigated through the mutual relationship between the land-use component and the transportation component of

TRANUS. In this study, we estimate the effects of AVs on the location choices of employment and residences produced as the output of the land use model iterated with the transportation model. While TRANUS's transportation model does not explicitly allow for the treatment of AVs as a mobility option distinct from convention motor vehicles devoid of advanced autonomy features, it can be accommodated quite readily thanks to some careful customization of the simulation system. The systematic procedures for developing land use and transportation models are discussed below. The specific dispositions involved in the customization are presented next.

3.1 Study area

The study is conducted in the city of Swindon, United Kingdom, for which an calibrated instance of TRANUS is already available (Tomás de la Barra et al., 2011). Swindon is a medium sized city in Southwestern United Kingdom, about half-way between Bristol and Oxford. In 2020, the city had an estimated population of 490,000, with a density of 222 persons per square kilometer (UK Census, 2020). The city has an historic urban center surrounded by a rather suburban and periurban hinterland encompassing a number of smaller villages. Figure 7.4a shows the layout of Swindon and the urban core of the city.

For modeling purposes, Swindon is broken down into 56 internal and 9 external zones. Figures 7.4b and 7.4c indicate the distribution of residential (i.e., residential and mixed lands) and employment (i.e., industrial, business parks and shopping centers, and mixed lands) land types in the city. Swindon's economy has been expanding thanks to strong performance in financial and professional services and advanced manufacturing and engineering (Swindon Borough Council, 2022). Nine external zones serve the purpose of accounting for meaningful external trips.

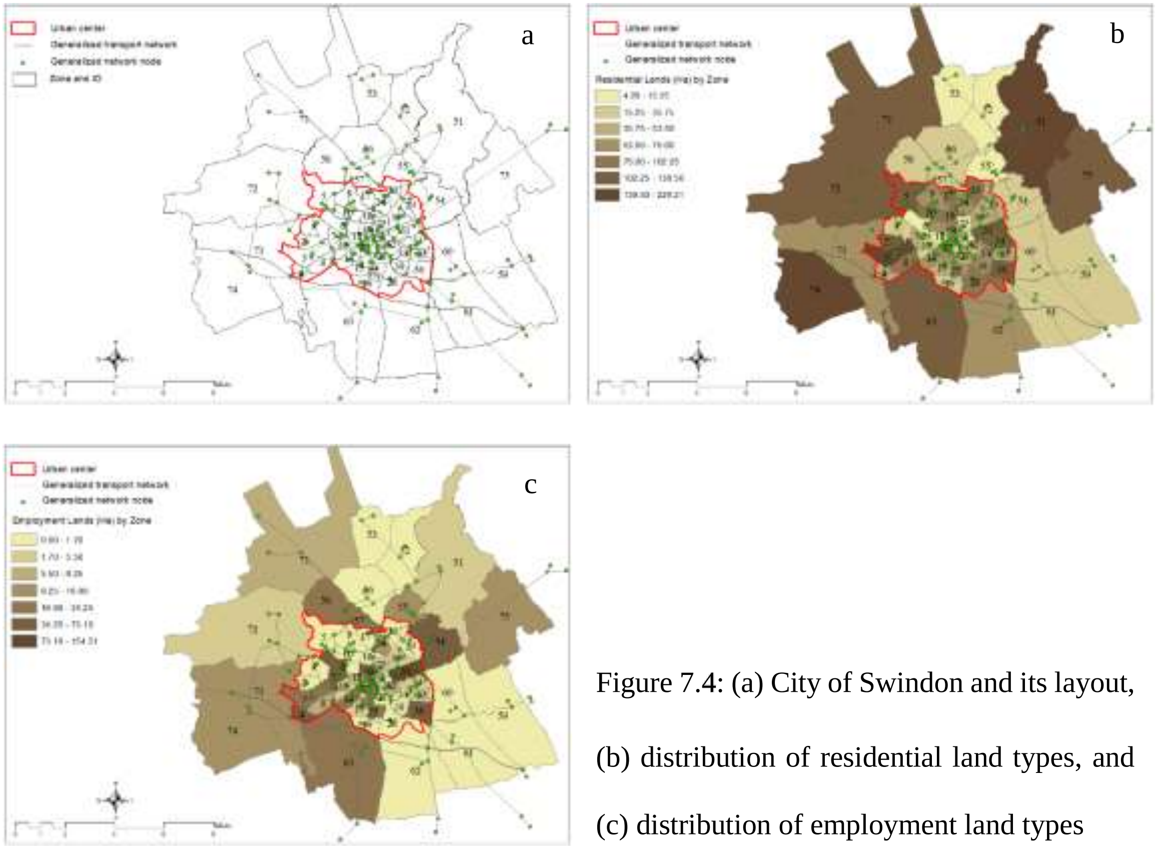


Figure 7.4: (a) City of Swindon and its layout, (b) distribution of residential land types, and (c) distribution of employment land types

This study uses the TRANUS LUTI model calibrated for Swindon as a baseline against which a series of alternative scenarios encompassing AV are being assessed with regards to land uses and their distribution across the urban region. Impacts on transportation, mobility, and accessibility metrics are also assessed, and results are reported in Chapter 6 for the same scenarios and variations thereof.

It is advantageous to use an existing calibrated model that has been fully vetted. This approach permits us to dedicate our attention on customizing TRANUS to represent the main distinctive features of AVs over vehicles with little or no automation, conduct a sensitivity analysis on the AV variants to better capture the range of possible futures of the urban land system in response to various specifications of AV deployments (since AVs are not an operational reality at this time). Furthermore, as Swindon is small enough and its spatial structure is simple enough, the main differences between AV treatment scenarios and the baseline can be teased out with greater ease than for a more complex and more heterogeneous urban region with multiple layers of central and outlying business centers. Also, it may be reasonable to assume that AVs would be implemented in smaller cities before mega cities as transportation systems are easier to monitor and their impact on land use systems may involve fewer feedback responses that may be hard to predict and simulate at the present time.

3.2 Land-use model

I briefly introduce the calibrated land-use model for Swindon in this section. I discuss in turn the activity sectors, the distribution of floor space and land for different activity types, and the generation of functional flows.

3.2.1 Activity sectors in the urban economy

The urban economy of Swindon was divided into employment and household sectors (Tomás de la Barra et al., 2011). These activity sectors are exogenous (i.e., depend on external forces) and induced (i.e., generated within the zones by other activities). Conventionally, employment sectors include industry, agriculture, government, retail and warehouse, office, education, health, while households are divided into high-income, medium-income, and low-income cohorts. Further specification of these sectors with types and elasticity (i.e., the measure of the sensitivity of a sector due to changes in other sectors) is given in Table 7.1.

Table 7.1: Activity sectors in the model

Activity sectors	Type	Elasticity
Employment sectors		
Industry and agriculture employment	Exogenous	0
Government employment	Exogenous	0
Retail and warehouse employment	Induced by household	0.8
Office employment	Induced by household	0.7
Education employment	Induced by household	0.8
Health employment	Induced by household	0.7
Household types		
High-income household	Induced by employment	0.6
Medium-income household	Induced by employment	0.7
Low-income household	Induced by employment	0.8

3.2.3. Distribution of floor space and land types

Every activity listed in Table 7.1 consumes some floor space and floor space consumes some land of certain types (Tomás de la Barra et al., 2011). Floor spaces include sheds, terraces and flats, detached and semi-detached houses and land types include industrial, business park, mixed land, residential land. Floor space and land type are non-transportable by nature; thus, they will be consumed in the same zone where they are produced.

In the model, a single activity may consume more than one floor space or land type. A multinomial logit choice model is used to assign floor space or land types for a specific activity sector when there is more than one option to choose from. Figure 7.5 illustrates the relationships between activities and floor space and between floor space and land types. It is assumed that the health and education sectors do not consume any type of defined floor space and land type; however, they consume a special type of land that is not included in the real estate market.

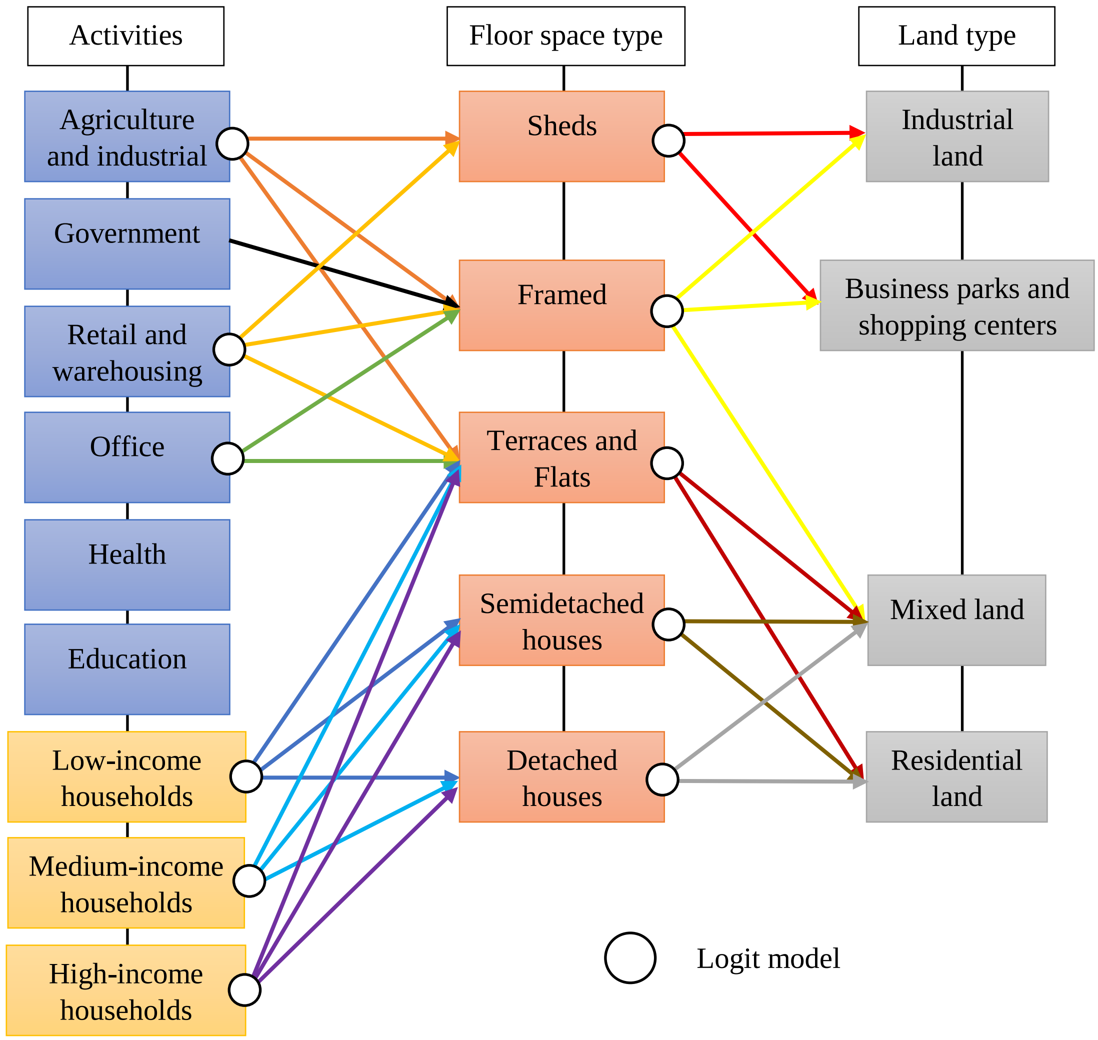


Figure 7.5: Choices between activities, floor space, and land type

3.2.3. Functional flow generation

Functional flow (i.e., the flow of jobs or households from one sector to another) is determined based on the state of the activity sector (e.g., exogenous, induced) (Tomás de la Barra et al., 2011). As indicated in Table 7.2, low-, medium-, and high-income households generate trips to work. On the other hand, trips attracted by retail and warehousing, office, education, and health activity sectors are defined as trips to services. The outputs of the functional flow are generated in the form of origin-destination (O-D) matrices. The transportation model uses these O-D matrices to generate actual trips of different types.

Table 7.2: Generated trip categories

Activity sector	Trip category
Low-income households	Trips to work (low income)
Medium income households	Trips to work (medium income)
High-income households	Trips to work (high income)
Retail and warehousing	Trips to services
Office	Trips to services
Education	Trips to services
Health	Trips to services

Different economic sectors and trip categories are defined in TRANUS to generate trip matrices automatically considering the following aspects.

a) Flows include commuter trips to work and trips to services and indicated as 1.

b) Trips are generated for a day and an expansion time factors is applied for weekdays and weekends to estimate trips for a month.

c) All flows are trips to work and services, thus, a factor of 1 is considered for all flows.

d) Trips are considered unidirectional (i.e., people typically go to work from home and come back home again after work) and a factor of 1 is used for both trips to production and consumption.

The major steps of the land use model from delineating study area to generating trip matrices are shown in Figure 7.6.

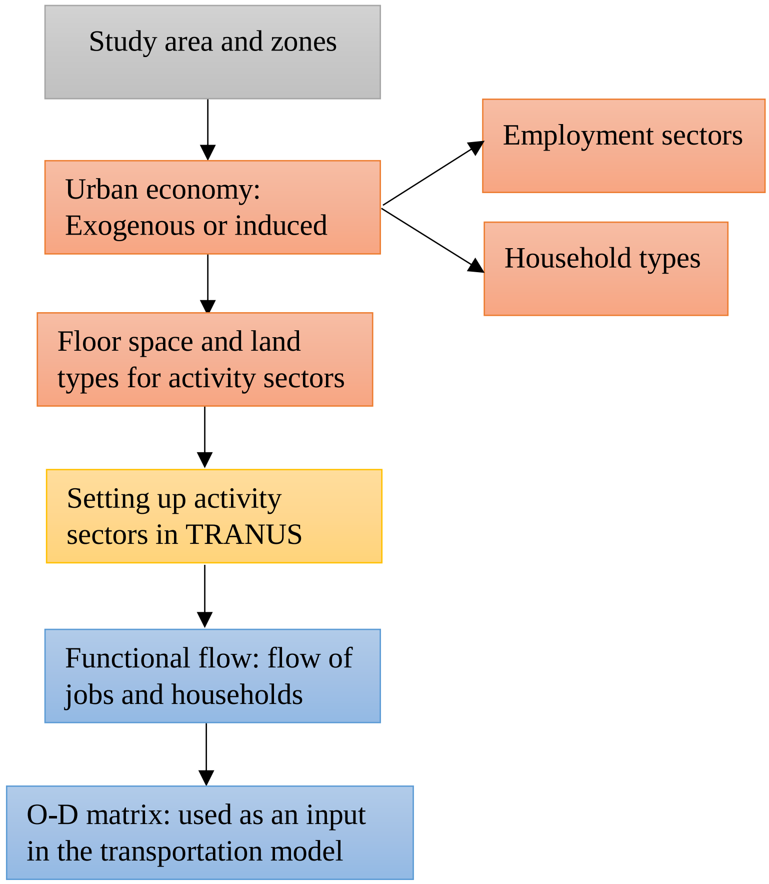


Figure 7.6: Different steps of land use model in TRANUS

3.3 Transportation model

The transportation model is the second component of the LUTI model in TRANUS which investigates the effects of AVs on people's travel patterns considering the existing transport facilities. As indicated in Figure 7.7, developing a transportation model in TRANUS mainly includes defining different components of transport demand and supply (Tomás de la Barra et al., 2011). Outputs of the land-use model are used in the transportation model as the demand component. The physical transportation network (i.e., links and nodes) are inputs of TRANUS and are assigned administrators and parameters (link types, length, capacity, speed, cost). Different transport operators are used to provide transport services. Different types of transport operators include Single-Occupancy

Vehicle (SOV), High-Occupancy Vehicle (HOV), AV, public transportation (e.g., bus, train), active transportation (e.g., walk, bicycle), and Park-and-Ride (P&R). In this study, AVs are defined as normal operator which indicate that AVs would move freely around the network. Additionally, AVs would be shared by household members which is reflected in occupancy setting in TRANUS and operated by battery. In TRANUS, types, combination, and parameters (e.g., occupancy, speed, costs) of different operators are assigned. Finally, operators are assigned to the transport network to generate traffic flows.

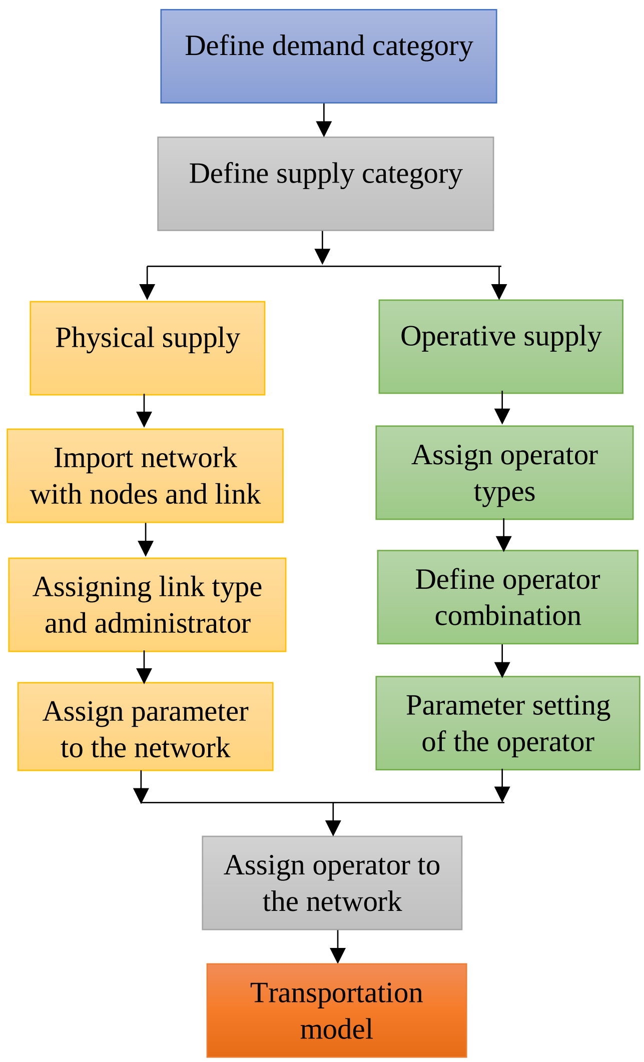


Figure 7.7: Different steps in the transportation model in TRANUS

TRANUS uses probabilistic multinomial logit models for assigning household trips to transport operators based on their utilities. Using the same logit model, TRANUS assigns operators to transport network based on their properties. A detailed discussion on the development of the transportation model is also provided in Chapter 6.

3.4 Hypothetical scenarios to estimate the effects of AVs

To investigate the potential impacts of AVs, a set of hypothetical scenarios are envisioned. Parameters and information/data on types and elasticity of activity sectors, floorspace, and land types presented in Tables 7.1 and 7.2, and Figure 7.5 are used to calculate the outputs of the scenarios in land use model. Different parameters of the transport network (e.g., link types, length, capacity, speed), data on operator types and parameter are discussed in Chapter 6 are used to calculate the outputs of the scenarios in the transportation model. The land-use model is set for up to 200 iterations with a convergence factor of 0.0001. On the other hand, the transportation model is set for up to 18 iterations with a convergence factor of 0.001. In both cases, a smoothing factor of one is assigned, which indicates that the values of each iteration are averaged with the values from the previous iteration with an equal proportion.

1) Baseline scenario

   Initially, a baseline scenario (B) is developed by considering the existing land use and transportation attributes of the Swindon model. Values of the parameters on activity sectors, transport nodes and links, and operators are used to estimate people's destination location choices under the current policy framework and without the adoption of AVs.

2) Scenario 1: Introduction of AVs on the local roads only

   Scenario 1 (S1) is developed to explore the potential impacts of AVs under the condition that AVs would be operated on local roads only. Access road, central narrow and wide, peripheral narrow and broad link types mentioned in Chapter 6 are selected for adopting AVs and examined the impacts of this policy option. Similar to the baseline scenario, parameters on activity sectors, transport nodes and links, and operators are used to develop this model.

3) Scenario 2: Introduction of AVs to the entire transportation network.

   Scenario 2 (S2) investigates the impacts of AVs when AVs would be allowed to navigate throughout the entire transportation network of the city. However, some mode-specific routes such as bus-only routes and lanes, railway, and cycle lanes are free from any AV operation. Scenario 2 also considers the above-mentioned parameters.

Sensitivity analyses are performed to check the robustness of the simulation results by changing model assumptions and values of the parameters. Table 7.3 indicates different criteria to assess the sensitivity of the model. Increasing AV occupancy and speed, and wait time, and allowing growth in jobs, sensitivity analyses are conducted to explore the changes in the travel patterns.

Table 7.3: Criteria for sensitivity analysis

Parameter	Base scenario	Changes in parameter
Growth in jobs	S2	5%, 10%, 15%, and 20% growth of jobs in industry and government sectors
Growth in jobs	B	5%, 10%, 15%, and 20% growth of jobs in industry and government sectors

To understand the potential impacts of AVs, the spatial distribution of households and employments in different hypothetical scenarios are calculated and compared. The total number of households in Swindon is estimated by adding the number of low-income, medium-income, and high-income households in each zone. Similarly, the number of employees in different activity sectors are aggregated to get the total employment in each zone. The change (%) in the number of households and employments under different scenarios is calculated using Excel and GIS techniques. On the other hand, the household trips to work and different activity sectors by different modes of transportation and AVs are added to get the total number of trips and AV trips, respectively, assigned on the transportation network.

4. Results

4.1 Impacts on people's household location

Using Swindon as a case study, this study estimates the potential impacts of AVs on the spatial distribution of households in different scenarios (Figure 7.8). The change (%) in the household location in S1 compared to B is illustrated in Figure 7.8a. According to Figure 7.8a, the adoption of AVs on local roads in S1 (Figure 7.9a) lead to an increase in the number of households in the North, East, and South-East areas of Swindon. A decrease in households is observed in the South-West corner of the city. On the other hand, a decrease in the number of households is noticed in the city center when AVs are adopted on local roads only. Overall, a 0.10% decrease in households is estimated in the city center, and a 0.29% increase in households is estimated in the periphery of Swindon in S1 (Figure 7.8d).

Figure 7.8b represents the change (%) in the household location in S2 compared to B. The adoption of AVs throughout the transportation network (Figure 7.9b) leads to a rise in households on the North, East, and South-West sides of the city. A decrease in households is observed in the city center. Due to the amenities and convenience provided by AVs, people would be interested to live in the periphery and outside of the city. Total, a 0.33% decrease and 0.64% increase in the number of households are estimated in the city center and periphery of Swindon, respectively, in S2 compared to B due to the wide adoption of AVs (Figure 7.8d).

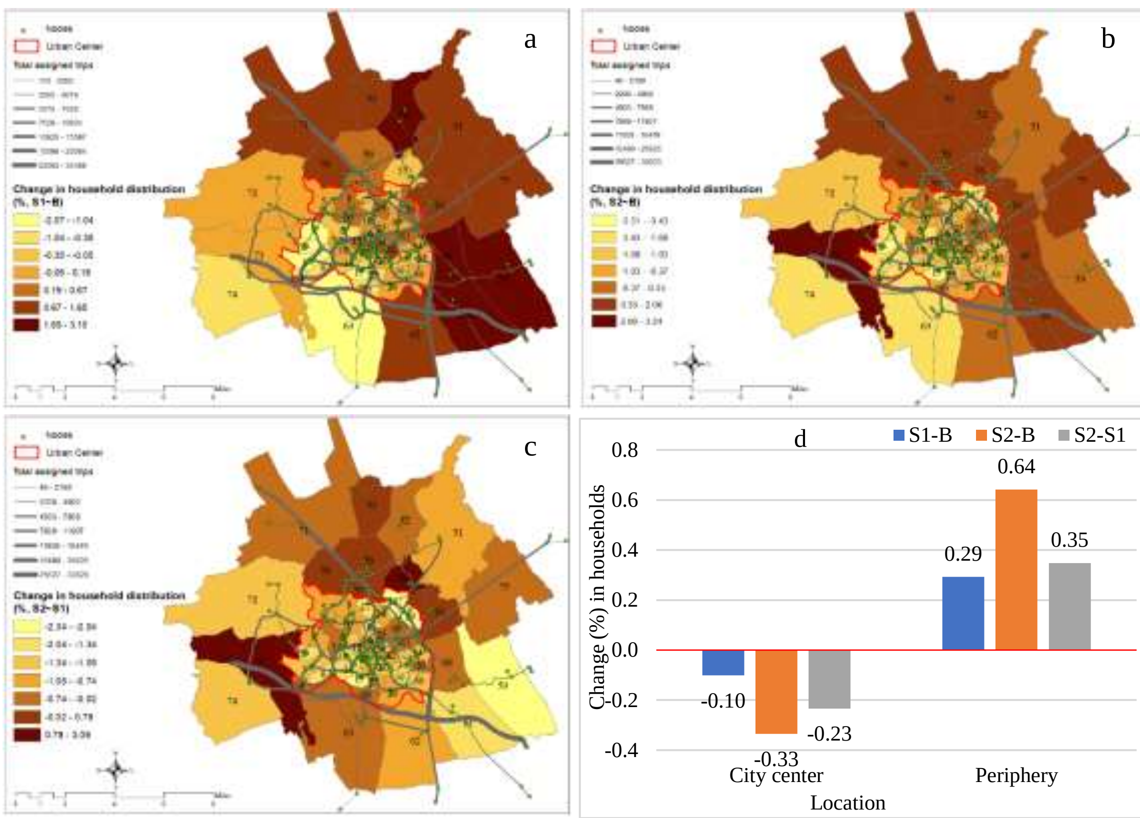


Figure 7.8: Impacts of AVs on people's household location
Figure 7.8a represents change (%) in the household location in S1 compared to B, 7.8b represents change (%) in household location in S2 compared to B, 7.8c represents change (%) in household location in S2 compared to S1, and 7.8d represents change in the total number of households in the city center and periphery of the city.

As indicated in Figure 7.8c, the wide adoption of AVs causes the reduction in households on the South, East, and North-West edges of Swindon and the increase in the South-West and North of the city in S2 compared to S1. Overall, the wide adoption of AVs encourages people to live in the periphery and surrounding areas of the city away from the city's bustling and hustling. In total, a 0.23% decrease and 0.35% increase in the number of households are estimated in the city center and periphery, respectively, under S2 compared to S1 due to the wide adoption of AVs (Figure 7.8d). The better connections and services provided by AVs encourage people to commute daily to the city where their jobs are located.

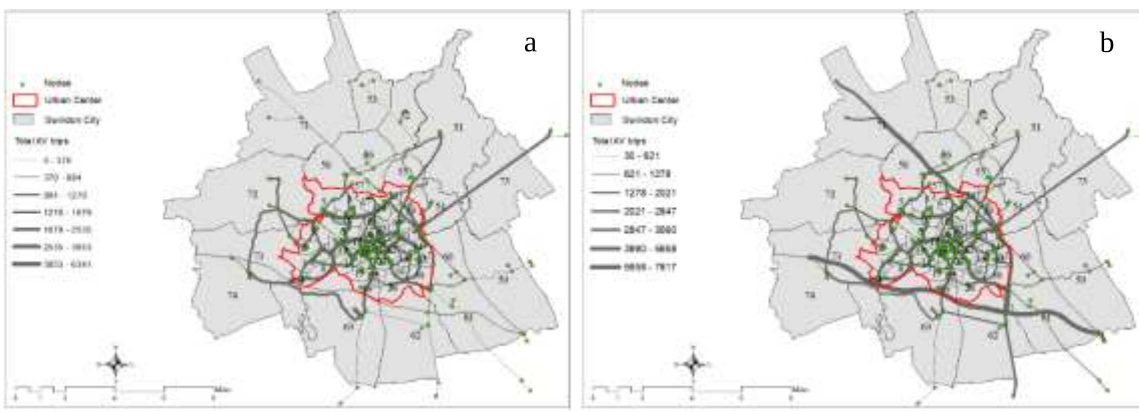


Figure 7.9: Total number of AV trips in S1 and S2
Figure 7.9a represents the AV loading in S1 and Figure 7.9b the AV loading in S2

4.1.1 Distribution of household locations without AVs

The spatial distribution of households under the growth in jobs and without adopting AVs is shown in Figure 7.10. Figures 7.10a, 7.10b, 7.10c, and 7.10d represent change (%) in household locations with 5%, 10%, 15%, and 20% growth in jobs, respectively compared to B. Considering different rates of growth in jobs, a similar pattern of household distribution is observed in Swindon. In Figures 7.10a to 7.10d, higher growth in the number of households is seen in the periphery compared to the city center. The availability of land for residential development in the rural hinterland and villages located in the periphery would be the home for new households induced by the increased economic activities within the city.

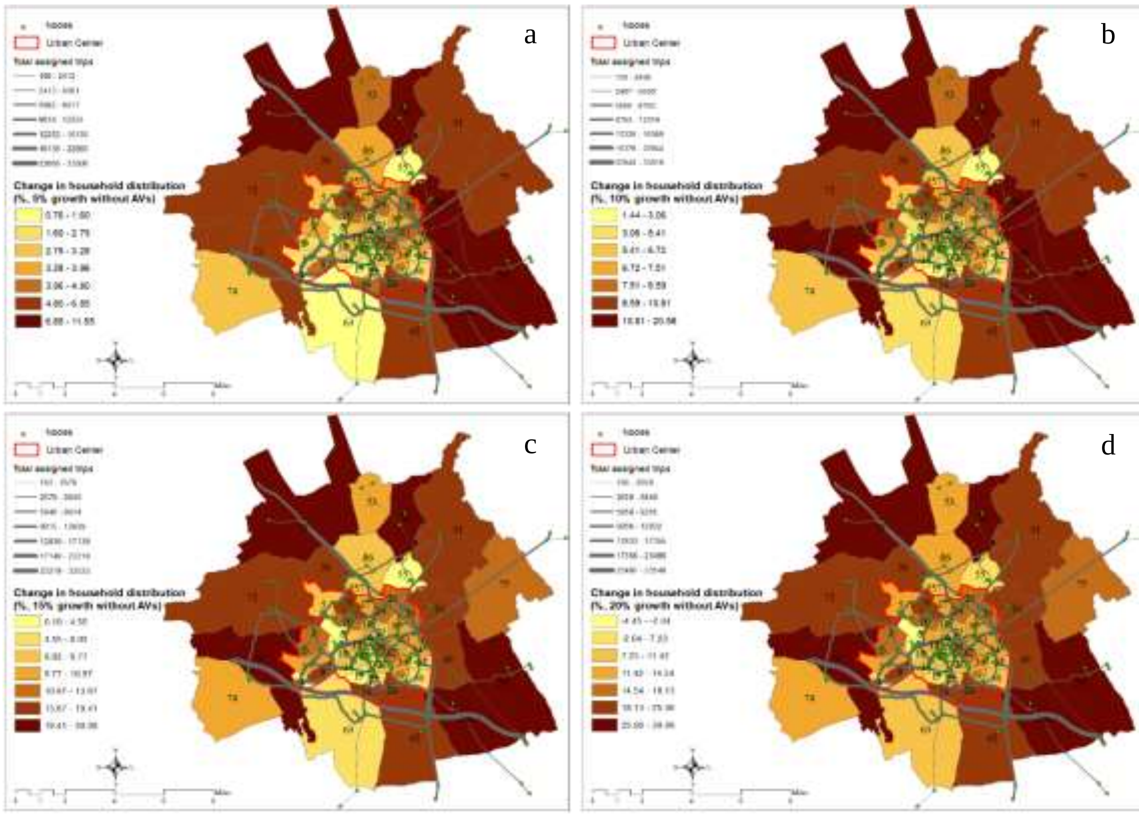


Figure 7.10: Distribution of household location under growth in jobs without AVs
Figure 7.10a, 7.10b, 7.10c, and 7.10d represent change in household location with 5%, 10%, 15%, and 20% growth in jobs, respectively compared to B.

4.1.2 Distribution of household locations with AVs

The spatial distribution of households under the growth in jobs and with the adoption of AVs is shown in Figure 7.11. Figures 7.11a, 7.11b, 7.11c, and 7.11d represent change (%) in household location with 5%, 10%, 15%, and 20% growth in jobs, respectively compared to S2. The figures indicate that the wide adoption of AVs throughout the transportation network leads to higher population growth in the city center. Higher population growth is also observed in the areas adjacent to the city center (e.g., zones 54, 55, 56, 57) and in the periphery (e.g., zones 52, 53, 63). In contrast, lower population growth is observed in the periphery, particularly in Zones 59, 61, 62, and 72.

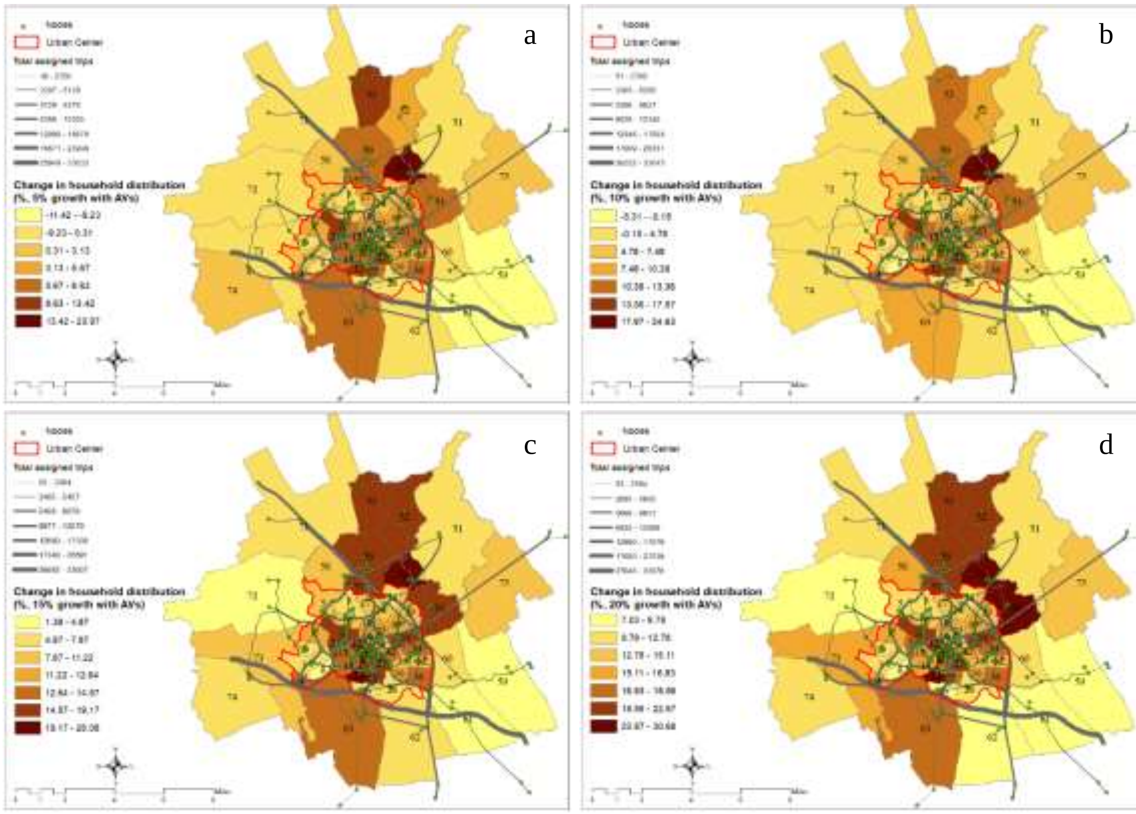


Figure 7.11: Distribution of household locations under growth in jobs with AVs
Figure 7.11a, 7.11b, 7.11c, and 7.11d represent change in household location with 5%, 10%, 15%, and 20% growth in jobs, respectively compared to S2.

In Figures 7.11a and 7.11b, a decrease in population in the periphery is observed. In contrast, I observe an increase in population in the same zones of the periphery, as indicated in Figures 7.11c and 7.11d. These scenarios point out the fact that a lower increase in jobs (5% or 10%) would lead to concentrated development in the city center, in addition to some peripheral development. On the other hand, a higher increase in jobs (15% or 20%) would also induce new settlements in the periphery, besides densifying the city center. The available lands in the periphery suitable for housing development would accommodate new developments. People would be interested to live in the new settlements located on the periphery due to better connectivity and amenities and convenience provided by AVs (Figure 7.12). However, it is observed that the overall population growth in the city center is higher than periphery. Thus, people sharing AV by household members are likely to live in the city center compared to the periphery.

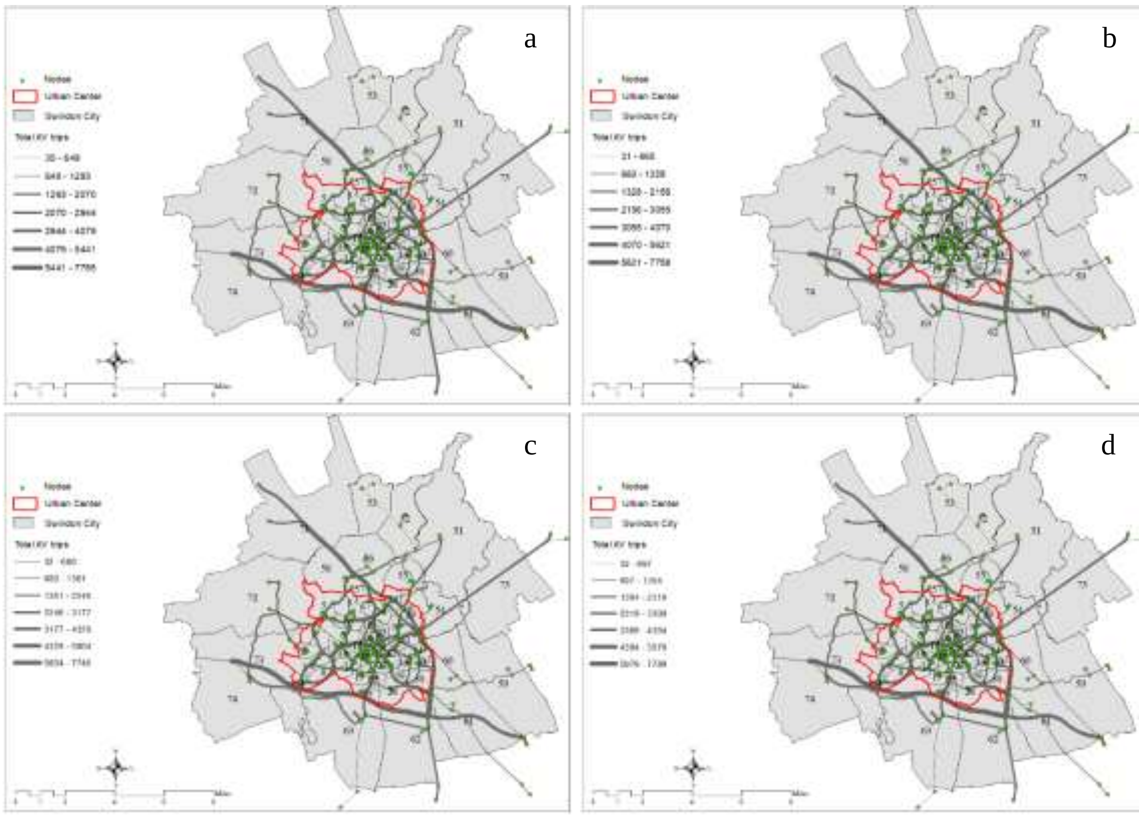


Figure 7.12: Total number of AV trips under 5%, 10%, 15%, and 20% growth of jobs
Figure 7.12a, 7.12b, 7.12c, and 7.12d represent AV loading with 5%, 10%, 15% and 20% growth in jobs, respectively.

The overall impacts of AVs on the spatial distribution of households in the city center and periphery, considering the growth in jobs, are illustrated in Figures 7.13a and 7.13b, respectively. As indicated in Figure 7.13a, higher growth in the number of households is observed in the city center under AV scenarios (4.51% to 15.47%) compared to non-AV scenarios (3.37% to 13.46%). In contrast, lower growth in households is reported in the periphery under AV scenarios (1.51% to 13.32%) compared to non-AV scenarios (4.76%

to 19.10%) (Figure 7.13b). The results show that AVs would induce more development in the city centers compared to the periphery and surrounding rural areas.

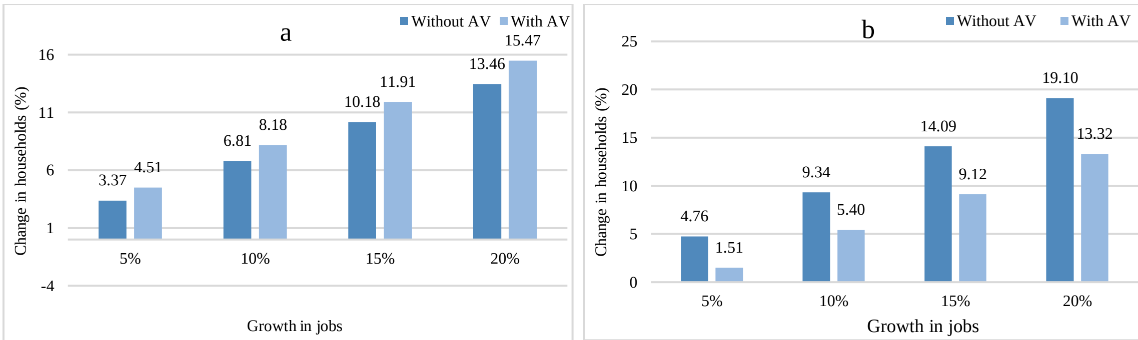


Figure 7.13: Change (%) in the total number of households in city core (a) and periphery (b)

4.2 Impacts on employment locations

This study also estimates the potential impacts of AVs on the spatial distribution of people's employment locations in different scenarios (Figure 7.14). The change (%) in the employment location in S1 compared to B is illustrated in Figure 7.14a. Figure 7.14a indicates that the adoption of AVs on local roads in S1 (Figure 7.9a) lead to an increase in the number of employments in the East and South-East corners of Swindon. A decrease in employment is observed in the South, West, and North-East corners of the city. In contrast, an increase in the number of employments is observed in the city center when AVs are adopted on local roads only. Overall, a 0.02% increase in employment is estimated in the city center, and a 0.08% decrease in employment is estimated in the periphery of Swindon in S1 (Figure 7.14d).

Figure 7.14b represents the change (%) in the employment location in S2 compared to B. The adoption of AVs throughout the transportation network (Figure 7.9b) leads to a rise in employment on the North-West and South-East corners of the city. A decrease in employment is observed in the South, South-West, and North-East edges of Swindon. On the other hand, an increase in employment is observed in the city center. Total, a 0.56% and 0.27% increase in the number of employments are estimated in the city center and periphery of Swindon, respectively, due to the wide adoption of AVs (Figure 7.14d).

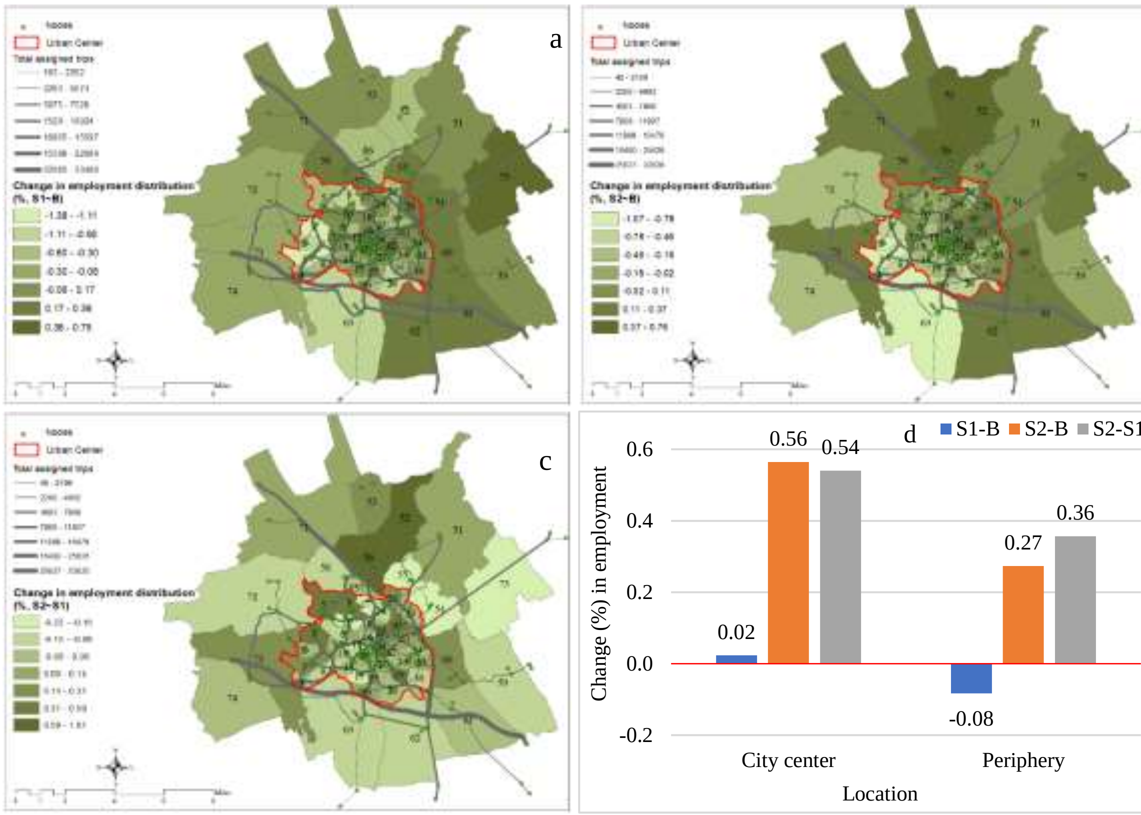
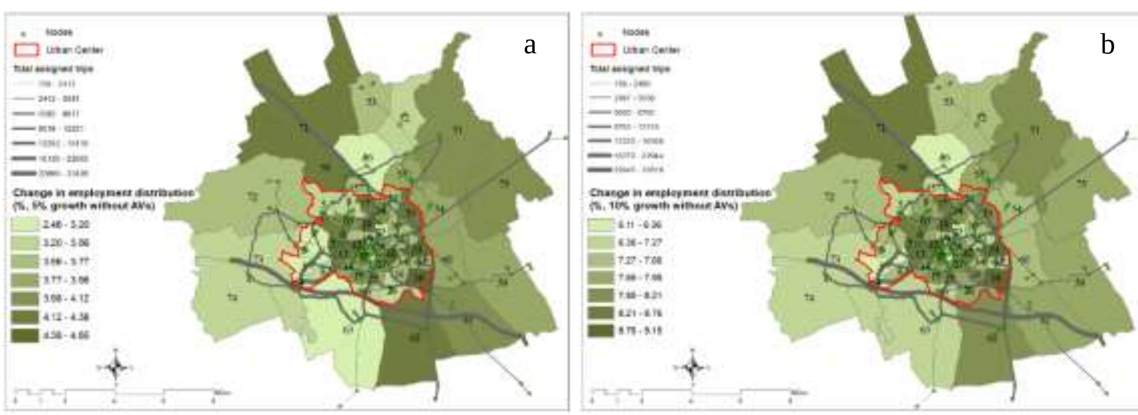


Figure 7.14: Impacts of AVs on employment locations
Figure 7.14a represents change (%) in employment location in S1 compared to B, 7.14b represents change (%) in employment location in S2 compared to B, and 7.14c represents change (%) in employment location in S2 compared to S1, and 7.14d represents change in the total number of employments in the city center and periphery of the city.

Figure 7.14c represents the change (%) in the employment location in S2 compared to S1. As indicated in Figure 7.14c, the wide adoption of AVs causes a reduction in employment on the South, East, and North-West edges and an increase in the South-West and North sides of the city under S2 compared to S1. On the contrary, employment is further increased in the city center under S2 compared to S1. Overall, the wide adoption of AVs leads to a 0.54% and 0.36% increase in employment in the city center and periphery of the city, respectively, compared to the adoption of AVs on local roads only (Figure 7.14d).

4.2.1 Distribution of employment locations without AVs

The spatial distribution of employment under the growth in jobs and without adopting AVs is shown in Figure 7.15. The change in (%) in employment distribution with 5%, 10%, 15%, and 20% growth in jobs is presented in Figures 7.15a, 7.15b, 7.15c, and 7.15d, respectively, compared to B. Considering the growth in jobs at different rates, a similar pattern of employment distribution is observed in Swindon. According to Figures 7.15a to 7.15d, higher growth in the number of employments is observed in the East, South-East, and North-West corners of Swindon. However, a higher growth in employment is observed in the city center compared to the periphery under non-AV scenarios (Figure 7.17a). The existing urban facilities and services likely attract more employment opportunities in the city centers compared to the rural hinterland and villages located on the periphery.



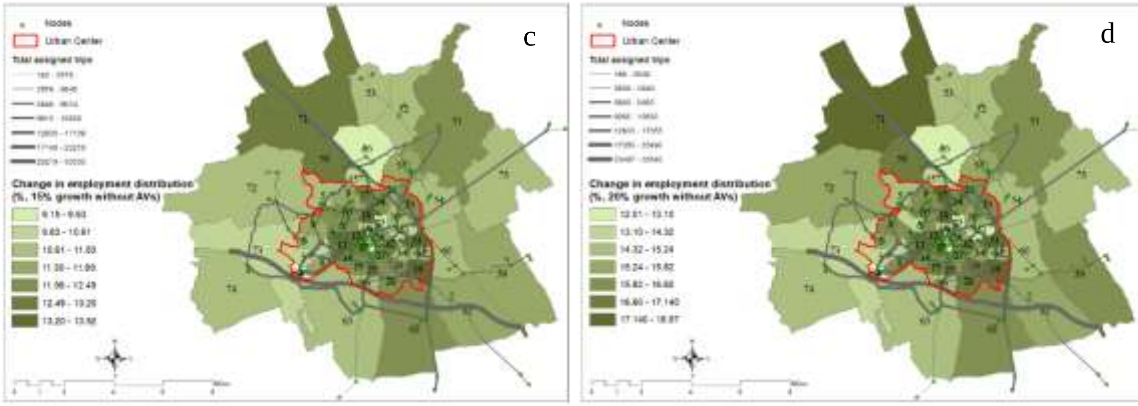


Figure 7.15: Distribution of employment locations under job growth and without AVs
Figure 7.15a, 7.15b, 7.15c, and 7.15d represent change in employment with 5%, 10%, 15%, and 20% growth in jobs, respectively compared to B.

4.2.2 Distribution of employment location with AVs

The spatial distribution of employment under the growth in jobs and with the adoption of AVs is shown in Figure 7.16. The change (%) in the number of employments under four scenarios such as 5%, 10%, 15%, and 20% growth in jobs is presented in Figures 7.16a, 7.16b, 7.16c, and 7.16d, respectively compared to S2. The figures indicate that the wide adoption of AVs throughout the transportation network leads to higher growth in the number of employments on the North and South-East sides of Swindon. Particularly, higher growth in jobs is observed in zones 51, 52, 53, 56, 59, 60, 61, and 71 in the periphery. Similar growth in the number of employments is also observed in the city center in all four scenarios. However, the study found not much discrepancy in the change of employment in the city center and periphery of Swindon considering the employment growth and after the adoption of AVs (Figure 7.17).

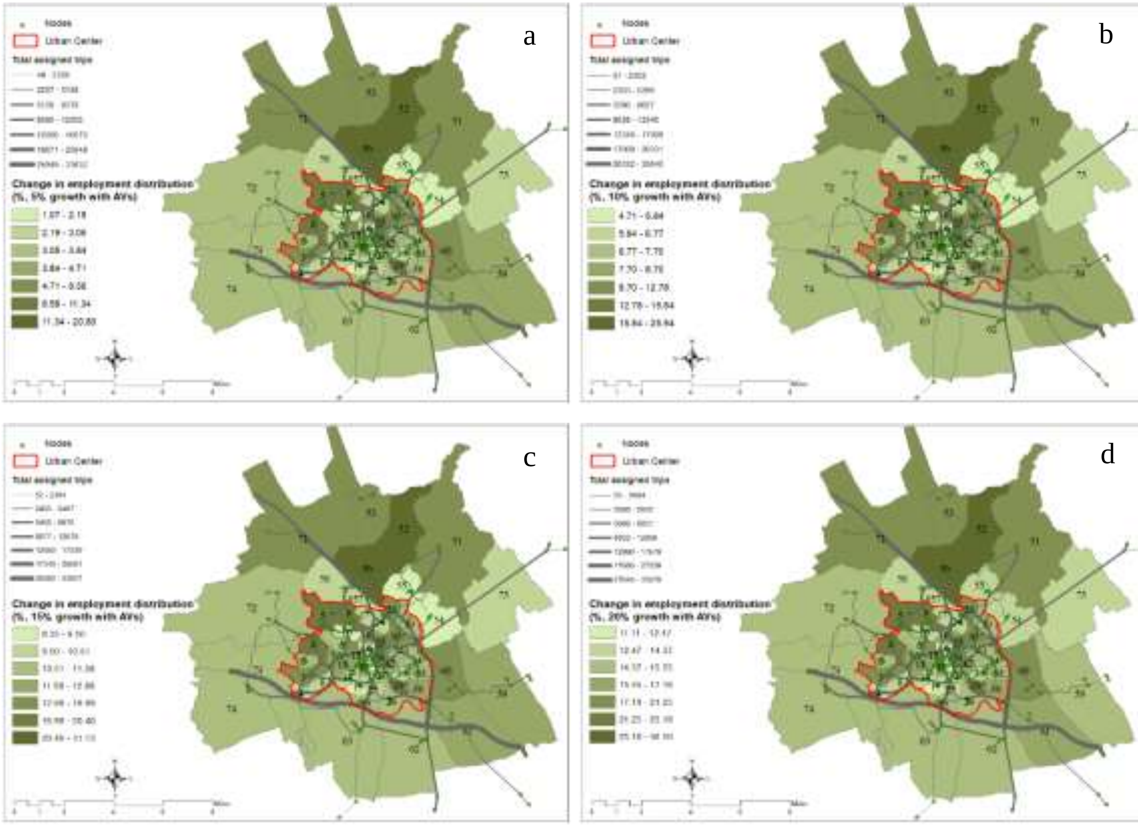


Figure 7.16: Distribution of employment location under job growth and with AVs
Figure 7.16a, 7.16b, 7.16c, and 7.16d represent change in employment location with 5%, 10%, 15%, and 20% growth in jobs, respectively compared to S2.

The overall impacts of AVs on the spatial distribution of employment in the city center and periphery considering the growth in jobs are illustrated in Figure 7.17a and Figure 7.17b, respectively. As indicated in Figure 7.17a, lower employment growth is observed in the city center under AV scenarios (3.17% to 14.82%) compared to non-AV scenarios (5.71% to 22.60%). The explanation of these findings lies in the fact that some small commercial development could be converted to residential and recreational uses because AVs would be able to get groceries from the supermarket by themselves. On the other hand, almost similar employment growth is observed in the periphery under AV (3.79% to 15.25%) and non-AV (3.68% to 15.26%) scenarios (Figure 7.17b). The results indicate that higher employment growth would happen in the city center compared to the periphery under the non-AV situation. On the other hand, AVs would lead to an even distribution of employment between city centers and the periphery considering growth in jobs. The reason lies in the fact that the wide adoption of AVs would facilitate the movement of people and provide flexibility to choose employment locations.

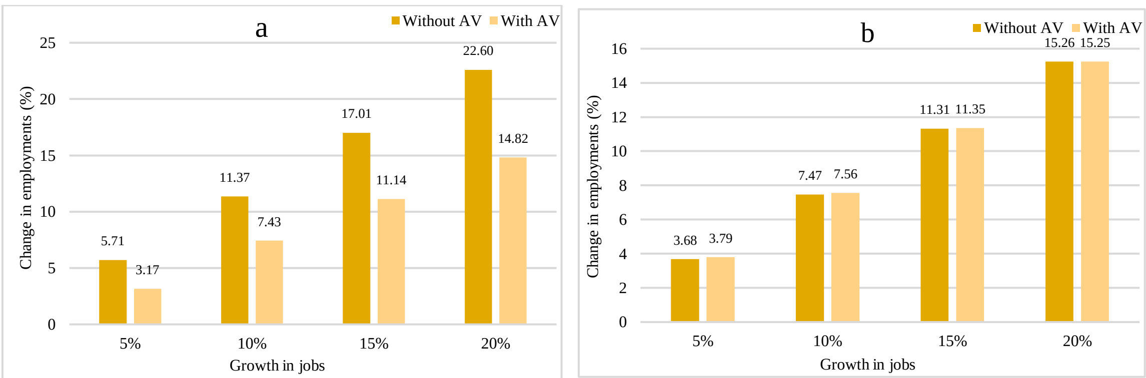


Figure 7.17: Change in the total number of employments in city core (a) and periphery (b)

5. Discussion

5.1 Impacts on household locations

The study results show that the adoption of AVs leads to a decrease in the number of households in the city center and an increase in households in the periphery of the city. The magnitude of the impacts is higher in the wide adoption of AVs throughout the transport network compared to the AV adoption on local roads only. The better transportation connections, services, and convenience provided by AVs encourage people to live outside of the city and commute daily to the city where their jobs are located. The study findings on the implications of AVs on household location choice are consistent with the current literature and support the hypothesis (H1) of this study. The extant literature showed that people can live, work, and shop at a greater distance because AVs would fetch groceries from supermarkets and collect children from school by themselves, reduce travel costs, and offer amenities for other activities (Milakis et al., 2017; Smith, 2012; Thakur et al., 2016). Thus, people could live in a residential area regardless of their job location.

A sensitivity analysis is also conducted to estimate the overall impacts of AVs on the spatial distribution of households in the city considering the growth in jobs under AV and non-AV scenarios. The result indicates a higher growth in the number of households in the city center compared to the periphery in AVs scenarios. The opposite trend is observed in non-AV scenarios (i.e., higher growth in households in the periphery compared to the city center). Thus, it is hypothesized that AVs would allow densification of the existing city center by releasing extra space from parking land areas along with peripheral new development over time which supports the hypothesis (H2) of this study. The findings are also supported by the existing literature where researchers mentioned that AVs would densify city centers and at the same time increase peripheral suburbanization by converting agricultural land to residential uses (Kang & Kim, 2019; Meyer et al., 2017).

5.2 Impacts on employment locations

This study also finds that the adoption of AVs on the local roads leads to an increase in the number of employments in the city center and a decrease in employment in the periphery of the city. On the other hand, the wide adoption of AVs throughout the transport network increases employment in the city center and periphery of the city. However, the increase in the number of employments in the city center is higher compared to the periphery. The extant literature reported that AVs are likely to reduce parking demand in city centers and residential areas by reducing car ownership (Milakis et al., 2017; Narayanan et al., 2020; Zhang et al., 2015). This extra space released from parking land would be used for developing economic and recreational activities (Dennis et al., 2017;

KPMG International, 2019) which will lead to more employment generation. This finding supports the hypothesis (H3) of this study that space released from parking demand in city centers and residential areas will be used for residential, economic activities, and recreational activities which will lead to more employment generation.

A sensitivity analysis is also conducted to estimate the overall impacts of AVs on the spatial distribution of employment location in the city considering the growth in jobs under AV and non-AV scenarios. Results show that employment growth is higher in the city center under non-AV scenarios compared to AV scenarios. However, an equal growth in employment is observed in the periphery under AV and non-AV scenarios. The finding indicates that the wide adoption of AVs would facilitate the movement of people and provide flexibility to choose employment locations throughout the city. The findings are consistent with the existing body of literature where researchers mentioned that AVs would encourage more economic development in the periphery and city centers besides residential development (Kang & Kim, 2019). However, they also mentioned that small and non-intensive commercial areas in city centers would be converted into residential areas because AVs would be able to bring goods from the supermarkets. Thus, a slightly lower increase in employment particularly retail employment would be observed in the city center.

6. Conclusions and directions for future research

This study significantly contributes to the literature by investigating the potential impacts of AVs on the spatial distribution of household and employment locations. The findings indicate that the adoption of AVs encourages people to live outside of the city center by increasing convenience and reducing travel costs. On the other hand, AVs would increase employment opportunities in the city center by inducing more economic activities. The study provides some policy guidelines which will be useful for the policymakers to manage future land-use patterns and control overall urban development. Since AVs are likely to increase urban sprawl, it is recommended to implement smart growth principles and take appropriate regulatory measures to control unplanned suburbanization (Smith, 2012). Space released from parking land could be redeveloped for pedestrian-friendly environments (Tao & Cao, 2022). Accordingly, policymakers and urban planners should explore the design opportunities to make the freed space attractive for different physical activities. Researchers also mentioned that AVs can complement public transport and support urban development strategies (Fraedrich et al., 2019). Thus, policymakers should start exploring the possible options to brace this potential. The precise and connected operation of AVs would require narrower driving lanes compared to conventional cars. Thus, existing wide lanes could be narrowed and dedicated lanes could be built for transit services or expanded sidewalks for walking and bicycling (Tao & Cao, 2022).

Despite some significant contributions to the literature, this study warrants further exploration to shed light on the discussion due to some limitations. First, I have assumed AV adoption on local roads and throughout the network rather than specifying the exact market share. Thus, a study is necessary to understand how ownership of AV (for example, 5%, 10%, or 20%, etc. market share of AVs) could influence people's destination location choices. Second, this study investigates the impacts of AVs on the spatial distribution of household and employment locations. Hence, another study should focus on exploring the effects of the built environment on the AV adoption intention of people. Third, there is inadequate evidence on how AV would influence the housing location of different income groups. Therefore, it is critical to know the equity issues of AVs concerning the housing choices of people which require further investigation. Fourth, to the best of our knowledge, previous studies rarely investigated the potential implications of AVs on public health. Thus, it is essential to conduct a study to assess the public health issues of AVs. Lastly, people's teleworking tendency and grave global epidemics could affect the travel behaviors of people. So, further study is required to realize how people would use AVs during massive teleworking and pandemic situations.

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CHAPTER 8: CONCLUSIONS

Autonomous Vehicles (AVs) are not in people's dreams anymore. They are becoming a reality day by day. Extant research has demonstrated that the ongoing development of AVs would influence urban transportation systems and the built environment. The research and development of cutting-edge technologies and a higher market share of AVs would transform human mobility patterns and protect people from traffic crashes.

Despite rapid advancement, the implementation of this novel technology is still restricted in the testing phase within a controlled environment. Most of the current commercially operated AVs include Level 1 ~ Level 3 autonomy (e.g., emergency braking, blind-spot detection, lane-keeping). Investigating current status of adoption, researchers mentioned that 50% of new vehicles would be Level 4 or 5 AVs by 2040, 50% of all vehicles would be AVs by 2060, and all vehicles would be AVs by end of this century. However, there are a lot of uncertainties associated with AVs which may cause interruption in the development of this novel technology. Due to the limited adoption of AVs for public use, most people are still unaware of AVs at this time. However, there is an urgent need to know people's perceptions about AVs and their behavioral intention to accept AVs. Additionally, policymakers and industry partners are interested to know the short-, medium-, and long-term effects of AVs to prepare policy guidelines for the successful implementation of AVs.

This dissertation strives to explain the research needs outlined above by conducting state-of-the-art literature reviews, developing empirical models, and performing simulations. Published scholarships were collected through a strategic search and analyzed critically to know the existing knowledge base. Data were collected from the 2019 California Vehicle Survey to identify the key determinants of AVs and Shared AVs (SAVs). The existing Swindon model developed within the TRANUS platform was considered to estimate the effects of AVs on destination location choices and travel behaviors.

Results show that people's socioeconomic profile, psychological factors, and knowledge and familiarity with AV technologies would affect AV and SAV use. Additionally, urban form (e.g., density, land use diversity), transportation factors (e.g., travel mode, distance, and time), affinity to new technology, and institutional regulations would influence AV and SAV adoption. However, people's psychological factors are the most influential factor compared to the built environment, other socioeconomic, and transportation factors. The study also found that the adoption of AVs would encourage people to live outside of the city center and increase employment opportunities in the city center by inducing more economic activities. Additionally, AVs would increase people's travel demand by providing transport services to all including mobility impaired individuals and reducing vehicle ownership, travel distance, travel time, travel costs, and vehicle hours traveled by reducing solo driving.

This dissertation significantly contributes to the literature by identifying gaps in the existing bodies of literature and providing guidelines for future research. Additionally, this dissertation provides policy directions to the professionals involved in transportation and urban planning for taking strategies compatible with AVs and concurrently managing people's travel demand and urban growth. Notwithstanding, this dissertation is affected by some major limitations as discussed.

First, given the number of existing studies on AVs, a systematic econometric meta-analysis could be conducted to estimate the effects of different factors on AV adoption and generalize the results of individual studies. Second, the dependent variables of the study represent the household's intention to purchase AVs and use SAVs and do not reflect personal choices. Thus, it is yet to fully capture the personal preference within the household. Third, some variables related to the built environment are aggregated at the county level to understand the effects of the built environment on AV purchase and use which is a coarse geographic unit. Thus, a finer granularity in the geographic unit (e.g., block group, census tract) should be used in future studies to get more focused insights. Fourth, I have assumed AV adoption on local roads and throughout the network rather than specifying the exact market penetration. Thus, a study is necessary to understand how ownership of AVs (for example, 5%, 10%, 20%, etc. market penetration of AVs) could influence people's location choices of people and travel patterns. Fifth, I investigated the impacts of AVs on the spatial distribution of household and employment locations and people's travel behaviors. Hence, further study should focus on assessing the effects of the built environment and people's current travel patterns on AV adoption intention of people.

Sixth, this dissertation partially estimated the effects of AVs on the built environment and transportation. A further study is necessary to estimate the effects of AVs on parking demand, roadway capacity, travel speed, household and transport energy use, carbon emission, and traffic safety. Seventh, house-to-house services provided by AVs would increase physical inactivity and related health problems. However, to the best of our knowledge, there is no empirical study to investigate the impacts of AVs on public health. Thus, it is essential to conduct a study to assess the public health implications of AVs.

Eighth, although it has been argued that AVs would increase the mobility of women, the elderly, children, and disabled persons, the research found that these strata of society hold negative opinions on AVs due to safety and security issues. Thus, a study investigating AV adoption disparities among different physical abilities, income, and racial groups is necessary to ensure justice and equity in transportation. Lastly, people's teleworking tendency and grave global epidemics could affect their travel behaviors. So, further study is required to realize how people would use AVs during massive teleworking and pandemic situations.