UNDERSTANDING ACCEPTANCE OF AUTONOMOUS MOBILITY SERVICES USING STATISTICAL AND DEEP LEARNING APPROACHES

A Thesis Presented to the Faculty of Graduate School

at the University of Missouri-Columbia

In Partial Fulfilment

of the Requirements for the Degree

Master of Science in Civil Engineering

By

Haimanti Bala

Dr. Sabreena Anowar, Thesis Supervisor

DECEMBER 2021

The undersigned, appointed by the dean of the Graduate School, have examined the thesis entitled

UNDERSTANDING ACCEPTANCE OF AUTONOMOUS MOBILITY SERVICES

USING STATISTICAL AND DEEP LEARNING APPROACHES

Presented by Haimanti Bala,

A candidate for the degree of Master of Science in Civil Engineering (Transportation)

And hereby certify that, in their opinion, it is worthy of acceptance.

Dr. Sabreena Anowar

Dr. Yaw Adu-Gyamfi

Dr. Suchithra Rajendran

ACKNOWLEDGEMENTS

I would like to appreciate my thesis supervisor Dr. Sabreena Anowar for her continuous support and encouragement in both my academic and research sectors in these two years. Also, for introducing and entrusting me with autonomous vehicle research. I would also like to thank Dr. Yaw Adu-Gyamfi for introducing me to data science and machine learning and providing continuous support in the big data analysis portion of this research.

I would also like to acknowledge Dr. Suchithra Rajendran as one of the thesis committee members for her time and consideration.

One portion of this thesis was conducting statistical analysis on survey data which was conducted in Singapore. I would like to thank Dr. Samuel Chng from the Singapore University of Technology and Design for providing the survey data and helping out with the research.

I would like to thank my parents, Binoy Krishna Bala and Gita Sarker, younger sister Shrabanti Bala, and my younger brother Debjyoti Bala for being my greatest source of support all these years and giving me the strength to overcome any adverse situation.

Lastly, I would also like to thank all my lab mates and friends for helping, guiding, and supporting me throughout my master’s journey and making my days in Columbia so much memorable and enjoyable.

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ABSTRACT

The emergence of vehicle automation and its subsequent growth has led to new transport service offerings, generally known as Autonomous Mobility Services (AMS), that have the potential to facilitate or even replace human-operated vehicles. AMS contains different forms of potential mobility options which may contradict current transport modal concepts in terms of functionalities. For example, an autonomous shuttle bus which is a form of autonomous transit may serve similarly as an autonomous taxi/robo-taxi in terms of functionalities, coinciding with the concept of Shared Autonomous Mobility Services (SAMS). Even if the functionalities or operational principles are different, peoples' perceptions of sharing rides in any of these services may be alike. Apart from these confusions in functionalities mentioned above, peoples' attitudes and acceptance of AMS, once it's implemented in any form in the public road environment, remains a significant research aspect. To address these issues, this thesis tried to first clearly distinguish different types of AMS. Second, it tried to assemble the progress till now in acceptance-related research of AMS while reviewing the previous study approaches, outcomes, policy implications, and future research directions. Third, this study attempted to understand the acceptance of AMS using statistical and deep learning approaches leveraging both survey and social media data. Fourth, this study tried to present the consequent applicabilities and limitations of using both types of data sources for autonomous vehicle acceptance research. Eventually, this thesis intends to present an overall idea of the AMS acceptance research with future directions leveraging both data sources in an individualistic or combined manner.

CHAPTER 1: INTRODUCTION

In the past decade, the automotive sector has been revolutionized that has led to transformative changes to the transportation industry. Gradually, vehicle automation is shifting from driver assistance to driver replacement (Shladover, 2018), aligning with Hoffman (2019) naming the twenty-first century as 'age of transition' with regards to the automobile industry. At present, the technological shift from the demonstration of prototypes to the production of models is proving the rapid commencement of the Autonomous Vehicle (AV) era. However, the shift towards a majority of the vehicles on our roads to be fully automated may take a while. When it happens, these Autonomous Mobility Services (AMS) are likely to bring transformational change in our mobility landscape with the possibility of yielding a variety of societal and environmental benefits. The prospective benefits include improved traffic safety and efficiency, reduction in congestion and vehicle exhaust-related emissions, and enhanced mobility solutions to the transportation disadvantaged population segments (Fagnant and Kockelman, 2015; Litman, 2015; Wadud et al., 2016). In addition, vehicle automation is expected to enable travelers to travel greater distances in a shorter period of time while making productive use (e.g., working, relaxing, talking to friends, sleeping, or reading) of the in-vehicle travel time.

As implementation of AVs will be a monumental stride towards achieving "smart-city" recognition, many cities in the world (36) are currently hosting or have committed to hosting AV trials in preparation for its uptake (Faisal et al., 2019). Currently, there are over 70 completed or ongoing autonomous shuttle pilots in different countries around the world (Nesheli et al., 2021). Moreover, 18 other cities are conducting studies on issues related to AV regulation, planning, and governance without starting AV piloting (Faisal et al., 2019). With the implementation of AVs, two different future scenarios may emerge in terms of broad market penetration and domination – *private ownership centric* mobility or *shared usage centric* mobility. However, it is likely that most cities and countries will eventually see a combination of these two scenarios. Suffice to say, the realization of the envisioned benefits of vehicle automation is very much dependent on the type of autonomous mobility service that comes to dominate along with the extent of acceptance and the speed of the adoption of the service. As with any new technology, the path to acceptance, adoption, and subsequent use of these tech-driven transportation solutions in the daily lives of people is filled with uncertainty. The uncertainty stems from several sources. First, the exact specifications and attributes that would be provided in the AVs remain unclear. Second, it is unclear what exactly will be the role of humans during its operation. Third, there is considerable concern and skepticism about the safety of the technology. Coupled with that uncertainty, general public disinterest in abnegating autonomy over their travel and in sharing vehicular space with strangers are other impediments against widespread AV adoption. Peoples' perceived risks and benefits towards AVs will play a central role in their acceptance of the technology. Peoples' acceptance is what will determine the market penetration and eventually the success of the technology.

1.1 Acceptance of Autonomous Mobility Services: An Overview

Both directions of Autonomous Mobility Services (AMS), i.e. private ownership centric mobility and shared usage centric mobility, have their associated possibilities and limitations. At the outset, private ownership of AVs is likely to be less affordable as well as less sustainable. For instance, privately owned AVs may drop off the passenger and lead to empty vehicle miles, increasing the already severe traffic congestion problem and other negative externalities associated with motorized vehicles (Lavieri and Bhat, 2019). In other words, negating the energy or environmental benefits of electric vehicle automation, in general. On the other hand, system-wide coordination and use of shared usage centric mobilities, i.e. Shared Autonomous Mobility Services (SAMS) can lead to the minimization of empty driving and the number of circulating cars, thereby ensuring more efficient use of vehicles and avoiding surges in congestion (Burns, 2013; Levin et al., 2017; Liu and Khattak, 2016; Wang et al., 2020). For instance, Spieser et al. (2014) found in a study of Singapore that the mobility needs of Singaporeans can be achieved using SAMS with only one-third of the passenger vehicles that are operational at present. Moreover, shared fleets can also lead to remarkable cost benefits than privately owned or operated autonomous vehicles (Fagnant and Kockelman, 2015; Gurumurthy and Kockelman, 2020). For instance, transit vehicle automation can help reduce the labor costs and manpower requirements of their operations (Dong et al., 2019; Larsen, 1997; Lutin and Kornhauser, 2014) leading to higher profit per kilometer for the operator (Shen et al., 2018). Furthermore, SAMS could foster the popularity of multimodal transportation systems by overcoming the inherent barriers concerning the first-and-last mile connectivity problem of the conventional public transit system and by increasing its accessibility (Chee et al., 2021; Krueger et al., 2016). It has the potentiality to reduce levels of private vehicle ownership in the long run and make the land use planning process more sustainable since less space would need to be assigned for parking purposes (Krueger et al., 2016; Levine et al., 2018). The parking spaces can be repurposed for the use of other economic activities leading to densification of land uses. While vehicle automation may not be the panacea to all urban transportation woes, the synergistic benefits of the convergence of vehicle automation and shared economy has the potential to revolutionize the future of the surface transportation landscape.

Whatever the potential benefits of AMS might be, its adoption by people as a regular transportation mode is uncertain due to several issues. Lack of clarity about the exact specifications and attributes of AMS, the role of humans during its operation, liability issues in incidents involving AVs are significant among them. Apart from those, possible safety concerns triggered from a series of AV related accidents and ensuing fatalities have led to increased concerns among the public about the technology readiness level of autonomous vehicles. Furthermore, heterogeneity in public interest in abnegating autonomy over their travel and in sharing vehicular space with strangers are other hurdles against widespread AMS, specifically SAMS adoption.

Testing of different forms of AMS has gathered momentum in recent years, with companies such as Cruise evaluating these technologies on city streets in San Francisco (Wayland, 2020). However, as AMS could be potentially disruptive, fostering public interest in such services is of paramount importance. Consumer interest is intricately intertwined with their perception and acceptance of and attitude towards the technology and the various services it has to offer. Therefore, for the automotive industry to improve the technology further to better meet the customer needs and the stakeholders such as city planners to devise more efficient and effective legislative strategies for promoting suitable service models, knowledge about public acceptance level and the factors that have the strongest effect on their acceptance is very crucial. In recognizing that need, researchers in the transportation community have devoted increased attention in recent years to examine the acceptance of AMS from different perspectives. In light of the burgeoning studies on AMS, synthesizing progress and understandings till now to draw a comprehensive picture cannot be understated.

In terms of AMS acceptance research, a significant number of studies have been conducted over the past decade. These studies can be broadly categorized into five groups: (1) studies on behavioral intention or willingness to use or adopt AVs; (2) studies on public perception such as perceived concerns or benefits; (3) mode choice studies investigating preference of AVs over conventional modes, (4) studies on the frequency of use of AVs for trip making, and (5) studies on willingness to pay for purchasing or using AVs. These studies rely heavily on traditional surveys and/or focus groups to collect data for their analysis. These participatory methods are useful sources of data for gleaning information on user acceptance of AVs along with their socio-demographic (age, gender, income, occupation, etc.), travel behavior (trip frequency, choice of mode, etc.), and attitudinal attributes. However, they are labor-intensive, prohibitively expensive, and limited by small sample sizes or low numbers of responses. Social media data offer new possibilities to overcome the limitations of traditional surveys.

With increasing internet access, social media platforms such as Facebook, Twitter, Instagram, YouTube, and Reddit have enabled interactions and opinion sharing between millions of users in real-time. As such, although less controlled than surveys, these platforms contain a treasure trove of low-cost, abundant, and voluntary information and represent a much broader demographic sample unlikely to participate in traditional surveys or focus groups. The posts and subsequent replies, shares/retweets capture citizens' voices or 'emotional pulses' – their opinions, emotions, feelings, thoughts, and views. Agencies can retrieve these user-generated contents and utilize them to understand the publics' and needs or sentiments. However, their use in the AV acceptance research has not been explored that much, despite gaining popularity in recent years.

1.2 Problem Statement

Autonomous vehicles are expected to be introduced as different transport mode offerings in the conventional human operated road-traffic scenario. These mode offerings, known as Autonomous Mobility Services (AMS) are likely to vary with the conventional concepts of mobility services. For example, an autonomous shuttle bus which is a form of autonomous transit may serve similarly as an autonomous taxi/robo-taxi in terms of functionalities, coinciding with the concept of Shared Autonomous Mobility Services (SAMS). Even if the functionalities or operational principles are different, people's perceptions of sharing rides in any of these services may be alike. Similarly, the absence of a human driver makes the concepts of autonomous carsharing and ridehailing similar. Therefore, possible automated modes should be clearly distinguished in terms of their functionalities. Apart from that, the acceptance of probable autonomous modes is a critical research genre for its difference in functionalities as well as variance in peoples' attitudes influences by demographic, socio-economic, geographic, and other factors. The current state of knowledge in terms of public acceptability and acceptance of AMS, methodologies used till now, predictors, and factors prominent in those studies are needed to be assembled. Apart from that, the data for acceptance studies have prioritized mostly surveys till now, with a few but increasing number of studies dealing with the big data analysis genre based on social media posts. Therefore, understanding AMS acceptance using both types of data sources would lead to a comparison of the advantages and limitations of using survey and social media data in AMS acceptance research. This will also lead to the discussion if both can be integrated in the future in order to leverage their advantageous sides.

1.3 Objectives of the Study

The objectives of this study are summarized below:

- Distinguishing different forms of Autonomous Mobility Services (AMS)
- Reviewing AMS based acceptance studies to understand the progress and outcomes till now
- Using multidimensional clustering approach to identify potential users of SAMS
- Using deep learning approaches to understand peoples' perception regarding AMS
- Applicabilities and limitations of using survey and social media data in AMS acceptance research
- Providing possible implications and future research directions

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction to Autonomous Mobility Services

Autonomous Mobility Services (AMS), in general terms, refers to the movement of passengers and/or freight using vehicles that are not human operated. AMS services can be divided into two terms: individual or private ownership centric mobility and shared usage centric mobility. The first one refers to ownership of private cars with automation features, envisioned to be leading to fully automated cars in the future. On the other hand, the latter one dealing with shared usage-centric mobilities is generally termed as Shared Autonomous Mobility Services (SAMS). In terms of the level of privacy available during travel, autonomous mobility services can be divided into two broad distinctions: (1) private or self-ridden, and (2) public or group-ridden. Privately hired ride services such as taxi as well as Transportation Network Company (TNC)/ ridehailing/ ridesourcing services for a single-rider (similar in functionalities as UberX, standard Lyft), and carsharing all fall under the self-ridden category. The travelers can access both taxi and TNC rides by pre-arranging trips in advance, or by e-hail. The primary difference between a taxi and a TNC ride is that only taxis are allowed to street hail whereas TNCs are not. Carsharing services with AVs build on the traditional concept of carsharing and refer to short-term access to a shared vehicle owned by a carsharing operator while the proprietor remains the legal owner (similar in functionalities as Zipcar, Car2Go). This type of service, where vehicles are shared sequentially, allows individuals to enjoy the pleasures and benefits of private vehicle use without the burdens of high capital costs and obligations associated with ownership and maintenance as they only pay a monthly and/or per-use fee. AVs used for carsharing services may come in a variety of body sizes and types, from compact to full-size sedans, and Sports Utility Vehicles (SUVs) to large-sized recreational vehicles suitable for long-distance travels/road trips. The group-ridden category includes both for-hire (ridesourcing and public transit) and not-for-hire (carpooling/vanpooling) shared ride services. This category involves simultaneous usage of vehicles by multiple, (un)related passengers, each of which accepts sharing space in the vehicle for the whole or part of the journey with others. Following the definition of SAE International (Shared and Digital Mobility, 2021), concurrently shared TNC ride service is referred to as ridesourcing (includes ridesplitting/ridepooling) service where a traveler is matched with other riders who may or may not have the same origin and/or destination using smartphone apps (similar in functionalities as

UberPOOL, Lyft Shared). The number of passengers in ridesplitting/ridepooling can range from a minimum of two to a maximum of seven passengers depending on the size of the vehicle. Under the umbrella of public transit falls traditional transit, feeder services providing access to and egress from transit stops (also known as first-and-last mile connectivity), micro-transit, and paratransit. The vehicles could be of varying sizes ranging from shuttles/vans, minibuses to full-sized buses with seating capacities ranging from three to 100. These vehicles could operate on either exclusive or non-exclusive/mixed right-of-way, could include fixed-route or flexible/dynamic-route services, and offer fixed schedules or on-demand services during off-peak hours. A natural extension of the service is the Mobility as a Service (MaaS) scenario that involves automated trip planning across multiple modes of transport such that various transport legs are synchronized to achieve trip optimization. Carpooling/vanpooling involves formal or informal sharing of rides between riders with similar origin-destination pairings using vehicles. The number of passengers can range between two to six passengers for carpooling vehicles while it may vary between seven to 15 passengers for vanpooling vehicles. In the current research, Autonomous Mobility Services (referred to as AMS from hereon) is defined as a service leading to both individual (privately owned vehicles) and collective use of vehicles, either asynchronously (car-sharing and private-hire) or synchronously (all subcategories of the group-ridden class), on an as-needed basis which subsumes the convergence of four concepts including shared mobility, information and communication system, vehicle propulsion, and vehicle automation. Figure 1 illustrates different types of AMS with brief definitions added in notes for better understanding.

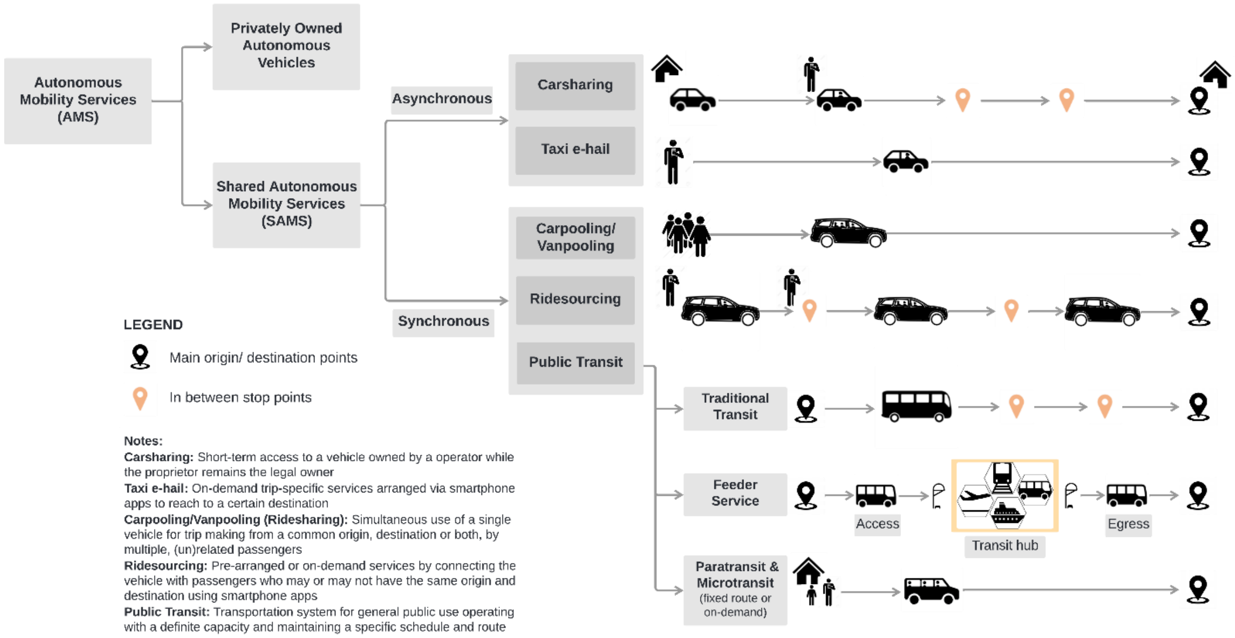


Figure 1: Different types of Autonomous Mobility Services

2.2 Acceptance of AMS: Review Approach

The study undertakes a systematic review of the studies conducted on AMS. Mainly peer-reviewed journal articles and conference proceedings including Procedia papers in the English language were considered for review. Books, publications in other languages, reports by government organizations or industries, and non-academic studies, and editorial papers were excluded from our review. The review process was done in two steps. First, the standard research databases (e.g., Google Scholar, Scopus, Web of Science, ScienceDirect) were employed for literature search on shared AMS using various queries. Second, a comprehensive cascading search (including backward as well as forward snowballing) was done on the references in SAMS related highly cited research articles. These two approaches ensured the inclusion of a broad range of literature on SAMS. After initially reviewing the titles and abstracts, approximately 125 articles, published between 2011 and 2021, were considered relevant to our context. Each of the 125 studies was read carefully to ensure that they fit within the scope of interest. Afterward, the studies were divided into two subcategories based on the type of AMS they provide.

Table 1 represents an overview of the studies, covering from 2011 to 2021, where AVs are considered as a means of public transport. Table 2 represents an overview of the studies, from 2014 and onward, that investigate various aspects related to the introduction and potential use of AVs as a shared mode except for public transit. In both tables, the studies are sorted by publication year (starting from the most recent). For each study, information is provided on the following: geographical location where the study was conducted, data collection scheme (survey type, nature of distribution, target population along with sample size, and sampling strategy), methodology used to analyze data, and the empirical context. Moreover, additional information on the type of sharing service is presented in Table 1 and transit vehicle specification used for test rides and the type of behavioral framework employed are presented in Table 2.

Table 1: Studies on Acceptance of Autonomous Shared Services (Public Transit)

Study	Vehicle Type (Propulsion) and Specifications	Study Area	Ride Exposure	Data				Behavior Theory	Econometric Model	Empirical Context
				Elicitation Method		Sample Type				
				Survey Type	Distribution	Target Population (Sample size)	Sampling Strategy			
Studies on intention to use										
Chee et al. (2021)	Shuttle (Electric) Route length: 0.8 km; Max speed = 20 kmph; Max # passengers: 11; Traffic: Mixed	Stockholm, Sweden	Yes	RP	On field (Two time periods)	General population (185)	Random sample	-	SEM	Service valuation and intention to use
Mouratidis and Serrano (2021)	Shuttle (NA) Route length: 1.5 km; Avg. speed: 18 kmph; Max # passengers: 9; Operator: Yes; Track: Predefined; Traffic: Mixed	Oslo, Norway	Yes	RP	On field (Before and after the ride)	Residents and visitors (117)	Convenience sample	-	Descriptive analysis, BL	Intention to use
Battistini et al. (2020)	Shuttle (NA) Route length: 10 km; Max # passengers: 11; Operator: Yes	Italy	No	RP	Online	University students and staffs (2,705)	Convenience sample	-	PCA, Correlation analysis	Intention to use; WTP
Bernhard et al. (2020)	Shuttle (NA) Route length: 0.6 km; Trip time: 5-10 mins; Avg. speed: 15 kmph; Max # passengers: 11; Operator: Yes; Track: Predefined; Traffic: Mixed	Mainz, Germany	Yes	RP	On field (Before and after the ride)	General population (942)	Convenience sample	UTAUT	Descriptive analysis; LR	Intention to use
Chen et al. (2020)	Bus (NA)	Chongqing, China	No	RP	Online and paper-based	General population (913)	Random sample	Extended UTAUT	SEM	Intention to use
Chng and Cheah (2020)	Transit (NA)	Singapore	No	RP	Online	General population (210)	Snowball sample	-	Descriptive analysis; LR	Intention to use
Feys et al. (2020)	Shuttle (NA) Route length: 0.35km; 1.5 km; Trip time: 5-10 mins; Avg. speed: 10-15 kmph; Max # passengers: 8-12;	Brussels, Belgium	Yes	RP	Online	General population (384); Students (220)	Convenience sample	Extended UTAUT	HMR	Intention to use

Study	Vehicle Type (Propulsion) and Specifications	Study Area	Ride Exposure	Data				Behavior Theory	Econometric Model	Empirical Context
				Elicitation Method		Sample Type				
				Survey Type	Distribution	Target Population (Sample size)	Sampling Strategy			
	Operator present: Yes; Track: Predefined; Traffic: Mixed									
Kassens-Noor et al. (2020)	Shuttle or bus (NA)	Michigan, USA	No	RP	Phone and on-board interception	Public transit users (1,468)	Convenience sample	-	Descriptive analysis; BL	Intention to use
Nordhoff et al. (2020a)	Shuttle (NA) Route length: 2.5 km; Avg. speed: 13 kmph; # stops: 8; Max. # passengers: 10; Operator present: Yes; Track: Predefined; Traffic: Mixed	Trikala, Greece	Yes	RP	On-board	Shuttle riders (315)	Convenience sample	Extended UTAUT	SEM	Intention to use
Papadima et al. (2020)	Shuttle (NA) Route length: 2.4 km; Avg. speed: 10 kmph; # stops: 8 Operator present: Yes; Track: Predefined; Traffic: Mixed	Trikala, Greece	Yes	RP; SP	Online	General population (158)	Snowball sample	-	SWOT; Conjoint analysis	Public acceptance; attribute preference
Rosell and Allen (2020)	Shuttle (Electric) Avg. speed: 8-11 kmph; Max # passengers: 12; Operator present: Yes; Track: Predefined	Spain	Yes	RP	Face-to-face	General population (1,062)	Convenience sample	-	SEM	Intention to use
Chen (2019)	Shuttle (Electric) Route length: 1.1 km; # stops: 2; Avg. speed: 15 kmph; Operator present: Yes; Track: Predefined; Traffic: Mixed	Taiwan	Yes	RP	Paper based	Shuttle riders (1,498)	Convenience sample	UTAUT	SEM	Intention to use
Dong et al. (2019)	Bus (NA) Operator present: Yes, no	Pennsylvania, USA	No	SP	Online	University employees (891)	Convenience sample	-	MMNL	Intention to use
Herrenkind et al. (2019)	Bus (Electric) Route length: 1 km; Avg. speed: 15 kmph; Max # passengers: 7; Operator	Germany	Yes	RP	Online	Bus riders (268)	Convenience sample	TAM	SEM	Intention to use

Study	Vehicle Type (Propulsion) and Specifications	Study Area	Ride Exposure	Data				Behavior Theory	Econometric Model	Empirical Context
				Elicitation Method		Sample Type				
				Survey Type	Distribution	Target Population (Sample size)	Sampling Strategy			
	present: Yes; Track: Predefined; Traffic: Mixed									
Nordhoff et al. (2019a)	Shuttle (Electric) Route length: 0.7 km; Trip time: 8-12 mins; Avg. speed: 8 kmph; Max # passengers: 12; Operator present: Yes; Track: 'Virtual'	Berlin, Germany	Yes	Semi-structured interview	Face-to-face	University employees (30)	Convenience sample	-	Descriptive analysis	Public acceptance (feeder to public transport system)
Roche-Cerasi (2019)	Shuttle (NA) Operator: No; Traffic: Mixed	Norway	No	RP	Online	Infrequent transit users (1,419)	Random sample	-	Descriptive analysis	Public acceptance (feeder to public transit)
Distler et al. (2018)	Shuttle – on demand (NA)	Luxembourg	Yes	RP	Workshop	General population (14)	Random sample	UTAUT and CTAM	Descriptive analysis	Public acceptability and acceptance
Nordhoff et al. (2018a)	Shuttle - first/last mile connector (Electric) Max # passengers: 8; Operator: No; Traffic: Mixed	Selected countries (116)	No	RP	Online	Cross-national sample (7,755)	Convenience sample	-	Descriptive analysis	Public acceptability
Rehrl and Zankl (2018)	Shuttle (Electric) Route length: 0.4 km; Trip time: 5 mins; Max. speed: 16 kmph; Max # passengers: 11; Track: Predefined; Traffic: Mixed	Koppl, Austria	Yes	RP	Online	Shuttle riders (294)	Convenience sample	-	Descriptive analysis	Public acceptance
Madigan et al. (2017)	On-demand shuttle (NA) Route length: 2.5 km; Avg. speed: 13 kmph; Max # passengers: 10; Operator: Yes; Track: Exclusive	Trikala, Greece	Yes	RP	Face-to-face via tablet application	Shuttle riders (at least once) (315)	Convenience sample	Adapted UTAUT	HMR	Intention to use
Motak et al. (2017)	Shuttle (Electric) Max # passengers: 6; Track type: Predefined	Clermont-Ferrand, France	Yes	RP	Paper based	Hospital complex visitors (500)	Convenience sample	TAM, TPB	HMR	Public acceptance
Nordhoff et al. (2017)	Shuttle (Electric)	Berlin, Germany	Yes	RP	Onboard	Shuttle riders (318)	Convenience sample	UTAUT	Descriptive analysis	Public acceptance

Study	Vehicle Type (Propulsion) and Specifications	Study Area	Ride Exposure	Data				Behavior Theory	Econometric Model	Empirical Context
				Elicitation Method		Sample Type				
				Survey Type	Distribution	Target Population (Sample size)	Sampling Strategy			
	Avg speed: 8 kmph; Operator: Yes; Traffic: Mixed									
Pakusch and Bossauer (2017)	Public transit (NA)	Nuremberg, Germany	No	SP	Online	Social network users (201)	Convenience sample	-	Descriptive analysis	Intention to use
Christie et al. (2016)	Shuttle (Electric) Route length: 1.8km; Avg. speed = 12 kmph; Max # passengers: 10; Operator: Yes; Track: University campus	Lausanne, Switzerland	Yes	RP	Paper based	General population (181)	Convenience sample	-	Descriptive analysis	Public opinion/ acceptance
Madigan et al. (2016)	Shuttle (NA) Route length: 1.7 km; Avg. speed: 12 kmph; Max # passengers: 12; Operator: Yes; Traffic: Mixed	La Rochelle, France; Lausanne, Switzerland	No	RP	Face-to-face via tablet application	Spectators of vehicle demonstration (349)	Convenience sample	Adapted UTAUT	Descriptive analysis; HMR	Public acceptability
Studies on Willingness Constructs										
Battistini et al. (2020)	Shuttle (NA) Route length: 10 km; Max # passengers: 11; Operator: Yes	Italy	No	RP	Online	University students and staffs (2,705)	Convenience sample	-	PCA, Correlation analysis	Intention to use; WTP
Anania et al. (2018)	School bus (NA) Operator: No; Traffic: Mixed	India; USA	No	SP	Online	MTurk users (610)	Convenience sample	-	Three-way ANOVA with mediation	Parents' willingness to let their children ride
Winter et al. (2018)	Bus (NA) Trip time: 30 mins; Operator: No; Traffic: Mixed	USA	No	RP	Online	General population (510; 571)	Convenience sample	-	Three-way ANOVA	Willingness to ride
Studies on mode choice										
Carteni (2020)	NA	Naples, Italy	No	SP	In-person interview	Transit riders (3,140)	Random sample	-	MBL	Public acceptability (mode choice)
Wien (2019)	Bus (NA)	Vaals, Netherlands;	No	SP	Online	Commuters (292)	Convenience sample	-	MBL	Mode choice

Study	Vehicle Type (Propulsion) and Specifications	Study Area	Ride Exposure	Data				Behavior Theory	Econometric Model	Empirical Context
				Elicitation Method		Sample Type				
				Survey Type	Distribution	Target Population (Sample size)	Sampling Strategy			
		Aachen, Germany								
Alessandrini et al. (2016)	Minibus (Conventional) Route lengths: 1~6km; Operator: No; Traffic: Mixed	12 cities in Europe	Yes	SP	Face-to-face; online; telephone	General population (3,326)	Random sample	-	FGM Copula based BL	Mode choice
Alessandrini et al. (2014)	Shuttle (Conventional) Operator: No; Traffic: Mixed	Selected cities across Europe (12)	No	SP	Face-to-face; online	Transit users (200)	Convenience sample	-	BL	Mode choice
Delle Site et al. (2011)	Bus (NA) Route length: 1.6 km; Avg. speed: 24 kmph; Max # passengers: 29	Rome, Italy	No	SP	Face-to-face	Parking area users (238)	Convenience sample	-	MNL, MMNL	Mode choice (parking lot to fair entrance)
Studies on user perception										
Chng and Cheah (2020)	Transit (NA)	Singapore	No	RP	Online	General population (210)	Snowball sample	-	Descriptive analysis	Benefits and concerns
Hilgarter and Granig (2020)	Shuttle (Electric) Route length: 0.64km; Avg. speed: 10 kmph; # stops: 3 Max # passengers: 11; Track: Predefined; Traffic: Mixed	Carinthia, Austria	Yes	Mixed method	On Field	Park visitors (19)	Convenience sample	-	Qualitative analysis	Public perception
Mirnig et al. (2020)	Shuttle (NA) Route length: 0.8km; 2km; Avg. speed: 8-12kmph; 5-15kmph; Trip time: 5mins; 24mins; # stops: 2; 6; Track: Test; real road	Austria	Yes	Manual observation and RP	Paper-based	Shuttle riders (24)	Convenience sample	-	Qualitative and descriptive analysis	Rider behavior during an emergency
Nordhoff et al. (2020b)	Shuttle (NA) Route length: 1.5km; Avg. speed: 10 kmph; # stops: 8; Operator: Yes;	Berlin, Germany	Yes	Mixed method	On-board	Shuttle riders (119)	Convenience sample	-	Descriptive analysis	Public perception; human-AV interaction

Study	Vehicle Type (Propulsion) and Specifications	Study Area	Ride Exposure	Data				Behavior Theory	Econometric Model	Empirical Context
				Elicitation Method		Sample Type				
				Survey Type	Distribution	Target Population (Sample size)	Sampling Strategy			
	Track type: Predefined; Traffic: Mixed									
Lopez-Lambas and Alonso (2019)	Bus (NA)	Malaga, Spain; Madrid, Spain	No	Focus group	-	General population (6-10)	Convenience sample	-	Qualitative and descriptive analysis	Public perception and acceptability
Salonen and Haavisto (2019)	Shuttle (NA) Route lengths: 0.7 km; Max. speed: 12 kmph; Max # passengers: 10; Operator: Yes; Traffic: Mixed	Espoo, Finland	Yes	Interview	Face-to-face	Shuttle riders (44)	Convenience sample	TIB	Qualitative analysis	Public perception
Straub and Schaefer (2019)	Shuttle (Electric) Route lengths: 0.8 km; Max # passengers: 6; Traffic: Mixed; first/last mile connector	USA	Yes	Observation	Face-to-face	Shuttle riders as operators (24); passengers (20); pedestrians (83)	Convenience sample	-	Qualitative analysis	Human-AV interaction
Zoellick et al. (2019)	Shuttle (Electric) Route lengths: 0.85 km; 1.2 km; Trip time: 10-15 mins; Max. speed: 12 kmph; Operator: Yes; Traffic: Mixed	Berlin, Germany	Yes	RP	Paper based	Campus visitors (125)	Convenience sample	-	Descriptive analysis, MANOVA, HMR	Public perception
Salonen (2018)	Bus (Electric) Route length: 0.95 km; Max speed: 13 kmph; Max # passengers: 10; Operator: Yes; Track: Exclusive	Vantaa, Finland	Yes	RP	Face-to-face	Bus riders (197)	Convenience sample	-	Descriptive analysis	Public perceptions of safety, security, and emergency management
Portouli et al. (2017)	Minibus (NA) Route length: 2.4 km; Avg. speed = 13 kmph; Max # passengers: 11; Operator: Yes; Traffic: Mixed	Trikala, Greece	Yes; No	RP	Face-to-face; Prepaid mail service	Minibus riders; General population (200;519)	Random sample	-	Descriptive analysis	Public perception
Eden et al. (2017)	Shuttle (NA) Route length: 1.5 km; Max speed: 20 kmph; Max # passengers: 11; Traffic: Mixed	Sion, Switzerland	Yes	Video-recorded data	On field (Before and after the ride)	General population	Convenience sample	-	Ethno-methodology, interaction analysis	Human-AV interaction

Study	Vehicle Type (Propulsion) and Specifications	Study Area	Ride Exposure	Data				Behavior Theory	Econometric Model	Empirical Context
				Elicitation Method		Sample Type				
				Survey Type	Distribution	Target Population (Sample size)	Sampling Strategy			
Piao et al. (2016)	Bus (NA) Route length: 1.4 km; Max # passengers: 10	La Rochelle, France	No	RP	Online; telephone	General population (425)	Random sample	-	Descriptive analysis	Public opinion on implementation
Studies on frequency of use										
Nordhoff et al. (2018b)	Shuttle (Electric) Route length: 0.7 km; Trip time: 8-12 mins; Max speed: 10 kmph; Max # passengers: 12; Operator: Yes; Track: 'Virtual'	Berlin, Germany	Yes	RP	Online	University employees and tourists (384)	Convenience sample	-	Descriptive analysis	Public acceptance (feeder service in urban and rural areas)

*AV = Autonomous Vehicle; BL = Binary Logit; CAV = Connected Autonomous Vehicle; CTS = Cybernetic Transport System; CTAM = Car Technology Acceptance Model; FGM = Farlie-Gumbel-Moregenstern; GDP = Gross Domestic Product; HMR = Hierarchical Multiple Regression; LOS = Level of Service; LR = Linear Regression; MNL = Multinomial Logit; ML = Mixed Logit; NA = Not Available; PCA = Principal Component Analysis; RP = Revealed Preference; SAV = Shared Autonomous Vehicle; SEM = Structural Equation Model; SP = Stated Preference; SWOT = Strength Weaknesses, Opportunities, and Threats; TAM = Technology Acceptance Model; TPB = Theory of Planned Behavior, TIB = Theory of Interpersonal Behavior; UTAUT = Unified Theory of Acceptance and Use of Technology; WTP = Willingness to Pay

Table 2: Studies on Acceptance of Autonomous Shared Services (Taxi/Shared ride/Pooled ride)

Study	Shared Service Type	Study Area	Data				Econometric Model	Empirical Context
			Elicitation Method		Sample Type			
			Type	Distribution	Target Population (Sample size)	Sampling Strategy		
Studies on intention to use								
Liu et al. (2020)	Non-dynamic (Taxi)	China	RP	Online	General population (454)	Convenience sample	LR	Intention to use
Wang et al. (2020a)	Non-dynamic (Taxi, Ride-share)	USA	RP	Online	General population (721)	Random sample	MNL	Intention to use
Wong and Rinderer (2020)	Non-dynamic (Taxi/Ride-hail)	Different countries	RP	Online	General population (206)	Random sample	LR	Intention to use
Yuen et al. (2020)	Non-dynamic (Taxi/Ride-share)	Da Nang, Vietnam	RP	Online	Residents (268)	Random sample	SEM	Intention to use
Barbour et al. (2019)	Non-dynamic (Carshare, Rideshare, Taxi, Public transit)	USA	RP	Online	AAA members (782)	Convenience sample	ML	Intention to use
Jing et al. (2019)	Non-dynamic (Taxi)	China	SP; RP	Online	General population (906)	Random sample	SEM	Intention to use
Wang and Akar (2019)	Non-dynamic (Carpool)	Seattle, USA	RP	Online	General population (3,515)	Random sample	BOP	Intention to use (mode choice)
Moreno et al. (2018)	Dynamic (Taxi, Rideshare)	Munich, Germany	SP	Online, field	Metropolitan area residents (106)	Convenience sample	BL; Simulation	Intention to use (mode choice)
Nair et al. (2018)	Non-dynamic (Taxi, carshare)	Seattle, USA	SP	Online, telephone	Households (1,365)	Random sample	ROP	Intention to use
Lavieri et al. (2017)	Non dynamic (Carshare)	Puget Sound, USA	SP	Online, telephone	Households (1,832)	Random sample	GHDM	Interest in using (mode choice)
Tussyadiah et al. (2017)	Non-dynamic (Ride-hail)	USA	RP	Online	General population (325)	Convenience sample	HMR	Intention to use
Studies on user perception								
Paddeu et al. (2020)	Non-dynamic (Rideshare)	UK	RP	Paper based	Social media researchers (56)	Convenience sample	ANOVA	Perceived comfort and trust in technology
Barbour et al. (2019)	Non-dynamic (Carshare, Rideshare, Taxi, Public transit)	USA	RP	Online	AAA members (782)	Convenience sample	MMNL	Perceived concerns

Study	Shared Service Type	Study Area	Data				Econometric Model	Empirical Context
			Elicitation Method		Sample Type			
			Type	Distribution	Target Population (Sample size)	Sampling Strategy		
Merfeld et al. (2019)	Non-dynamic (Carshare, Rideshare)	Germany	RP	Online	Scholars; managerial experts (40)	Convenience sample	Descriptive statistics	Drivers and barriers of future developments
Studies on mode choice								
Gurumurthy and Kockelman (2020)	Dynamic (Ride-splitting)	USA	RP	Online	General population (2,588)	Convenience sample	MNL	Mode choice (long-distance travel)
Cai et al. (2019)	Dynamic (Ride-hail, Rideshare)	Singapore	SP	Online; field	Transit users; drivers (1,477)	Convenience sample	Logit Kernel	Mode choice for commuting trips
Lavieri and Bhat (2019)	Dynamic (Ride-hail, Carpool)	DFWA, USA	SP; RP	Online	Commuters (1,607)	Convenience sample	GHDM	Choice between ride-hailing and ride-sourcing SAMS
Stoiber et al. (2019)	Non-dynamic (Ride-sourcing, Public transit)	Switzerland	SP	Online	General population (679)	Random sample	Repeated measures OL	Mode choice; ownership/subscription choice
Webb et al. (2019)	Non-dynamic (Private taxi)	Brisbane, Australia	SP	Online (before and after showing video)	Residents (172)	Convenience sample	MNL	Mode choice
Nazari et al. (2018)	Non-dynamic (Taxi, Carshare, access and egress mode)	Puget Sound, USA	SP	Online, telephone, smartphone	Households (2,726)	Random sample	Multivariate OP	Mode choice
Haboucha et al. (2017)	Non-dynamic (Carshare)	Israel, USA, Canada	SP	Online	Commuter drivers (721)	Convenience sample	NL Kernel	Mode choice
Heilig et al. (2017)	Dynamic (Carshare, ride-share)	Stuttgart, Germany	-	-	-	-	NL; ABM	Mode – destination choice
Chen and Kockelman (2016)	Dynamic (Ride-share)	Austin, USA	-	-	-	-	MNL; ABM	Mode choice; pricing impact on market share
Krueger et al. (2016)	Dynamic and non-dynamic (Taxi, Rideshare)	Australia	SP	Online	Metropolitan area residents (435)	Convenience sample	MMNL	Mode choice
Yap et al. (2016)	Non-dynamic (Egress mode)	Netherlands	SP	Online	General population (761)	Convenience sample	MMNL	Mode choice

Study	Shared Service Type	Study Area	Data				Econometric Model	Empirical Context
			Elicitation Method		Sample Type			
			Type	Distribution	Target Population (Sample size)	Sampling Strategy		
Studies on willingness constructs								
Gurumurthy and Kockelman (2020)	Dynamic (Ride-splitting)	USA	RP	Online	General population (2,588)	Convenience sample	Hurdle model	WTP; WTP to anonymize location
Konig and Grippenkoven (2020)	Dynamic (Ride-splitting)	Germany	SP	Online	General population (150)	Convenience sample	LR with Huber function; BL	WTS; Refusal rate of sharing rides
Krueger et al. (2020)	Non-dynamic (Ride-hail; Ride-sourcing)	NYC, USA	SP	Online	General population (1,507)	Random sample	Bayesian logit	WTP
Wang et al. (2020)	Non-dynamic (Taxi, Rideshare)	USA	RP	Online	General population (721)	Random sample	MNL	WTS
Studies on Frequency of Use								
Bansal and Kockelman (2018)	Non-dynamic (Private taxi)	Texas, USA	RP	Online	General population (1,088)	Convenience sample	OP	Frequency of use under different WTP
Bansal et al. (2016)	Non-dynamic (Rideshare)	Texas, USA	RP	Online	General population (347)	Convenience sample	OP	Adoption rate under different pricing schemes
Studies on miscellaneous topics								
Berrada et al. (2020)	Non-dynamic (Taxi)	Palaiseau, France	SP	Face-to-face	General population (600)	Random sample	MFA; HCA	Identify user clusters
Pettigrew et al. (2019)	Non-dynamic (Rideshare)	Australia	RP	Online	General population (1,624)	-	LPA	Identify latent user clusters

*AAA = American Automobile Association; ABM = Agent Based Simulation; ANOVA= Analysis of Variance; BL = Binary Logit; BOP = Bivariate Ordered Probit; DES = Discrete Event Simulation; DFWA = Dallas-Fort Worth-Arlington; DRS = Dynamic Ride Share; GHDM = Generalized Heterogeneous Data Model; GAMS = General Algebraic Modeling System; HCA = Hierarchical Cluster Analysis; LCA = Life Cycle Assessment; LPA = Latent Profile Analysis; LR = Linear Regression; LRT = Light Rail Transit; MBL = Mixed Binary Logit; MFA = Multiple Factor Analysis; ML = Mixed Logit; MMNL = Mixed Multinomial Logit; MNL = Multinomial Logit; MOD = Mobility on Demand; NL = Nested Logit; OL = Ordered Logit; OP = Ordered Probit; ROP = Rank Ordered Probit; PCA = Principal Component Analysis; PLS-SEM = Partial Least Square Structural Equation Model; RP = Revealed Preference; SAV = Shared Autonomous Vehicle; SEM = Structural Equation Model; SP = Stated Preference; VKT = Vehicle Kilometers Traveled; VTT = Value of Travel Time; WTA = Willingness to Accept; WTP = Willingness to Pay; WTS = Willingness to Share

Some important insights can be obtained from the tables. First, unsurprisingly, the study areas of the majority of these studies are in the economically developed western countries. The majority of the studies focused on a single country while others reported findings from multi-country studies. European countries are at the forefront of piloting the implementation of AV as public transit (24 out of the 26). There were only two studies outside of Europe: Taiwan and USA (Chen, 2019; Straub and Schaefer, 2019). However, research on other forms of AV mobility services predominantly originated from the US. Second, the studies varied in terms of their data elicitation method and sampling strategies. The most commonly used data collection tools included stated preference (SP) and revealed preference (RP) surveys. However, a clear preference for the RP approach was observed (29 vs 16 studies in Table 1 and 23 vs 10 studies in Table 2 used RP surveys). Third, the majority of the studies conducted online surveys. The use of online surveys obviates the social desirability bias introduced by the presence of an interviewer (Rahimi et al., 2020). However, the collected sample using online surveys tends to be composed of individuals who are comparatively younger, more educated, and of higher income ranges. Only a few studies used paper-based instruments or conducted face-to-face or on-field interviews. The target population of the surveys varied as well; some surveys focused on specific groups of people (such as university students, tourists, or transit riders), while other surveys were distributed to the general population. Convenience sampling was the sampling method chosen by most studies and the number of respondents ranged from 6 people participating in focus groups to 7,755 people who responded to a survey distributed in 116 countries (Lopez-Lambas and Alonso, 2019; Nordhoff et al., 2018a). Fourth, the majority of the reviewed studies only conducted and presented descriptive analysis results of the survey data. Depending on the research question, econometric models applied in the research studies range from linear regression analysis (and/or its variants) to multinomial logit (MNL) regression models (and/or its variants) to ordered probit (OP) models. To investigate the potential endogeneity of the multiple decision processes, some studies applied advanced discrete choice models such as the Structural Equation Models (SEM), multivariate models, and the Generalized Heterogeneous Data Model (GHDM). Finally, there was a large diversity in terms of the scope and objectives of the reviewed studies. The decision variables investigated range from respondents' intention to use SAMS to public perception, acceptance, and attribute preferences of SAMS, to consumer preferences of SAMS over the conventional mode of transportation.

Some additional information from Table 1 includes the following. Shared taxis and ridesharing are the two most commonly investigated SAMS configurations. Acceptance of AV carsharing services has also been widely examined. Table 2 provides us with additional details regarding AV shuttle configurations used in the study as well as the behavioral framework used to examine the behavioral intention to use. In terms of shuttle configurations, we can see that the seating capacity of the shuttles varies between 6-12, maximum speed tends to be on the lower side (≤20 kmph). The vehicles are usually operated on a predefined test route and the route length varies from 0.6-10 km. The Unified Theory of Acceptance and Use of Technology (UTAUT) and its variants were the most commonly used behavioral framework employed by the studies. Only one study used the Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM) (Motak et al., 2017) while another one used Theory of Interpersonal Behavior (TIB) (Salonen and Haavisto, 2019).

2.3 Synthesis of Survey based AMS Studies

Each reviewed study had different objectives and investigated different research questions. The studies reviewed in the current research will be discussed across four aspects: (a) dimensions of public acceptability and acceptance; (b) the empirical analysis framework used to investigate public acceptability and acceptance, and (c) the empirical analysis outcomes – factors affecting public acceptability and acceptance.

2.3.1 Dimensions of Public Acceptability and Acceptance

More often than not, transportation researchers use the term 'acceptance' and 'acceptability' interchangeably. However, according to Jamson (2010), there is a significant difference between the two concepts in terms of the dimensions of time. Acceptability denotes *prospective* judgment toward a technology or service to be introduced in the future which the users have no exposure to. More specifically, it could be referred to as an attitude. On the contrary, acceptance refers to the *post hoc* assessment and behavioral reactions of users towards a technology or service after exposure or use. In other words, acceptability defines how much a system is liked, whereas acceptance defines how much it would be used (Rudin-Brown and Jamson, 2013). It is to be noted that the distinction essentially implies that acceptability may not lead to acceptance or that acceptance is not necessarily indicative of acceptability. However, since both constructs play a major role in shaping road users' behavior, separating them in this way is very useful. It allows researchers to take a diagnostic approach towards the popularization of the technology under question – evaluating what features could be improved (via acceptability) as well as quantifying the impact in the field (acceptance).

In the context of vehicle automation, the distinction between acceptability and acceptance is of particular relevance (Cartenì, 2020; Distler et al., 2018) since AV technology and its services are yet to be market-ready and only in a handful of countries users are presented with the opportunity for test rides. Keeping that in mind, for our review, studies where participants were allowed to test ride an AV, either virtually (immersive virtual reality (VR)) or physically (in-person) were classified as ‘acceptance’ studies. On the other hand, research studies where the respondents are either provided a brief description (Chng and Cheah, 2020) or shown a short animated video at the beginning of data collection (Lavieri and Bhat, 2019; Wong and Rinderer, 2020) to familiarize them with the concept of autonomous mobility, were included in the category of ‘acceptability’ studies. We observed that both acceptability and acceptance of SAMS has been examined and surveyed from several different dimensions including: (1) behavioral intention or willingness to use or adopt the shared services for personal use and/or recommend others to use that when the services are available in the market; (2) public perception such as perceived concerns or perceived value or perceived trust or drivers, barriers and implementation preferences; (3) mode choice - preference of SAMS over alternative modes, (4) frequency of use of the service, and (5) willingness constructs (willingness to pay (WTP) for using shared service; willingness to share (WTS) rides with strangers). The majority of the time, no distinction was made between trip types; however, there were several exceptions when the analysis was carried out specifically for touristic/discretionary trips (Battistini et al., 2020; Tussyadiah et al., 2017) or daily commute/mandatory trips (Battistini et al., 2020).

2.3.1.1 Intention to Use

We found that intention to use SAMS was explored in a variety of ways in the literature. For instance, some researchers used a behavioral ‘intention to use’ construct measured on a five or seven-point Likert scale with the anchors ranging from strongly agree or extremely likely to strongly disagree or extremely unlikely. In other studies, it was either captured as a binary response (yes/no) about whether or not the respondents would be willing to use SAMS (Barbour et al., 2019; Wang et al., 2020) or a multinomial response expressing interest in the future adoption or use of SAMS as no interest, SAMS only (individually or with other passengers), AV ownership only, and both AV ownership and SAMS (Lavieri et al., 2017; Moreno et al., 2018). In contrast, other studies provide respondents with rating options to understand the acceptance of the services.

Respondents in most of the studies, irrespective of actual riding experience, generally expressed positive opinions about SAMS and showed their willingness to use the services if and when they are available on the market (Bernhard et al., 2020; Chee et al., 2021; Kassens-Noor et al., 2020; Mouratidis and Cobeña Serrano, 2021; Nordhoff et al., 2018b; Nordhoff et al., 2017). As expected, the proportion of people with positive intention to use SAMS varied substantially cross-culturally. The variability might be attributable to the existing road infrastructure, transportation culture (transit centric vs private vehicle centric), and peoples' level of exposure to the AV technology in the region. For example, lower willingness to use SAMS in the form of taxi, ride-share, or ride-hailing services was observed amongst respondents from North America, Europe, and Australia compared to respondents from Asia. More specifically, more than 80% of the respondents from Singapore and China found SAMS to be a desirable service which not only they intend to use themselves (Liu et al., 2020) but are also willing to recommend to people in their circle (Liu et al., 2020). The desirability dropped to 35~45% in the case of Australian, European, and American participants (Barbour et al., 2019; Wang et al., 2020a; Stoiber et al., 2019; Wang and Akar, 2019; Webb et al., 2019; Gurumurthy and Kockelman, 2020); Bansal and Kockelman, 2018; Moreno et al., 2018). The percentage is slightly higher among the younger cohort between ages 18 and 35 (Nair et al., 2018).

European respondents may be more welcoming to the idea of the introduction of AVs as public transit. Interestingly, the level of acceptance varied substantially from country to country. For example, the majority of the German respondents find autonomous shuttles to be useful, think these shuttles will be an important part of the traditional public transportation system (Nordhoff et al., 2017; Pourtuli et al., 2017), and are willing to use the service regularly in the future if it's included as a part of the fleet by the transit agency (Pakusch and Bossauer, 2017). On the other hand, only 50% of the Norwegian respondents did not find the autonomous shuttle to be a useful transport mode (Roche-Cerasi, 2019). Interestingly, despite the general positive intention towards the uptake of the service, the respondents are unwilling to use SAMS in lieu of the current mode of transport (Nordhoff et al., 2017) or replace their privately owned vehicles (Rehrl and Zankl, 2018). Not surprisingly, the degree of approval for autonomous transit is found to be even lower amongst participants from the US cities (Kassens-Noor et al., 2020).

Research has shown that repeated exposure to any new technology leads to an increase in the public's level of comfort toward the technology and thereby, its acceptance. Autonomous shuttle trials have been going on for a little more than a decade now, especially in European cities (Bernhard et al., 2020). This allowed the citizens of those countries to have multiple interactions with the technology. The study by Chee et al. (2021) provides some interesting insights on longitudinal changes in factors that motivate users' decision to continue using an automated shuttle service. They found that in the long term, ride quality/comfort is the primary service attribute that influences the continuance of intention to avail the service. The impact of valence, in terms of the pleasantness of the rides, on intention-to-ride was also resonated in both Mouratidis and Cobeña Serrano (2021) and Bernhard et al. (2020). Respondents in both studies suggested improving the driving style of AVs, particularly by reducing the incidences of abrupt and hard braking. In Eden et al. (2017), usage of seatbelts was suggested by the survey participants to improve the safety of passengers.

2.3.1.2 Public Perception

The studies included in this category examine public attitudes and perceptions including potential benefits and concerns towards SAMS as well as human-AV interactions. Overall, respondents feel positive about AVs and the services the technology offers. However, studies emphasized that acceptance and subsequent adoption of SAMS depends to a large extent on an individual's trust in the technology and its perceived value (Wong and Rinderer, 2020), benefits, and concerns (Chng and Cheah, 2020).

The majority of the perception studies are conducted considering the application case of AVs as public transit. Perceptions of benefit influence intention to use (Chng and Cheah, 2020) positively while perceptions of concern negatively influence intentions to use SAMS. The primary benefit that was consistently pointed out by the respondents was that introduction and integration of autonomous shuttles with the conventional public transit system will create better travel opportunities for the elderly and disabled people (Portouli et al., 2017; Roche-Cerasi, 2019). Among other benefits, it would also improve the transportation of goods immensely (Hilgarter and Granig, 2020). Respondents also foresee that the introduction of driverless transit will result in better vehicle navigation, smoother vehicle operation on the road by reducing traffic congestion and energy consumption, thereby mitigating traffic-generated pollution (Battistini et al., 2020).

In terms of potential concerns, in-vehicle security in the absence of a human driver on board was found to be a significant concern for deployment of AMS on a broader scale (Dong et al., 2019; Kassens-Noor et al., 2020; Roche-Cerasi, 2019; Salonen, 2018), especially during night time services (Piao et al., 2016). The presence of a company employee is found to somewhat assuage the personal safety concerns of respondents (Nordhoff et al., 2019a); however, they tend to favor higher levels of monitoring and involvement from the employee on-board instead of him/her just providing customer service. Interestingly, the absence of staff was not an issue for frequent users of autonomous shuttle services in Trikala, Greece (Portouli et al., 2017). Vehicle operational safety and technical issues (e.g., traffic crashes caused by technical errors, confusion when an unprecedented situation occurs) were the other top concerns voiced by the respondents (Chng and Cheah, 2020; Feys et al., 2020; Dong et al., 2019; Lopez-lambas and Alonso, 2019; Roche-Cerasi, 2019; Bansal et al., 2016). However, in some studies, respondents agreed that there was less risk of a traffic crash for autonomous transit than for conventional transit (Portouli et al., 2017; Salonen, 2018). Among others, respondents expressed concerns about potential hazards ensuing from AVs sharing the roadway with pedestrians (Battistini et al., 2020) and conventional vehicles (Bansal et al., 2016; Battistini et al., 2020), particularly in complex urban situations (Feys et al., 2020), legal liabilities in case of a traffic crash (Chng and Cheah, 2020), increased investment costs for vehicles and infrastructural improvement (Lopez-Lambas and Alonso, 2019), potential reduction in funding for traditional transit (Battistini et al., 2020), job loss due to automation (Tussyadiah et al., 2017), and affordability of the service (Bansal et al., 2016).

2.3.1.3 Mode Choice

Mode choice studies examine preferences towards SAMS in comparison with other modal alternatives while controlling for different exogenous factors. We found that the mode representation varied significantly from one study to another. The majority of the researchers investigated respondents' choice between using current transport modes (e.g., conventional gasoline-driven auto mode, transit, bicycle, walk, airplane), private AVs, and SAMS for trip making. For instance, Cai et al. (2019) categorized mode alternatives into premium-level AV, economy-level AV, shared AV services, transit, walk, private vehicle. Stoiber et al. (2019) suggested that including existing conventional transport options in the mode choice scenario enables respondents to choose the option they are already familiar with, ultimately underestimating their possible acceptance of sharing or pooling. In light of that other researchers focused only on the choice between owning a private

AV or choosing to use SAMS (and/or different configurations of SAMS) should they become available. For instance, in Nazari et al. (2018), respondents were asked to express their interest in the following alternatives: privately owned AV, and four SAMS configurations (rental, taxi with no driver, taxi with driver, access/egress). In another study, Krueger et al. (2016) used SAMS with and without dynamic ride share (DRS) capabilities as two different alternatives. The three modal alternatives in Webb et al. (2019) represented proportions of trips made by shared electric autonomous vehicle (SEAV) trips and conventional gasoline operated vehicles (e.g. three alternatives being only conventional vehicles, 50% of trips by SEAV and rest by a conventional vehicle, 80% of trips by SEAV and rest by a conventional vehicle). Dong et al. (2019) investigated whether employee-on-board matters for monitoring the vehicle operations as well as providing customer service in terms of willingness to use SAMS.

In terms of data collection, the majority of the prior studies investigate the modal preferences in some hypothetical contexts using stated preference (SP) surveys or conjoint analysis. Others have used revealed preference (RP) region or city-specific travel survey data. SP approach allows the analyst to explore various attributes that affect choice behavior, most often unavailable under real world conditions. In addition, modes that have varying attribute levels across multiple attributes can be easily generated with rigorous experimental design. On the other hand, employing RP data significantly limits the potential mode and service attribute levels that can be explored in the analysis. In our review, we observed that the following modal and service attributes are usually considered in the studies: (1) level-of-service (LOS) attributes include ticket/ride fare, trip cost per km traveled or per direction of travel, yearly membership cost, access distance, waiting time (Fagnant and Kockelman, 2015; Krueger et al., 2016) or response time (Stoiber et al., 2019), access time (on-foot), egress time (on-foot), in-vehicle travel time, service frequency, and unexpected delay (Gurumurthy and Kockelman, 2020; Lavieri and Bhat, 2019), (2) service and vehicle attributes include power train (electric, gasoline), seating capacity (number of persons on board), on-board comfort, service type, and surveillance and information provision, and (3) contextual attributes include lighting condition and weather.

Haboucha et al. (2017) found that Americans tend to favor conventional gasoline-driven cars, whereas Israelis are more likely to adopt AVs, either as privately owned or shared services. Choice of SAMS is also found to be dependent on trip type. For instance, Tussyadiah et al. (2017) reported that respondents are more willing to use self-driving taxis as tourists. This inclination was found in the case of SAV for long distance business travel as well (Gurumurthy and Kockelman, 2020). Krueger et al. (2016) found increased willingness to use SAVs for shopping and medical trips. Nordhoff et al. (2019b) reported that people tend to use autonomous shuttles in adverse weather conditions, in closed areas (e.g., exhibitions, large factories, airports, university campuses, retirement homes, hospitals), in suburban areas generally underserved by conventional transit, urban touristic/unfamiliar regions, or for the transport of goods. *Ceteris paribus*, respondents tended to show a higher relative preference for automated transit service (Delle Site et al., 2011). In fact, a large percentage of respondents in Trikala, Greece expressed their desire regarding permanent operations of the automated shuttle service in their city (Papadima et al., 2020). However, both Alessandrini et al. (2014) and Alessandrini et al. (2016) observed that the preference to be limited to services operating "within a major facility" (e.g. a technology park or university). This is interesting, since it signals the possibility that users may not trust automation in mixed-traffic conditions. Moreover, the preference for autonomous transit diminishes for regular public transport users (Wien, 2019). However, as access or egress option, autonomous vehicles have gained positive responses (Yap et al., 2016; Nazari et al., 2018). In Yap et al. (2016), it has been preferred as a last mile or egress transport option than metro and bicycle by individuals using first class carriages in train in their multimodal trip. However, the result was the other way around for second class carriage travelers. On the other hand, both commuter and non-commuter respondents showed comparatively higher interest in AV-access/egress option than other autonomous vehicle services (own, rental, taxi with driver, taxi with no driver) in Nazari et al. (2018) study.

2.3.1.4 Frequency of Use

The studies included in this category investigated acceptance/acceptability by asking the respondents how often they would use the SAMS with the underlying assumption that the higher the usage, the higher is the acceptance. We found only one study that examined the frequency of use (Bansal et al., 2016). In their study, different adoption rates were introduced (relying on SAMS less than once a month, at least once a month, at least once a week, entirely on it) for different pricing scenarios (USD 1, 2 and 3 per mile). The analysis results indicated that tech-savvy individuals experiencing crashes in the past are more likely to be frequent SAMS users irrespective of the pricing scenarios. On the other hand, licensed drivers and older persons tend to be less frequent users. Apart from this study, both Nordhoff et al. (2017) and Nordhoff et al. (2018b) reported that people are willing to use automated shuttles 1-3 days a week. In the latter study, one-thirds of the respondents expressed their intention to use it daily.

2.3.1.5 Willingness Constructs

If we assume that a portion of the population is willing to use SAMS, the next logical question that arises in our mind that how much would people be willing to pay to avail themselves of any form of SAMS? According to Asgari and Jin (2019), with respect to vehicle automation, better services in terms of cost, time, quality, convenience will increase peoples' willingness to pay more. The Willingness to Pay (WTP) aspect, i.e., the highest price an individual is willing to pay for a product or service, is well documented for AV technology. However, research on WTP for SAMS is sparse, particularly if the service is in the form of public transit. In our review, only a handful of studies were found on the topic that explicitly examined it. To examine the WTP, researchers have adopted several different approaches. For instance, some have evaluated it by directly asking the respondents how much money they would be willing to pay for availing the services, with or without investigating the influencing factors. Others have computed it based on model parameters from mode choice models – using the ratio of the estimated coefficients for travel time and cost attributes, thereby identifying the trade-offs between travel time and cost.

The results of the majority of studies show reluctance to pay more for SAMS than the cost (e.g., the fare for currently available transit or per-mile cost of current rideshare services) of existing transport alternatives. For instance, for automated shuttles, users are willing to pay for tickets, but they expect the price to be comparable to the current transit fare (Alessandrini et al., 2016). In a study conducted in the US by Bansal et al. (2016), 41% of respondents were interested to use SAMS at least once a week given the cost structure of USD1 per mile which is less than the present Uber or Lyft cost structure (slightly more than USD1.5 per mile). Battistini et al. (2020) found that the attitude prevails with regards to using SAMS for touristic purposes as well. The majority of the respondents in their survey are only willing to pay between €2 to €4 for a short 10 km trip in urban areas for tourist reasons. Interestingly, Carteni (2020) found that an average transit user in Italy is willing to spend up to €2.16 Euros per trip for the bus/taxi fare or travel 9 minutes longer per trip using traditional bus/taxi instead of using the SAMS for the same trip clearly demonstrating the reluctance of an average taxi or bus user to use shared autonomous services. Only travelers who frequently use on-board information and communication technologies are willing to spend up to

€1.41/trip or to travel 5 minutes extra for using self-driving shared mobility services. In the US context, Bansal and Kockelman (2018) reported that unemployed, lower-income households (< USD30,000 annual income) and frequent travelers have the lowest WTP for using SAMS, only USD 1 for per mile of travel. On the other hand, people who frequently travel for social or recreational purposes (USD 2 and 3 per mile) and disabled individuals (USD3 per mile) are willing to play slightly higher.

In addition to the conventional WTP, some researchers proposed other innovative willingness measures to understand the acceptability of SAMS. One of the concerns stated by respondents in different countries is the concern over data privacy. Privacy sensitivity was negatively associated with the probability of choosing a pooled ride in a SAMS (Lavieri and Bhat, 2019). So, some researchers examined respondents' WTP to anonymize locations of travel. As expected, Gurumurthy and Kockelman (2020) found that respondents in the US who were concerned about privacy are more likely to be willing to pay more to anonymize their travel location data. The other concern is the disinclination of people to share vehicular space with strangers. In another US-based study, Bansal et al. (2016) included questions asking about respondents' comfort with ridesharing services in different settings, such as riding a shared vehicle with strangers. Only half of the respondents in their survey expressed their comfort in sharing a ride with a stranger during daytime, while 90% opted for sharing it with friends and family members to feel comfortable. Women, especially non-Hispanic Caucasians and individuals with high income are highly unwilling to share vehicular space with a stranger (Wang et al., 2020). With that in mind, researchers examined if and how much people are willing to pay to avoid sharing rides with strangers through various constructs including willingness to accept (WTA) (Konig and Grippenkoven, 2020) and willingness to share (WTS) (Lavieri and Bhat, 2019). WTA provides an indication of how much a discount in price of a shared ride is needed to attract a critical mass of travelers. Thus, it stands in contrast to the construct of WTP. WTS is a unique trade-off measure defined as the money value attributed by the individual to traveling alone compared to riding with strangers. The estimates of WTS in their study indicated that peoples' willingness to pay to not have an additional passenger in their journey increases significantly for leisure travel (89.71 cents) than for commute travel (48.71 cents). As an indicator for the willingness to choose shared rides, Konig and Grippenkoven (2020) computed the refusal rate (% of shared rides refused by the respondents) instead of WTS.

2.3.2 Empirical Analysis Framework

Researchers adopted several different types of theoretical behavioral frameworks and applied multifarious analysis methods including simple descriptive statistics to complex econometric models for examining people's acceptability and acceptance of shared autonomous services. The diversity in research approaches signifies the diversity of the research questions. In the following two subsections we provide a succinct conceptual description of analysis methodologies and the behavioral theories germane to the empirical context of the research paper.

2.3.2.1 Theoretical Behavioral Models

A number of theoretical social-psychological models have been developed to explain and predict SAMS acceptability and acceptance. These include the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), Unified Theory of Acceptance and Use of Technology (UTAUT), and Theory of Interpersonal Behavior (TIB). Apart from that, one of these behavioral frameworks was extended by other general constructs or constructs from other theoretical models. Explanation about significant predictors behind the intention to adopt SAMS is obtained by the application of these models (Jing et al., 2019).

The TPB was developed as a social psychology theory (Ajzen, 1991) and has been widely applied to understand a variety of behaviors, including technology adoption. It posits that one's attitude to the emerging technology, belief about how others around them approve or support its use (subjective norm) and perception of how easy it is to use AVs (perceived behavioral control) combine to produce adoption intentions. The TAM was developed as an information systems theory (Davis, 1989) and has been widely utilized when explaining the acceptance and adoption of innovative technologies. It posits that one's perception of the utility of and ease of using newer technologies determines adoption intentions. The UTAUT2 is the most recent of the behavioral theories and is a comprehensive theoretical model that synthesizes earlier theories including the UTAUT, TPB, TAM, and the diffusion of innovation theory (Venkatesh et al., 2012). It posits that one's perception of the utility of the technologies, ease of using of them, price value, mobility habit, and the anticipated enjoyment of the experience of using AVs (hedonic motivation) influence attitudes towards the technologies and consequently adoption intention. Both the TPB and TAM are simpler and more generic models and thus, while powerful in explaining adoption intentions, they are augmented with additional variables to increase their explanatory power for SAMS adoption. In Lee et al. (2019), they added self-efficacy (the belief in one's ability to use autonomous technologies), relative advantage (of using autonomous technologies), and psychological ownership to TAM while Jing et al. (2019) added level of knowledge of AVs and perceived risk (of using such technology) to TPB in their respective investigations. In another study, Yuen et al. (2020) also used the TPB but combined it with the UTAUT2 to develop a more comprehensive model in their investigation. In all three studies, the authors found good explanatory power in predicting SAMS adoption intentions and had also advanced theoretical understanding in this area. Researchers have also begun exploring the use of other general theories of social behaviors that have been applied in the wider mobility behavior research to study SAMS acceptance. For instance, Salonen and Haavisto (2019) applied the TIB (Triandis, 1977) to study the experiences, perceptions, and feelings of passengers of AV shuttle buses in Finland and found the theory useful for explaining both the rational and irrational nature of SAMS perceptions and acceptance.

2.3.2.2 Descriptive and Qualitative Analysis

In the majority of studies on acceptance and acceptability of SAMS, data analysis primarily comprised of descriptive statistic calculations (means, medians, standard deviations) and univariate analysis (frequencies or percentages, cross-tabulations) of different variables such as demographics. Some studies extend their calculation by computing correlation coefficients between socio-demographics and behavioral constructs. A significant number of studies employed factor analysis (Chee et al., 2021; Chen, 2019; Chen et al., 2020; Yuen et al., 2020; Nordhoff et al., 2020a) to reduce the number of variables to identify higher order factors that explain perceptions and acceptance of SAMS. Some studies used the exploratory approach to create new factors to explain SAMS acceptance (Wang et al., 2020; Wang and Akar, 2019; Wien, 2019). In some studies, researchers developed clusters based on a broad range of predictor variables specifically respondents' socio-demographic characteristics and SAMS related attitudes and intentions (Berrada et al., 2020; Pettigrew et al., 2019). For instance, Berrada et al., (2020) identified five types of potential users (conservatives, skeptics, late adopters, early adopters, explorers) using Multifactorial Analysis (MFA) and consecutive Hierarchical Cluster Analysis (HCA). In another study, Pettigrew et al. (2019) defined five distinct market segments (non-adopters, ride-sharing, ambivalent likely adopters, and first movers) with Latent Profile Analysis (LPA). In terms of qualitative analysis, inductive qualitative content analysis was the most common approach adopted (Hilgarter and Granig, 2020; Salonen and Haavisto, 2019).

2.3.2.3 Econometric Modeling Frameworks

From the literature review, it was observed that several econometric models ranging from standard to advanced are used to analyze decision variables involving SAMS acceptability, acceptance, and subsequent usage intentions. The category of standard models includes simple linear regression and its variants, multinomial logit and its variants, ordered logit and its variants, ordered probit and its variants, and structural equation model.

Linear regression (LR) models are used to test the relationship between behavioral intention to use with different exogenous factors including behavioral constructs (Liu et al., 2020; Wong and Rinderer, 2020; Tussyadiah et al., 2017; Chng and Cheah, 2020; Feys et al., 2020; Madigan et al., 2017; Motak et al., 2017; Madigan et al., 2016; Zoellick et al., 2019). Other decision variables investigated using LR include perceived concerns (Wong and Rinderer, 2020), and willingness to accept (Konig and Grippenkoven, 2020).

When the response variables were discrete in nature, researchers examined them using discrete econometric frameworks. Among the gamut of models, the most commonly applied is the binary logit (BL) model to examine the yes/no response about willingness to use SAMS (Alessandrini et al., 2014; Barbour et al., 2019; Moreno et al., 2018; Kassens-Noor et al., 2020; Carteni, 2020, Wien, 2019; Alessandrini et al., 2014). These models capture an individual's trade-off between the perceived benefits of using SAMS over other modes and vice-versa. A natural extension of the BL model is the multinomial logit (MNL) model that is applicable when the response variable has two or more alternatives that are either ordered or unordered. The modal preference studies reviewed for the current paper fall in this category. MNL models are based on the random utility maximization (RUM) principle. It postulates that decision-making units (individuals or households) associate a certain level of utility with each mode type and eventually choose the mode that yields the maximum utility or satisfaction. The MNL model provides advantages such as increased flexibility in model specification, closed-form solution, simplicity from computational perspectives, etc. However, this flexibility often causes the estimation of more parameters.

Another issue of the traditional MNL model is its susceptibility to violate the independence of irrelevant alternatives (IIA) property. Those cases can be solved by the nested logit (NL) model, which is a generalization of the MNL model as the NL model allows for correlation between the utilities of alternatives within the common nests (Koppelman and Sethi, 2005). Heilig et al. (2017) used the NL model in their study.

SAMS is still not available in the market; hence, SP surveys are commonly used by researchers to collect public preference and acceptance data. In these surveys, respondents provided their choices to multiple hypothetical scenarios. As a result, we observe repeated choices made by each decision-maker. Hence, panel effects might be present; that is, there might be unobserved factors affecting the choices made. Moreover, when newer transportation services as the SAMS is eventually introduced, people may also have different sensitivity towards different attributes. That is, there might be the presence of unobserved heterogeneity across respondents. To account for these effects, mixed logit models have been used by the researchers (Wien, 2019; Carteni, 2020; Dong et al., 2019; Krueger et al., 2016; Barbour et al., 2019; Yap et al., 2016). Since the model does not have a closed-form solution, the likelihood needs to be maximized, using maximum simulated likelihood methods. Halton sequence can be used to evaluate the multidimensional integrals.

When the response variable is inherently ordered such as when the respondents are asked to express their SAMS adoption rate on a frequency scale ranging from never use, less than once a month, at least once a month, at least once a week, never use (Bansal and Kockelman, 2018) or when the respondents indicate their willingness to relinquish their private vehicle on a Likert scale ranging from extremely unlikely, unlikely, unsure, likely, extremely likely (Menon et al., 2019), researchers have used ordered response (OR) models such ordered probit (OP) to model these choices. These models are derived from a latent variable framework where a single continuous latent variable reflects the propensity of a respondent selecting one of the possible responses. The latent variable cannot be measured directly but is mapped to the observed response levels. OP model is a parsimonious model due to the restriction of monotonic effects of the exogenous variables. Instead of choosing one single mode, respondents are sometimes asked to provide ratings of the modal options. Here, they may get to choose from a set of choices where they also get to rank the preferences. That means the individual would choose the mode in rank 2 if the first alternative was not available. These choices are inherently ordered and might be interrelated. To model such choice situations researchers have used the rank OP model (Nair et al., 2018).

A limited number of researchers have developed multivariate modeling approaches. To enhance our understanding of the dependent variable of interest, in these approaches, we draw additional information for the observation by augmenting with another dependent variable (Anowar and Eluru, 2018). The choice dimensions are econometrically joined together by using common stochastic terms and the parameters for each choice dimension are estimated simultaneously thereby allowing us to parse the influence of exogenous variables accurately. In the literature, these models are specified as the *endogenous static* models (Anowar et al., 2014). Structural Equation Model (SEM) is the most commonly applied in SAMS research (Chee et al., 2021; Chen, 2019; Herrenkind et al., 2019; Jing et al., 2019; Nordhoff et al., 2020a; Rosell and Allen, 2020; Yuen et al., 2020). Theoretically, SEM has two components, factor analysis/measurement model and structural equation/model. The measurement models identify latent constructs underlying a group of manifest variables (or indicators) while the structural equations describe the directional relationship among latent and observed variables. The SEM system enables us to separate out three types of effects. These are: total, direct and indirect effects of the explanatory variables. The direct effect can be interpreted as the response of the "effect" variable to the change in a "cause" variable while the indirect effect is the effect that a variable exerts on another variable through one or more endogenous variables. The total effect is the sum of the direct and indirect effects of a variable. Among others, two articles used multivariate OP (Wang and Akar, 2019; Nazari et al., 2018), and one article used copula-based BL (Alessandrini et al., 2016). Among all the multivariate models, the Generalized Heterogeneous Data Model (GHDM) is the most sophisticated one where ordinal, nominal, and count, and continuous endogenous variables are modeled simultaneously (Bhat, 2015). The model had been applied in Lavieri and Bhat (2019) and Lavieri et al. (2017).

2.3.3 Empirical Analysis Outcome

In this section, we will summarize the empirical analysis outcomes of the public acceptability and acceptance studies. We will categorize and discuss the analysis outcomes in the following manner: (1) socio-economic and demographic factors; (2) attitudinal factors; (3) current mobility pattern; and (4) residential location.

2.3.3.1 Individual and Household Characteristics

The majority of the studies reported that socio-demographic and socio-economic attributes significantly impact the adoption of SAMS, but the results are somewhat heterogeneous. Some or all of the attributes that were consistently found significant in the studies include age, gender, physical disability, education level, employment status, household income, lifecycle stage, and existing vehicle fleet composition. This suggests that findings may be context-specific.

In terms of the influence of age, in the majority of studies, younger individuals (less than 35 years) displayed a higher tendency to choose SAMS for their trips (Krueger et al., 2016; Wang and Akar, 2019;

Lavieri et al., 2017; Webb et al., 2019). However, contradictory results were found by Lavieri and Bhat (2019) for commute trips. The disinclination (Nair et al., 2018; Gurumurthy and Kockelman, 2020) or indifference (Haboucha et al., 2017) of the older individuals could be attributed to either of them being set in their ways and being less open to newer technologies or they are being inclined to use the technology after a critical diffusion point (Becker and Axhausen, 2017). It might also be the case that they perceive the AV technology as less helpful and more challenging to use (Golbabaei et al., 2020b). Even the elderly group of travelers showed heterogeneity among them in their intention to use different modes (Krueger et al., 2016).

The majority of the studies found that compared to females, males were more open towards emergent vehicular technologies, expressed more interest in using SAMS (Haboucha et al., 2017; Lavieri et al., 2017; Moreno et al., 2018; Bernhard et al., 2020), and were willing to spend more (Bansal et al., 2016) for availing the service. The disinterest of women, which may have been influenced by women's concern regarding traveling with a stranger (Rahimi et al., 2020), for using SAMS was more pronounced for commute trips (Lavieri and Bhat, 2019). Interestingly, both Barobour et al. (2019) and Lavieri and Bhat (2019) observed that among women in general and non-Hispanic Caucasians were less possibility of using shared automated vehicles, which may be caused by cultural norms that exist among them. American females are even less willing to let their children ride in autonomous transit (Anania et al., 2018).

Contemporary research shows that perceptions towards and acceptance of innovation are positively correlated with educational level. We also observed that people with higher educational profiles were more willing to use shared AVs (Wang and Akar, 2019; Haboucha et al., 2017) as they perceive the technology to be safer (Pettigrew et al., 2019). The positive attitude may also be attributed to their better technological know-hows. However, considerable population heterogeneity across education profiles was reported by Barbour et al. (2019). Nair et al. (2018) found that individuals with Bachelor's degrees are more inclined towards using SAMS in the form of car share than people achieving comparatively higher or lower education.

Full time employees and self-employed individuals are more likely to carpool with AVs for commuting (Nazari et al., 2018). However, Gurumurthy and Kockelman (2020) found that the presence of workers in the household reduces their WTP to share a ride. One plausible explanation might be their constrained activity patterns that make them prefer traveling alone. That is why night shift workers are less interested in sharing a ride when going to work or returning from work.

Some studies reported interesting results on the effects of income on intention to use SAMS. Overall, no clear trend was observed regarding the willingness of people from different income groups to adopt different forms of SAMS, as the services are not available in the market and their prices are not established yet (Pakusch et al., 2018). Individuals with higher income or belonging to affluent households are less inclined to use SAMS as carshare services (Nair et al., 2018), particularly for commute or leisure trips (Lavieri and Bhat, 2019). This indicates individuals having higher incomes showed higher desire for personalized SAMS. The probable SAV user group was suggested to be the medium income group (USD75,000-125,000) for the reason that low-income people are unable to afford SAV and high-income people prefer private AV ride to shared services (Gurumurthy and Kockelman, 2020). Lower income individuals are more likely to be either the non-adopters or the first movers of shared mobility services (Pettigrew et al., 2019).

An increase in the number of children in the household also has a positive influence when choosing SAMS (Haboucha et al., 2017). This finding aligns with Nazari et al. (2018) who suggested that adding members in households, whether children or adults, influences choosing SAMS carpooling for commute trips, which is logical because additional members in the household mean increase in additional work or school-related trips too and they will tend to commute together to decrease travel costs. Interestingly, in several studies, individuals expressed their trust to let children use SAMS as a safer transport option (Webb et al., 2019; Haboucha et al., 2017; Krueger et al., 2016).

Expectedly people having large vehicle fleets in the households were less willing to use SAMS (Barbour et al., 2019; Wang and Akar, 2019). It was found that respondents from households having only one licensed driver do not behave uniformly and other unobserved factors affect their decision when it comes to the adoption of SAMS. Individuals without a driver's license are interested in AV technology for short-term rental and taxi with a driver, which indicates those peoples' interest in enjoying the enhanced mobility provided by SAMS. Mobility impaired people (or people with disabilities) showed significantly lower willingness to ride and use SAMS than people without (Kassens-Noor et al., 2020).

Apartment dwellers living in urban areas or residents living in an area with greater land use mix diversity are found to be more open towards adopting SAVs (Lavieri et al., 2017; Nazari et al., 2018; Wang and Akar, 2019), particularly dynamic ridesharing services. This is probably because that more diversity in land-use makes ride matching easier with others living in the neighborhood (Nazari et al., 2018) and also because individuals living in higher-density neighborhoods generally don't require long-distance travel to reach certain destinations and may face parking problems (Lavieri et al., 2017). Residential location not only influenced the acceptance of AVs but also respondents willing to share rides. For example, Gurumurthy and Kockelman (2020) found that residents from densely populated but less employed areas show less willingness to share rides.

2.3.3.2 Attitudinal Factors

A considerable number of studies have tried to find out the attitudinal factors in influencing the public acceptability and acceptance of SAMS. The correlations between behavioral constructs with acceptability/acceptance and subsequent intention to use in the reviewed studies are shown in Figure 2 and Figure 3. In both figures, the behavioral constructs from different models have been shown with colored circles whereas solid lined arrows connecting the circles represent significant correlations found in at least one of the reviewed studies. As can be seen from the figures, researchers have found both original UTAUT constructs (performance expectancy, effort expectancy, social influence, facilitating condition) and UTAUT2 constructs (adding hedonic motivation, price value, and habit with UTAUT constructs) influence behavioral intention either directly or indirectly as an intermediary between attitude and behavioral intention (Herrenkind et al., 2019; Chen, 2019). The significance of TAM constructs (perceived usefulness, perceived ease of use, attitude) and TPB constructs (attitude, subjective norm, perceived behavioral control) has been studied as well (Herrenkind et al., 2019; Motak et al. 2017).

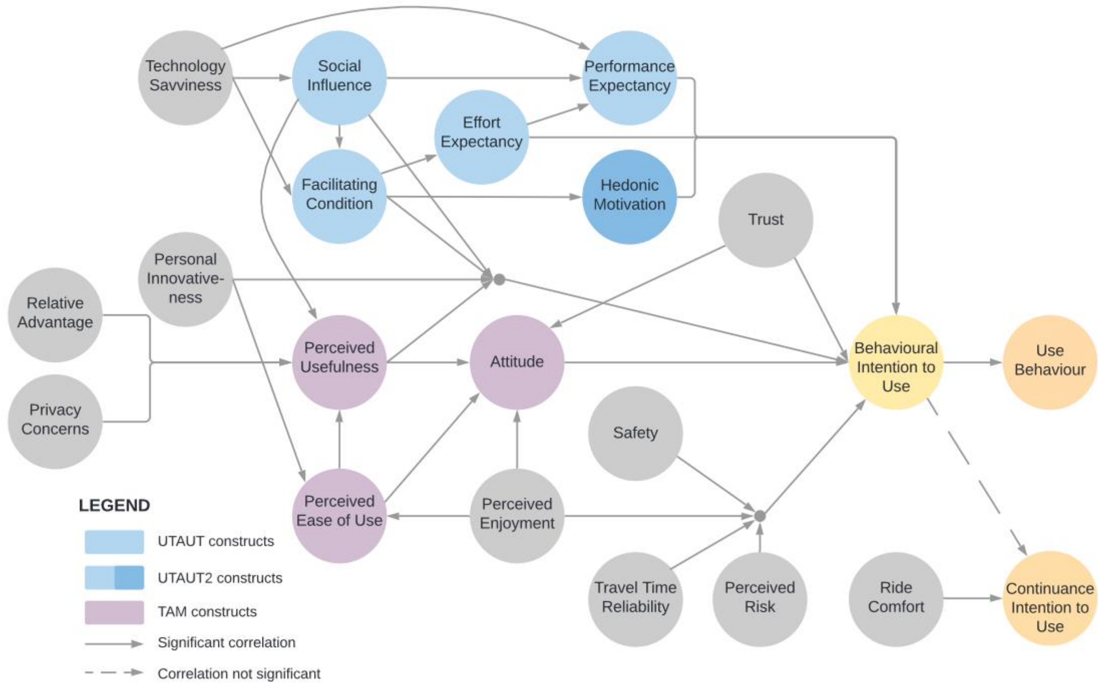


Figure 2: Correlations between behavioral predictors of adoption (automated public transit)

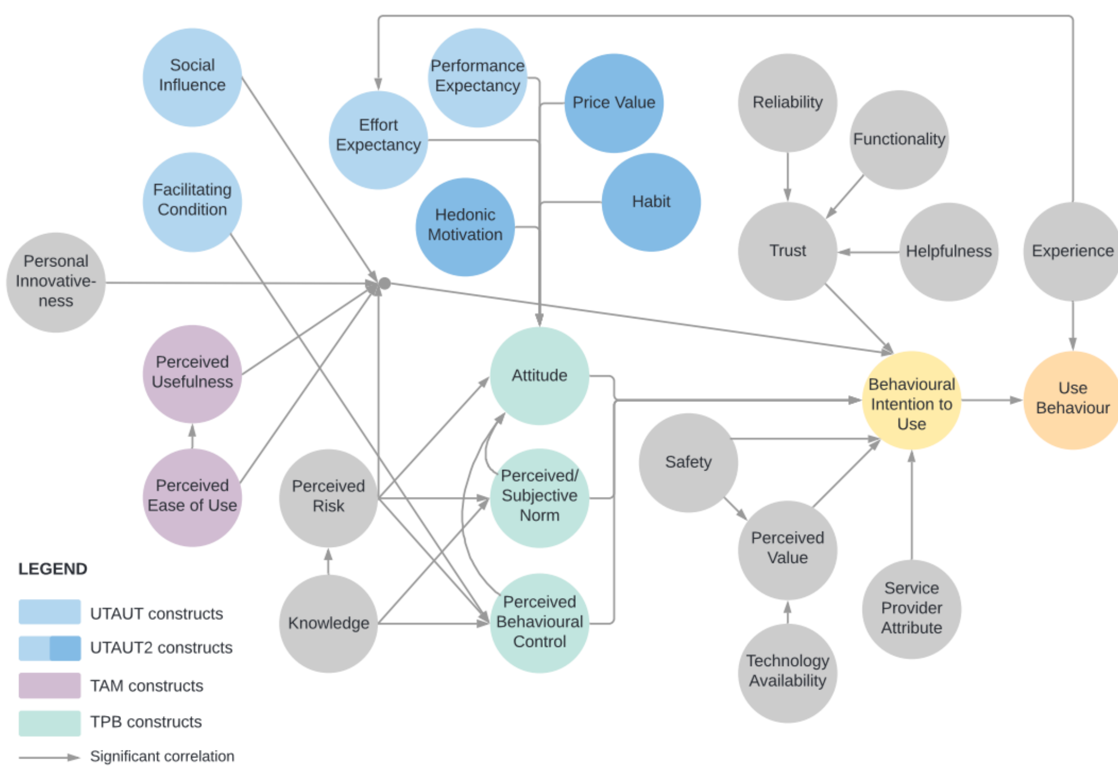


Figure 3: Correlations between behavioral predictors of adoption (SAMS without public transit)

Of the different behavioral constructs, perceived usefulness or performance expectancy was consistently found to positively impact people's intentions to use SAMS (Bernhard et al., 2020; Liu et al., 2020; Nordhoff et al., 2020a). The finding emphasizes the necessity of good system performance including service reliability as well as connectivity with other available transport services. Such multimodal integration will enable people to obtain their travel purpose in an efficient manner, thereby popularizing the shared autonomous services. In fact, performance expectancy affects both acceptability and acceptance (Bernhard et al., 2020). In some studies, its effect was moderated by effort expectancy (Nordhoff et al.,2020a; Liu et al.,2020; Herrenkind et al., 2019) and social influence (Nordhoff et al.,2020a; Herrenkind et al., 2019). Interesting results were found in terms of effort expectancy or perceived ease of use construct. For example, Bernhard et al. (2020) found respondents' perceived ease of use to vary significantly before and after actually riding the autonomous shuttle. More specifically, before the drive, participants were rather skeptical about the ease of using autonomous services. However, after the ride, the ratings that they provided for the ease of using the service were much higher. Thus, perceived ease of use can be considered more important for acceptability, but less important for acceptance.

Facilitating condition construct has rarely been explored in the literature. It is equivalent to perceived behavioral control, technical support, self-efficacy, compatibility, lifestyle fit, and hedonic motivation. Facilitating conditions have a strong positive influence on SAMS acceptability and acceptance (Madigan et al., 2017; Nordhoff et al., 2020a). It influences behavioral intention directly, as well as by moderating both effort expectancy and hedonic motivation. The impact of facilitating conditions was found to be influenced by technology savviness (Nordhoff et al., 2020a). Facilitating conditions having positive influences on intentions expresses the importance of supplying the required resources to encourage people to use SAMS when it is introduced (Madigan et al., 2017).

Trust in the new technology has been found to have a direct association with both attitude (Chen, 2019) and intention to use SAMS (Chen, 2019; Herrenkind et al., 2019; Nordhoff et al., 2017; Yap et al., 2016; Tussyadiah et al., 2017). It can be perceived as one of the most important enablers as well as deterrents towards both the initial uptake and continuance decision with respect to SAMS (Paddeu et al., 2020). Current transit users with higher levels of trust in AV technology are found to prefer self-driving buses (Wien, 2019). However, people are skeptical about self-driving public transport in mixed traffic (Alessandrini et al., 2016).

Intention to use autonomous taxis has been seen to be positively affected by all of the three trust constructs (reliability, functionality, helpfulness) for respondents travelling as tourists (Tussyadiah et al., 2017). However, for residents, helpfulness was not significant (Tussyadiah et al., 2017).

Valence or pleasantness of service or perceived enjoyment (hedonic motivation) was found to be a strong predictor of SAMS acceptance and usage (Feys et al., 2020; Nordhoff et al., 2020a; Yuen et al., 2020; Madigan et al., 2017). It has also a moderating effect on both attitude and intention to use (Chen,2019; Herrenkind et al., 2019). The other influential factor affecting people's intention to use SAMS was social influence or tendency to rely on people within one's social circle (Liu et al., 2020; Yuen et al., 2020; Chen et al., 2020). It was interesting to observe that the construct was found significant for studies conducted in Asia, namely China.

To better understand attitudes towards SAMS, researchers identified latent behavioral constructs using a combination of exogenous factors. For instance, Lavieri and Bhat (2019) identified three constructs: (a) privacy-sensitivity, (b) time-sensitivity, and (c) interest in the productive use of the travel time. In another study, Wang et al. (2020) identified four latent psychological factors: (a) pro-technology, (b) driving enjoyment, (c) regulating traffic, and (d) risk avoidance.

2.3.3.3 Level of Service and Vehicle Attributes

The other two important attributes that are likely to influence acceptance of SAMS are level-of-service characteristics and vehicle configurations. Intuitively, the most significant determinant behind peoples' willingness to use SAMS is how well these services perform with respect to travel cost and time in comparison to already available travel alternatives (Madigan et al., 2016; Roche-Cerasi, 2019; Wong and Rinderer, 2020). We observed that vehicle automation is not valued without good service features like faster travel times or lower cost than conventional modes (Alessandrini et al., 2014; Krueger et al., 2016; Krueger et al., 2020; Liu et al., 2017; Yuen et al., 2020). If detour results in travel time increase people tend to reject the option of sharing the ride as well (Konig and Grippenkoven (2020). A survey in Singapore by Cai et al. (2019) demonstrated that drivers are more sensitive to in-vehicle-travel time compared to regular transit users. In a recent study, Krueger et al. (2016) found heterogeneous sensitivity for in-vehicle-travel time for SAMS with and without ridepooling, suggesting the potential presence of two distinct consumer markets. Moreover, there is an upper limit to the maximum amount of time the users are willing to wait (out vehicle traveling time) for SAMS. For instance, approximately 80% of respondents in Christie et al. (2016) study expressed their unwillingness for waiting more than 6 minutes daily for such services.

When asked about the travel cost, residents of Trikala, Greece opined that if an autonomous transit service operates on a permanent basis, its fare should be commensurate with the existing conventional public transit service (Papadima et al., 2020). Similar results were reported by Cartenì (2020). In another study, Chen and Kockelman (2016) found that as the fares of electric SAMS increase from USD 0.75 to USD1.00 per mile, the modal share of the service decreases from 39% to 14%. We found that on-board comfort (Delle Site et al., 2011), as well as spaciousness inside the vehicle (Bernhard et al., 2020), positively influenced AV public transit acceptance. Seating orientation (facing forward or backward) inside the vehicle is another vehicle attribute that was found to impact people's intention to use by shaping peoples' trust. Among other service attributes, Christie et al. (2016) reported that 61% of the respondents considered a frequency of a shuttle every 7 to 10 minutes to be sufficient.

2.3.3.4 Current Mobility Pattern

The current mobility pattern of the respondents was found to be an influential factor in shaping their acceptance of SAMS in several of the studies. Frequent car users with higher mileage have relatively more negative attitudes are towards SAMS. They are also less willing to use the service for their commute trips (Haboucha et al., 2017; Krueger et al., 2016; Nordhoff et al., 2020b; Rahimi et al., 2020). Interestingly, people making 3-4 trips per day were more likely to use SAMS than people who are more or less mobile compared to them (Moreno et al., 2018) plausibly because they consider SAMS to be a convenient mode for high-frequency short distance trips. In addition, commuters who drove alone to work and whose commute length was more than 45 minutes, were more disinclined to adopt SAMS (Barbour et al., 2019). On the contrary, individuals with multimodal travel habits or who are regular users of transit, taxi or other ride-sharing services showed a greater inclination towards adopting SAMS (Asgari et al., 2018; Krueger et al., 2016; Nair et al., 2018; Tussyadiah et al., 2017). This may be because current transit users believe that SAMS is a potential solution to the first-/last-mile problem of mass transit services. Yap et al. (2016) confirmed the finding by reporting that first class train riders in the Netherlands find SAMS as a better fit for their last mile trips compared to other egress modes.

2.4 Autonomous Vehicle Centered Big Data Analysis Approaches

Several recent studies have focused on exploring the usability of social media data in different areas of transportation including transportation planning and safety, traffic prediction, real-time traffic management during planned and unplanned events (e.g., sports events), and traffic information dissemination. Discussing all of those studies is beyond the scope of this research. Therefore, we will limit our review to studies (presented in Table 3) germane to the empirical context of this paper. Several observations can be made from the Table. First, Twitter is the primary source of social media data used by researchers followed by YouTube. Additionally, some studies have used newspaper articles and Reddit (Bakalos et al., 2020; Buch et al., 2018; Kinra et al., 2020). Second, opinion on AVs has been examined using topic modeling, and sentiment analysis. Topic modeling is typically used to gain an understanding of the key topics in the mined text dataset; and sentiment analysis is utilized to assess the polarity of a text, thus, understanding the users' feelings about that particular topic of discussion. Both sentence-level and document-level classifications were observed in this regard. The methodologies applied for sentiment analysis ranged from lexicon-based approach (Kinra et al., 2020; Kwarteng et al., 2020; Zhou et al., 2020) to machine learning methods such as neural networks (NN), Support Vector Machine (SVM), Random Forest (RF), etc. (Dutta and Das, 2021; Kohl et al., 2018; Kohl et al., 2017; Sadiq and Khan, 2018). Third, researchers have found that some people are optimistic about the future of AV while others hold serious reservations. Safety of AVs is the most important issue to the general public as safety-related effects consistently emerged as both benefit and concern across different studies (Kohl et al., 2017). Negative attitudes are associated with cybersecurity of the in-vehicle technology, labor market impact, and effect on existing congestion (Sadiq and Khan, 2018). Finally, a significant number of studies focus on evaluating the change (emergence or shift) in public emotion towards AV in response to the news of an AV being involved traffic crash leading to fatality (Adikari and Alahakoon, 2021; Jefferson and McDonald, 2019; Li et al., 2018; Penmetsa et al., 2021). All of these studies found an increase in negativity (with more prominence towards emotions such as 'fear' and 'anger') about AV in tweet texts after their involvement in fatal crashes. In addition to increased negativity, Adikari and Alahakoon (2021) also observed an increase in toxicity in social media demonstrating a negative ambiance among citizens towards AV after the crash incident.

Table 3: Studies Dealing with Autonomous Vehicle Centered Big Data Analysis Approaches

Study	Data Source	Empirical Context	Approach	Methods/ Models Used	Main Findings
Adikari and Alahakoon (2021)	Twitter	Change in public perception towards AV after fatal pedestrian crash	Emotion modeling; Toxicity detection	Bi-GRU+CNN	Toxicity of texts increased slightly on the day of the crash but more after the crash
Dutta and Das (2021)	Twitter	User sentiment related to self-driving cars	Sentiment analysis	Hierarchical attention- based LSTM	Positive sentiments are higher towards AV-related tweets.
Penmetsa et al. (2021)	Twitter	Change in user sentiment after Uber-pedestrian crash and Tesla Model X crash happening in 2018	Sentiment analysis	VADER	Tweet frequency about the involved car companies increased on the day of the crash
Bakalos et al. (2020)	Twitter, Reddit	User sentiment regarding autonomous mobility	Sentiment analysis	BERT LSTM	Negative tweets mentioning cyber-security, robotics, hacking-related issues
Kinra et al. (2020)	Twitter, Newspapers	Peoples' perception regarding driverless cars in Denmark	Topic modeling; Document classification; Sentiment analysis	LDA; Lexicon based approach by SentiStrength software	Labor market effects generating concerns among the Danes
Kwarteng et al. (2020)	Twitter	User sentiment on driverless automobile technology	Sentiment analysis	VADER	Higher positive sentiment than both neutral and negative
Jefferson and McDonald (2019)	Twitter	Change in tweet frequency and sentiment after Tesla Autopilot crash	Term and tweet frequency analysis; Sentiment analysis	'set_nc_sentiments' function in 'syuzhet' library	Decrease in positive sentiment on the day of the crash
Zhou et al. (2020)	Youtube	Analysis of comments on videos regarding autonomous vehicles' takeover transition	Sentiment analysis; Topic analysis	fastText; VADER	Comments regarding automation capability were more frequent; extreme positive and negative opinions on non-driving related tasks.
Buch et al. (2018)	Twitter, Newspapers	Analyzing public opinion regarding driverless cars in Denmark	Topic modeling; Sentiment analysis	LDA; Lexicon based approach by SentiStrength software	Topics related to 'traffic and congestion' and 'labour market effects' most prominent.
Kohl et al. (2018)	Twitter	Anticipating acceptance of self-driving cars	Longitudinal study and risk-benefit classification	SVM	Presence of relation between occurrences related to autonomous vehicles and tweet content; discussions regarding Google Car were the

Study	Data Source	Empirical Context	Approach	Methods/ Models Used	Main Findings
					most frequent among all companies.
Li et al. (2018)	Youtube	Introducing annotated autonomous vehicle related 50k comment dataset	Sentiment analysis	Natural Language API	User's trust dropping after the incident and then rebuilding over time.
Sadiq and Khan (2018)	Twitter	Analyzing tweets regarding self-driving cars	Topic modeling; Sentiment analysis	Gibbs sampling topic modeling by Mallet; Random Forest	'night', 'vision' being prominent in positive tweets; negative tweets having words such as 'disruptive', 'difficult', 'sleep', 'crashes' etc.
Kohl et al. (2017)	Twitter	Longitudinal risk-benefit perception changes regarding self-driving cars	Longitudinal study and risk-benefit classification	SVM	People tweeting more about risks than benefits.

Note: API = Application Programming Interface; BERT = Bidirectional Encoder Representations from Transformers; Bi-GRU = Bidirectional Gated Recurrent Unit; CNN = Convolutional Neural Network; LDA = Latent Dirichlet Allocation; LSTM = Long Short-Term Memory; SVM = Support Vector Machine; VADER=Valence Aware Dictionary for Sentiment Reasoning.

CHAPTER 3: SURVEY-BASED STATISTICAL APPROACHES TO UNDERSTAND ACCEPTANCE OF AUTONOMOUS MOBILITY SERVICES

3.1 Preamble

Introducing Autonomous Vehicles (AV) into the transportation system, be it private ownership or shared usage centric mobility, is envisioned to yield a variety of benefits as discussed earlier. However, any type of AMS acceptance by people depends on several factors. The key challenge to the widespread adoption of SAMS is contingent upon peoples' perception of this technology and their willingness to accept the services it has to offer (Bansal and Kockelman, 2017). This essentially implies that the vehicle automation industry will not only need to overcome the technological challenges associated with the design but also prevail against the social barriers for successful marketplace penetration. However, despite the recent proliferation of literature on autonomous mobility-related research, knowledge on public perception of the technology or their willingness to accept/use the shared AV services is still incipient. In addition, the sample populations examined in these studies are rarely grouped according to their motivations, tendencies or psychological mindsets.

Against this backdrop, this study proposes a multidimensional typology of potential users of AV public transit drawing from attitudinal factors. Once the user groups are identified, the remainder of the study makes effort to understand the following research questions:

1. What are the potential user groups found in the analysis and their attitudinal characteristics?
2. How do these user groups compare to empirical observations of travel behavior?
3. What are the user groups like in terms of their sociodemographic characteristics and benefit-concern perception?

In general, different individuals have different purposes and intentions for travel. Hence in terms of the automotive industry perspective, a range of service attributes and experiences should be provided to attract different market segments. The service providers need to have a clearer understanding of why the service is required or adopted by people. Then, they will be able to create or modify their service to meet consumer needs and implement suitable advertising strategies to reach and persuade the consumer to use the service. Ultimately, the aim is to be inclusive when introducing autonomous road transit because it is meant to be public transit for all. Based on the outcome of the analyses, we identify ways that policymakers and stakeholders can use the typology to better conceptualize and implement targeted legislative strategies to encourage people to adopt AV public transit as their preferred mode.

3.2 Proposed Methodology

To accomplish the research objective, we conducted factor and reliability analysis respectively to reduce dimensionalities in the variables of concern from the questionnaire survey and come up with some specific factors. Then cluster analysis was done on the final factors to profile potential autonomous transit users. A multinomial regression analysis was done as well to understand the association of different socio-demographic factors in the potential user groups. Figure 4 illustrates the workflow of the study.

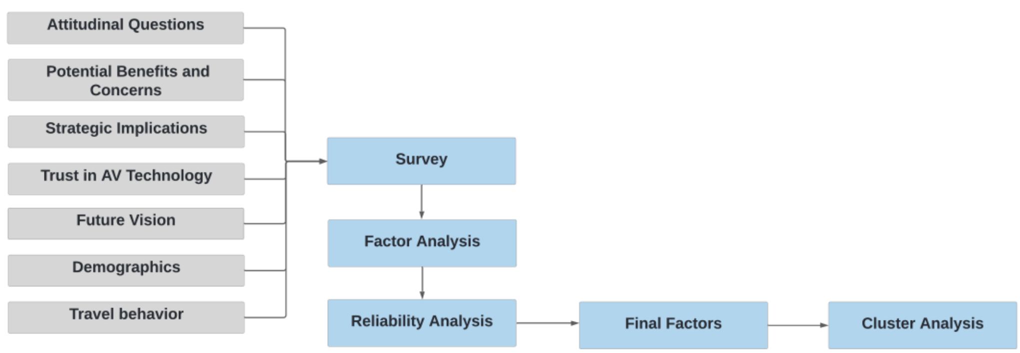


Figure 4: Workflow of the study (study-1)

3.3 Data

3.3.1 Study Region

The implementation of AV based services will be a monumental stride towards achieving “smart-city” recognition. Hence, in preparation for the future AV uptake, 36 cities of the world are currently hosting or have committed to hosting AV trials (Faisal et al., 2019). Nesheli et al. (2021) reported over 70 completed or ongoing autonomous shuttle pilots in different countries around the world. Moreover, 18 other cities are conducting studies on issues related to AV regulation, planning, and governance without starting AV piloting

(Faisal et al., 2019). The study region for our study, Singapore, is known as one of the countries being at the forefront in AV technology development and prototyping. Even in Autonomous Vehicle Readiness Index by KPMG Singapore held the top place among the countries ready to adopt AVs (KPMG, 2020).

3.3.2 Data Source and Description

The primary data source for the current study is a survey generated to examine public attitudes, concerns, benefits, etc. towards implementing autonomous public transit in Singapore. It was an online survey with 48 questions and was conducted between July and August in 2018. The respondents were recruited through two options: open calls for research participation on the university's website, and snowball sampling. No incentives were offered to the participants for taking in the part in the survey. A brief write-up with pictures of the trials was presented to the respondents prior to answering the survey questions to ensure that each of them had a similar understanding. The survey was completed by 210 participants, of which 162 observations were obtained when missing and inconsistent responses were excluded. In the final sample, 46.3% were female and 71.6% were daily public transit users, slightly higher than the population share (67%). This sample was youth-dominated (slightly more than half, 51.2% were below 30 years of age), and among the participants two-thirds held at least a bachelor's degree. Also, the sample had an overrepresentation of students (23.5%). However, the responses between students and non-students were not significantly different (suggested by sensitivity analyses). Table 4 shows the general sample composition in terms of different demographic characteristics.

Table 4: Sample Composition (N=162)

Demographics	Percentages of Respondents
Gender	Males: 53.7% Females: 46.3%
Age	18-29 years: 51.2% 30-39 years: 11.7% 40-49 years: 19.1% 50-59 years: 9.9% 60 years and above: 8.1%
Education	Secondary school and below: 8.6% Tertiary: 21.6% Undergraduate degree: 41.4% Masters and above: 23.5% Other qualifications: 4.9%
Employment Type	Employed: 66.0% Unemployed: 6.2%

Demographics	Percentages of Respondents
	Retired: 4.3% Student: 23.5%
Personal Monthly Income	Less than SGD 2,000: 21.6% SGD 2,000 - SGD 3,999: 32.7% SGD 4,000 - SGD 5,999: 14.2% Greater than SGD 6,000 - $7,999: 11.7% Prefer not to say: 19.8%
Marital Status	Married: 39.5% Separated/Divorced: 2.5% Single: 58.0%
Residential Status	Singaporean/ Permanent Resident: 84.6% Foreigner: 15.4%
Number of children in the household	None: 79% 1: 4.9% 2: 11.1% 3 or more: 4.9%
Physical disability	No: 87.0% Yes: 13.0%
Valid driver’s license	Yes: 72.2% No: 27.8%

3.4 Questionnaire Development

The questionnaire was divided into six main parts: (1) attitudinal questions, (2) potential benefits and concerns, (3) strategic implications, (4) trust in the AV technology, (5) future vision, and (6) demographics (gender, age, education level, employment, income level, presence mobility impairment, possession of driving license, their traditional transport mode usage, household size, and vehicle fleet portfolio).

In general, as discussed in the literature review, a considerable number of behavioral models have been applied to understand shared mobility service acceptance. These include the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Theory of Planned Behavior (TPB), and Theory of Interpersonal Behavior (TIB). Among these models, UTAUT is known for its comprehensiveness as a theoretical behavioral model that synthesizes earlier theories including the TPB and TAM (Venkatesh et al., 2012). This model assumes that an individual’s behavioral intention to use a technology is influenced by performance expectancy (i.e., degree to which the technology is perceived to be useful), effort expectancy (i.e., degree to which using the technology is perceived to be easy to use), social influence (i.e., degree to which using the technology is appreciated in the social circle of the individual), and facilitating conditions (i.e., degree to which the individual believes to have the resources to use the technology) (Venkatesh et al., 2003).

In our study, we augmented the traditional UTAUT constructs with additional factors such as overall attitude, strategic implications, trust, future transport scenarios, and personal innovativeness with contextualization to Singapore when necessary. The result was 41 attitude statements in total, hypothesized as pertaining to the constructs identified. In addition, 8 statements measuring 'concerns' and 7 statements measuring 'benefits' were included in the survey. We used 3-item measures to know respondents' intention to adopt and acceptance towards autonomous road public transit when available. Participants responded to the attitudinal questions on 5-point Likert scales, ranging from 'strongly disagree' to 'strongly agree'.

3.5 Factor and Reliability Analysis

Before the psychological profiling of respondents was undertaken, factor analysis was conducted to learn the initial correlation among the measures (responses to attitudinal questions). First, principal component analysis with varimax rotation was done with a total of 41 attitudinal statements. After that, the factor solutions, its' reliabilities, and correlations among items were analyzed in order to make the construct reliable. Also, items having low item-wise correlations were deleted. These generated a final four-factor solution with eigenvalues greater than 1.0. The result was also analyzed by scree plot that indicated the number of factors to be appropriate. Cumulatively, the four factors accounted for 75.28% of the total variance. Moreover, these factors had sufficient internal reliability (Cronbach's alpha ≥ 0.80) and hence were selected to be used in the psychological profiling using k-means clustering technique. Finally, the factors were named based on the basic characteristics of the included attitudinal statements within each factor. The assigned labels are as follows: (1) Perception and trust; (2) Implementation preference; (3) Personal innovativeness; and (4) Future vision. Table 5 shows these 4 factors defining the final set of variables and factors.

Table 5: Summary of the Factor Analysis

Factor	Attitudinal Statements	Loading	Cronbach's Alpha
Perception and trust in AV transit	**Overall, I can trust autonomous vehicles.**	**0.878**	0.96
	Autonomous vehicles are safe.	0.860	
	Autonomous vehicles are dependable.	0.856	
	Autonomous vehicles are reliable.	0.850	
	I would feel comfortable in an autonomous vehicle.	0.836	
	Using autonomous vehicles in public transit will enhance my journey when using public transit.	0.829	

	Using autonomous vehicles in public transit would make traveling more convenient.	0.826	
	Using autonomous vehicles in public transit will improve my comfort during the journey.	0.815	
	Having autonomous vehicles in public transit improves the quality of public transit.	0.798	
	Having autonomous vehicles in public transit makes it more convenient.	0.770	
Implementation preferences for AV transit	**Comprehensive public education campaign to ensure better understanding of how the autonomous technology works and what are the possibilities and limitations.**	**0.866**	0.85
	Clearer clarification of liability when an autonomous vehicle causes an accident.	0.809	
	Free test rides should be offered in order to experience personally what riding an autonomous vehicle is like.	0.790	
	Knowing that users were involved in the design of autonomous vehicles for public transit use.	0.780	
Technology affinity	**I like to experiment with new technologies.**	**0.851**	0.86
	If I hear about a new technology, I would look for ways to experiment with it.	0.825	
	Among my peers, I am usually the first to try out new technologies.	0.780	
Future city vision	**City centers will be car-free.**	**0.905**	0.80
	Most roads and streets will be redesigned to give priority to pedestrians, bicycles and public transit.	0.851	

3.6 Cluster Analysis

The variables obtained from the factor analysis were used to conduct a k-means cluster analysis. K-means cluster analysis groups each tract into one of a pre-determined number of clusters based on selected variables such that internal similarity is maximized while similarities between groups are minimized. In our case, the optimal number of the cluster was the 5-factor solution since it resulted in the greatest differences among derived cluster groups and provided more logical results than others. Once the cluster solution was finalized, the segments were profiled and evaluated based on the groups' socio-demographic characteristics, current travel preferences, and future intentions to use AV-based public transit.

3.7 Analysis Results

3.7.1 Profiling of Clusters

The cluster analysis generates multiple groups of respondents with similar attitudes to future AV public transit services. Therefore, each of these clusters consists of a distinct psychographic profile. The first step in identifying those profiles of the respondents is to examine the mean factor scores (standardized variables with mean zero and variance one across the sample) for each of the clusters identified. The mean scores were subjected to analysis of variance (ANOVA). The results clearly show that no one cluster has the highest or lowest mean factor scores on every factor. Instead, each cluster has mixed combinations of high and low scores on the various factors. Table 6 shows the relative percentages of each cluster along with their centroids. Each cluster was then named commensurate with its characteristics.

Table 6: Mean Factor Scores of the Corresponding Clusters

Factors	Group 1: Pragmatists (24.0%)	Group 2: Tech-savvy Green Crusaders (23.5%)	Group 3: Skeptics (8.0%)	Group 4: Obstinate Pessimists (10.5%)	Group 5: AV Transit Enthusiasts (34.0%)
Perception and trust in AV transit	0.19^{2,3,5}	**-0.54**^{1,3,5}	**-1.54**^{1,2,4,5}	-0.41^{3,5}	**0.73**^{1,2,3,4}
Implementation preferences for AV transit	0.40^{4}	0.39^{4}	0.37^{4}	**-2.11**^{1,2,3,5}	0.01^{4}
Technology affinity	**-1.14**^{2,3,4,5}	**0.75**^{1,3,4}	-0.07^{1,2}	-0.28^{1,2,5}	0.39^{1,4}
Future city vision	**0.50**^{3,5}	**0.62**^{3,5}	**-1.34**^{1,2,4,5}	0.05^{3}	-0.48^{1,2,3}

Note: Superscript items indicate the groups which are significantly different from one another in terms of means obtained by ANOVA post hoc analysis (Scheffe test). Bold numbers indicating factor scores (absolute value) greater than 0.50.

The first cluster has 39 individuals (24.0%) who believe in greener transport solutions for future cities but avoid experimenting with new technologies. They think that AVs will make traveling by public transit somewhat comfortable and convenient and strongly supports public outreach and education campaigns for promoting AV transit. This group has the highest percentage of females and individuals who are highly educated. This cluster is named "*Pragmatists*".

The second cluster includes 38 respondents (23.5%) and is characterized by high scores on both technology affinity and future city vision. However, they disagree that autonomous public transit will improve the quality of traveling and do not perceive the technology to be reliable and safe but are in favor of free test rides, public educational campaigns on AV technology, and user involvement in their design.

Although being a young dominant sample, this group has a substantial number of middle-aged (30-49 years) people. These individuals can be named "*Tech-savvy Green Crusaders".*

The third cluster is very small, including only 13 individuals (8%). They have strong trust issues regarding AVs and strongly disagree that the introduction of AVs in public transit will have any beneficial impact on the travel experience. They also do not believe that transportation in future cities will be sustainable mode oriented. However, they are somewhat in favor of public involvement and outreach prior AV transit being implemented. All respondents of this group are Singapore nationals. This group also has the highest number of individuals with disabilities. Most of them have full- or part-time employment and have an income in the range of SGD 2,000-3,999. We label this group as "*Skeptics*".

The fourth group is made up of 17 individuals (10.5%) and showed the strongest disinclination towards any kind of implementation strategies for promoting AV public transit. They do not perceive AV transit to be useful in enhancing the existing transportation system and are somewhat tech-averse. Non-Singaporeans who have low to middle income are part of this group. Because of their lack of interest in technology and autonomous vehicles, we name them "*Obstinate Pessimists*".

The last cluster contains 55 individuals, and it is the largest one (34.0%). Compared to other groups, this group has the highest level of trust in autonomous technology and strongly believes that introduction of AVs in public transit will enhance the quality of the trip in general. They are also interested in trying out new technologies in the market. This group is predominantly comprised of young adults (<30 years). This cluster is labeled as "*AV Transit Enthusiasts*". Figure 5 illustrates a radar chart representing these five clusters with corresponding factor centroid values.

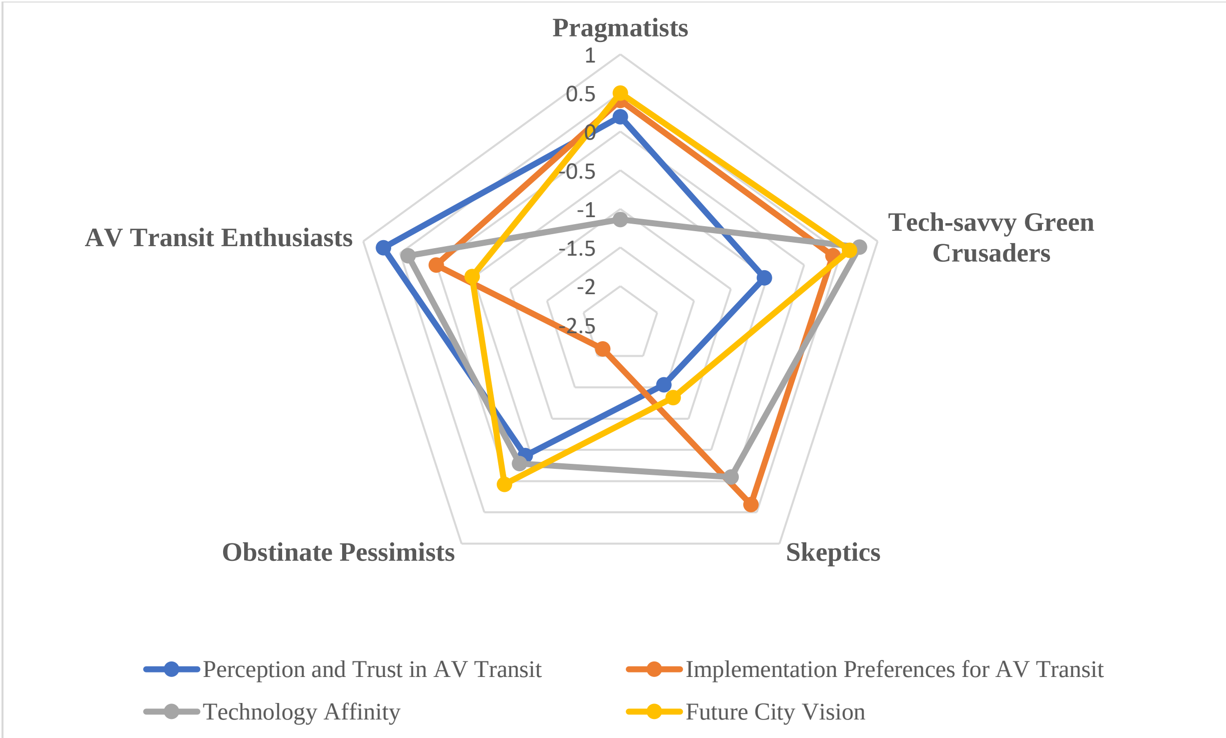


Figure 5: Radar chart showing the clusters

3.7.2 Cluster Members' Demographics and Travel Characteristics

Notable individual and household socio-economic differences among the clusters are apparent from Table 7. However, the differences were not statistically significant. Using a small sample size may be one of the reasons behind this outcome. It may also be due to the methodology adopted that involved classifying the respondents based on factors gained from attitudinal attributes. The interplay of those factors may have caused the demographic effects to be weakened. An alternative approach can be focusing on other aspects while deriving the factors. Pragmatists have the highest share of females. The Enthusiasts are primarily composed of young adults (<30 years) while all other groups have substantial percentages of middle-aged (30-49 years old) people. The majority of the respondents in all the clusters have at least a bachelor's degree, the range being 52.9% (Obstinate Pessimists) to 69.2% (Pragmatists). Interestingly, Skeptics have the highest share of employed individuals while other groups have a mixture of students and retired or unemployed people.

Table 8 presents the travel-related behavior of the individual clusters. Car owners were most prevalent in the Obstinate Pessimists cluster (76.5%) while Pragmatists have the highest share of transit pass holders (33.3%). Interestingly, all the groups have significant percentages of people with prior accident involvement history, ranging from 65.5% (AV Transit Enthusiasts) to 78.9% (Tech-savvy Green Crusaders). The self-reported mode choice pattern indicated that the majority of the people in all the clusters except Obstinate Pessimists are daily transit users (more than 65%). The Obstinate Pessimists group has higher numbers of people who use cars for their trips either as drivers or passengers. The percentage of taxi or ridesharing users was comparatively small in all the groups, the Green Crusaders group had the highest share (18.4%).

3.7.3 Cluster Members' Perceived Benefits and Concerns with Regards to AV Transit

Table 9 shows the distribution of perceived benefits and concerns across the clusters. We observed that the perception of benefits aligned with the behavioral characteristics of the clusters discussed previously. In all cases, Enthusiasts were in agreement that AV transit is a safe and reliable mode and will make transportation services more accessible to people without driver's licenses and with disabilities. Pragmatists and Green Crusaders groups were equally split between positive and neutral attitudes. Skeptics and Obstinate Pessimists were either neutral or expressed negative views. All groups had substantial percentages of people expressing concerns related to AV's capability to operate itself and respond to unexpected situations and/or accidents caused by technical errors.

Table 7: Personal Characteristics of Each Group

	Group 1: Pragmatists (%)	Group 2: Tech-savvy Green Crusaders (%)	Group 3: Skeptics (%)	Group 4: Obstinate Pessimists (%)	Group 5: AV Transit Enthusiasts (%)	Sample Average (%)
Singaporean	92.3	78.9	100.0	70.6	83.6	84.6
Female	61.5	47.4	38.5	35.3	40.0	46.3
Disability Present	10.3	13.2	23.1	17.6	10.9	13.0
Age (years)						
<30	46.2	42.1	46.2	58.8	60.0	51.2
30-49	33.3	39.5	30.8	29.4	23.6	30.9
>=50	20.5	18.4	23.1	11.8	16.4	17.9
Have child in household	15.4	26.3	23.1	29.4	18.2	21.0
Having at least an undergraduate degree	69.2	68.4	61.5	52.9	63.6	64.8
Employment status						
Student	20.5	18.4	7.7	29.4	30.9	23.5
Employed (Fulltime/ parttime)	64.1	68.4	92.3	64.7	60.0	66.0
Unemployed/ Retired	15.4	13.2	0.0	5.9	9.1	10.5
Monthly income (in SGD)						
<2,000	23.1	13.2	0.0	29.4	29.1	21.6
2,000-3,999	23.1	34.2	61.5	29.4	32.7	32.7
4,000-5,999	23.1	13.2	15.4	5.9	10.9	14.2
6,000-9,999	0.0	5.3	15.4	11.8	5.5	5.6
>10,000	5.1	10.5	7.7	0.0	5.5	6.2

Table 8: Travel Behavior of Each Group

	Group 1: Pragmatists (%)	Group 2: Tech-savvy Green Crusaders (%)	Group 3: Skeptics (%)	Group 4: Obstinate Pessimists (%)	Group 5: AV Transit Enthusiasts (%)	Sample Average (%)
Resources						
Has driving license	71.8	78.9	76.9	76.5	65.5	72.2
Owns a car	51.3	47.4	38.5	76.5	41.8	48.8
Has monthly or concession pass for public transit	33.3	23.7	23.1	23.5	21.8	25.3
Exposure to autonomous vehicles						
Has knowledge about autonomous vehicles	56.4	68.4	38.5	70.6	69.1	63.6
Has previous experience of riding AV	20.5	26.3	7.7	23.5	25.5	22.8
Owns a car with limited or advanced automated features	46.2	36.8	38.5	64.7	32.7	40.7
Concerns						
Has difficulty finding parking space	30.8	23.7	46.2	35.3	29.1	30.2
Previously involved in accident	71.8	78.9	76.9	76.5	65.5	72.2
Self-reported mode choice scenarios						
Uses bus or train						
Daily	66.7	76.3	76.9	58.8	74.5	71.6
Frequently (daily or 1/3 days per week)	74.4	84.2	92.3	76.5	87.3	82.7
Uses taxi or ridesharing						
Daily	10.3	18.4	15.4	5.9	9.1	11.7
Frequently (daily or 1/3 days per week)	23.1	44.7	46.2	29.4	32.7	34.0
Walk more than 500 meters per trip						
Daily	51.3	71.1	46.2	58.8	61.8	59.9
Frequently (daily or 1/3 days per week)	74.4	84.2	61.5	88.2	87.3	81.5
Uses car as driver						
Daily	20.5	13.2	23.1	29.4	10.9	16.7
Frequently (daily or 1/3 days per week)	30.8	21.1	23.1	52.9	29.1	29.6
Uses car as passenger						
Daily	10.3	15.8	23.1	29.4	5.5	13.0
Frequently (daily or 1/3 days per week)	35.9	47.4	61.5	52.9	43.6	45.1

	Group 1: Pragmatists (%)	Group 2: Tech-savvy Green Crusaders (%)	Group 3: Skeptics (%)	Group 4: Obstinate Pessimists (%)	Group 5: AV Transit Enthusiasts (%)	Sample Average (%)
Cycling						
Daily	5.1	7.9	0.0	11.8	9.1	7.4
Frequently (daily or 1/3 days per week)	10.3	15.8	0.0	29.4	14.5	14.2

Table 9: Perception of Benefits and Concerns of Each Group

	Group 1: Pragmatists (%)	Group 2: Tech-savvy Green Crusaders (%)	Group 3: Skeptics (%)	Group 4: Obstinate Pessimists (%)	Group 5: AV Transit Enthusiasts (%)	Sample Average (%)	Chi-Square	p-value
Perception of benefits								
Introducing autonomous vehicles in public transit would lead to shorter travel times.								
Agree	43.6	39.5	7.7	11.8	74.5	46.9	34.34	0.00
Neutral	43.6	39.5	23.1	64.7	20.0	35.2	14.41	0.01
Disagree	12.8	21.1	69.2	23.5	5.5	17.9	30.41	0.00
Introducing autonomous vehicles in public transit would improve public transit reliability.								
Agree	61.5	50.0	7.7	23.5	85.5	58.6	40.16	0.00
Neutral	28.2	34.2	23.1	35.3	14.5	25.3	6.07	0.19
Disagree	10.3	15.8	69.2	41.2	0.0	16.0	46.74	0.00
Introducing autonomous vehicles in public transit would improve travel comfort.								
Agree	41.0	28.9	0.0	17.6	76.4	44.4	41.92	0.00
Neutral	43.6	47.4	38.5	58.8	20.0	37.7	12.66	0.13
Disagree	15.4	23.7	61.5	23.5	3.6	17.9	25.86	0.00
Autonomous vehicles in public transit are safer than having manual driving.								
Agree	30.8	34.2	0.0	23.5	63.6	39.5	25.40	0.00
Neutral	48.7	34.2	0.0	35.3	30.9	34.0	10.72	0.03
Disagree	20.5	31.6	100.0	41.2	5.5	26.5	51.61	0.00
Introducing autonomous vehicles in public transit would reduce traffic jams.								
Agree	41.0	50.0	0.0	23.5	58.2	43.8	18.30	0.00
Neutral	41.0	31.6	7.7	41.2	21.8	29.6	8.20	0.09
Disagree	17.9	18.4	92.3	35.3	20.0	26.5	33.48	0.00
Introducing autonomous vehicles in public transit could solve the transport problems of older or disabled people.								
Agree	59.0	42.1	23.1	17.6	61.8	48.8	16.07	0.00
Neutral	12.8	36.8	23.1	35.3	20.0	24.1	7.77	0.10
Disagree	28.2	21.1	53.8	47.1	18.2	27.2	11.06	0.03
Introducing autonomous vehicles in public transit could solve the transport problems of people without a driving license.								
Agree	69.2	78.9	23.1	41.2	83.6	69.8	26.56	0.00
Neutral	23.1	10.5	30.8	35.3	9.1	17.3	10.22	0.04
Disagree	7.7	10.5	46.2	23.5	7.3	13.0	17.11	0.00

	Group 1: Pragmatists (%)	Group 2: Tech-savvy Green Crusaders (%)	Group 3: Skeptics (%)	Group 4: Obstinate Pessimists (%)	Group 5: AV Transit Enthusiasts (%)	Sample Average (%)	Chi-Square	p-value
Perception of concerns								
Autonomous vehicles in public transit may not drive as well as human drivers do.								
Agree	66.7	50.0	76.9	52.9	47.3	55.6	6.40	0.17
Neutral	10.3	31.6	23.1	29.4	27.3	24.1	5.83	0.21
Disagree	23.1	18.4	0.0	17.6	25.5	20.4	4.55	0.34
Introducing autonomous vehicles in public transit could lead to job loss.								
Agree	79.5	81.6	92.3	70.6	76.4	79.0	2.50	0.64
Neutral	10.3	10.5	0.0	17.6	12.7	11.1	2.55	0.64
Disagree	10.3	7.9	7.7	11.8	10.9	9.9	0.38	0.98
Introducing autonomous vehicles in public transit could be dangerous while there are also human-operated cars on the streets.								
Agree	87.2	84.2	100.0	76.5	61.8	77.8	14.74	0.01
Neutral	5.1	5.3	0.0	17.6	23.6	12.3	12.39	0.02
Disagree	7.7	10.5	0.0	5.9	14.5	9.9	3.30	0.51
Introducing autonomous vehicles in public transit could cause accidents triggered by technical error.								
Agree	92.3	86.8	92.3	70.6	87.3	87.0	5.36	0.25
Neutral	7.7	10.5	7.7	23.5	9.1	10.5	3.63	0.46
Disagree	0.0	2.6	0.0	5.9	3.6	2.5	2.45	0.65
Autonomous vehicles in public transit may not be secure from hackers.								
Agree	87.2	92.1	100.0	64.7	81.8	85.2	9.97	0.04
Neutral	10.3	7.9	0.0	29.4	9.1	10.5	8.39	0.08
Disagree	2.6	0.0	0.0	5.9	9.1	4.3	5.72	0.22
Autonomous vehicles in public transit could be confused in unexpected/unprecedented situations.								
Agree	97.4	84.2	92.3	76.5	81.8	86.4	7.00	0.14
Neutral	2.6	13.2	0.0	11.8	12.7	9.3	5.01	0.29
Disagree	0.0	2.6	7.7	11.8	5.5	4.3	4.83	0.31
Introducing autonomous vehicles in public transit could lead to legal liability issues when a crash is caused by the vehicle.								
Agree	94.9	84.2	100.0	58.8	78.2	83.3	14.76	0.01
Neutral	2.6	15.8	0.0	29.4	12.7	11.7	10.68	0.03
Disagree	2.6	0.0	0.0	11.8	9.1	4.9	6.83	0.15
Public transit fares would increase when autonomous vehicles are introduced in public transit.								

	Group 1: Pragmatists (%)	Group 2: Tech-savvy Green Crusaders (%)	Group 3: Skeptics (%)	Group 4: Obstinate Pessimists (%)	Group 5: AV Transit Enthusiasts (%)	Sample Average (%)	Chi-Square	p-value
Agree	48.7	52.6	69.2	23.5	40.0	45.7	7.87	0.10
Neutral	35.9	28.9	30.8	52.9	38.2	36.4	3.18	0.53
Disagree	15.4	18.4	0.0	23.5	21.8	17.9	3.95	0.41

3.8 Discussions

Our study obtained five groups with strong psychological differences in terms of attitude towards autonomous transit despite having a small sample size and a lesser number of factors. Of the five classes identified, two groups tend to be polar opposites - one with high positivity towards AV transit while the other exhibiting extreme resistance towards it. The other three groups signify the range of people who can be motivated to adopt the service with suitable strategies such as providing opportunities for test rides. This pattern aligns with the outcomes of Berrada et al. (2020), and Pettigrew et al. (2019).

Our study found 58% of the respondents have the possibility to be the early adopters of AV transit service, falling under either the Enthusiasts or the Pragmatists group. The Enthusiasts have a very positive attitude towards the introduction of AVs in transit but do not show interest in test rides, educational campaigns, or other implementation strategies. However, 74.5% of them think that AVs will shorten travel times in transit, which is significantly higher than the sample average of 46.9%. It appears that the high enthusiasm is stemming from unrealistically high service quality expectations from AV transit. Thus, this may not translate into longer-term commitment, if proper service quality is not maintained. Chee et al. (2021) found that initial attraction towards availing the service is governed by perceived safety and travel time reliability but in the long term, ride quality or comfort is the primary service attribute that influences the continuance of intention to use AV shuttle service.

Pragmatists and Tech-savvy Green Crusaders probably are the most crucial two groups in terms of AV transit implementation in Singapore. Pragmatists have a somewhat positive attitude towards AV transit but rated themselves low in technology savviness, suggesting that they would wait for others' reviews to start using the service. On the other hand, Tech-savvy Green Crusaders, who are frequent transit users (76.3%), do not believe that AV transit would enhance their journey by making traveling more convenient and comfortable. However, they are technology aficionados who believe that increasing the public's knowledge about the technology through outreach campaigns and exposure through test rides are important pre-implementation steps of AV transit. This implies that with the right marketing policies this group of people may be attracted. For example, real-time information about the vehicle arrival and departure through mobile applications, on-board entertainment as well as information about upcoming stops, internet access at the stations and on-board are some of the technological facilities that the service providers could implement to make AV transit more appealing to this segment of the population. More than 70% of the Tech-savvy Green Crusaders walk more than 500 meters per trip, whereas the sample average is 59.9%. Therefore, they can be the potential user group for AV-based feeder services. Further studies are needed to understand if introducing AV feeder service options could help build trust among this pro-sustainable transportation population segment. If these groups adopt AV-based mode options, they may ultimately increase acceptability by influencing other market segments in terms of giving trials and discussing positive aspects of the AV technology (Konig and Neumayr, 2017).

Unlike enthusiasts, Skeptics have extreme reservations towards the idea of autonomous transit, which may be governed by their lack of enough knowledge and riding experience (both being visibly much lower, 38.5% and 7.7%, than sample average of 63.6% and 22.8% respectively). However, they are dominantly transit users (76.9% daily transit users) and are keen on strategies that would address the liability concerns when AVs are involved in crashes. Obstinate Pessimists primarily car users, as drivers or passengers. Interestingly, 70.6% of them have prior knowledge about autonomous vehicles and 64.7% already own a car with limited or advanced driver assistance gears. This is the segment of the population who are fond of cars and car travel and thus have negative feelings towards all other modes of travel.

CHAPTER 4: BIG DATA ANALYSIS AND DEEP LEARNING APPROACHES TO UNDERSTAND ACCEPTANCE OF AUTONOMOUS MOBILITY SERVICES

4.1 Preamble

This section of the study intended to examine public opinion with regards to AMS through sentiment and topic analysis using social media data. As discussed in the literature review section, several studies attempted sentiment analysis of autonomous vehicle-based posts/comments in different social media. This study intended to differ from the previous studies by accounting for regional variances in sentiments regarding AVs and trying to find out if AV testing and demonstration program has something to do with it. In this regard, the US was taken as the location of concern. USA is the home to tech giants such as Google, Amazon, Tesla, and Uber who are investing heavily in the technical development, prototyping, and field testing of AV technology in the hopes of commercializing their product and selling it on a larger scale in the coming decade. Autonomous Vehicle Readiness Index, released in July 2020, recognized the US as one of the few countries ready to implement AVs (KPMG, 2020). At the time of conducting this study, level 4 automated cars have been permitted to test drive in a dense urban environment in California (Wayland, 2020). According to the AV Test Initiative web database launched by National Highway Traffic Safety Administration (NHTSA), 23 states in the US are actively involved in either AV testing or demonstration or both. In 21 of the states (27 out of 93 testing programs), the general public was allowed to do a test ride (NHTSA).

To accomplish the objective, a supervised learning framework was developed by concatenating hand-crafted features with sentiment-specific word embeddings. We trained a deep learning model based on the long-short term memory (LSTM) architecture, which is able to encode sentiments from a set of 39,144 tweets extracted from the popular microblogging platform Twitter. The study is the first to use social media feeds to analyze and compare sentiments toward AV deployments. By leveraging machine learning for sentiment classification, we are able to scale the models developed in the current study for state-wise comparison of AV sentiments. This will facilitate self-driving vehicle technology companies as well as authorities and policy makers to gain more insights on differences in peoples' opinions across states and how to leverage this insight to invest in research and technology that would ultimately transform the transportation sector. For this study, our goals are to determine:

1) if the geotagged tweets are reflective of state-specific differences in twitter sentiments i.e. if tweet sentiments of US states where testing or demonstration are being or have been conducted are significantly different from states with no testing or demonstration history,

2) what are the highly discussed topics regarding autonomous vehicles,

3) what are the issues and probable solutions for further improvement of this kind of study.

4.2 Proposed Methodology

A series of steps were undertaken to accomplish our research goals. First, we obtain state-specific tweets on AVs using Twitter search Application Programming Interface (API) version 2. Second, we preprocess the tweets so that the data quality is improved and the chances for dimensionality problems and misclassification are reduced. Third, we classify the tweets to explore population polarity using a deep learning-oriented classification algorithm. Fourth, we conduct topic modeling to identify hot topics from the tweets. Figure 6 illustrates the workflow of the study in detail.

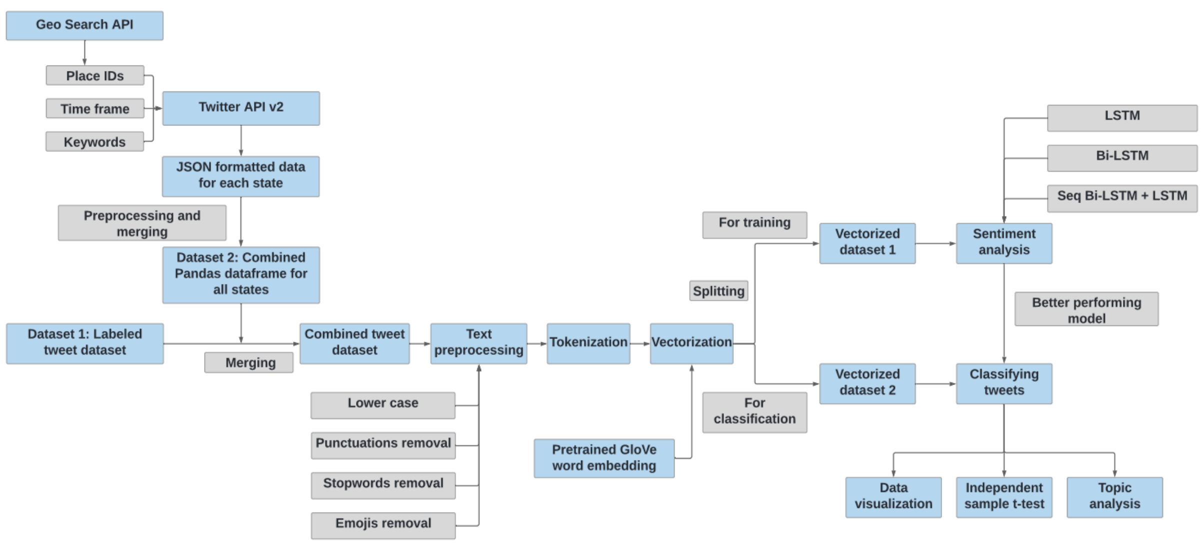


Figure 6: Workflow of the study (study-2)

4.3 Data

4.3.1 Data Source

For our analysis, we captured data from Twitter. It is a social media site where users express their views or opinions regarding concurrent events and issues in a concise manner due to the platform's restriction on post size (within 280 characters to be exact). According to Bakalos et al. (2020), Twitter had gained a minimum of 321 million active online users by the year 2018 with nearly 500 million tweets (i.e., individual posts) per day. As such, it provides real-time textual data with a wide variety of topics. Moreover, it offers different forms of comprehensive application programming interfaces (API) that give people the opportunity to query and subsequently obtain required data. Social media's popularity and its ease of data extraction were the primary two reasons for selecting it for our study. As our interest was in obtaining an overall picture of the public's view on autonomous vehicles across states, we limited the timeline of the extracted data from the 1st of April 2017 onwards. We deliberately chose this starting date since the earliest AV testing program was conducted by Waymo in Arizona on April 4, 2017 (NHTSA).

4.3.2 Data Extraction

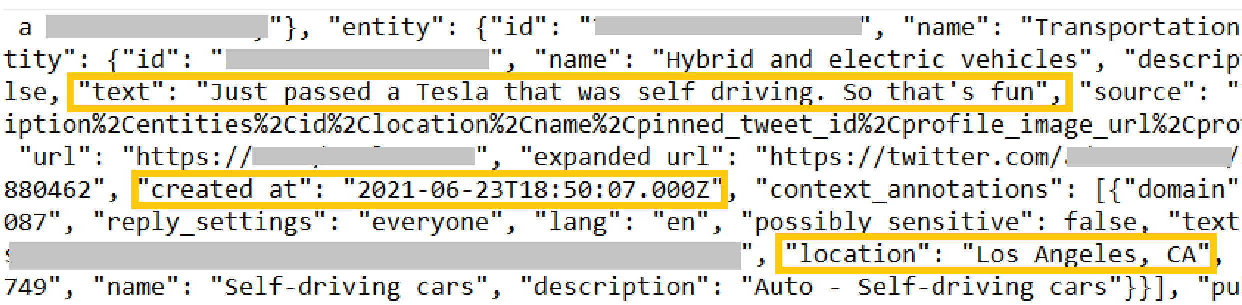
4.3.2.1 Training and Testing Dataset

For our study, we used a pre-labeled dataset for the year 2015 on the topic of AVs created and distributed by CrowdFlower[1]. The dataset consists of 6879 tweets that are classified into three categories – positive (1878), negative (776), and neutral (4225). However, for our analysis, we excluded the neutral category and only considered positive and negative tweets. In this dataset, a tweet like "It'll be cool when cars are fully autonomous, cause I'm totally gonna sleep while my car drives" was labeled as positive, while a tweet like "If I need to constantly supervise the car it's not autonomous" was labeled as negative. We used this pre-labeled dataset for training and testing the sentiment model in the subsequent analysis.

[1] https://data.world/crowdflower/sentiment-self-driving-cars

4.3.2.2 Classification Dataset

As mentioned before, the classification dataset consisting of tweets about AVs was obtained using the Twitter search API 2.0 which can be accessed from the Twitter developer's account categorized for academic research. This API required parameters such as specifying search keywords, place ids, timeframe, etc. to gain area-specific autonomous vehicle-related tweets. Note that we used a separate geo search query to obtain twitter defined place IDs. Hence, a separate JSON file was created for each state. Since we were interested in examining the public perception of AVs, keywords were carefully selected and used in extracting the tweets. The filtering process ensured that tweets having of the following terms are included in the extracted data: 'autonomous', 'self-driving', 'driverless', 'automated vehicle' etc. It should be mentioned that retweets were not considered for this analysis. The data extracted from the API for each state included the tweet, the username of it’s creator, the date and time when the tweet was posted, the location of the user, and a unique identifier of that specific tweet. These were stored in a JSON formatted file (see Figure 7).



Note: Any personal information has been blocked out for privacy purposes

Figure 7: Snippet of raw JSON-formatted data

Extracted JSON formatted data for all states were then combined and sorted into a single Pandas data frame using Python Programming Language. Only the tweets in English (language attribute 'en') were taken into account for further analysis and a separate query was applied to remove non-relevant tweets. In this data frame, three columns with labels 'serial_no', 'state_id' (representing states), and 'AV_test' (a categorical variable where 1 represents AV testing program, 2 represents AV demonstration, 3 represents AV testing and demonstration both, and 0 represents none) were added (illustrated in Figure 8). This is the dataset that we intend to classify.

	text	created_at	serial_no	state_id	AV_test
1	Just passed a woman sleeping at the wheel in h...	2021-06-25T20:32:17.000Z	10	GA	2
3	[redacted] So far the only two things from th...	2021-06-24T17:45:38.000Z	10	GA	2
4	I have some bad news for [redacted] about the ...	2021-06-23T05:24:59.000Z	10	GA	2
6	Sir the only cars that appreciate are self-dri...	2021-06-09T13:36:32.000Z	10	GA	2
7	Big news from Toronto: new autonomous driving ...	2021-06-08T15:59:55.000Z	10	GA	2
8	Wish I had a video of the dual rotor [redacted]..	2021-06-06T11:59:18.000Z	10	GA	2
9	I mean if [redacted] had been making autonomous ...	2021-06-04T16:51:13.000Z	10	GA	2
10	[redacted] Unless they own specific ...	2021-06-03T19:54:38.000Z	10	GA	2

Note: Any personal information has been blocked out for privacy purposes

Figure 8: Snippet of the processed Pandas data frame

4.4 Data Pre-processing and Tokenization

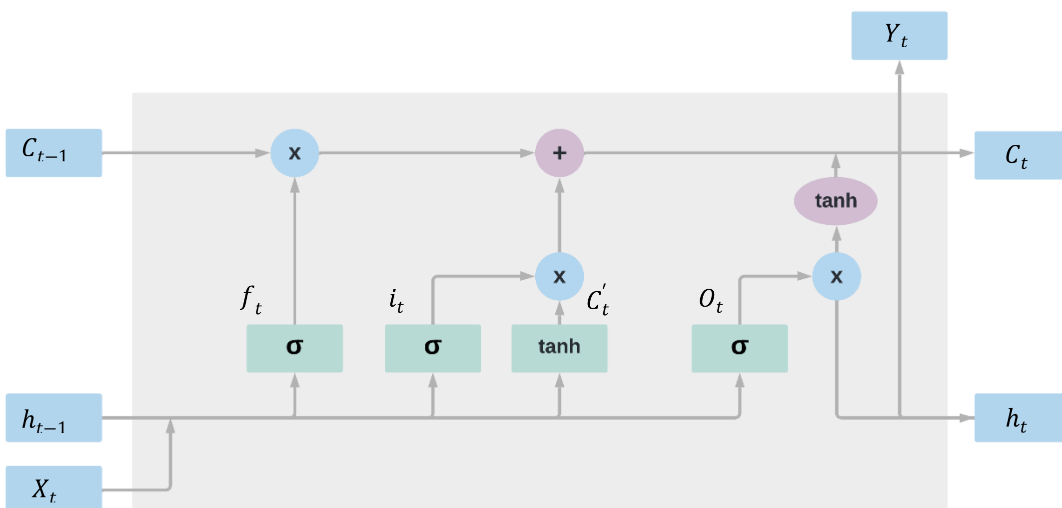
Pre-processing of the input data is one of the very important steps in the classification procedure. More specifically, during pre-processing the data is normalized and prepared for the classification algorithm so that it can run smoothly and provide meaningful outputs. In this step, we merged the classification dataset with the training dataset for text prepossessing. using Python Natural Language Toolkit (NLTK) library. First, all characters in the tweet texts were converted to lower case. Second, we removed punctuations, stop words (and, the, etc.), emojis, and hyperlinks. Afterward, the preprocessed tweets were tokenized. Tokenization refers to indexing the words so that each word gets a specific index value. The created corpus was then vectorized using twitter specific pre-trained Global Vectors (GloVe) word embedding, which is a log-bilinear regression model that accounts for the co-occurrence of words to assemble them in the vector space (Pennington et al., 2014). After performing the aforementioned steps, we obtained the texts of the tweets containing only the words useful for the deep learning classification.

4.5 Sentiment Analysis

Sentiment analysis is a method for estimating the sentiment or the polarity for a set of tweets that may relate to a specific topic, a spatial region, or a timestamp. More specifically, it involves looking up words or phrases in a created dictionary and calculating a sentiment score. Eventually, the sentiment scores are divided into categories. For sentiment analysis, we used a sentiment analysis approach called Long-Short Term Memory

(LSTM) which is a modified version of the Recurrent Neural Network (RNN) model. It is well-known for capturing long-term dependencies while dealing with the input sequential data and is extensively used in text classification.

A traditional Recurrent Neural Network (RNN) is often subjected to the vanishing gradient problem, for which the values of the weights are not changed. LSTM model has the capability of solving this issue by accounting for a hidden layer that retains a portion of their previous cell information whereas the previous cell information carries information from their previous cells (Hochreiter and Schmidhuber, 1997). Apart from that, this neural network contains units termed input, forget, and output gates which are capable of controlling information flow in the network (Gers et al., 2000). In this way, required information of a long sequential data or text corpus is saved in the hidden layer. A basic building block for the LSTM model has been provided in Figure 9.



C_{t-1} : Memory from previous block
C_t : Memory from current block
Y_t : Output data
X_t : Input data
h_t : New hidden state
h_{t-1} : Previous hidden state
f, I, o: Forget, Input and Output gate
σ, tanh: Activation functions
+ : Element wise summation
× : Element wise multiplication

Figure 9: Graphical representation of a general LSTM building block

For our study, we intended to develop three types of LSTM architectures and classify data with the one with the highest accuracy. These LSTM frameworks contained a combination of LSTM, dense, and embedding layers, ultimately forming different Deep Neural Network (DNN) architectures. Three LSTM forms considered are single or one-directional, both directional, and both directional with another one-directional LSTM layer. For implementing the LSTM model, all three forms of LSTM frameworks required an input matrix with three dimensions. To meet this requirement, the processed tweets were shaped in such a way in the time of vectorization that the number of tweets represents one axis where each tweet is assembled in each row for a specific length which is the maximum tweet length (40). The third dimension was the dimension of the word embedding model (200 in this case).

We used the labeled set of tweets for sentiment analysis. These tweets were divided into two datasets: training (90%), and testing (10%). The remaining portion of the vector was the classification data. After that, the training data was input in all three types of LSTM based models i.e., LSTM, Bi-LSTM, and sequential Bi-LSTM with an additional LSTM layer. Cross-entropy loss was taken as the loss function as it was a classification problem. After that, all three models were run with different combinations of parameters and dense layers to obtain the best performing configuration for this dataset. The optimal configurations for all three model architectures have been presented in Table 10. It should be mentioned that both positive-negative and positive-neutral-negative sentiment classifications were attempted initially with the same architectures keeping only the activation functions different (softmax for multilevel classification). However, finally, the first one running for 10 epochs was selected for further analysis for accuracy purposes.

Table 10: Implemented Three Types of LSTM-based Modeling Architectures

Model	Architecture
LSTM	lstm = LSTM(256)(embedded_sequence) x = Dense(128, activation='relu')(lstm) x = Dropout(0.2)(x) x1 = Dense(labels_index, activation='sigmoid')(x) model = Model(sequence_input, x1) model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
Bi-LSTM	model = Sequential() model.add(Embedding(vocab_size, embedding_dim, max_seq_length, trainable = False)) model.add(Bidirectional(LSTM(256, return_sequences=True))) model.add(Flatten()) model.add(Dense(10, activation="relu")) model.add(Dense(labels_index, activation='sigmoid')) model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

Model	Architecture
Sequential Bi-LSTM, LSTM	model = Sequential() model.add(Embedding(vocab_size, embedding_dim, max_seq_length, trainable = False)) model.add(Bidirectional(LSTM(126, return_sequences=True))) model.add(LSTM(56)) model.add(Flatten()) model.add(Dense(10, activation="relu")) model.add(Dense(labels_index, activation='sigmoid')) model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

4.6 Topic Modeling

Topic modeling is one of the most popular unsupervised algorithms for text summarization or finding clusters of frequently occurring words in a text corpus. In other words, it is a model for extracting the latent semantic structure of a dataset. We implemented the Latent Dirichlet Allocation (LDA) algorithm to extract topics because of its probabilistic approach for topic sorting within a large-sized corpus. The output of LDA is a selection of topics that are described by keywords that occur in the identified topic. In addition, a corpus was made by the list of words of that dictionary. The LDA function was implemented restricting the topic range from 3 to 20. The optimal number of topics was determined based on coherence score (a measurement that has the capability of considering the proximity of word tokens in the corpus to some extent (Syed and Spruit, 2017). Topics with higher coherence scores are preferred. All the tweets were classified into topics based on the optimal model and topic-wise sentiment percentages were calculated.

4.7 Analysis Results

A total of 41,498 geotagged tweets were retrieved from the query. After filtering out non-relevant tweets, the final dataset contained 39,144 tweets. The frequency of the retrieved tweets varied across states, ranging from 26 (Wyoming) to 7,903 (California). It is interesting to observe that, geotagged tweet frequencies about AVs were relatively higher in states with AV testing or demonstration history (illustrated in Figure 10). This is expected since the citizens of these states have broader exposure to the AV technology and deem it important enough to share their views about it.

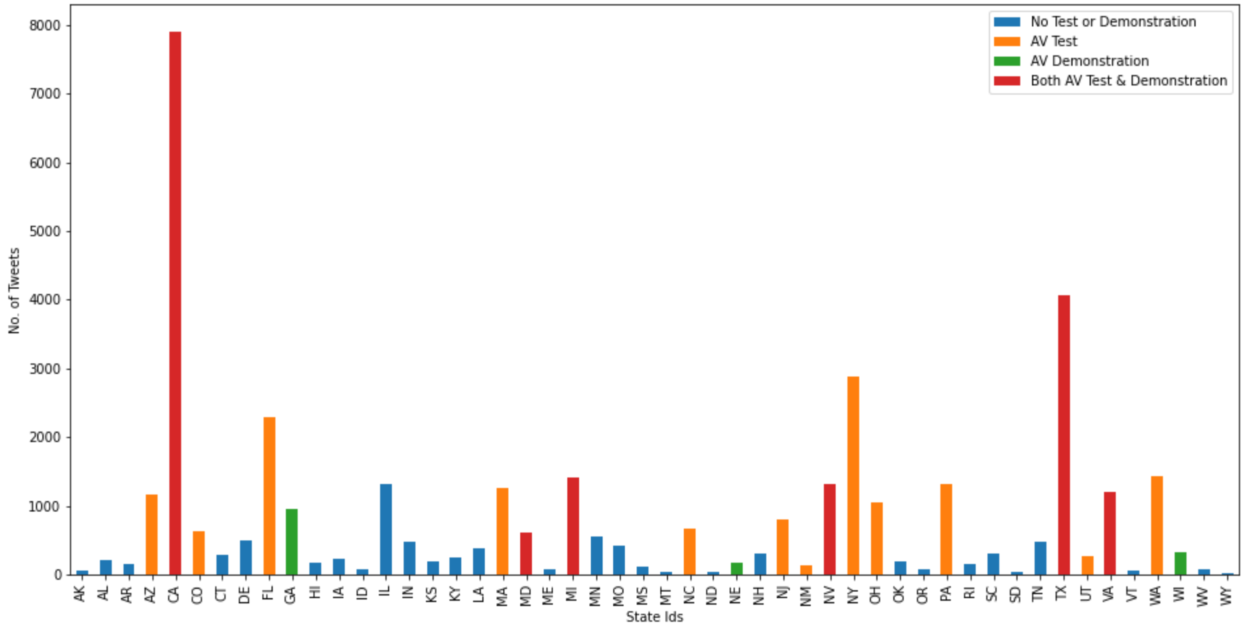
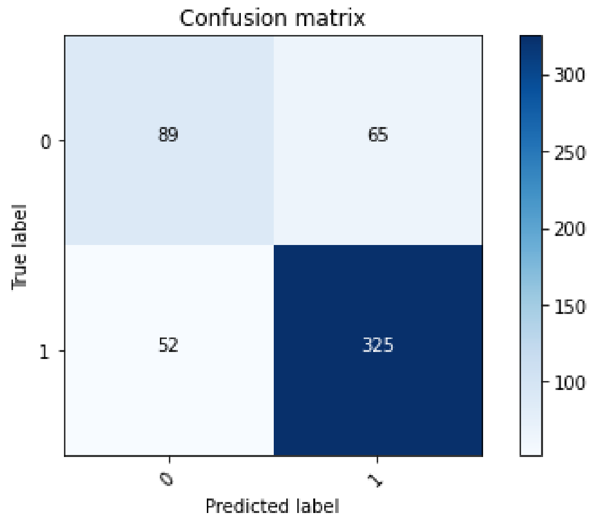


Figure 10: State-specific geotagged tweet frequencies (04/01/2017 to 06/30/2021)

We found that the LSTM model performed better than the Bi-LSTM and sequential Bi-LSTM, LSTM combination (as referenced in Table 10). The test accuracy of the LSTM model was 78% whereas for the other models the accuracies were 72% and 69%, respectively. The better-performing LSTM model generated 0.02 training loss and 0.91 validation loss values. When the confusion matrix was plotted with the test data for the LSTM model, it was seen that the model was having issues predicting the negative sentiments (see Figure 11). This was primarily because the model was having difficulty detecting the sentiments for sentences with sarcastic tones and also for complex sentences that contained both positive and negative words. A similar LSTM model with three-level sentiment categorization provided a maximum accuracy of 68%.



Note: positive labeled as '1' and negative as '0'

Figure 11: Confusion matrix of the final LSTM model

As the LSTM model with two sentiments performed better and provided better accuracy, the extracted tweets related to autonomous vehicles were classified into positive and negative sentiments with the same trained model. The state-specific sentiment percentages are provided in Table 11 and illustrated with a choropleth map in Figure 13. These positive percentages have been calculated by dividing the number of positive tweets in each state by total tweets from that state.

$$\textit{Positive sentiment Percentages (\%)} = \frac{Positive\ labeled\ tweets\ of\ any\ state}{Total\ tweets\ of\ that\ state} \times 100$$

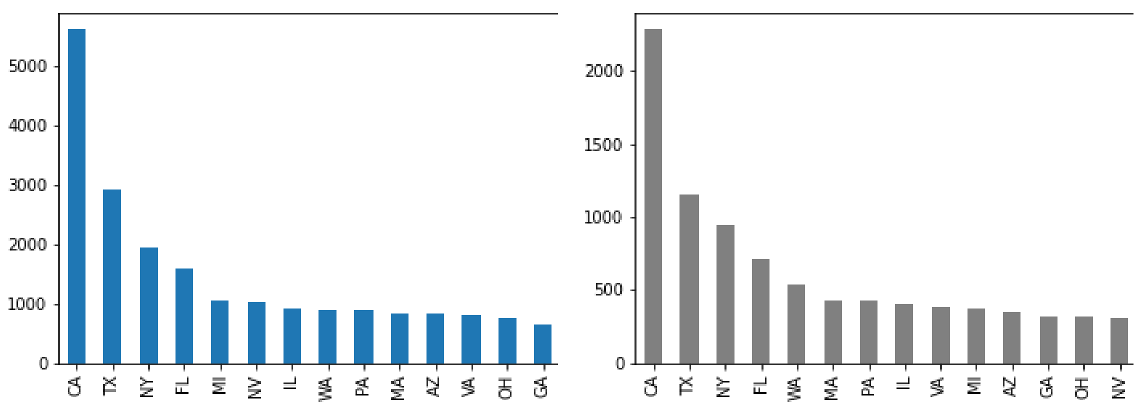
The table demonstrates that the majority of the tweets generated from the states are positive in nature meaning that people generally are positive towards AVs. Among the states, Delaware (80.36%), Montana (79.17%), Oregon (78.57%), and Nevada (76.57%) are the states that had the higher percentages of positive tweets. This is interesting because, except Nevada, none of these states are testbeds for AV testing or demonstration. On the other hand, Alaska (53.33%), Alabama (60.19%), Rhode Island (60.81%), and West Virginia (61.11%) are the states with the lowest percentages of positive tweets. The tweet frequency graphs showed that California, Texas, New York, and Florida – the states with the largest population density as well as a wealthier economy and complex transportation system - are getting a higher number of positive and negative tweets (illustrated in Figure 12).

Table 11: State Wise Sentiment Analysis Results

Sl No.	State Name	Abbreviation	AV Testing*	AV Demonstration*	Positive Tweets (%)
1	Alabama	AL	-	-	60.19
2	Alaska	AK	-	-	53.33
3	Arizona	AZ	√	-	70.37
4	Arkansas	AR	-	-	63.64
5	California	CA	√	√	71.10
6	Colorado	CO	√	-	70.31
7	Connecticut	CT	-	-	64.86
8	Delaware	DE	-	-	80.36
9	Florida	FL	√	-	68.95
10	Georgia	GA	-	√	66.91
11	Hawaii	HI	-	-	64.07
12	Idaho	ID	-	-	68.75
13	Illinois	IL	-	-	69.70
14	Indiana	IN	-	-	70.38
15	Iowa	IA	-	-	71.62
16	Kansas	KS	-	-	68.78
17	Kentucky	KY	-	-	68.29
18	Louisiana	LA	-	-	71.06
19	Maine	ME	-	-	63.51
20	Maryland	MD	√	√	64.19
21	Massachusetts	MA	√	-	65.98
22	Michigan	MI	√	√	73.55
23	Minnesota	MN	-	-	67.67
24	Mississippi	MS	-	-	61.47
25	Missouri	MO	-	-	68.92
26	Montana	MT	-	-	79.17
27	Nebraska	NE	-	√	67.40
28	Nevada	NV	√	√	76.59
29	New Hampshire	NH	-	-	67.86
30	New Jersey	NJ	√	-	65.55
31	New Mexico	NM	√	-	62.22
32	New York	NY	√	-	67.11
33	North Carolina	NC	√	-	64.75
34	North Dakota	ND	-	-	65.91
35	Ohio	OH	√	-	70.52
36	Oklahoma	OK	-	-	66.67
37	Oregon	OR	-	-	78.57
38	Pennsylvania	PA	√	-	67.91
39	Rhode Island	RI	-	-	60.81
40	South Carolina	SC	-	-	67.99
41	South Dakota	SD	-	-	73.33
42	Tennessee	TN	-	-	67.15
43	Texas	TX	√	√	71.67
44	Utah	UT	√	-	66.67

Sl No.	State Name	Abbreviation	AV Testing*	AV Demonstration*	Positive Tweets (%)
45	Vermont	VT	-	-	66.07
46	Virginia	VA	√	√	67.76
47	Washington	WA	√	-	62.58
48	West Virginia	WV	-	-	61.11
49	Wisconsin	WI	-	√	64.92
50	Wyoming	WY	-	-	69.23

*These statistics only consider testing programs that provided services to the public; not programs concerning delivering goods, test team only, or employee riders.



Positive tweets Negative tweets

Figure 12: Tweet frequency plots for top 15 states by sentiment

These states are the states with AV testing and/or demonstration program history. This may be the indicator that in the states where AV testing and demonstration programs were conducted or are ongoing currently have more people talking about the topic, and the exposure to the technology is shaping their polarity of their opinions. We observed that the frequency of positive tweets was slightly higher in states with AV testing or demonstration record than that observed in states with no testing or demonstration. However, the difference was not found statistically significant (see Table 12).

Table 12: Descriptive Statistics and Independent Sample t-test Results

Descriptive statistics						
Variable		AV_TD	N	Mean	Std. Deviation	Std. Error Mean
Positive Tweet Percentages		1	21	67.953	3.588	0.783
		0	29	67.603	5.797	1.076
Independent sample t-test						
Variable	Variance assumption	Levene's Test for Equality of Variances		t-test for Equality of Means		
		F	Sig.	t	df	Sig. (2-tailed)

Positive Tweet Percentages	Equal	1.949	0.169	0.245	48	0.808
	Not equal			0.263	47.032	0.794

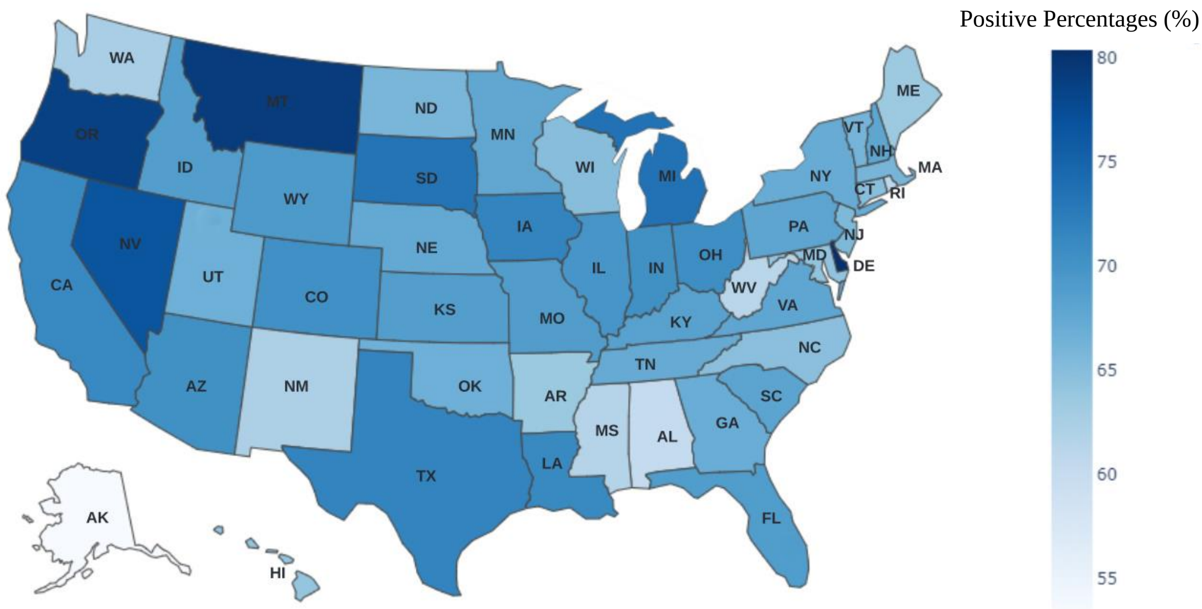


Figure 13: Choropleth map of USA with positive sentiment percentages by state

In the topic analysis, the LDA model with 10 topics got a comparatively higher coherence score. Therefore, the final model was interpreted with 10 topics (Table 13). This demonstrates that the tweets posted by people covers diversified topics discussed in the extracted tweet dataset where topics coded 0, 6, and 9 came out to be the most prominent topics (illustrated in Figure 14). Topic coded '0' having the most positive percentages indicates that tweets discussing the future visions are getting more positive responses than negative. On the contrary, topic '9' has substantial negative tweets corresponding to it, thus lowering its overall positive tweet percentage value.

Table 13: Topic Analysis Result Summary

Topic Code	Prominent Keywords within the Topic	Positive Sentiment (%)
0	**Autonomous, self-driving, vehicle, car, via, driverless, new, future, transportation, city**	**81.98**
1	Autonomous, AI, vehicle, robot, autonomousvehicles, selfdriving, selfdrivingcars, robotics, iot, would	75.51
2	Autonomous, system, amp, land, domain, world, state, student, vehicle, team	65.99
3	Autonomous, robot, photo, position, time, boat, wpt, modeauto, startup, group	71.15
4	Car, selfdriving, driverless, autonomous, future, vehicle, tech, job, technology, AI	75.29
5	Autonomous, Florida, country, oracle, Miami, truck, database, amp, community, engineer	67.89
6	**Car, driving, self, selfdriving, driver, uber, human, driverless, Tesla, pedestrian**	**67.33**
7	Autonomous, amp, vehicle, aire, buenos, city, region, today, team, great	73.24
8	Autonomous, vehicle, real, tweet, battery, truck, law, human, amp, robot	66.20
9	**Car, autonomous, driving, self, people, selfdriving, don’t, like, think, Tesla**	**59.36**

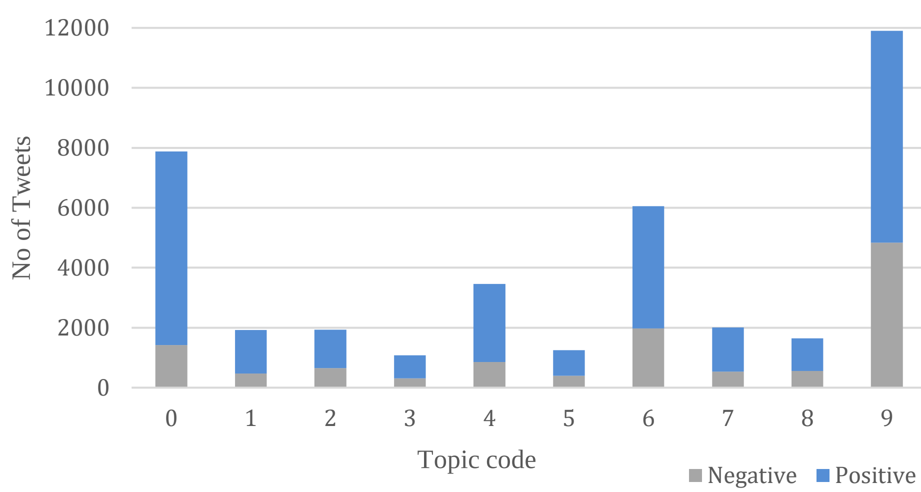


Figure 14: Topic frequency graph with corresponding sentiments

4.8 Discussions

The main takeaways from the study are as follows. First, the extracted geolocated tweets are only a small subset of the huge number of tweets posted on Twitter as many users turn their location off during posting anything in it. Therefore, among many states, the number of geotagged tweets regarding autonomous vehicles varied greatly. To redeem the differences in the number of tweets in different states, the idea of considering percentages of positive sentiments while doing the AV testing and non-testing group comparison was implemented. However, developing a sentiment analysis model that would pick up positive, negative sentiments properly remains one of the most difficult tasks to this date and gives erroneous predictions with sentences having sarcastic tones or complex structures with both positive and negative words.

When considering the states conducting AV testing and demonstration, only the states where testing or demonstration programs were or are providing services to the public were considered, eliminating other options like testing dealing with delivering goods, employee riders, and test team only (NHTSA). This was being done for the latter mentioned options having the possibility of not getting public exposure.

In terms of obtained results, the positive tweet percentages were higher in all cases, most probably because of maximum neutral tweets falling under the positive classification and the model having problems detecting negative sentiments. However, from the Choropleth map, the positive percentages showed variation by state though it was not significantly different for AV testing and non-testing states, as evident by the t-test. Even if the mean between the groups was a bit different, though not significant, it is very difficult to imply that peoples' perceptions in AV testing or demonstration and non-testing states are different. It's because many external factors and events may influence peoples' posting nature on social media, which have been suggested by Kohl et al. (2018) as well.

Another issue is that in Twitter or any other social media, a substantial number of posts are provided by commercial entities and news portals. This is understandable because the commercial entities and news portals have been actively posting to make people familiarize themselves with autonomous vehicles' technological advancements and general features. These tweets posted by commercial entities are reflections of the ongoing trend rather than peoples' perceptions. Detecting these tweets and separating them from personal tweets is a complex problem that could not be done in this study. To address this problem to some extent, sentiment classification of three outcomes i.e., positive, neutral, and negative may prove out to be effective to some extent. This is because when any commercial entity posts anything on any social media rather than any individual sharing their thoughts, sentences are subtle to some extent. Therefore, these subtle tweets would fall under the genre of neutral ones. Keeping this viewpoint, this study also intended to develop a positive, negative and neutral classification model. However, the developed model was unable to detect subtle differences between positive and neutral or negative and neutral sentiments properly, giving an accuracy of 68%. This is understandable because the lines between positive and neutral tweets are blurred in many cases for even humans to classify them precisely. However, the complexity of text classification has made it one of the most popular researched genres. Therefore, with the ongoing advancement in deep learning research, it can be hoped that advanced deep learning frameworks with data preprocessing schemes will be able to do multilevel sentiment classification with remarkable accuracy and certainty in near future.

CHAPTER 5: IMPLICATIONS AND FUTURE RESEARCH DIRECTIONS

5.1 Applicabilities and Limitations of Survey and Social Media Data in AMS Acceptance Research

From the approaches taken in this research to understand the acceptance of autonomous mobility services, some issues were observed while analyzing both the data. Survey data, in general, proves out to be more reliable in acceptance research with specific research purposes. For example, intention to use any type of AMS, profiling of potential AMS users, mode choice among several types of AMS or any of the AMS, and other conventional options, etc. It's because survey data provide researchers the liberty of asking specific questions necessary for their research. Therefore, peoples' individualistic travel preferences and attitudes along with their socio-economic characteristics (age, gender, income, occupation, etc.), travel behavior (trip frequency, choice of mode, etc.) are known through survey data. However, survey data have several restrictions and limitations, some of which are less number of responses, unrepresentativeness, labor and cost intensiveness, etc. For example, our first approach which dealt with statistical analysis on survey data had a small sample size (N = 162) and overrepresentation of young adults (51.2% under 30 age group). Therefore, it is not representative of the wider Singapore population. Nonetheless, the study was carried out as this is the population group to be targeted for successful implementation of AV transit in Singapore as they form the bulk of transit users. Apart from the above-mentioned issues, survey responses can be influenced by the introductory description of the AMS of concern. For example, in our survey-based study, the introductory paragraph about autonomous shuttles gave a reference to already implemented driverless metros. This may have caused people to relate to this new AMS in a comparatively more positive attitude. Furthermore, surveys can be also affected by demand characteristics bias i.e. the tendency of the responders of appreciating or preferring (consciously or subconsciously) the new service more positively considering the purpose of the study instead of expressing their actual attitude towards it.

Different social media like Facebook, Twitter, Instagram, YouTube, and Reddit provide people platforms to provide or express instantaneous remarks on any topic which contain autonomous vehicle-related posts as well. This huge amount of data can be utilized in AMS acceptance research by leveraging the advancements of big data analysis and machine learning, which gives a broader demographic sample with comparatively less labor, time, and cost. However, apart from the specific research limitations discussed previously, some constraints should be considered while utilizing this data source in AMS acceptance research. First, posts by commercial entities deflect the general peoples' opinion. Second, one person may provide several posts on the same topic with different sentiments. Third, the sentiments of the posts cannot be associated with the post providers' socio-demographic characteristics for privacy purposes. This is the reason social media data is good, in general, for regional level analysis where opinions of a larger sample within a region can be obtained in an integrated manner. Also, for longitudinal studies where changes in emotional pulses over the time period can be obtained.

5.2 Future Research and Policy Implications

From the literature reviews, it was evident that most AMS acceptance studies, especially studies with any type of AMS demonstration or ride experience, have been conducted in economically developed western countries among which the European region is at the forefront. These studies reported variation in perception or attitude towards AMS with regards to demographic characteristics, some multiregional studies reported regional variation as well. Therefore, for implementing any form of AMS, both survey and social media data can be utilized. In that case, preliminary regional level social media opinion mining or sentiment analysis, especially longitudinal study, can provide information on opinion change of people over a time period regarding that topic. However, as geotagged tweets are less in amount, as was found in our study for some states, it is encouraged to consider an extended time period or larger study area. Apart from that, special focus should be given to filter out noises from social media data, to be specific identifying and removing posts by commercial entities. Apart from the above, trying to find better performing models that predict sentiments of the posts with maximum accuracy will always be one of the issues of prime importance and needs to be worked on further.

Combining survey and social media data is another direction that can be explored in terms of AMS acceptance research. This can be done in two ways. First, analyzing posts on several social media data regarding a particular form of AMS for a specific region and comparing it with the analysis from a survey conducted in the same region to understand if both outcomes are relatable or not. Second, finding sentiment scores or percentages from the regional level analysis and trying to understand if that has any association with the characteristics of the population through statistical or econometric modeling.

Studies on user profiling (particularly of SAMS) based on psychological or attitudinal attributes are very rare. Our study tried to address this gap by using factor and cluster analysis to classify survey respondents in Singapore into five distinct user types: AV Transit Enthusiasts, Pragmatists, Tech-savvy Green Crusaders, Skeptics, and Obstinate Pessimists. However, the typology study conducted in this thesis is area-specific and the findings here are specifically applicable for Singapore. As every country have their distinct transport culture, rules, and regulations, policy considerations, governing body, etc., which set them apart from one another. Therefore, while planning for any form of AMS implementation, validating the insights specific to that region is recommended. However, based on the results,

Table **14** suggests some potential interventions tailored towards specific groups identified in the study. Outreach campaigns and free test rides would be beneficial for attracting Pragmatists, Tech-savvy Green Crusaders, and Skeptics. The campaigns should focus on issues including operational characteristics of AV transit in mixed traffic and how the job loss would be addressed. Furthermore, to capture the interest of Pragmatists, reviews from early users should be publicized. Audio and visual instructions on-board and at stations should be provided to familiarize people with AVs features in a practical manner. Overall, though these policy suggestions are specific to the Singapore transit users, they may work as a guideline for policymakers to carry out typology studies for the area where any form of AMS would be implemented and consecutive policy decisions to influence specific groups.

Table 14: Suggested Interventions to Attract Autonomous Public Transit Users

Groups	Self-reported intention to use (%)	Positive aspects	Constraints and concerns	Potential to adopt	Policy Suggestions
Group 1: Pragmatists	Yes: 76.9 Neutral: 15.4 No: 7.7	• Has neutral to somewhat positive attitude towards AV transit • Interested in free test rides	• Would wait for others to use it first • May not adopt it if the initial reviews from the public aren't good after its implementation	High	• Include interviews and reviews from early users in the advertisement campaigns • Give free test rides
Group 2: Tech-savvy Green Crusaders	Yes: 78.9 Neutral: 15.8 No: 5.3	• Interested in new technologies • Interested in free test rides, educational campaigns • Thinks that future cities will be bicycle and pedestrian friendly and transit oriented	• Skeptical about AV transit being able to improve the overall quality of travel • May stick to the traditional transit if facilities aren't convenient	High	• On-board features and facilities should be better current transit vehicles • Offer free test rides • Can be potential users of AV feeder services
Group 3: Skeptics	Yes: 30.8 Neutral: 23.1 No: 46.2	• Interested in free test rides, educational campaigns	• Has high reservation about AV technology and services • Neutral to negative attitude towards trying out new technologies	Moderate	• Offer free test rides • Extensive campaigns to make people familiarize themselves with AV transit
Group 4: Obstinate Pessimists	Yes: 35.3 Neutral: 41.2 No: 23.5	• Neutral towards pedestrian, bicycle and transit friendly transportation system	• Highly uninterested in free rides and outreach campaigns • 76.5% already owns a car and 64.7% owns a car with advanced driver assistance gears	Very low	• Promoting transit-oriented development vision in different platforms
Group 5: AV Transit Enthusiasts	Yes: 85.5 Neutral: 14.5 No: 0.0	• Has the highest positive attitudes towards AV transit • Has high trust in AV technology • Potential early adopters	• Driven by high expectations of the concept of AV • May plan to use it directly skipping free test rides, educational campaigns • Possibility of disappointment if AV service quality is not satisfactory	Very high	• Audio and visual instructions on-board and at stations

CHAPTER 6: CONCLUSIONS

Though AMS acceptance research has been flourishing in the last decade only, the directions of future research and implementational aspects are vast. One portion of this thesis was limited to profiling a group of people based on their attitudinal statements regarding a particular form of SAMS. On the other hand, another portion focused on finding area-specific sentiments and their variation by extracting data from a popular social media platform. Both the studies, though very different, indicated variation among people in terms of regional, and demographic characteristics and attitudinal preferences. However, if the result of the typology study is generalized to some extent, it is noticed that even the most positive group (AV Transit Enthusiasts) who exhibited strong interests in AV transit and trust in AV technology expressed their agreement towards some concerning issues such as possible job loss for humans, accidents caused by technical errors, driverless transit becoming confused in unprecedented situations, etc. These concerns from the most positive group of people, who have the possibility of being the early adopters and also influence others to trial and eventually adopt SAMS, indicates how important it is to address those issues and convey the measures to the public. The authority and policymakers should work in a planned and strategic way to address these issues clearly and convey them to the people to improve and encourage public engagement and knowledge to ensure a higher adoption rate of autonomous transit or any form of AMS in general. On the other hand, the differences in the number of tweets in different states obtained with the same query indicate that some states are very active in terms of autonomous vehicle-related posts, whether by commercial entities or humans. However, the positive sentiment percentages were not higher for those states, indicating the pattern that people are discussing both positively and negatively in the states with AV testing and demonstration history. Looking at the limitations faced in this study along with the tendency of social media always being impacted by external events (such as autonomous vehicle-related crashes, uprise or downfall of vehicle autonomy companies, etc.) that cause occasional post surges and corresponding sentiment changes, commenting directly on peoples' preferences is difficult. Instead, this study intends to emphasize the fact that peoples' outreach to technology is important to build trust and influence their perception and acceptance. Hence, authorities should arrange more demonstration and test ride programs, way before the actual AMS implementation. Apart from that, future research endeavors should be made to work with the social media data for AMS acceptance research eliminating the limitations discussed in this study and with more complex or well-performing modeling frameworks.

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