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by

Sangwan Lee

A dissertation submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
in
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Dissertation Committee:
Liming Wang, Chair
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Abstract

New mobility technologies, such as shared mobility services (e.g., car-sharing) and, more importantly, autonomous vehicles (AVs), continue to evolve. The supply-side advancement will likely disrupt and transform transportation mode choice behaviors, and create a new paradigm since they are emerging and becoming increasingly feasible alternatives to the existing modes of transportation. Accordingly, this dissertation employs discrete choice modeling (DCM) and machine learning (ML) using a U.S. nationwide stated choice experiment to understand how travelers adopt new transportation modes or continue to use conventional modes of transportation.

This dissertation consists of three papers. The first examines future market shares of each available mode of transportation in the era of AVs, factors influencing mode choice behaviors, and their marginal effects using a mixed logit model. The second uses interpretable ML to investigate the optimal algorithm (i.e., stochastic gradient boosting decision tree model) in greater depth, including feature importance and non-linear marginal effects. Focusing on methodology, the final paper assesses the limitations of ML when applied to transportation mode choice modeling and suggests future research directions for methodological improvements by comparing ML to DCM.

The dissertation contributes to three major elements of the current understanding of transportation mode choice behavior in the era of AVs and...
choice modeling as follows: First, consumers in the AV era could choose from a variety of transportation modes likely to coexist, including private AVs, shared mobility services, and conventional transportation modes. This dissertation thus makes a significant contribution by examining more comprehensive transportation mode choice behaviors and expanding demand-side discussions. Second, since current transportation planning efforts have relied on estimates and expectations, this dissertation contributes to the decision-making process by offering crucial underlying knowledge not currently available. Third, this dissertation assesses the limitations of ML for transportation mode choice modeling and suggests potential future avenues for methodological improvement.
Acknowledgments

This study would not have been possible without the assistance and support of numerous individuals. First and foremost, I would like to express my gratitude to my family. My wife, parents, and mother-in-law have provided me with great assistance and support with my graduate studies. Also, I am grateful that my little son has been an enormous source of motivation for me to make progress and complete my dissertation.

Furthermore, committee members, including Dr. Liming Wang, Aaron Golub, David Yang, and Greg Schrock, supported me and offered crucial suggestions, advice, and comments throughout my research. I would also like to express my gratitude to professors who have assisted me throughout my undergraduate and graduate studies, including Dr. Michael Smart, Byungsun Chai, and Connie Ozawa, for their invaluable assistance and advice.

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<td><strong>Discrete Choice Modeling</strong></td>
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<td>DCM</td>
<td>Discrete Choice Modeling</td>
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<td>MNL</td>
<td>Multinomial Logit Model</td>
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<td>NL</td>
<td>Nested Logit Model</td>
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<td>Mixed Logit Model</td>
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<td>ML</td>
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<td>MCL</td>
<td>Multiclass Logit Model</td>
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<td>NB</td>
<td>Naïve Bayes</td>
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<td>SVM</td>
<td>Support Vector Machine</td>
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<td>ANN</td>
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<td>XGBoost</td>
<td>Extreme Gradient Boost Decision Tree Model</td>
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Chapter 1. Introduction

1.1. Overview

This dissertation consists of three papers as follows: The first article in Chapter 4 investigates future market shares of each transportation mode in the era of autonomous vehicles (AVs), factors influencing transportation mode choice, and their marginal effects using discrete choice modeling (DCM). The second paper in Chapter 5 employs interpretable machine learning (ML) to investigate the optimal algorithm with a higher prediction accuracy in greater depth, including feature importance and non-linear marginal effects. Finally, the third paper in Chapter 6 assesses the limitations of ML when applied to transportation mode choice modeling and suggests future research avenues for further methodological improvements by comparing ML to DCM, which has been a widely-used approach over decades.
1.2. Motivation and Contribution

1.2.1. Understanding Transportation Mode Choice Behavior

New mobility technologies, including autonomous vehicles (AVs), continue to evolve. Firms have developed and tested AVs over the last decade and may become available to the broad public in the proximate future (Fagnant & Kockelman, 2015). This supply-side advancement in the transportation mode will likely disrupt and reshape travel behavior (Wiseman, 2018; Singleton, 2019), creating a new paradigm of transportation mode choice behaviors that have not yet been observed. For instance, consumers in the era of AVs will be able to choose from the variety of modes of transportation shown in Figure 1 that will be highly likely to co-exist, including private AVs, conventional automobiles, and shared mobility services. However, previous literature has explored only a subset of the modes shown in Figure 1, particularly private AVs and conventional personal cars. None of the studies has put both AVs, shared mobility services, and currently available transportation modes side-by-side in an experiment on future travel behavior, although all will likely co-exist. Considering the critical research gap and motivation, this dissertation contributes to exploring more comprehensive transportation mode choice behaviors using the U.S. nationwide stated choice experiment.
Whether you are ready or not, AVs are on the horizon. Specifically, automobile manufacturers have already offered semi-autonomous systems, and complete automation will be available in the near future (Thompson, 2016). Accordingly, transportation planning sectors have started to actively support these newly developing forms of transportation (Clark et al., 2016; Kim et al., 2022). Examples include publications from the United States Department of Transportation (USDOT) that set forth the principles for preparing for the future of vehicle automation and basic implementation techniques for implementing those principles, as illustrated in Figure 2 (National Highway Traffic Safety Administration, the United States, 2017; U.S. Department of Transportation, 2018). However, although there have been considerable efforts so far, transportation planning for AVs has depended mainly on speculative forecasts of travel demand that will be altered by AVs (Millard-Ball, 2018).
As a result, developing robust mid- to long-term transportation strategies has been difficult due to the uncertainties surrounding consumer reactions and the magnitude of their overall impact on travel behavior. Therefore, transportation planners and researchers should prioritize understanding and forecasting the demand for travel using reliable data and advanced modeling techniques that can
produce accurate projections of travel behavior. In this regard, this dissertation contributes to offering crucial underlying knowledge to the decision-making process of transportation planning. Furthermore, the findings are intended to provide government policymakers and automobile companies with valuable insights into the dynamics of future travel demand, the influential factors, and the potential effective strategies to encourage more people to use a particular transportation mode in the era of AVs.

1.2.3. Transportation Mode Choice Modeling

Discrete choice modeling (DCM) (McFadden, 1974) has been established and widely used in transportation mode choice modeling research over the past decades (Hess & Daly, 2014). Machine learning (ML) has been used lately to solve complex related tasks, including transportation mode choice modeling, with high predictability (Ran & Hu, 2017; Sidey-Gibbons & Sidey-Gibbons, 2019). Due to their strengths (L. Zhou et al., 2017; Simeone, 2018), empirical studies in the field of transportation mode choice modeling have increasingly used ML (Omrani, 2015; Hussain et al., 2017; Golshani et al., 2018; Yan et al., 2020; Truong et al., 2021). Although ML extends the reach of choice modeling and offers different valuable insights (Yan et al., 2020; Hillel et al., 2021), there have been several limitations, such as interpretability, of the recently developed modeling approach. Despite ongoing methodological improvements to address these, there are still limitations that existing studies have not examined. Therefore,
this dissertation contributes to improving our understanding of the relative strength and shortcomings of ML when applied to transportation mode choice modeling, and suggesting future research avenues for further methodological improvements.

1.3. Structure

This dissertation is divided into three major sections: (1) overviews of the dissertation in Chapter 1, AVs in Chapter 2, and transportation mode choice modeling in Chapter 3 that assist readers in gaining a general understanding of this dissertation, (2) each of three papers in Chapters 4, 5, and 6, and (3) a final chapter that concludes this dissertation.
Chapter 2. Background to Autonomous Vehicles

2.1. Introduction

This chapter offers background information on autonomous vehicles (AVs) to assist readers in developing a fundamental grasp of this new mode of transportation. The following subsections cover various topics related to AVs, including their definition, level of automation, essential tasks and functions, and potential consequences.

2.2. Definition

2.2.1. Autonomous Vehicle

The term "autonomous vehicle (AV)" (sometimes known as the self-driving vehicle) refers to a form of motorized vehicle that operates on current roadways with little or no direct human intervention due to computerization (Fagnant & Kockelman, 2015). As a result of technological advancements and improvements,
AVs replace human drivers with artificial systems that perform jobs in a human-like manner (Ionita, 2017). AVs are required to learn in teaching mode and from experiences, perform approximate reasoning, which is more than true/false logic, and behave autonomously (Ionita, 2017).

### 2.2.2. Private and Shared Autonomous Vehicle

HERE Technologies (2017) categorizes AVs into two types of transportation modes: (1) autonomous Car-as-a-Product (private AVs) and (2) autonomous Car-as-a-Service (shared AVs). In detail, while private AVs (PAVs) refers to the ownership model, shared AVs (SAVs) utilize completely autonomous vehicles as a part of the "service model" notion.

In detail, PAVs means that each traveler uses the mode independently, as to how the conventional personal car operates. Similarly, but differently, SAVs allow more than one rider to share a ride (Stoiber et al., 2019; Turoń & Kubik, 2020). SAVs have two types: (1) shared ownership and (2) shared use by combining not only ride-sharing services, carpools, or taxis but also car-sharing services with AVs (Metz, 2018). SAVs with mobility-on-demand services have the following distinct characteristics (Krueger et al., 2016; Hyland & Mahmassani, 2020):

- A mobile application is used by riders to request trips, and the request contains the riders' pick-up and drop-off locations.
Riders are presumed to be willing to wait and, in some cases, to take a ride with strangers in order to complete their journey.

The SAV controllers make every effort to serve the pick-up as quickly as possible and keep riders' waiting and in-vehicle times to a minimum.

2.3. The Levels of Automation

As illustrated in Figure 3, the Society of Automotive Engineers has defined six levels of automation, ranging from 0 (no automated features) to 5 (fully automation) (Narayanan et al., 2020; Turoń & Kubik, 2020). The first three levels (level 0 to 2) fall into the category called intelligent driver assisting systems and are defined as follow (Ionita, 2017):

- Level 0 (no automation): human drivers are solely responsible for vehicle control.
- Level 1 (driver assistance): Adaptive cruise control and parking assistance are examples of minimal driver assistance provided by the car.
- Level 2 (partial automation): the vehicle gives drivers so-called hands-off capabilities because vehicles can control accelerating, braking, and steering.

The remaining three levels (level 3 to 5) represent systems of AVs that are capable of taking over the driver’s tasks and are defined as follow:
- **Level 3 (conditional automation):** Vehicles can control all aspects of driving, but drivers must be prepared to respond immediately in an emergency.

- **Level 4 (high automation):** Because of the high level of automation in the vehicle, drivers may be able to engage in so-called "minds-off" operations.

- **Level 5 (complete automation):** Only AVs are expected to drive autonomously under any circumstances, whereas autonomous systems at levels 4 and 5 can make decisions without human intervention or control (Milakis et al., 2017).

![Figure 3 The levels of automation (Source: National Highway Traffic Safety Administration, the United States, 2017, p.4)](image)

2.4. **The Basic Tasks and Functions**

2.4.1. **High-Level Illustration**
Generally, AVs operate in a three-phase process known as “sense-plan-act” (Behere & Torngren, 2015). Figure 4 depicts a high-level overview of the many activities required for driving AVs and their subordinate duties to deploy automation acceptable (Ionita, 2017).

Figure 4 The basic tasks and functions of autonomous vehicles (Source: Ionita, 2017, p.4)

2.4.2. Detailed Illustration

Figure 5 illustrates fixed modules in modern autonomous driving systems (Talpaert et al., 2019). First, AVs collect low-level data through sensing. Specifically, sensor infrastructure includes, for example, cameras, radars, LiDARs
(the Laser equivalent of Radars), and GPS-IMUs (GPS and Inertial Measurement Units provide an instantaneous position) (Bagloee et al., 2016; Litman, 2021).

As part of the Perception module, the collected data from sensing is frequently transformed into higher-level descriptions used in other applications. Perception estimates the positions of various descriptors such as the location in the lane, cars, pedestrians, traffic lights, and other semantic objects, among others. For instance, ADAS is currently being implemented by automakers such as Tesla, which includes adding a camera for lane-keeping and collision avoidance and low-speed cruise control in stop-and-go traffic, where a single radar is frequently ineffective (H. Zhou et al., 2022).

Scene understanding is responsible for high-level scene comprehension tasks such as detection, classification, and localization, which are then fed into the vehicle's driving policy/planning module. Path Planning is the process of predicting actors' future trajectories and maneuvers. For instance, a static shortest path from point A to point B with dynamic traffic information constraints is used in conjunction with dynamic traffic information constraints to calculate the path. Vehicle control orchestrates the high-level orders for motion planning by using simple closed-loop systems based on sensors from the Perception task performed by the Perception task.
2.5. Technological Growth Trajectory

2.5.1. Early Tests

The "No Hands Across America" road test, one of the first long-distance AV road tests, was introduced in 1995 (Van Brummelen et al., 2018). AVs navigated the vehicle across the U.S. while humans-controlled acceleration and braking in this event. In each of these tests, AVs drove autonomously for 90–98 percent of the travel, utilizing primitive lane departure warning systems, lane-keeping systems, and inter-distance/speed regulation systems to aid in their navigation.

Another initial significant contribution was made by the Defense Advanced Research Projects Agency (DARPA). The successful Grand Challenge test in 2004 helped publicize AVs' development. Many companies, including
Mercedes-Benz, Volvo, and Tesla, have been working on and testing AVs (Narayanan et al., 2020; Sousa et al., 2017).

Since Google released the first vehicle automation in 2010 (Teoh & Kidd, 2017), firms have significantly invested in and accelerated technological development. In addition to private car manufacturers, governments have implemented and released pilot programs to provide the platform for SAV, such as taxis and shuttles, with self-driving systems (Kim et al., 2022).

2.5.2. Technology Development

Technologically, Advanced Driver Assistance Systems (ADAS) defines the complex real-time embedded systems and concepts that guide the development of AVs (Shaout et al., 2011; Ionita, 2017). So far, there have been various types of embedded systems in vehicles, such as adaptive cruise control, pre-crash system, blind spot information system, lane departure warning system, and autonomous parking assistance systems (Kukkala et al., 2018). In addition, the semi-autonomous features (also called assistive technologies), such as adaptive cruise control, land-keeping, land departure warnings, collision avoidance, and parking assistant systems, are now commercially available (Millard-Ball, 2018).

Despite the significant technological improvements, there have been major remaining challenges, such as AV perception in severe weather conditions or complex urban environments and the development of safety measures. Accordingly, the next generation of ADAS is paving the way for level 5 of
automation by developing state-of-the-art technologies, such as advanced
detection systems, advanced route reconfiguration systems, and vehicle-to-
everything communication systems that provide the AV with the ability to
exchange information with others (Haas et al., 2020).

2.5.3. Technology Readiness

KPMG International (2020) published an AV readiness index, which measures
AVs' preparedness by considering policy and regulation, technology and
innovation, infrastructure, and consumer acceptance. The index reveals that
Singapore and the Netherlands were in first and second place, respectively, with
the United States in fourth place (23.99).

In particular, Singapore has dramatically increased the scope of its
automated vehicle testing to include all public highways on the western side of
the city-state. American technology companies such as Waymo, General Motors,
and Ford have continued to dominate the development of AVs, placing the
country at the top of the technology and innovation development rankings for
2017. Additionally, communities like Detroit and Pittsburgh have undertaken
unique initiatives to promote AVs. Specifically, because of AV businesses such as
Argo AI and Aurora, Pittsburgh has been testing 5-level AVs since 2015. Also
noteworthy is that South Korea experienced the greatest increase of any other
country, primarily due to the extensive government-funded AV pilot programs
and available infrastructures, such as 4G coverage and mobile connection speed.
2.6. Market Penetration

2.6.1. Theories on the Market Penetration of a New Technology

Technology Diffusion Theory (TDT) provides a fundamental understanding of the general process of the market penetration of new technology. TDT is based on the "tipping point," describing how the typical spread of innovations works. It also serves as a foundation for considering what kind of activities successfully support the spread of innovations (Rogers, 2010; Ghezzi et al., 2013). Rogers (2010) identified the five steps of a technology-adoption decision (see Figure 6).

- The knowledge stage: individuals come to get awareness knowledge (the knowledge of the existence of new technology), how-to knowledge (the knowledge of how to use it), and principles knowledge (the information on how and why it works) (Ismail, 2006; Wani & Ali, 2015).

- The persuasion stage: Individuals form their attitudes regarding the new technology throughout this period. The degree of ambiguity around its application can rise or decrease.

- The decision stage: Individuals either accept or reject the new technology, depending on their preferences. However, the choice may be reversed at a later time, with four possible outcomes: (1) continuation of adoption, (2) later adoption, (3) discontinuation of adoption, and (4) persistent rejection of the adoption.
The implementation stage: Prior to this point, the decision-making process is merely a mental exercise. Individuals at this stage use technology regularly, which affects altering their behavior. Since then, technology has lost its distinguishing characteristic as a novel notion.

The confirmation stage: Individuals are constantly embracing it. On the other hand, some people choose to stop using it, switch to a better option, or reject the technology.

Figure 6 Model of five stages in the innovation-decision process (Source: Rogers, 1983, p.165)

Additionally, the S-curve in Figure 7 depicts the possible shift in the proportion of new technology market penetration over time due to technological advancement (Litman, 2021). To be more specific, during the first development
phase, the prospective market proportion would expand faster than before. After then, however, the new technology would spread and expand significantly, finally reaching saturation and diminishing.

Figure 7 The S-curve development pattern of market penetration of autonomous vehicles (Source: Litman, 2021, p.25)

2.6.2. **Theories on User Behavior**

Because theoretical frameworks assist in capturing exciting patterns and mechanisms behind the uncertain processes of AV adoption, this subsection summarizes and synthesizes theoretical frameworks for contextualizing individual users' behaviors on AVs in order to indicate the extent to which a theory explicitly accounts for relevant contextual conditions (Venkatesh et al., 2016). As a result, the theories presented in the following subsections have been successfully used to explain the causes of distinct behaviors in various situations.
2.6.2.1. **Technology Acceptance Model**

The technology-acceptance model (TAM) provides a theoretical framework to analyze user acceptance of new technology. Davis et al. (1989) establish the early contribution to capturing user motivation to system use by adding two main variables: (1) the perceived usefulness and (2) perceived ease of use of the technology. Since then, many scholars have extended the TAM models by adding additional factors and moderating effects. For instance, Venkatesh and Davis (2000) incorporated additional factors into the original model, such as subjective norms, voluntariness, and internalization. Venkatesh et al. (2012) included three new constructs, hedonic motivation, price, and habit. They also explained the moderating effects of socio-demographic features (e.g., age and gender). The United Theory of Acceptance and Use of Technology in Figure 8 has been proposed in the consumer context by adopting more detailed features, including attributes of location, environment, organization, user, technology, and task (Venkatesh et al., 2016).
2.6.2.2. Theory of Reasoned Action

The theory of reasoned action (TRA) was established to capture the unique motivational elements that influence the likelihood of completing a specific behavior in a given situation (Fishbein, 1967; Glanz et al., 2008). As seen in Figure 9, the theory of planned behavior says that behavioral intention, governed by personal attitudes and social normative perception, is a critical predictor of
future behavior. According to attitude theory, people who have a positively valued expectation, preference, or perception are more likely to have a favorable attitude toward performing a given behavior, which leads to a higher intention to perform the behavior. Furthermore, according to the subjective norm, individuals will have a positive subjective norm that drives them to perform the behavior when a referent individual performs or likes the action.

Figure 9 Theory of reasoned action and theory of planned behavior (Source: Glanz et al., 2008, p. 70) (Note: Upper light area shows the theory of reasoned action, and the entire figure shows the theory of planned behavior.)
2.6.2.3. **Theory of Planned Behavior**

The theory of planned behavior (TPB) also provides a theoretical framework for explaining how individuals' motivational factors influence their decisions to conduct particular conduct (Ajzen, 1985). As an addendum to the TRA framework, Ajzen (1991) incorporated an extra construct, namely, perceived control over the performance of the behavior (also known as a person's volitional control), to account for factors outside of the individual's control. The shaded boxes in Figure 9 show that perceived control is determined by the factors that function as facilitators or barriers to behavioral performance (control beliefs), weighted according to their perceived power or impact (Ajzen & Madden, 1986).

2.6.2.4. **Socio-Ecological Models of Behavior**

To capture the influence of many influences on individual behaviors, notably in the health-related field, Glanz and colleagues (2008) developed Socio-ecological models of behavior (SEMB). Based on four components, (1) personal traits, (2) policy environment, (3) physical/built environment, and (4) social environment, the theoretical framework may be used to explain the influence of travel habits on individuals (Acheampong & Cugurullo, 2019). More specifically, personal qualities often comprise socio-demographic traits and attitudes, perceptions, and knowledge held by individuals (Acheampong & Siiba, 2018). Second, the policy environment consists of infrastructure-related variables, public awareness initiatives, and incentive-based policies, among other things (Acheampong &
Cugurullo, 2019). Last but not least, neighborhood features such as population density and land-use diversity are captured by the physical environment (Ewing & Cervero, 2010). Fifth and last, the social environment consists of social networks and social support systems and the influence of other individuals such as family members, coworkers, and friends (McLeroy et al., 1988).

2.6.2.5. **Theory of Environmentally Significant Behavior**

The theory of environmentally significant behavior gives an underlying understanding of the elements that contribute to a given conduct's significance in the environment (Nordlund et al., 2016). Guagnano and colleagues (1995) claim, in particular, that behavior is influenced by both personal attitudes and environmental variables (contextual factors). As part of an expansion developed by Stern (2000), four factors influencing environmental behavior are proposed: (1) contextual forces (e.g., persuasion, advertising, and regulations), (2) personal capabilities (e.g., knowledge, power, and socio-demographic characteristics), (3) habits or routines, and (4) attitudinal factors (e.g., specific personal moral norms).

2.6.2.6. **A Synthesis**

Theories of user behaviors, including the technology acceptance model (Davis et al., 1989), have been developed to better explain the motivating influence on intentions and behaviors within an expectancy-value frame of reference (Madden et al., 1992; Hankins et al., 2000). The theoretical background provides insights
into broad notions surrounding the adoption of AVs in general. First, the behavioral theories emphasize the necessity of demand-side discussions to better understand travel behavior in the age of AVs (J. P. Zmud & Sener, 2017) since automobile manufacturers and transportation planners will push the modal transportation shift, as well as, more crucially, by potential users. Second, rather than a single factor (such as price), the transition to AVs is influenced by several factors at the same time (e.g., consumer characteristics, spatial arrangements, and cultural meaning). Thus, this research underlines the relevance of demand-side discussion, which is supported by behavioral theories. Furthermore, it adopts conceptual frameworks for transportation mode choice behaviors and explains how various circumstances influence transportation mode choice behaviors (Bamberg et al., 2003; Haustein & Hunecke, 2007).

2.6.3. Market Penetration Forecast

Many forecasts say full automation will be available by 2050 or sooner (Singleton, 2019). The advancement of technology in the transportation sector can usher in a new and disruptive mobility paradigm that can address many of the present transportation difficulties and externalities (Sousa et al., 2017; Martínez-Díaz & Soriguera, 2018). According to the hypotheses presented above, the fundamental process of AV adoption takes place throughout time, including the phase of AV adoption and an individual's decision on whether or not to adopt. The historical adoption trajectory of a new transportation mode may imply the
market penetration of AVs. Specifically, a large-scale passenger airline network did not emerge until the 1920s, although the Wright Brothers flew in 1903 (Vance, 1986). Therefore, it would take years to show a significant AV ridership.

It can be difficult to generalize the findings of prior studies on the market share of AVs and SAVs on an empirical basis because the methodologies, geographic scope, and context of the studies all differ significantly. Nonetheless, past research has offered a forecast for market penetration within a short period. For instance, regarding the market penetration of AVs, Zmud et al. (2016) found that self-driving automobiles were preferred by 52 percent of those who responded to an online Stated Preference survey. J’son & Partners Management Consulting (2017) forecasted that by 2025, the market share of autonomous vehicles would be around 8 percent, 21 percent by 2030, and 50 percent by 2035, respectively. Litman (2021) predicted that by 2045, autonomous vehicles would account for half of all trips. In addition to AVs, Liu et al. (2017) forecasted that the proportion of total trips using SAVs would be 16.7 percent. Statista (2021) reported that approximately 42 percent of respondents showed a willingness to use AVs as of March 2020, while 20% said they never ride in AVs.

2.7. Stakeholders

Omeiza et al. (2021) identified several stakeholders, (1) end-users, (2) developers and technicians, and (3) regulators and insurers. End-users include passengers and auxiliary drivers of AVs, and agents outside AVs, such as pedestrians, bicyclists,
and other conventional transportation users. AV developers and automobile technicians are also important stakeholders. Furthermore, system auditors, regulators (e.g., politicians and transportation planners), accident investigators, and insurers are all included in the regulatory and insurance communities.

2.8. Potential Impacts

A book chapter titled “Transportation and Urban Form - Stages in the Spatial Evolution of the American Metropolis” illustrated four different eras based on the innovations in transportation modes or infrastructures (Muller, 2004). It divides history into four periods: (1) the walking-horsecar era (1800-1890), (2) the electric streetcar era (1890-1920), (3) the recreational automobile era (1920-1945), and (4) the highway era (from 1945 to the present) (1945-present).

Assuming that autonomous vehicles (AVs) will become the norm in the future, the development of this new means of transportation could usher in a new era. This modern technology would likely impact travel behavior and people’s way of life (Shabanpour et al., 2018), as the previous technological developments in transportation have done. Milakis et al. (2017) divided the anticipated consequences into three categories based on their understanding of the ripple effect, which explains the successively spreading repercussions of a given event over various fields. First-order, second-order, and third-order impacts were considered (see Figure 10).
2.8.1. The First Order Impact

Further, the first-order ripple effects (the brightest blue circle immediately adjacent to Vehicle Automation in Figure 10) are the specific subject of this paper, pertaining to direct effects on traffic capacity, congestion levels, travel...
costs, and mode selection. For example, the cost of AVs would be higher than the
cost of conventional vehicles because of the advanced technologies involved in
the vehicle. In contrast, the value of travel time would decrease because of the
comfortability, safety, multi-tasking, reduced congestion, and improved fuel
efficiency that AVs would provide. The introduction of AVs will also most likely
result in transportation mode shifts, such as decreasing public transportation
ridership (which was mentioned previously), as discussed in the preceding
subsection.

2.8.2. The Second Order Impact
The second-order ripple effects have three ramifications: location selection, land
use, and economic development. In particular, technical advancements in
transportation modes considerably impact spatial structures and layouts. For
example, following the passage of the 1956 Interstate Highway Act, new
motorways and the expansion of automobiles transformed spatial patterns in the
postwar city, which had grown significantly in size and became multi-centric
(Duany et al., 2001; Rodrigue, 2020).

Similarly, autonomous vehicles (AVs) are expected to alter the way
people travel, ultimately altering their decisions about where to live. For example,
Zhang and Guhathakurta (2018) found that people would move further away from
their workplaces due to the introduction of SAVs in the agent-based simulation.
Moore et al. (2020) also predicted a substantially increased extent of urban sprawl (potentially up to a 68% increase).

2.8.3. The Third Order Impact

The third-order ripple effects (the deepest blue circle on edge) relate to the indirect consequences of AVs on a wide range of issues, including the environment, the economy, public health, and social equity, among others. For example, AVs may be able to positively influence populations that have been excluded from conventional transportation modes. In particular, because the technologies would provide greater comfort and convenience of driving, they would have a better transit alternative, which would allow them to become more accessible. Additionally, AVs have the potential to replace vocations such as drivers with computer automation. In empirical investigations, the third-order impacts, on the other hand, remain unknown.

2.9. Conflicting Viewpoints on Potential Impacts

AVs are acknowledged to have various benefits and concerns (Schmidt et al., 2015; Bagloee et al., 2016; Gruel & Stanford, 2016; Taeihagh & Lim, 2019; Gkartzonikas & Gkritza, 2019; Howard & Dai, 2014). The non-technical issues are more likely to influence the adoption of new technologies than technological ones, and AVs are one of these technologies (Othman, 2021). For instance, Thomas et al. (2020) observed perceived benefits and concerns that potential
users would have through a survey (see Figures 11 and 12). On the one hand, most respondents said that AVS would provide benefits such as reduced travel time, reduced traffic congestion, fewer car accidents, reduced emissions, the creation of new jobs, and lower insurance prices. On the other hand, in terms of concerns, crashing/malfunctioning (safety issue), purchase price, liability for incidents, interaction with non-AV, performance in unexpected situations, hacking, and safety would be the top concerns expressed by respondents. The following subsections summarize several direct and indirect benefits of AVs' promising development and concerns and issues resulting from this development in detail.

Figure 11 Benefits of autonomous vehicles (Source: Thomas et al., 2020, p.1237)
2.9.1. Benefits

2.9.1.1. Reduced Travel Time

The first advantage of AVs can be found in “the positive utility of travel concept (Mokhtarian & Salomon, 2001),” which suggests that during a trip, passengers can reap benefits from a variety of factors other than merely arriving at their destination. As a result of travel-based multi-tasking (as depicted in Figure 13) and enjoyable travel experiences, AVs would minimize subjective values of travel time (Kockelman et al., 2017). AVs would also result in gains in subjective well-being due to reducing driving-related stress and the enhancement of flexibility to relax and transition mentally. Figure 14 empirically shows what people are willing to engage in multiple secondary tasks, such as reading, eating, and using phones, in AVs (Kyriakidis et al., 2015).
2.9.1.2. Increased Safety

AVs have the potential to significantly reduce the number of accidents and save lives (Thompson, 2016). Specifically, there have been numerous accidents and causalities; for instance, the U.S. Department of Transportation’s Fatality Analysis Reporting System (2019) reported around 33,000 fatal motor vehicle
crashes in 2019 across the U.S, which caused approximately 36,000 deaths. AVs would demonstrate safe operation because the form of transportation must adhere to legal requirements, such as speed limits and stop signs (Metz, 2018).

Furthermore, given that human errors have accounted for a significant high portion of the causes of vehicle accidents (Smith, 2013), AVs would significantly lower accident rates considerably by reducing or eliminating human errors (Webb et al., 2019). According to studies, most people believe that AVs would be a relatively safe means of transportation, although some have expressed reservations (Schoettle & Sivak, 2014; Hulse et al., 2018). The results of a survey conducted by Motional (2021) indicated that respondents feel that AVs will contribute to eliminating a number of the most common causes of road accidents. Among other things, AVs, according to 54 percent of respondents, will lower their anxiety about intoxicated drivers on the road, as well as inattentive drivers (52%), exhausted drivers (48%), and aggressive drivers (46%).

2.9.1.3. Energy Conservation and Emission Reductions

Automation may play a big part in reducing vehicle emissions because it is being developed to improve acceleration, braking, and speed variation, increasing fuel efficiency and lowering carbon emissions (Thompson, 2016; Wadud et al., 2016). Additionally, AVs with electric propulsion would emit no emissions, which would benefit the environment. SAVs can further promote more sustainable mobility by lowering the use of private automobiles, facilitating multi-modal
travel behavior, and reducing environmental loads on the environment (Krueger et al., 2016).

### 2.9.1.4. Reduced Traffic Congestion

AVs would reduce vehicle conventional car ownership, reducing traffic congestion (Fagnant & Kockelman, 2015). Empirically, Carrese et al. (2019) found a 10% reduction in the traffic volume in Rome, Italy.

### 2.9.1.5. Reduced Travel Costs

SAVs have the potential to lower the overall cost of taxis and ride-hailing services by eliminating the need for drivers that costs in taxis typically amount to 45 percent of total charges (Webb et al., 2019).

### 2.9.1.6. Reduced Parking Demand

After a commute or non-commute journey, autonomous vehicles could return home (so-called "parking on the move"), decreasing the requirement for on-street parking spaces. The gain would aid in the more efficient use of urban land.

### 2.9.1.7. Transportation Equity

AVs can be a promising means of transportation for those who face obstacles or cannot obtain a driver's license due to inability to drive, health issues, age, or other socio-demographic characteristics (Becker & Axhausen, 2017). It assists
persons who have faced difficulties in gaining access to social services, amenities, and work in becoming more self-sufficient when it comes to traveling. Mainly, shared AVs would be an affordable way for the marginalized people to access self-driving technology and its associated benefits (Howard & Dai, 2014). Expanding opportunities for those excluded from the current automotive-dominant market would reduce the cost of the technology and, more importantly, enhance network benefits.

2.9.1.8. Increased Operational Efficiency

Experiments by Wu et al. (2021) demonstrated that compared to conventional public transportation systems, which have generally operated with fixed routes and schedules, autonomous modular buses (AMB) demonstrate quicker trip times and fewer transfers. Additionally, AMB has drawn attention because of its flexibility in scheduling and operation and, more critically, because it has removed driver labor costs while simultaneously reducing traffic congestion (Hyland & Mahmassani, 2020). Other integrated systems and technologies, such as timetable synchronization and optimal service zone design, can further reinforce the advantages.

2.9.2. Concerns and Issues
2.9.2.1. **Insignificant Travel Time-Saving Benefit**

The projected value of time reduction may not be significant for the following reasons (Singleton, 2019). First, riders may experience motion sickness and discomfort, impairing their multitasking ability (Le Vine et al., 2015; Diels & Bos, 2016). In this regard, Sivak and Schoettle (2016) reported that around 60% of those who answered the survey claimed that they would refrain from participating in any activities such as reading, sleeping, or texting. Additionally, they discovered that almost 50% of them stated that they expected to have at least moderate motion sickness in AVs. Second, Singleton (2019) argued that although AVs would allow passengers to engage in more activity engagement throughout the trip, it is possible that in-vehicle time in AVs would still be coping with commuting constraints. Third, Jain and Lyons (2008) stated that as opposed to a burden or disutility, travel time could be thought of more as a gift because it provides travelers with transition time and time out to prepare for activities at their destination, enjoy the trip, escape from obligations, and spend some quality time alone or with close friends and family. As a result, because the benefits have already been factored into current value of time estimates, the impact of AVs on VOT is likely to be minor (Metz, 2018). Fourth, in terms of the length of travel time, interviewees in a study of Zmud et al. (2016) answered that because they would not be moving from their current residence and, more significantly, because they would not be changing their routines and routes, their VMT would remain constant.
2.9.2.2. Increased Safety Concern

However, safety concerns would coexist (Bennett et al., 2020). AVs cannot completely eliminate automobile accidents since none of the human errors implies that none of the machine errors exist (Taeihagh & Lim, 2019); for example, in 2016, the Tesla autopilot was involved in a deadly crash, demonstrating the incapacity of technology to prevent accidents in some conditions (Banks et al., 2018). Also, Google has been developing automated cars and testing them since 2009 under employee supervision. However, several crashes have been reported, although the rate of crashes per million vehicles traveled miles (2.19) was lower than that of vehicles driven by humans (6.06) in Mountain View, California (Teoh & Kidd, 2017). Additionally, AVs would be involved in crashes with pedestrians and other transportation modes, such as conventional vehicles and public transit.

Moreover, since the algorithm may prioritize AV riders' safety over anything else (Coca-Vila, 2018), it can endanger the safety of other individuals, particularly walkers and passengers on conventional modes of transportation. According to a survey by Statista (2021), the primary concern among 61 percent of potential customers globally regarding AVs is the possibility of safety risk due to machine error or malfunction. Similarly, Motional (2021) also reported that Consumer perception of AV safety continues to be the most significant source of contention. Specifically, only 15 percent of people today believe that autonomous vehicles are currently safe and reliable, and 40 percent said they would feel
comfortable sharing the road with one. Moreover, they had a high level of confidence in existing driver assistance vehicle technologies, such as aided parking and emergency braking, and they would be prepared to ride in a driverless car if it met specific safety requirements.

2.9.2.3. Increased Travel Demand

Because those who are not permitted to drive, such as the elderly and those without driver's licenses, would increase the demand, traffic congestion could intensify due to the introduction of autonomous vehicles (Metz, 2018). In a similar vein, SAVs would attract more passengers from public transit due to their lower costs and rising demand for automobiles.

2.9.2.4. Increased Data Privacy Issue

Since AVs require personal information to improve efficient movement and ensure safety, there is concern over who should have access to and control that information (Dhar, 2016). The information is sensitive because it contains all information, including location-based movement data and identification and profiles of AV riders. There is a possibility of using the information for other purposes, such as marketing and surveillance of AV users (Taeihagh & Lim, 2019). Furthermore, there would be cybersecurity dangers to antivirus software, which would allow hackers to gain control of the information.
2.9.2.5. Liability Issue

There would be a liability issue in the case of an accident (Dhar, 2016; Shabanpour et al., 2018). Since AV riders will no longer control the vehicle, part of the responsibility would need to shift from people to other agents, such as vehicle firms. Thus, it would be challenging to specify how liability is apportioned between the agents, including manufacturers, suppliers, and software engineers (Taeihagh & Lim, 2019). Accordingly, the corresponding effects on insurance costs have been unknown so far.

2.9.2.6. High Expected Purchase Price

Previous studies have found that the willingness to pay for AVs was around $7,000 (Bansal et al., 2016) or $4,500 (Daziano et al., 2017). It means that autonomous vehicles will most likely be more expensive than regular automobiles, which may prevent some segments of the public from utilizing them.

2.9.2.7. Unemployment

A few studies acknowledged that autonomous vehicles (AVs) posed a threat to employment (Taeihagh & Lim, 2019). The majority of those at risk would be drivers and mechanics. For instance, Bischoff and Maciejewski (2016) found that it is anticipated that taxi fleets will be reduced to 10% of the current amount of taxi use in Berlin. Also, Clements and Kockelman (2017) argued that when AVs
dominate the automotive industry, drivers in the trucking and delivery industries may become less needed. Thus, AVs would harm employment.
Chapter 3.  Transportation Mode Choice Modeling

3.1.  Introduction
This chapter briefly discusses the two schools of thought in transportation mode choice modeling: (1) discrete choice modeling (DCM) and (2) classification supervised learning in machine learning (ML) (Karlaftis & Vlahogianni, 2011). This chapter also presents empirical studies that use them. Ultimately, this chapter offers a basic understanding of the methodological approaches used in this dissertation.

3.2.  Discrete Choice Modeling
3.2.1.  Theoretical Background
Discrete Choice Modeling (DCM) explores a decision maker’s transportation choice of one alternative from a finite set of alternatives (Koppelman & Bhat, 2006). Thus, DCM can explore why an individual uses a particular transportation mode from a set of modes under various factors (Stopher & Mayburg, 1975). Its
fundamental decision rule follows utility-based choice theory (also called utility maximization theory); in other words, an individual will choose an alternative \( j \) if the utility of the alternative \( j \) is more significant than other alternatives (Koppelman & Wen, 1998). The underlying utility maximization theory enables DCM to provide valuable information on the demand-side perspective in the market (McFadden, 1980). The theory is also applied to other fields of study, such as psychology (Manski, 2013); for instance, the psychological interpretation of the theory is that decision-makers carry a distribution of utility functions in their mind and select one among a set of choices (Luce & Suppes, 1965). The theory admits the effects of perception, state of mind, and characteristics of consumers and provides the logical and unified foundation of consumer behavior in the market. Moreover, it assumes that decision-makers conduct rational behavior (bounded rationality), which means a consistent and calculated decision process in which the individuals follow their objectives. Lastly, parameter estimations in the utility specifications are estimated using maximum likelihood estimation (M. E. Ben-Akiva & Lerman, 1985). The estimated parameters can be used to provide explanations for why individuals choose each alternative. The estimations can also be used to extract crucial behavior indicators, such as marginal effects and the value of time.

3.2.2. Brief Discussion on Models
3.2.2.1. Multinomial Logit Model

The Multinomial Logit (MNL) model is a widely used choice model in diverse fields, including transportation (McFadden, 1974). The crucial assumptions of the MNL model are (1) the error components are extreme-value (or Gumbel) distributed, and (2) the error components are identically and independently distributed across alternatives as well as individuals (the IIA property) (Koppelman & Bhat, 2006).

Among them, independence from irrelevant alternative (IIA) property is one of the most widely discussed aspects. The IIA property, which implies equal competition between all alternatives, can restrict the ratio of the predicted probabilities for alternatives. For instance, in MNL on travel behaviors, single-occupied vehicles and carpooling are likely similar to other alternatives, such as transit and walking. The similarities can lead to a correlation between the errors associated with the alternatives, which violates assumptions that underlie MNL. As a result, the violation of this assumption can lead to inconsistent and biased parameter estimations and marginal effects (McFadden, 1974). Therefore, although MNL has provided the foundation of DCM, its behavioral limitations have motivated scholars to develop advanced models, such as Nested Logit, Mixed Logit, and Latent Class Choice models (Hensher et al., 2015). The following subsections introduce the advanced models.
3.2.2.2. Nested Logit Model

The Nested Logit (NL) model is a new member of the generalized extreme value family of logit models (Wen & Koppelman, 2001). NL assumes that some alternatives share common components in their error terms; it allows the correlation between the error terms of groups of alternatives (Williams, 1977). Discussion on the red and blue bus conundrum shows why NL outperforms MNL.

Suppose there are only two transportation modes, cars, and red buses. In this case, the theoretical share of each mode would be close to 50%. Imagine exactly duplicate bus, called blue buses, is introduced. Under the IIA property, the share for the three models would change to approximately 33.3%. However, since the red and blue buses share the same characteristics, the share should be 50% for cars, 25% for the red bus, and 25% for the blue bus. Thus, the model to permit patterns of non-independence of alternatives can outperform MNL because NL adds flexibility to MNL by grouping similar alternatives into a single category (McFadden, 1980).

3.2.2.3. Mixed (Random Parameter) Logit Model

“Mixed logit models, also called random-parameters or error-components logit, are a generalization of standard logit that do not exhibit the restrictive
“independence from irrelevant alternatives” property and explicitly account for correlations in unobserved utility over repeated choices by each customer (Revelt & Train, 1998, p. 647).” Along with the efforts to relax the strict assumption (e.g.,
IIA property) of the MNL model, random heterogeneity in the choice process has been a concern in producing unbiased and reliable parameter estimation (Vij & Krueger, 2017). When each individual completes multiple-choice experiments, theoretically, the experiments completed by the same respondent are likely to share some characteristics that may be unobserved by the researcher.

In this regard, among the family of logit models, the Mixed Logit (MXL) model has been widely used due to its ability to address random heterogeneity (McFadden & Train, 2000a; K. E. Train, 2009). MXL is appropriate because it overcomes limitations of the closed-form Multinomial Logit Model and Nested Logit model and assumes that the random parameters follow a distribution whose parameters are estimated (Revelt & Train, 1998; Hensher & Greene, 2003). Moreover, MXL is a highly flexible model that can approximate any random utility function (McFadden & Train, 2000b).

Accordingly, there are advantages. First, the model allows the parameter estimation associated with the observed variable to vary randomly across individuals. Second, the model produces efficient estimation when the same customers repeatedly choose alternatives (M. Ben-Akiva et al., 1993). Thus, MXL can significantly improve the behavioral realism in the MNL model through standard logit probabilities over a density of parameters (Hensher & Greene, 2003).
3.2.2.4. Latent Class Choice Model

“The underlying theory of the latent class model posits that individual behavior depends on observable attributes and latent heterogeneity that varies with factors unobserved by the analyst (Greene & Hensher, 2003, p. 3). The Latent Class Choice Model (LCCM) has been an alternative approach to address random taste heterogeneity by allocating individuals probabilistically to a set of heterogeneous classes that differ behaviorally from each other (D. Jain et al., 1990; Molin et al., 2016).

The difference between MXL and LCCM is that parameter heterogeneity in the formation is modeled with discrete distribution, which refers to classes, instead of continuous distribution (e.g., normal or log-normal distribution) in MXL (Beck et al., 2013). In other words, LCCM assumes that individuals are distributed heterogeneously with a discrete and finite number of sub-population groups that share similar characteristics within the data (Hensher et al., 2015; Mindrila, 2020).

LCCM consists of two sub-models, (1) the latent class membership model and (2) the class-specific choice model (Vij et al., 2013). The latent class membership model formulates the probability that belongs to the classes as a function of the characteristics of individuals (Matyas & Kamargianni, 2021). To estimate the class membership model, analysts first identify the number of classes based on the characteristics of respondents. The class membership is not directly observed but modeled up to a probability using a class assignment model. Then,
the second sub-model estimates the choice probabilities across identified classes (Walker & Li, 2007).

3.2.3. Application to Empirical Studies

For decades, DCM has been the dominating model in empirical research (F. Wang & Ross, 2018). The majority of the research has focused on parameter estimation to investigate factors influencing transportation mode choice, marginal effects or elasticities to forecast the decision under various scenarios, and other economic behavior outcomes, such as the value of time and the marginal rate of substitution.

3.2.3.1. Multinomial Logit Model

Ewing et al. (2004) used MNL to investigate the association between the mode of transportation chosen by students and three characteristics (i.e., travel time, built environment, and socio-economic factors). They discovered that the amount of time spent traveling has a large and unfavorable impact on walking and bicycling. In addition, sidewalk coverage was a major determinant in students' decision to walk to school, but population density and land-use diversity were unimportant factors. When the MNL model was used to estimate point elasticity, the findings revealed that the probability of bicycling was sensitive to travel time (the elasticity was -2.63), whereas the probability of walking was less susceptible to the trip attributes (the elasticity of -0.66). Additionally, car ownership has been shown to significantly reduce the likelihood of walking, with an elasticity of -
1.16. Wardman et al. (2007) used revealed preference and expressed preference data from the United Kingdom to investigate transportation mode choice during the commute trip, emphasizing bicycle. They discovered elements that influence the likelihood of using a bicycle, such as trip features (e.g., cost and time of travel), socio-demographic variables (e.g., gender), and the built environment (e.g., traffic congestion and advanced bike facilities). In addition, the study looked into the potential effects of several policy scenarios on the use of active transportation modes. For example, a completely segregated bikeway, a decreased daily fee for parking, more parking spots, and better cycling conditions were all considered convincing scenarios to encourage bicycling. McDonald (2008) used data from the 2001 National Household Travel Survey to investigate the mode of transportation that children used to get to and from school. The study discovered that trip factors such as travel time and the built environment, such as population density, substantially impacted participants' mode selection; however, gender and race did not affect their decision to travel by car. Given the elasticity of -0.75, the marginal effects revealed that the amount of time spent walking to school was the most important factor in deciding whether or not to walk to school. Furthermore, authorities will be unable to accomplish a considerable rise in the amount of walking if the majority of youngsters reside more than 12 kilometers away. Hamre and Buehler (2014) looked into how different commuter benefits for automotive, public transportation, and active transportation affected transportation choices when it comes to commuter benefits. The estimation of MNL model-free
car parking parameters was found to be positively correlated with vehicle utilization. In addition, amenities associated with public transportation and active transportation, such as a transit pass, bike parking, and showers with lockers, had a substantial impact on the likelihood of utilizing public transportation, walking, and cycling as opposed to driving a car in the study.

3.2.3.2. Nested Logit Model

Because of two factors: (1) the nested structure between options based on similarity and (2) the violation of the IIA, a body of previous literature has chosen NL over MNL (Abraham & Hunt, 1997). For example, Dissanayake and Morikawa (2002) used a nested structure with the two levels to study household transportation mode choice in Bangkok, Thailand. They discovered that the length of time spent traveling and the distance traveled to the destination were the most important considerations. They also ran simulations to see how the road pricing policies might affect the situation (e.g., a 10 percent increase in road pricing). According to the findings, an increase in road pricing was beneficial in alleviating congestion across five scenarios since it raised the likelihood of people using alternate modes of transportation and lowered the likelihood of people using automobiles. According to Blumenberg and Smart (2010), the effect of independent variables, with a particular emphasis on immigrant status, on transportation mode choice among driving, carpooling, public transit, and non-motorized modes was investigated. The researchers discovered that immigrants
were more likely than native-born Americans to participate in carpooling both inside and outside of their households. Ermagun and Samimi (2015) used the three-level NL model with four choices to investigate the method of transportation for school trips they were considering (car, school bus, public transit, and walk). Socio-demographic characteristics (e.g., gender), attitude factors (e.g., perceived safety), and the built environment (e.g., population density) were shown to be the most significant contributors to the utility function of walking, according to the parameter estimates. The elasticities demonstrated that it was projected to increase the likelihood of students walking to school under various circumstances, including increased travel time and cost of autos, decreased car ownership, improved proximity to public transportation, and decreased overall trip distance. A study conducted by Eldeeb et al. (2021) in Hamilton City, Canada, examined the relationship between built environment qualities and transportation mode choice and discovered that these attributes significantly impacted both. To be more specific, the findings of the NL study revealed that features of the built environment such as sidewalk density, bike lane density, and land use entropy were significant predictors of the likelihood of people utilizing active transportation modes. In an unusual twist, for the simulation exercise, this article constructed profiles that represented the majority of the people in the city and forecasted the likelihood that each profile would choose walking or bicycling as a mode of transportation.
3.2.3.3. Mixed (Random Parameter) Logit Model

As a result of the fact that MXL allows for both observed and unobserved preference heterogeneity (Willigers & van Wee, 2011), it has been increasingly popular for transportation mode choice modeling in recent years. For example, Murray-Tuite et al. (2021) investigated transportation mode choice in settings including alcohol consumption. Among the significant factors associated with travel behavior were socio-demographic characteristics (e.g., age, gender, household income, employment status, and educational attainments), attitudinal factors (e.g., comfort with credit card usage), and geographic factors (e.g., the distance between cities) (e.g., the location where alcohol was consumed and residential location). Additionally, the results of marginal effects revealed that when adults do not have children, the projected chance of driving after ingesting alcohol is 0.029 lower than when they have children. The anticipated likelihood of using ride-sharing services decreased by 0.142 percentage points for each additional age. Using the stated choice experiment survey, Lee et al. (2016) investigated the transportation mode choice between high-speed rail, full-service airlines, and low-cost airlines on the Seoul-Jeju route in South Korea, comparing the three modes. Results from MXL revealed that trip attributes (e.g., travel time), level of service (e.g., fare and frequency), and other considerations (e.g., duty-free shopping availability) were significant determinants in the decision to travel. Additionally, the importance of time, frequency, and safety for business passengers outweighed the importance of these factors for leisure passengers. The
stated choice experiment in Boston and Philadelphia was utilized by Dong et al. (2021) to evaluate customers' preferences between public transit and ride-sharing service. Using ride-sharing services, the researchers discovered that traveling and waiting significantly reduced the total time spent traveling and waiting. Gender, income, and age were all crucial socio-demographic aspects to consider as well. The results of the MXL simulation suggested that increasing the fare of ride-sharing services would considerably enhance the likelihood of people using the developing method of transportation. The factors that influence transportation mode choice between an automobile, public transportation, and walking were investigated by Di Ciommo et al. (2014) in the context of two new stations opening in Madrid, Spain. According to the findings of the article, travel time and cost were essential factors in mode selection. Two social capital network factors, engagement in voluntary activities and receipt of social services, were associated with some interesting findings (e.g., child care). The two factors were statistically significant, but the results were inconclusive. Specifically, those who participated in voluntary activities had a lower likelihood of using public transit and walking, but those who received social services had a higher likelihood of using these two modes.

3.2.3.4. **Latent Class Choice Model**

Like MXL, LCCM has been created and deployed in the transportation mode choice modeling domain; however, as compared to the other three models
discussed above, the number of applications has been somewhat limited. Vij and colleagues (2013) aimed to determine the influence of lifestyles on the choice of habitual transportation mode. They discovered that different sub-groups of the population behaved differently regarding their mode of transportation preference. It was discovered that habitual automotive drivers and multi-modal individuals exist and that these individuals can be classified as either responsive or insensitive to journey time based on the results of the study. Individual preferences for Mobility as a Service (MaaS) memberships in Greater Manchester, United Kingdom, were investigated by Matyas and Kamargianni (2021), who used an LCCM model with three classes to account for random heterogeneity in order to address random heterogeneity. They discovered that acquiring a membership was negatively associated with the participant's age. Additionally, those with a high level of education and a high level of money were more likely to purchase the expanded membership. Fu (2021) investigated how the habit of using a certain mode of transportation affects the mode choice behavior when commuting between cars, buses, and e-bikes. Similar to earlier studies, this study discovered heterogeneous groups in the population based on socio-demographic traits as well as cognitive components associated with the idea of planned behavior. Additionally, the report discovered that frequent automobile users alternated between driving and taking public transportation. Eldeeb and Mohamed (2020) evaluated user preferences concerning the quality of public transportation services. These groups were divided into direct travel enthusiasts, cost-conscious
consumers, and real-time information supporters. Furthermore, the three sub-
groups demonstrated distinct preferences for transportation service attributes and
a readiness to pay for service upgrades.

3.3. **Machine Learning**

3.3.1. **Overview**

A machine learning (ML) algorithm is a set of algorithms that allows them to
learn and enhance their performance due to their experiences (Mitchell, 2006;
Alpaydin & Bach, 2014). Because of large amounts of data and computing
capacity, machine learning (ML) is increasingly being utilized to tackle
complicated tasks, such as transportation mode choice modeling, with high
forecast accuracy (Ran & Hu, 2017; Sidey-Gibbons & Sidey-Gibbons, 2019). In
terms of its fundamental principle, it is based on optimization theory; in other
words, it goes through a large number of candidate algorithms in order to discover
one that optimizes the overall performance (Jordan & Mitchell, 2015). ML
generally has a four-step process: data processing, learning, evaluation, and
prediction phases (L. Zhou et al., 2017). This technique is proper when (1) theory-
based approaches are inapplicable, (2) sufficiently large training data sets are
available, and (3) the task does not necessitate explicit reasoning from the
algorithm (Simeone, 2018).

Machine learning is rapidly being used to aid with decision-making
prediction in various fields including medical diagnosis and financial assessment
ML has been used in a variety of settings, including industry and academics (Sidey-Gibbons & Sidey-Gibbons, 2019). Specifically, diverse industries, such as financing, advertising, medical care, and a wide range of empirical studies, such as transportation planning and engineering, have recently employed it (Jordan & Mitchell, 2015; Saria et al., 2018). Likewise, ML can be used as a new tool to tackle transportation mode choice modeling.

ML is the study of computer algorithms capable of improving their performance at a task-based on prior experience. ML has steadily gotten more mathematical and successful in applications (Mjolsness & Decoste, 2001). For engineering sectors, the major benefits of adopting ML are as follows: (1) enhanced innovation; (2) process optimization; (3) resource optimization; and (4) enhanced product quality (Cioffi et al., 2020).

### 3.3.2. Taxonomy

Figure 15 shows the multi-dimensional taxonomy of machine learning.

- The target of learning: ML can be classified into two categories: representation (learning new representations of data) and task (learning desired or predefined outputs).

- The timing of data availability: ML can be classified into two categories: batch learning (models that learn on the entire training data) and online learning (models that continuously learn new data).
Nature of learning feedback: ML can be classified into three types: supervised learning (regression and classification), unsupervised learning, and reinforcement learning.

- **Supervised learning**: Supervised learning aims at learning a mapping or unknown dependency between input and labeled output (Simeone, 2018). There are two types of supervised learning: (1) classification with the discrete outcomes and (2) regression with the continuous outcome (Ran & Hu, 2017).

- **Unsupervised learning**: Unsupervised learning attempts to detect the regularities in unlabeled inputs, such as clustering and dimensionality reduction. Unlike supervised learning, it does not involve predefined outcomes (Sidey-Gibbons & Sidey-Gibbons, 2019). For instance, clustering algorithms, such as the K-mean cluster and Gaussian Mixture model, attempt to find hidden patterns in the dataset and then classify instances into a certain number of clusters (Z. Huang, 1998; Na et al., 2010).

- **Reinforcement learning**: Reinforcement learning can be seen as a specific type of supervised learning. However, it attempts to predict the output of the system (e.g., policy), which is a sequence of actions. For instance, instead of being taught what to do, algorithms should discover which activities produce the best results.
3.3.3. Supervised Learning Algorithms

There are various supervised classification ML algorithms. This subsection briefly discusses the algorithms and the details are as follows.

3.3.3.1. Multiclass Logit Model

Multiclass Logit Model (MCL) is a family of Logit models that handles the multi-class classification problem. MCL deals with cases where the decision boundaries are linear functions of the input features. MCL applies regularization (e.g., ridge and lasso) to lower the risk of over-fitting (Sidey-Gibbons & Sidey-Gibbons, 2019). The C hyperparameter controls the amount of regularization. MCL usually serves as a baseline classifier in machine learning (Hagenauer & Helbich, 2017).
3.3.3.2. **Naïve Bayes**

Naïve Bayes (NB) is a probabilistic method based on Bayes’ theorem (McCallum & Nigam, 1998). As a baseline classifier for large data sets, NB works well. However, since NB assumes complete independence between all predictors, NB has a limitation when the model has highly correlated predictors due to a strict assumption (i.e., class conditional independence) (Singh et al., 2016; Zhao et al., 2020).

3.3.3.3. **Support Vector Machine**

Support Vector Machine (SVM) is inherently a complex binary classifier (Cortes & Vapnik, 1995). SVM finds a separating linear decision boundary called hyperplane (optimal decision surface) that maximizes the distance between data points of different classes. In other words, SVM finds the optimal hyperplane to maximize the distance between the hyperplane and instances and then achieve more confidence when classifying data points (X. Zhou et al., 2019). Some approaches to handling a multiclass classification problem in SVM include the one-against-one and one-against-rest approaches (Weston & Watkins, 1998). SVM can use kernels (e.g., linear, polynomial, sigmoid, and Gaussian). SVM can also use regularization parameters.
3.3.3.4. **Artificial Neural Network**

Artificial Neural Network (ANN) mimics the neuronal network structure of the brain to make decisions in a humanlike manner (Svozil et al., 1997). The complex structure allows researchers to handle strong assumptions of conventional techniques, such as normality, linearity, and class independence (Singh et al., 2016). ANN is composed of an input layer, hidden layers, and an output layer (Rojas, 2013). The input layer contains input features, and the output layer includes predicted values. The hidden layer includes a certain number of neurons attached to activation functions. The activation functions include linear, sigmoid, ReLU (rectified linear unit), and ELU (exponential linear unit). A Deep Neural Network refers to a network with many hidden layers.

3.3.3.5. **Decision Tree Model**

Decision Tree (DT) predicts a classification outcome by splitting training data based on the splitter for input features (Breiman et al., 2017). DT runs a sequential and hierarchical decision based on features. The recursive binary split is the most commonly used DT, which splits the training data to result in the most significant reduction in Gini impurity or entropy of the data. After splitting, two new child nodes are created. The same algorithm is applied until a stopping condition is set by hyperparameters. However, DT is susceptible to overfit; in other words, the number of instances in the child (leaf) nodes may become too
small, called the data fragmentation problem (Singh et al., 2016). Thus, growing and pruning the tree should be used.

3.3.3.6. **Ensemble Models**

Ensemble models (EM) have been proposed to address issues of DT, such as over-fitting and pruning (Ardabili et al., 2020). EM produces better-aggregated solutions that combine the decisions from multiple decision tree models to improve the prediction performance (Assi et al., 2019). EM usually includes bagging (also called bootstrap aggregating) and boosting. Bagging fits the same underlying algorithm to each bootstrapped copy of the original training data and then creates a final prediction by averaging the predictions from the different copies (Bi et al., 2019). Boosting trains multiple models with subsets of data in a sequential fashion. The algorithms of EM are Random Forest Model (RF), Gradient Boosting Decision Tree Model (GBoost), Ada Boosting Decision Tree Model (AdaBoost), Stochastic Gradient Boosting Decision Tree Model (SGBBoost), and Categories Boosting Decision Tree Model (CatBoost) Extreme Gradient Boosting Decision Tree Model (XGBoost).

3.3.4. **Strengths**

There are several advantages. The first advantage is for ML to create and discover a prediction algorithm that is more accurate in predicting performance than any other methodological technique now in use (Mohammed et al., 2016). Second, as
the name implies, machine learning (ML) is used to develop an algorithm that automatically learns and improves via experience, predicts future data, or does a variety of other activities (L. Zhou et al., 2017). After the optimal algorithm is effectively trained, it can continuously learn from and make predictions about new instances as they occur without human intervention (Sidey-Gibbons & Sidey-Gibbons, 2019; Khanzode, 2020). Third, researchers are not required to describe the linkages that need to be estimated in ML; instead, the algorithm can discover the correlations as a result of the process of building the model (van Cranenburgh et al., 2022). Fourth, ML can handle and discover high-dimensional problems and data (Wuest et al., 2016).

3.3.5. Application to Empirical Studies

In recent years, ML (supervised learning for classification) has become increasingly popular in travel mode choice modeling (Yan et al., 2020). Compared to empirical investigations with DCM, research that has used ML has remained somewhat limited in comparison. Furthermore, even fewer studies have used stated choice experiment data in conjunction with machine learning to investigate travel behavior in the age of autonomous vehicles, while the remaining studies have primarily used revealed preference data in conjunction with currently available transportation modes (Hillel et al., 2021). Previously conducted research has been divided into two generations: (1) first-generation research, which focuses solely on model comparison in terms of prediction accuracy, and (2)
second-generation research, which compares the prediction accuracy of algorithms while also providing Explainable AI, such as feature importance. The following subsections provide a thorough examination of the empirical application of the theory in the real world.

Mohammadian and Miller (2002) investigated the applicability of two modeling strategies, the nested logit model and the Artificial Neural Network, to transportation mode choice modeling by employing two different modeling techniques. They discovered that both models held great promise, with the ML method generating a greater prediction performance than the other. Zhang and Xie (2008) aimed to find a better model for fitting and testing outcomes by using commute-trip data obtained in San Francisco, California, with six different modes of transportation in six different locations. When comparing the Support Vector Machine to the Artificial Neural Network and the multinomial logit model, they concluded that the Support Vector Machine was the superior model for travel mode choice modeling due to its superior prediction performance and ease of implementation. Researchers discovered that fewer cases resulted in lesser accuracy when predicting the future. With the use of Support Vector Machines, Artificial Neural Networks, and the multinomial logit model, Omrani (2015) investigated travel mode selection in the city of Luxembourg (cars, public transportation, walking, and bicycling). Specifically, the Artificial Neural Network outperformed two other models in terms of prediction, according to the findings of the article. Using multinomial logit and Random Forest models,
Sekhar et al. (2016) investigated the mode choice behavior of commuters in Delhi, with the results published in 2016. The Random Forest Model (98.9 percent) performed significantly better than the econometrics model (77.3 percent). To estimate and predict household car ownership demand in Singapore, Paredes et al. (2017) used machine learning to conduct their research. A random forest ensemble model with the highest prediction accuracy (0.799) was the most accurate, whereas Extreme Gradient Boosting had a slightly lower prediction accuracy (0.798). A comparison between artificial neural networks and the multinominal logit model was conducted by Hussain et al. (2017) to determine the most optimal algorithm for forecasting transportation mode. A consistent finding with other studies was shown in the paper, which was that the prediction accuracy of the Artificial Neural Network (82.6 percent) was much higher than that of the econometrics model (72.6 percent). To provide practical recommendations on model selection for travel behavior analysis, Wang et al. (2021) compared 6,970 machine learning algorithms with the 2017 National Household Travel Survey (NHTS). Overall, they concluded that Artificial Neural Networks, ensemble models, and the Random Forest Model could serve as baseline algorithms for travel mode choice modeling, although the accuracy of the predictions varied widely among the methods. In particular, they discovered that ensemble models had the best predictive performance, despite the fact that they had a very high computation cost.
3.3.6. Interpretability of Machine Learning

3.3.6.1. Importance of Interpretability

Several factors contribute to the demand for accurate and interpretable models. First and foremost, Murdoch et al. (2019) suggested the PDR framework (predictive accuracy, descriptive accuracy, and relevancy) as a paradigm for statistical analysis. In addition to improved prediction performance, it is necessary to offer information about the model and data through so-called relevant and suitable interpretation (Knox, 2018). Users and audiences would be more likely to embrace and comprehend models if systems were more transparent and interpretable (Bibal & Frénay, 2016; Mercado et al., 2016; Miller, 2019; Poursabzi-Sangdeh et al., 2021) if systems were more transparent and interpretable. More importantly, it directly relates to the purpose of scientific investigation (Carvalho et al., 2019). Human curiosity, learning facilitation, finding meaning in the world, and integrating the model into our daily lives are all made possible by the interpretability of models. As a result, models with much enhanced predicted accuracy but with no interpretability may be meaningless (Dietvorst et al., 2014; Rudin, 2019).

3.3.6.2. Interpretability Issue

It has lately been a hot topic to discuss the issue of interpretability in machine learning research (Tomsett et al., 2018). The authors of Doshi-Velez and Kim (2017) asserted that one metric, such as prediction accuracy, is insufficient to
characterize the majority of real-world jobs. To put it another way, it is critical to understand why and how a specific forecast was formed because an accurate prediction only represents a portion of the original problem (Carvalho et al., 2019). Although machine learning offers many advantages (e.g., capturing complicated relationships, prediction accuracy), much of the research has concentrated on these advantages rather than the limitations of machine learning's inherent explanatory capacity (Karlaftis & Vlahogianni, 2011). As a result, academics have frequently blindly built black-box algorithms.

There are a variety of factors that contribute to this problem. First and foremost, many users (laypeople) have difficulties comprehending complicated machine learning algorithms, which is closely related to the usability issue of interpretability (L. Zhou et al., 2017). As illustrated in Figure 16, the higher accuracy of prediction does not necessarily imply greater interpretability than econometrics (Karlaftis & Vlahogianni, 2011; Silva et al., 2018; Molnar et al., 2020). Second, data science and social science have distinct viewpoints on the same problem (Carvalho et al., 2019). While the backward approach, which emphasizes forecast performance, dominates from a data science standpoint, the essential component of social science is the ability to derive insights from the data collected. A third reason for the necessity for interpretability is when there is a misalignment between the aims of ML and what users expect to gain from the experience (Lipton, 2018; Bhatt et al., 2020). In particular, machine learning research has concentrated on the engineers or inventors of machine learning
systems (Tomsett et al., 2018). In many circumstances, stakeholders or examiners, on the other hand, are looking for insights from algorithms.

![Image of scatter plot showing prediction accuracy and interpretability trade-off](image)

Figure 16 Prediction accuracy and interpretability trade-off (Source: Rudin, 2019, p.3)

3.3.6.3. **Interpretable Machine Learning: Explainable AI**

ML has been criticized due to the black-box modeling approach (Klaiber & von Haefen, 2019). To address the issue, discussion on Explainable AI (XAI) (also called interpretable machine learning) has recently attracted much attention (van Cranenburgh et al., 2022) because of its capability to offer behavioral insights (Zhao et al., 2020) that are understandable to humans (Doshi-Velez & Kim, 2017; Gilpin et al., 2018).

Recent studies have attempted to develop Explainable AI (XAI) techniques to handle the constraints of machine learning algorithms (Burkart & Huber, 2021). The first and straightforward approach is to employ auditable algorithms (also called white-box models), such as linear regression, logistic regression, and decision tree models, so that researchers can directly interpret the
effects of input features on the prediction. For example, they can trace and explore the decision rules in the learned structure of the decision tree model on how the model makes predictions (Freitas, 2014). Thus, the white-box algorithms are considered convenient and manageable instruments for meaningful interpretation and transparency as a trade-off for the limited predictive ability and convenience (Vovsha, 2021).

Additional advanced approaches include (1) global model-agnostic and (2) local model-agnostic approaches (Rodríguez-Pérez & Bajorath, 2020; Molnar, 2021). For the global model-agnostic methods, the impurity-based or permutation-based feature importance measure (Strobl et al., 2007) and partial dependence plots (Apley & Zhu, 2020) have been widely-used to describe the relationship between input features and output targets on a global level (Hagenauer & Helbich, 2017; Molnar et al., 2021). For instance, Partial dependence (PD), proposed by Friedman (1991), estimates the expected effects of a particular input feature on the outcome target after marginalizing the influences of other input features (Hastie et al., 2016; D. Lee et al., 2019; Molnar et al., 2021). PD plot visualizes PD with a line graph. The curve in the PD plot shows the average predicted effect of the input feature on the probability of a specific classification. In the line graph, the x-axis shows the values of the input features, and the y-axis shows the corresponding predicted probability of a particular classification. It is noted that only observed values of the input features should be
used, while the PD plot should leave out the prediction for other undefined values because they typically produce constant prediction (Krause, Perer, & Ng, 2016).

Additionally, the localized interpretation enables audiences to comprehend how a given instance is predicted (Krause, Perer, & Ng, 2016). The localized interpretation can be critical because it provides information that global interpretation cannot offer. For instance, it shows how the algorithm behaves on a case-by-case basis, how the essential features for given instances differ, and what impacts input features have on an instance (Krause, Perer, & Bertini, 2016). Several local model-agnostic methods explain individual predictions, such as SHapley Additive exPlanations (SHAP) values (Sundararajan & Najmi, 2020). In detail, a unified model explanation system, Shapley Additive exPlanations (SHAP), has been recently employed (Feng et al., 2021; D. Wang et al., 2022), which is capable of producing feature attributes for a single instance and allows further understanding of the prediction behavior of the algorithm (S. Lundberg & Lee, 2017). SHAP estimates the magnitude and direction in which a feature is responsible for a change in a particular model output (Rodríguez-Pérez & Bajorath, 2020; Ndichu et al., 2022). SHAP can produce several plots for direct interpretation (S. M. Lundberg et al., 2019). For instance, the local feature dependence plot describes the effect of a selected input feature on the prediction of every single instance, while the dependent plot shows the average or confidence intervals of the effect. Also, the local interaction plot decomposes the effect of an input feature into the main effect and interaction effect with another
input feature on the prediction. Moreover, the force plot shows the contribution of all input features to a single prediction.

3.3.7. The Application of Interpretable Machine Learning

Xie et al. (2003) studied transport mode choice behavior amongst single-occupied autos, carpool, transit, bicycle, and walking in San Francisco, California, using Decision Tree and Artificial Neural Network. They showed that the prediction performance of the Artificial Neural Network was the greatest (78.2%) compared to the Decision Tree and Multinomial Logit Model. Important input elements included journey duration, out-of-pocket expense, car ownership, and household income. Truong et al. (2021) evaluated travel decision behavior between vehicle, foot, bus, and cab in Hanoi, Vietnam using the Support Vector Machine. They first observed that the method had a prediction accuracy of 76.1%, which was greater than the multinomial logit model (72.9%). Also, the significant variables for the transportation mode choice were parking charges and household income. Assi et al. (2019) examined the resilience and convergence of algorithms, such as Artificial Neural Networks, Support Vector Machine, and ensemble models, using a trip survey of Saudi Arabian students. They observed that the prediction accuracy of the ensemble model (98.8 percent) was greater than other techniques. Also, trip time, household income, and educational attainment were the main input features in transport mode choice modeling. Hagenauer and Helbich (2017) studied mobility mode choice between walk, bike, public transit, and vehicle
using travel survey data between 2010 and 2012 in Netherland. They observed that Random Forest performed much better than other machine learning classifiers. The permutation-based variable importance results suggested that the most relevant feature was trip distance. Golshani et al. (2018) revealed that Artificial Neural Network (87.2 percent) was superior to DCM (63.9 percent) in terms of prediction accuracy. Regarding the interpretation of the black-box model, they concluded that trip duration, petrol price, transportation fair, and vehicle ownership were the main criteria to forecast an individual decision between auto, transit, walk, and bike. Also, there were non-linear correlations in the Artificial Neural Network method between the essential input features and the chance of choosing the output targets. Zhou et al. (2019) studied spatial and temporal traffic patterns of bike-sharing services and taxis in Chicago from 2014 to 2016. Regarding model performance, they observed that ensemble models enhanced predicted accuracy at a significant rate. For interpretation of the machine learning, they uncovered crucial elements predicting people’s decision to utilize bike-sharing services over the cab, such as the density of bike-sharing parking spaces, seasonal and weather conditions, and journey distance. Wang and Ross (2018) investigated the Delaware Valley 2012 regional household travel survey. They observed that an ensemble model, the Extreme Boosting Decision Tree Model, demonstrated greater prediction accuracy than the multinomial logit model. The variable relevance in the optimal algorithm revealed that journey time and distance were the top two critical input features to forecast transportation mode
choice between vehicle, bike, walk, and transit. Since the multinomial logit model has considerable explanatory power due to its interpretable parameter estimate findings, they included parameter estimation of the model. The results of the model suggested that trip variables (e.g., peak time), personal variables (e.g., household size and gender), and neighborhood characteristics (e.g., population density) were strongly linked with the mode choice. Bas et al. (2021) evaluated the adoption of electric vehicles by employing Support Vector Machines, Artificial Neural Networks, Gradient Boosting Decision Tree, and Random Forest Models. They observed that the difference in prediction accuracy of the models was minimal, whereas that of Support Vector Machine, Artificial Neural Networks, and Extremely Gradient Boosting Decision Tree were slightly greater than others. Residential location, intrinsic condition of the electronic cars (e.g., the type of engine and vehicle price), and attitudinal characteristics (e.g., pro attitude toward technology) were essential input aspects when classifying persons to adopt the sustainable automobile. Yan et al. (2020) evaluated a zone-to-zone (census tract in this study) demand for ride-sharing service, such as Uber and Lyft, in Chicago by employing Random Forest. They observed that the ensemble model outperformed the Poisson regression model in terms of prediction accuracy. The results of variable importance showed that the number of commuters in the census tract was the most significant input features and contributed roughly 30 percent to the predictive ability of the model. Also, the built environment features, such as employment density at the origin and
destination, were also key elements in rider-sharing service demand prediction. Ali et al. (2021) explored a classification problem to choose from private automobiles or public transit in Kuantan City, Malaysia. Similar to prior studies, the ML method, Artificial Neural Network, acquired a greater prediction accuracy than the DCM model. The results of feature importance suggested that trip features, such as wait time, walking distance, and journey time, were crucial.

3.4. **Comparison between the Two Approaches**

In the seminal study, Breiman (2001) stated that “there are two cultures in statistical modeling to reach conclusions from data. One assumes that a given stochastic data model generates the data. The other uses algorithmic models and treats the data mechanism as unknown (p. 199).” In a similar vein, transportation mode choice modeling has two objectives in studying the data: (1) to extract information about how nature relates the output variable to the input factors (i.e., interpretation) and (2) to forecast what the choices will be (i.e., prediction) (Vovsha, 2021). Accordingly, this subsection mainly discusses theoretical differences between DCM and ML, although the two methodologies have similarities, such as statistical approach and shared concepts. Table 1 depicts a brief overview of the similarities and differences.

3.4.1. **Discrete Choice Modeling**
DCM takes a knowledge-based modeling approach in that all parameters have interpretably meaning and capture the relationship between factors (Paredes et al., 2017; Ran & Hu, 2017). Specifically, its core premise links with behavioral theory (utility maximization theory), which can help formalize understanding of how decision-makers make choices. The utility maximization theory has been long acknowledged as a center of choice theory in micro-econometrics (Samuelson, 1948; Mcfadden, 2001). Due to the connection with the behavioral theory, the parameter estimations are not just regression coefficients but give a richer and more behavioral interpretation of the representative decision-making process of the population (McFadden, 1980; Wild & Pfannkuch, 1999; Mullainathan & Spiess, 2017). Additionally, the theoretical framework offers a solid basis for forecasting in new settings, such as policy interventions, because the theory-based model can capture the causal correlation between covariates and a decision choice (Brathwaite, 2018; Aboutaleb et al., 2021).

However, DCM has limitations because it follows strict statistical assumptions (e.g., IIA property and error distribution specification). Under certain circumstances, it may produce biased estimations and predictions (F. Wang & Ross, 2018). Moreover, the linear utility function cannot fully capture the non-linearity of attributes, despite the ability to handle the issue by introducing additional variables, such as polynomial and interaction terms (Bentz & Merunka, 2000).
3.4.2. Machine Learning

ML (also called the non-parametric method) has more flexible modeling structures (Xie et al., 2003), which allows the data to speak for itself. ML is generally built for a reliable and accurate prediction, and empirical studies have generally found that it can outperform DCM in predictive capability (Golshani et al., 2018). Also, ML can draw complicated relationships between input features and output targets, which DCM may not be able to identify (Xie et al., 2003). For instance, Artificial Neural Network can easily capture non-linear properties through additional units, such as hidden layers, without predetermined functional forms (Sayed & Razavi, 2000). Moreover, ML promises to handle multi-collinearity, outliers, noise data, and missing values more efficiently (Gupta & Lam, 1996).

However, while ML has been reaching a greater predictive performance with complexity, its internal logic and inner working systems are usually hidden in the black-box to the user, which raises the interpretability issue (Paredes et al., 2017; Carvalho et al., 2019; D. Lee et al., 2019). Additionally, the absence of a robust behavioral theory discourages researchers from establishing the validity of the behavioral interpretation of model parameters (Ran & Hu, 2017). Specifically, ML may not offer statistical interpretation easily, such as parameter estimation and marginal effects (Mohammadian & Miller, 2002). Furthermore, ML algorithms have historically emphasized causal inference more than classical statistical approaches (Bi et al., 2019; Murdoch et al., 2019). Lastly, ML usually
cannot capture the innate nested structures between similar transportation modes or correlate unobserved features between instances.

Table 1 Similarities and differences between discrete choice modeling and machine learning (Source: van Cranenburgh et al., 2021; Karlaftis & Vlahogianni, 2011; Bi et al., 2019; Aboutaleb et al., 2021)

<table>
<thead>
<tr>
<th>Similarity</th>
<th>Discrete Choice Modeling</th>
<th>Machine Learning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statistical theory</td>
<td>Grounded in statistical theory</td>
<td>Grounded in statistical theory</td>
</tr>
</tbody>
</table>

**Shared concepts**

- Alternative
- Binary logit function
- Multinomial logit function
- Efficient experiment design
- Estimation
- Observation
- Attribute, covariate
- Residuals
- Dimensionality
- Label
- Imbalanced data
- Output class
- Sigmoid function
- Softmax function
- Active learning
- Training and learning
- Instance
- Feature, input
- Errors
- Number of covariates
- Value of dependent variable
- Data set in which some categories have much less frequency than others

**Differences**

**Approaches**

- Parametric approach
- Theory-driven modeling
- Knowledge-based model
- Both parametric and non-parametric approach
- Data-driven modeling
- Black-box model

**Application**

- Classification problems
- Classification and regression problems

**Theoretical framework**

- Utility maximization theory
- None

**Aim or Philosophies**

- Formalizing understanding of how decision-makers make a choice
- Offering insights on the data and its relationship
- Unbiased parameter estimation
- Putting data at the center and identifying the best course of action
- Providing an efficient representation of the data in terms of accuracy and computation cost
Testing using the goodness of fit and residuals examination and predicting the phenomenon under study. Learning optimization via error minimization. Testing using new data, comparison with other algorithms.

<table>
<thead>
<tr>
<th>Strengths</th>
<th>Limitation</th>
<th>Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interpretability</td>
<td>Assumptions (e.g., IIA)</td>
<td>Multinomial logit model, nested logit model, mixed logit model</td>
</tr>
<tr>
<td>Prediction</td>
<td>Interpretability and explainability</td>
<td>Support vector machine, artificial neural network, decision tree, ensemble models (e.g., random forest model and gradient boosting decision tree model)</td>
</tr>
</tbody>
</table>

3.4.3. Empirical Comparative Studies

3.4.3.1. Predictability

The majority of previous literature comparing DCM to ML has primarily examined model performance (i.e., prediction accuracy), and they generally conclude that ML outperforms DCM (Xie et al., 2003; F. Wang & Ross, 2018; Golshani et al., 2018; Truong et al., 2021). For instance, Mohammadian and Miller (2002) observed that both models held great promise, with the ML (Artificial Neural Network) generating a greater prediction performance than DCM (Nested Logit Model). Zhang and Xie (2008) concluded that the Support Vector Machine was the superior travel mode choice modeling model. Omrani (2015) found that Artificial Neural Network outperformed two other models in terms of prediction.

In recent years, many studies have revealed that ensemble models, such as Random Forest and Gradient Boosting Models, produce the best prediction.
accuracy score. For example, Wang et al. (2021) compared 6,970 machine learning algorithms and found that ensemble models attained the best predictive performance. Moreover, Sekhar et al. (2016) findings indicated that Random Forest Model performed significantly better than the Multinomial Logit Model. Paredes et al. (2017) also discovered the superiority of the Random Forest Model when predicting.

3.4.3.2. Interpretability

A few recent studies have compared DCM and ML in terms of prediction accuracy and behavioral outcomes (Ali et al., 2021), and there has been no consensus on the interpretability benefits. For instance, Lee et al. (2018) compared the Multinomial Logit Model (MNL) and Artificial Neural Network (ANN) and conducted the sensitivity tests for automobile and transit costs on mode choices in addition to the prediction accuracy. They concluded that although MNL is commonly used to estimate coefficients to comprehend behavioral patterns, creating an appropriate logit model becomes more challenging when the modeled behaviors are complicated. Moreover, MNL is prone to unobserved biases and typically impracticable for detecting the complex relationships of explanatory variables. On the other hand, ANN can capture nonlinearity and biases in data, suggesting that ML can be promising for the future of transportation mode choice modeling.
However, Zhao et al. (2020) compared two DCM models (e.g., Mixed Logit Model) and seven ML algorithms (e.g., Random Forest Model). They found that Random Forest Model was the best-performing model. Regarding feature importance, DCM and ML produced broadly consistent results. Although ML captured non-linear relationships in marginal effects, they concluded that ML showed unreasonable outcomes and tradeoffs between higher prediction accuracy and behavioral insights. Vovsha (2021) found similar findings to Zhao et al. (2020) that DCM provided more sound elasticities and parameter estimation since DCM contains a strong microeconomic theory (i.e., utility maximization).
Chapter 4.  Transportation Mode Choice in the Era of Autonomous Vehicles: Results from the U.S. Nationwide Stated Choice Experiment

4.1.  Introduction

Consumers would be able to choose from various modes of transportation in the era of autonomous vehicles (AVs) for commute and non-commute trips. Specifically, a new generation of transportation options has emerged in the shape of shared mobility services, such as ride-hailing, car-sharing, and bike-sharing. Moreover, AVs would be made available to the general public as a matter of course (Fagnant & Kockelman, 2015). The supply-side innovations are expected to disrupt and transform travel behavior, creating a new paradigm of transportation mode choice behaviors that have not been observed before. Consequently, it is vital to explore and understand the reactions of customers to the choice patterns when all potential emerging transportation modes would be available. However, understanding customer reactions has remained relatively
limited; for instance, none of the studies has put AVs, shared mobility services, and currently available modes side-by-side in an experiment, even if they would likely co-exist.

Therefore, this study investigated the choice patterns of emerging modes in addition to existing modes for commute and non-commute trips using a mixed (random parameter) logit model with the U.S. nationwide stated choice experiments. This study contributes to expanding our understanding of future transportation mode choice behaviors and offers crucial underlying knowledge to help develop a more solid long-term transportation planning.

This paper is organized as follows. Section 2 reviews and synthesizes previous literature and finds research gaps. Section 3 describes the stated choice experiment survey data and methodological approaches. Section 4 presents and interprets the results of this study. Finally, sections 5 and 6 discuss notable findings and conclude this paper.

4.2. Literature Review

The literature review consists of four subsections: (1) the forecast of market shares, (2) factors influencing transportation mode choices, (3) marginal effects, and (4) methodological approaches and research design of previous literature.

4.2.1. Market Share Forecast
Given that full automation will be available by 2050 or sooner (Singleton, 2019), previous literature has explored the market share of AVs, and generally expected that AVs would account for half of the trips (J. Zmud et al., 2016; Litman, 2021). For instance, J’son & Partners Management Consulting (2017) forecasted that by 2030, the market share of AVs would be around 21 percent and 50 percent by 2035, respectively. Also, Liu et al. (2017) forecasted that the proportion of total trips using shared AVs (SAVs) would be 16.7 percent.

4.2.2. Factors Associated with Transportation Mode Choice

Previous research has emphasized factors influencing the adoption of PAVs and SAVs. A literature review by Becker and Axhausen (2017) categorized the factors into primarily four groups: (1) alternative-specific features (e.g., travel time), (2) socio-demographic characteristics (e.g., gender), (3) attitudinal factors (e.g., technology awareness), and (4) transportation-related features (e.g., driver’s license).

First, previous studies have explored alternative-specific features, such as travel time, and found that these are significant factors influencing the adoption of PAVs and SAVs (Webb et al., 2019; Lavieri & Bhat, 2019; Clayton et al., 2020). For instance, Stoiber et al. (2019) found that travel cost, time, and waiting time had substantial effects on the new mode of transportation chosen. Krueger et al. (2016) revealed that travel time, waiting time, and fares were important predictors...
of whether or not people would use SAVs. Furthermore, according to Philipsen et al. (2019), the exact pickup and arrival times were critical for SAV acceptance.

Second, a body of previous literature has examined the association between sociodemographic variables and the adoption of PAVs and SAVs, and concluded that the choice patterns would most likely differ across different population sub-groups (Krueger et al., 2016; J. Zmud et al., 2016; Hulse et al., 2018; Guo et al., 2021; Rahimi et al., 2020). For instance, Tan et al. (2020) found that young people, students, and employees of businesses and organizations were among those who were more likely to use AVs than other travelers. Similarly, Webb et al. (2019) suggested that personal attributes such as income, age, employment status, marital status, and the number of children impacted whether or not respondents would use SAVs in their homes.

Third, another body of literature has examined attitudinal factors (Haboucha et al., 2017; Shabanpour et al., 2017; Asgari & Jin, 2019; Lavieri & Bhat, 2019; Guo et al., 2021; S. Wang et al., 2020; Hossain & Fatmi, 2022), particularly in the context of technology acceptance theory (Davis et al., 1989). For instance, Acheampong and Cugurullo (2019) found that personal attitudes, such as public worries and anxieties, perceived AV usefulness, and attitude toward the environment were associated with the adoption of PAVs and SAVs. A qualitative analysis of Zmud et al. (2016) suggested that persons who expressed a greater degree of intention to adopt AVs were those who (1) had a favorable
opinion of them, (2) were not concerned about data privacy, and (3) had trustworthy people who valued utilizing AVs.

Fourth, regarding transportation-related features, Webb et al. (2019) discovered that car ownership had a significant and negative impact on whether or not SAVs were accepted. Finally, some other research highlighted the importance of individual modality styles: for example, Krueger et al. (2016) discovered that respondents with multimodal patterns had a higher proclivity to employ SAVs than those with monomodal patterns. Zmud et al. (2016) also discovered that people who had any physical impediments to driving had a higher intention to use AVs. Interestingly, Hossain and Fatmi (2022) found that the experiences with advanced vehicle technologies, such as parking assist and lane control, were significant factors to impact AV adoption.

4.2.3. Marginal Effects

A few studies have estimated marginal effects or elasticities to assess the influence of policy scenarios, particularly on the adoption of PAVs and SAVs. For example, Webb et al. (2019) conducted a sensitivity analysis on pricing and discovered that as the cost of travel per kilometer quadrupled, the likelihood of using SAVs increased by 3 percent, and the likelihood of choosing a conventional car decreased by 6 percent. Haboucha et al. (2017) recommended policies to encourage SAVs, including increased parking prices, decreased SAV costs, increased cost of a conventional cars, and education programs. Moreover,
Shabanpour et al. (2018) found the favorable influence of (1) raising driver culpability for AV accidents, (2) establishing special lanes for AVs, and (3) granting subsidies to cut the purchase price.

4.2.4. Methodological Approaches and Research Design

This subsection reviews previous literature that has used discrete choice modeling (DCM) with stated choice experiments. As shown in Table 2, a body of literature with DCM has engaged by using the multinomial logit model (Shabanpour et al., 2018; Webb et al., 2019; Tan et al., 2020; S. Wang et al., 2020), mixed logit model (Krueger et al., 2016; Shabanpour et al., 2017), and other choice models (Maeng & Cho, 2022). More importantly, the table indicates that the number of choices used in their stated choice experiments has ranged between four and six. Furthermore, the sample size has been relatively small (approximately 400 to 1,200). There have been two attempts to collect representative nationwide data.

Table 2 Summary of modeling and research designs used in selected previous studies

<table>
<thead>
<tr>
<th>R1</th>
<th>R2</th>
<th>R3</th>
<th>R4</th>
<th>R5</th>
<th>R6</th>
<th>R7</th>
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<tbody>
<tr>
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<tr>
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<td>MNL</td>
<td>MXL</td>
<td>MXL</td>
<td>NLK</td>
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<tr>
<td>Transportation Modes</td>
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<tr>
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<td>O</td>
<td>O</td>
<td>O</td>
<td>O</td>
<td>O</td>
</tr>
<tr>
<td>SAV</td>
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<td>O</td>
<td>O</td>
<td>O</td>
<td>O</td>
<td>O</td>
</tr>
<tr>
<td>CAR</td>
<td>O</td>
<td>O</td>
<td>O</td>
<td>O</td>
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<tr>
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<td>O</td>
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<td>O</td>
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<tr>
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### Results

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<th>O</th>
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<tbody>
<tr>
<td>Marginal effects</td>
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<td></td>
<td></td>
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<td></td>
<td>O</td>
<td>O</td>
</tr>
</tbody>
</table>

#### Research Design

<table>
<thead>
<tr>
<th>Sample size</th>
<th>1204</th>
<th>680</th>
<th>403</th>
<th>1253</th>
<th>435</th>
<th>657</th>
<th>1,000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Study area</td>
<td>Australia</td>
<td>The U.S.</td>
<td>China</td>
<td>The U.S.</td>
<td>Australia</td>
<td>Israel, Canada, U.S.</td>
<td>South Korea</td>
</tr>
<tr>
<td>Nationwide data</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

Models: multinomial logit model (MNL), mixed logit model (MXL), nested logit kernel model (NLK), multiple discrete-continuous extreme value model (MDCEV) Alternatives: private autonomous vehicle (PAV), shared autonomous vehicle (SAV), personal car (CAR), car-sharing service (CS), ride-hailing service (RH), bike-sharing service (BS), carpool (CP), public transportation (PT), and active transportation (AT) Research: R1: Webb et al. (2019), R2: Wang et al. (2020), R3: Tan et al. (2020), R4: Shabanpour et al. (2017), R5: Krueger et al. (2016), R6: Haboucha et al. (2017), R7: Maeng and Cho (2022)

### 4.2.5. Research Gaps and Contribution of this Study

The literature review above indicates several research gaps that this study aims to fill. First and foremost, no studies have attempted to explore a wide range of transportation modes available in the AV era in a research setting, although diverse modes will coexist and compete. It is a critical research gap since Ben-Akiva and Lerman (1985) proposed that transportation mode choice modeling should have a set of mutually exclusive and, more importantly, collectively exhaustive transportation modes. Second, only a few studies on emerging modes have looked at representative samples across the United States (J. P. Zmud &
Sener, 2017). Third, a few studies have explored commute and detailed non-commute trips in the era of AVs. Fourth, while most existing studies have concentrated their attention on statistical inference on the coefficients of interest, studies that have simulated the effects of policy scenarios through the use of marginal effect or elasticity estimation have remained limited. Fifth, the previous studies have had a somewhat small response size of stated choice experiments.

Therefore, this paper examined the data that (1) provides a comprehensive set of potentially available transportation modes to respondents in the stated choice experiment, (2) gathers geographical representative and relatively large samples across the U.S., (3) collects detailed information on respondents and trip attributes, (4) includes both commute and detailed non-commute trips. With the data, this research attempts to answer three questions: (1) what are the expected market shares of each transportation mode available in the era of AVs? (2) how are diverse factors in Table 5 associated with choosing the transportation modes? and (3) what are the estimated marginal effects?

4.3. Research Design

4.3.1. State Choice Experiment Survey Data

4.3.1.1. Overview

This study used stated choice (SC) experiment survey data collected in a project (L. Wang et al., 2018) funded by the National Institute for Transportation and Communities at Portland State University. This study employed the data set since
the SC research is appropriate for this research that investigates hypothetical circumstances (Rose & Bliemer, 2009; Gkartzonikas & Gkritza, 2019). However, the experiments can suffer from hypothetical bias in this study since respondents may have difficulties envisioning fully automated vehicles (Fifer et al., 2014). Nonetheless, the SC experiment is an appropriate research approach since it has the potential to explore transportation mode choice patterns when this technology is still in its infancy (Milakis et al., 2017).

4.3.1.2. Sampling Process

The sampling frame for the SC experiment was defined as all individuals with internet connection in the 50 most urbanized areas, such as San Francisco-Oakland, California, in the United States, based on population size. Participants in the poll were recruited with incentives using Amazon Mechanical Turk and the InfoUSA email distribution lists.

Table 3 shows the essential characteristics of the respondents. Overall, the survey data was generally representative in gender, household income, educational attainment, student status, job status, and race/ethnicity, although there was a discrepancy in age groups.

Table 3 Selected descriptive statistics on the respondents

<table>
<thead>
<tr>
<th>Categories</th>
<th>Data Study area</th>
<th>ACS Study area</th>
<th>The U.S.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>43.0%</td>
<td>49.0%</td>
<td>50.8%</td>
</tr>
<tr>
<td>Male</td>
<td>57.0%</td>
<td>51.0%</td>
<td>49.2%</td>
</tr>
<tr>
<td>Age</td>
<td>15-24</td>
<td>25-34</td>
<td>35-44</td>
</tr>
<tr>
<td>-----------</td>
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<td>-------</td>
<td>-------</td>
</tr>
<tr>
<td>12.3%</td>
<td>13.8%</td>
<td>13.5%</td>
<td>13.8%</td>
</tr>
<tr>
<td>13.8%</td>
<td>15.4%</td>
<td>13.1%</td>
<td>13.0%</td>
</tr>
<tr>
<td>13.5%</td>
<td>13.8%</td>
<td>12.6%</td>
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</tr>
<tr>
<td>52.3%</td>
<td>15.4%</td>
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</tr>
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<td>19.6%</td>
<td>13.1%</td>
<td>12.6%</td>
<td>13.2%</td>
</tr>
<tr>
<td>9.5%</td>
<td>13.0%</td>
<td>12.6%</td>
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</tr>
<tr>
<td>4.2%</td>
<td>12.0%</td>
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<td>12.8%</td>
</tr>
<tr>
<td>2.1%</td>
<td>14.0%</td>
<td>15.3%</td>
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</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Household Income</th>
<th>Less than 44,999</th>
<th>$45,000 - $99,999</th>
<th>More than $100,000</th>
</tr>
</thead>
<tbody>
<tr>
<td>36.4%</td>
<td>46.0%</td>
<td>17.6%</td>
<td></td>
</tr>
<tr>
<td>30.3%</td>
<td>40.5%</td>
<td>29.2%</td>
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<tr>
<td>33.1%</td>
<td>39.2%</td>
<td>27.7%</td>
<td></td>
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</table>

<table>
<thead>
<tr>
<th>Education Attainment</th>
<th>Less than College</th>
<th>Some College, no or associate degree</th>
<th>Bachelor’s degree</th>
<th>Graduate or professional degree</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.8%</td>
<td>28.6%</td>
<td>46.4%</td>
<td>17.1%</td>
<td></td>
</tr>
<tr>
<td>36.4%</td>
<td>28.3%</td>
<td>21.8%</td>
<td>13.6%</td>
<td></td>
</tr>
<tr>
<td>39.6%</td>
<td>28.9%</td>
<td>19.4%</td>
<td>12.0%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Student Status</th>
<th>Student</th>
<th>Non-student</th>
</tr>
</thead>
<tbody>
<tr>
<td>35.2%</td>
<td>26.9%</td>
<td>26.1%</td>
</tr>
<tr>
<td>64.8%</td>
<td>73.1%</td>
<td>73.9%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Employment Status</th>
<th>Employed</th>
<th>Unemployed</th>
</tr>
</thead>
<tbody>
<tr>
<td>73.6%</td>
<td>65.3%</td>
<td>63.1%</td>
</tr>
<tr>
<td>6.7%</td>
<td>3.8%</td>
<td>3.7%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Race/Ethnicity</th>
<th>Non-Hispanic White</th>
<th>Non-Hispanic Black</th>
<th>Asian</th>
<th>Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>64.4%</td>
<td>68.4%</td>
<td>13.3%</td>
<td>9.7%</td>
<td>12.6%</td>
</tr>
<tr>
<td>68.4%</td>
<td>14.1%</td>
<td>7.3%</td>
<td>7.3%</td>
<td>10.2%</td>
</tr>
<tr>
<td>72.7%</td>
<td>5.4%</td>
<td>5.4%</td>
<td>5.4%</td>
<td>9.3%</td>
</tr>
</tbody>
</table>

Note:
Survey: the stated choice experiment survey collected in 2018
ACS: American Community Survey 2014-2018 (5-year estimates) at the Zip code level. The study area of ACS examined 1,871 Zip codes from the 50 U.S. urbanized areas. The U.S. of ACS examined 33,122 Zip codes across the U.S.

### 4.3.1.3. Transportation Mode Choices

The SC experiment of this study took a single-alternative selection approach instead of rating/ranking/degree of preference of alternatives, which means that each respondent chose the most preferred alternative among a choice set. Each respondent received three different forms of transportation for each experiment (see Figure 17). It appeared reasonable to provide three alternatives to each respondent rather than all of the alternatives, as suggested by Caussade et al.
(2005), who found that the optimal number of alternatives to minimize error variance in the SC experiment was somewhere between three and four.

Figure 17 An example of a stated choice experiment (Source: Wang et al., 2018, p.26)

Furthermore, each respondent carried out five experiments, one for the commute and one for the non-commute trip, with ten experiments in total. Given the findings of Caussade et al. (2005), who discovered that ten choice circumstances resulted in the least detrimental influence on the validity of the experiment, the number of experiments administered to each respondent seemed to be appropriate.

Each experiment presents alternative-specific attributes associated with the assigned transportation mode (see Figure 17), including in-vehicle time, out-of-pocket cost, wait time, and walk time. Instead of setting all attributes levels at random, the experiment considered a combination of revealed trip characteristics and estimated attribute levels from previous studies or open-source data, such as the National Household Travel Survey (NHTS), to set the reasonable range of attributes.
4.3.1.4. Additional Data Collected in the Survey

The survey gathered extensive information on respondents. For instance, respondents answered questions on socio-demographic characteristics such as age, household income, gender, race/ethnicity, and employment status. Additionally, each respondent was asked a series of questions about their attitudes regarding technology, AVs, and alternative transportation modes. Regarding transportation-related characteristics, respondents shared information on driver's license, car and bike ownership, and barriers using current transportation modes.

4.3.2. Methodological Approach

4.3.2.1. Mixed (Random Parameter) Logit Model

This study employed the Mixed Logit (MXL) Model (also called Random Parameters Logit Model) with Halton of 500 draws using NLOGIT software for the following reasons. First, the discrete choice model based on the random utility maximization framework (McFadden, 1974) is appropriate to analyze the choice behaviors of respondents in the SC experiments and their association with variables. Second, since each respondent in our survey completed multiple-choice experiments, theoretically, the experiments completed by the same respondent are likely to share some characteristics that may be unobserved by the researcher. Thus, it suggests the need to account for unobserved heterogeneity (also called random heterogeneity) in the population of respondents (McFadden & Train,
MXL was suitable because it overcomes limitations of the closed-form Multinomial Logit Model and assumes that the random parameters follow a distribution whose parameters are to be estimated (Revelt & Train, 1998; Hensher & Greene, 2003). Lastly, since the maximum likelihood estimation of MXL is computationally expansive (Bhat, 2003; Milton et al., 2008; K. Train, 2000), the final model used Halton of 500 draws typically employed in previous literature. Additionally, this study searched for the best MXL specification with a forward stepwise approach adopted from the previous literature (Murray-Tuite et al., 2021). The final model kept only significant covariates in the utility functions in the Multinomial Logit Model and used the same set of covariates in the final MXL.

4.3.2.2. Probability Estimation Function

The structure of estimating probability in MXL model is shown below (Koppelman & Bhat, 2006; K. E. Train, 2009):

\[
P_{ni} = \int \left( \frac{\exp(\beta_i X_{i} + \varepsilon_{i})}{\sum_{i=1}^{t} \exp(\beta_{ni} X_{ni} + \varepsilon_{ni})} \right) f(\beta) d(\beta)
\]

Where \( P_{ni} \) is the probability that individual \( n \) chooses alternative \( i \), \( X_{ik} \) denotes a vector of observed variables to individual \( n \) chooses alternative \( i \), \( \beta_{ni} \) represents parameter estimation (coefficient) in the utility functions. \( f(\beta) \) indicates a density function of a normal distribution, which is the most common assumption for a random coefficient structure. Due to the density function, the
parameter estimation with the random coefficient has a normal distribution with
the mean and standard deviation.

Furthermore, the probability estimation requires further complicated
procedures due to the structures of SC experiments. Since all nine alternatives
were not shown to respondents in the experiments, the estimation proceeds on the
subset of alternates (three in this study). Thus, final probability estimation should
use a formula for the probability that the person chooses alternative $i$ conditional
on the subset $K$ for the person. The final probability estimation is described as
follows (K. E. Train, 2009):

$$
P_n(i|K) = \frac{P_n i q(K|i)}{\sum_{j \in F} P_n j q(K|j)}
$$

Where $P_n(i|K)$ denotes the conditional probability that the respondent
chooses alternative $i$ over a subset of alternatives $K$. $q(K|i)$ represents the
probability that the subset $K$ is selected given that the respondent chooses
alternative $i$. $q(K|i) = 0$ for any $K$ that does not include $i$ and $q(K|i) = 0$ for
any $j$, not in $K$. $F$ is the complete set of alternatives.

Due to the uniform conditioning property framed by McFadden (1977),
the probability of selecting alternative $i$ among subset of alternatives $K$ becomes
equal to that of selecting alternative $j$ among subset of alternatives $F$. However,
since researchers in the SC experiment did not assign an equal probability of
selection to all non-chosen alternatives, this property was not satisfied.
4.3.2.3. Marginal Effect Estimation

This study also estimated direct and cross marginal effects (also called derivatives) to simulate the effects of policy scenarios. It provides information on the impact of covariates (i.e., alternative-specific attributes) on the outcome probability of a given choice alternative (Murray-Tuite et al., 2021).

Direct marginal effects are estimated as in the equation below (Koppelman & Bhat, 2006; K. E. Train, 2009):

$$\frac{\partial P_{ni}}{\partial x_{ni}} = \beta_{ni} P_{ni} (1 - P_{ni})$$

Where $\frac{\partial P_{ni}}{\partial x_{ni}}$ is the marginal effect of a variable $x_{ni}$ on the probability of individual $n$ choosing alternative $i$.

Cross marginal effects are estimated as in the equation below:

$$\frac{\partial P_{nj}}{\partial x_{ni}} = -\beta_{ni} P_{ni} P_{nj}$$

Where $\frac{\partial P_{nj}}{\partial x_{ni}}$ is the cross marginal effect of a variable $x_{ni}$ on the probability of individual $n$ choosing alternative $j$.

4.3.2.4. Alternatives

This study had nine alternatives, such as private autonomous vehicles (PAVs) and shared autonomous vehicles (SAVs) (see Table 4). In detail, the SC experiment considered PAV and SAV distinctly, which was stated in the experiment and assigned to the respondents. HERE Technologies (2017) categorizes AVs into two types of transportation modes: (1) autonomous Car-as-a-Product (PAV and
(2) autonomous Car-as-a-Service (SAV). PAV means that each traveler uses the mode independently, as to how the conventional personal car operates. Similarly, but differently, SAV allows more than one rider to share a ride (Stoiber et al., 2019; Turoń & Kubik, 2020). SAVs have two types: (1) shared ownership and (2) shared use by combining not only ride-sharing services, carpools, or taxis but also car-sharing services with AVs (Krueger et al., 2016; Metz, 2018; Hyland & Mahmassani, 2020). 

Table 4 Final set of alternatives in the best fit Mixed Logit Model

<table>
<thead>
<tr>
<th>Alternatives</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private Autonomous vehicle (PAV)</td>
<td>Self-driving car</td>
</tr>
<tr>
<td>Shared autonomous vehicle (SAV)</td>
<td>Self-driving car with the unknown passenger</td>
</tr>
<tr>
<td>Ride-hailing service (RH)</td>
<td>Uber, Uber pool, Lyft, Lyft Line, and so on</td>
</tr>
<tr>
<td>Car-sharing service (CS)</td>
<td>Zipcar, Car2Go, and so on</td>
</tr>
<tr>
<td>Bike-sharing service (BS)</td>
<td>Biketown, and so on</td>
</tr>
<tr>
<td>Personal car (CAR)</td>
<td>Drive a personal car</td>
</tr>
<tr>
<td>Carpool (CP)</td>
<td>Carpool and vanpool</td>
</tr>
<tr>
<td>Public transportation (PT)</td>
<td>Transit, bus, and taxi</td>
</tr>
<tr>
<td>Active transportation (AT)</td>
<td>Walking and biking</td>
</tr>
</tbody>
</table>

4.3.2.5. Variable Used in the Mixed Logit Model

Table 5 shows the final set of variables used in this study. The variables consisted of five parts: (1) alternative-specific attributes, (2) trip purposes, (3) socio-demographic characteristics, (4) attitudinal factors, and (5) transportation-related features.

Regarding four attitudinal factors, this study conducted an explanatory factor analysis on twelve attitudinal questions to reduce the dimensionality and improve interpretability (see Table 6). The parallel analysis and scree plot of
eigenvalues suggest that the optimal number of components was four. The interpretation of the factor loadings also indicates that four factors better captured the underlying latent constructs. Thus, this study defined the four latent factors in Table 6.

Table 5: Descriptions and descriptive statistics on the variables used in the best fit Mixed Logit Model

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Description</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alternative-specific attributes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IV</td>
<td>In-vehicle time in minutes</td>
<td>11,118</td>
<td>15.90</td>
<td>15.51</td>
</tr>
<tr>
<td>Wait</td>
<td>Wait time in minutes</td>
<td>11,080</td>
<td>8.92</td>
<td>10.04</td>
</tr>
<tr>
<td>Walk</td>
<td>Walk time in minutes</td>
<td>11,220</td>
<td>4.17</td>
<td>9.97</td>
</tr>
<tr>
<td>Cost</td>
<td>Out of pocket cost in dollars</td>
<td>10,996</td>
<td>11.70</td>
<td>39.15</td>
</tr>
<tr>
<td>Trip purposes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commute</td>
<td>1 if the trip purpose is commute-trip, 0 otherwise</td>
<td>11,239</td>
<td>0.41</td>
<td>0.49</td>
</tr>
<tr>
<td>Shopping</td>
<td>1 if the trip purpose is for shopping or errands, 0 otherwise</td>
<td>11,239</td>
<td>0.37</td>
<td>0.48</td>
</tr>
<tr>
<td>Recreation</td>
<td>1 if the trip purpose is recreational or social, 0 otherwise</td>
<td>11,239</td>
<td>0.19</td>
<td>0.39</td>
</tr>
<tr>
<td>Meal-out</td>
<td>1 if the trip purpose is for eating a meal out, 0 otherwise</td>
<td>11,239</td>
<td>0.15</td>
<td>0.36</td>
</tr>
<tr>
<td>Medical</td>
<td>1 if the trip purpose is for medical or dental, 0 otherwise</td>
<td>11,239</td>
<td>0.10</td>
<td>0.30</td>
</tr>
<tr>
<td>Personal</td>
<td>1 if the trip purpose is for family and personal business or obligations, 0 otherwise</td>
<td>11,239</td>
<td>0.08</td>
<td>0.27</td>
</tr>
<tr>
<td>School</td>
<td>1 if the trip purpose is for going school or daycare, 0 otherwise</td>
<td>11,239</td>
<td>0.03</td>
<td>0.18</td>
</tr>
<tr>
<td>Socio-demographic characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>1 if the respondent is female, 0 otherwise</td>
<td>11,192</td>
<td>0.43</td>
<td>0.49</td>
</tr>
<tr>
<td>Age</td>
<td>The age of the respondent in 2018</td>
<td>11,192</td>
<td>34.12</td>
<td>10.45</td>
</tr>
<tr>
<td>White</td>
<td>1 if the respondent is non-Hispanic White, 0 otherwise</td>
<td>11,132</td>
<td>0.64</td>
<td>0.48</td>
</tr>
<tr>
<td>Rent</td>
<td>1 if the respondent rents current residential place, 0 otherwise</td>
<td>11,102</td>
<td>0.45</td>
<td>0.50</td>
</tr>
<tr>
<td>Low income</td>
<td>1 if the household income of the respondent is below $44,999, 0 otherwise</td>
<td>11,162</td>
<td>0.36</td>
<td>0.48</td>
</tr>
<tr>
<td>High income</td>
<td>1 if the household income of the respondent is above $100,000, 0 otherwise</td>
<td>11,162</td>
<td>0.18</td>
<td>0.38</td>
</tr>
<tr>
<td>Graduate</td>
<td>1 if the respondent has graduate or professional degree, 0 otherwise</td>
<td>11,192</td>
<td>0.17</td>
<td>0.38</td>
</tr>
<tr>
<td>College</td>
<td>1 if the respondent attains less than high-school, high-school diploma, or GED, 0 otherwise</td>
<td>11,192</td>
<td>0.08</td>
<td>0.27</td>
</tr>
<tr>
<td>Adult</td>
<td>The number of adults in the household of the respondent</td>
<td>11,032</td>
<td>2.17</td>
<td>1.06</td>
</tr>
<tr>
<td>Children</td>
<td>The number of children in the household of the respondent</td>
<td>11,022</td>
<td>0.72</td>
<td>1.05</td>
</tr>
</tbody>
</table>

### Attitudinal Factors

| Enjoy-Driver | Factor 1: Enjoy driving | 8,751 | -0.01 | 0.87 |
| Pro-Tech | Factor 2: Pro-attitude toward technology | 8,751 | 0.01 | 0.83 |
| Pro-AVs | Factor 3: Pro-attitude toward autonomous vehicles | 8,751 | -0.01 | 0.99 |
| Pro-Alt | Factor 4: Pro-attitude toward alternative transportation modes | 8,751 | -0.01 | 0.78 |

### Transportation-related features

| License | 1 if the respondent has a valid driver license, 0 otherwise | 11,192 | 0.93 | 0.26 |
| Car ownership | 1 if the respondent owns a car, 0 otherwise | 11,192 | 0.72 | 0.45 |
| Bike ownership | 1 if the respondent has a bike, 0 otherwise | 11,192 | 0.40 | 0.49 |
| Transit pass | 1 if the respondent has a transit pass, 0 otherwise | 11,192 | 0.31 | 0.46 |
| Parking pass | 1 if the respondent has a parking pass, 0 otherwise | 11,192 | 0.22 | 0.41 |
| Barriers | 1 if the respondent faces barriers to driving a car, taking public transportation, or walking, 0 otherwise | 11,126 | 0.21 | 0.41 |

Table 6 Factor loadings for attitudinal variables
<table>
<thead>
<tr>
<th>Question</th>
<th>Factor 1 (F1)</th>
<th>Factor 2 (F2)</th>
<th>Factor 3 (F3)</th>
<th>Factor 4 (F4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Do you agree that technology will provide solutions to many of our problems?</td>
<td>0.05</td>
<td>0.73</td>
<td>0.11</td>
<td>-0.04</td>
</tr>
<tr>
<td>Do you agree that it is important to keep up with the latest trends in technology?</td>
<td>0.09</td>
<td>0.65</td>
<td>0.07</td>
<td>0.07</td>
</tr>
<tr>
<td>Do you agree that new technology makes life more complicated?</td>
<td>0.09</td>
<td>-0.30</td>
<td>0.00</td>
<td>0.28</td>
</tr>
<tr>
<td>Do you agree that I am dependent on my technology?</td>
<td>0.10</td>
<td>0.45</td>
<td>0.10</td>
<td>0.05</td>
</tr>
<tr>
<td>Do you agree that I like walking?</td>
<td>-0.01</td>
<td>0.07</td>
<td>-0.02</td>
<td>0.61</td>
</tr>
<tr>
<td>Do you agree that I like riding a bike?</td>
<td>0.11</td>
<td>0.02</td>
<td>0.05</td>
<td>0.57</td>
</tr>
<tr>
<td>Do you agree that I like taking public transportation?</td>
<td>-0.11</td>
<td>-0.03</td>
<td>0.10</td>
<td>0.51</td>
</tr>
<tr>
<td>Do you agree that being a driver is an important part of who I am?</td>
<td>0.80</td>
<td>0.00</td>
<td>0.03</td>
<td>0.07</td>
</tr>
<tr>
<td>Do you agree that I like driving?</td>
<td>0.68</td>
<td>0.06</td>
<td>0.00</td>
<td>0.10</td>
</tr>
<tr>
<td>Do you agree that I need a car to do many of the things I like to do?</td>
<td>0.52</td>
<td>0.14</td>
<td>-0.01</td>
<td>-0.14</td>
</tr>
<tr>
<td>Has what you have seen or heard about AVs been mostly positive?</td>
<td>0.05</td>
<td>0.05</td>
<td>0.99</td>
<td>0.13</td>
</tr>
<tr>
<td>Has what you have seen or heard about AVs been mostly negative?</td>
<td>0.01</td>
<td>-0.14</td>
<td>-0.36</td>
<td>-0.02</td>
</tr>
</tbody>
</table>

Note:
Factor 1 (F1): Enjoy driving
Factor 2 (F2): Pro attitude toward technology
Factor 3 (F3): Pro attitude toward autonomous vehicles (AVs)
Factor 4 (F4): Pro attitude toward alternative transportation modes (ALTs)

4.4. Findings

This section is divided into three subsections, each of which corresponds to one of the three research questions addressed in this study: (1) market share summary in the era of autonomous vehicles (AVs) using descriptive statistics in Tables 7 and 8, (2) factors influencing transportation mode choice using mixed logit (MXL) model in Table 9, and (3) direct and cross marginal effect estimation based on the final MXL model in Table 10.
4.4.1. Market Share Summary

4.4.1.1. Market Shares of Available Transportation Modes

Table 7 shows that approximately 12.6% of respondents would use private AVs (PAV) and 11.6% would use shared AVs (SAV). Furthermore, this study found that roughly 50.1% of experiments chose the conventional personal car (CAR). Also, the introduction of AVs would not eliminate the need for conventional alternative transportation modes, such as carpool (CP), public transportation (PT), and active transportation (AT). Finally, the market shares of shared mobility services, such as ride-hailing (RH), car-sharing (CS), and bike-sharing (BS) services, were 5.8%, 3.5%, and 1.3%, respectively, in the experiments.

4.4.1.2. Market Shares by Trip Purposes

Table 7 displays market share forecasts broken down by trip purposes (e.g., commute) and indicates that there were significant differences, despite the less stark discrepancy in general. For instance, the predicted market shares of PAV and SAV increased if the trip purposes were recreational and social (P2 in the table) or family and personal businesses and obligations (P7), although the increase was marginal. In CAR, the travel demand declined by approximately 10% in trip purposes for recreation and personal businesses. CP was preferred for school trips (P7) but not for commutes (P1).

Table 7 Market shares in stated choice experiments by trip purpose

<table>
<thead>
<tr>
<th>Modes</th>
<th>Total</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
<th>P7</th>
</tr>
</thead>
</table>

98
## 4.4.1.3. Market Shares by Individual Characteristics

This study further broke out responses of stated choice experiments into several population groups based on individual characteristics, such as age, income, and gender (see Table 8). There were several notable findings. First, the elderly were significantly less likely to choose PAV (4.7%) and SAV (1.8%), while they show a significantly higher travel demand for CAR (70.6%) in the era of AVs. Second, students showed a slightly higher likelihood to adopt PAV (14.5%) and SAV (13.5%) as well as CS (5.3%) and RH (9.4%). Third, in the era of AVs, those who have barriers to currently available transportation modes showed a considerable...
difference in transportation mode choice; specifically, they were significantly more likely to adopt PAV (14.9%) and SAV (17.0%).

Table 8 Market shares in stated choice experiments by individual characteristics

<table>
<thead>
<tr>
<th>Modes</th>
<th>Total</th>
<th>G1</th>
<th>G2</th>
<th>G3</th>
<th>G4</th>
<th>G5</th>
<th>G6</th>
<th>G7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autonomous Vehicles</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PAV</td>
<td>12.6%</td>
<td>4.7%</td>
<td>13.7%</td>
<td>11.6%</td>
<td>9.2%</td>
<td>13.6%</td>
<td>14.5%</td>
<td>14.9%</td>
</tr>
<tr>
<td>SAV</td>
<td>11.6%</td>
<td>1.8%</td>
<td>13.1%</td>
<td>11.7%</td>
<td>11.0%</td>
<td>11.5%</td>
<td>13.5%</td>
<td>17.0%</td>
</tr>
<tr>
<td>Shared Mobility Services</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RH</td>
<td>5.8%</td>
<td>7.1%</td>
<td>7.0%</td>
<td>6.9%</td>
<td>11.8%</td>
<td>6.7%</td>
<td>9.4%</td>
<td>14.6%</td>
</tr>
<tr>
<td>CS</td>
<td>3.5%</td>
<td>2.4%</td>
<td>3.5%</td>
<td>3.5%</td>
<td>3.4%</td>
<td>3.8%</td>
<td>5.3%</td>
<td>7.6%</td>
</tr>
<tr>
<td>BS</td>
<td>1.3%</td>
<td>1.2%</td>
<td>1.6%</td>
<td>1.7%</td>
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<td>3.1%</td>
<td>1.3%</td>
<td>4.9%</td>
<td>2.2%</td>
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Groups:
G1: A population group of people who are more than 64 years old
G2: A population group of people who are people-of-color
G3: A population group of people who earn below $44,999 per year
G4: A population group of people who attain high school, a high-school diploma, or a GED
G5: A population group of people who are female
G6: A population group of people who are a full-time student
G7: A population group of people who have barriers to driving a car, taking public transportation, or walking

Transportation modes: private autonomous vehicle (PAV), shared autonomous vehicle (SAV), car-sharing (CS), ride-hailing (RH), bike-sharing (BS), personal car (CAR), carpool (CP), public transportation (PT), and active transportation (AT).

4.4.2. Factors Influencing Transportation Mode Choices

Table 9 shows the estimated coefficients in the best mixed logit (MXL) specification, including standard error, z-statistics, p-value, and model statistics.

Of the 68 variables, 11 variables were found to have heterogeneous effects across
respondents and estimated random parameters based on the statistical significance of the standard deviation. The McFadden R-squared of 0.714 suggests that the best fit MXL model showed a good fit.

4.4.2.1. Private Autonomous Vehicle

For the private autonomous vehicles (PAV) alternative, nine variables had statistically significant impacts on an individual’s probability of choosing the mode. Of the factors, two had heterogeneous effects across individuals. They had normally distributed random parameters based on the statistical significance of the standard deviation. Specifically, based on a normal distribution, 61.3% of individuals were more likely to choose AVs when respondents had a pro-technology attitude. The second factor with heterogeneous effects was related to out-of-pocket cost. With an estimated coefficient mean of -0.328 and a standard deviation of 0.201, only 5.1% of respondents were more likely to choose PAV if the cost increased. Regarding the fixed effects, interestingly, in-vehicle time was not a statistically significant predictor of choosing PAV, while it was found to be significant in the multinomial logit model. Female respondents were more likely to choose PAV. As expected, the log odds of choosing PAV increased by 0.258 if respondents had a positive attitude toward AVs. Also, respondents were more likely to choose PAV for recreational trips. As observed in the previous subsection, the direction of parameter estimates of age was negative.
4.4.2.2. **Shared Autonomous Vehicle**

For shared autonomous vehicles (SAV), seven factors were statistically significant in their utility function. Of the seven factors, two had random parameters. When out-of-pocket costs decreased, most respondents (95.5%) were more likely to choose SAV. Moreover, with an estimated parameter mean of -0.074 and a standard deviation of 0.085, 80.8% of them were likely to choose SAV if the wait time decreased. Additionally, respondents were more likely to choose SAV for commute trips. The parameter estimates of -0.026 for the age covariate suggest that older respondents were less likely to adopt the new technology.

4.4.2.3. **Ride-Hailing Services**

For ride-hailing services (RH), seven coefficients were statistically significant. For this alternative, there are two factors with an estimated random parameter. With an estimated parameter mean of -0.122 and a standard deviation of 0.117, 85.2% of respondents were more likely to choose RH if the in-vehicle time decreased. Also, 92.8% of them were more likely to choose RH if the out-of-pocket cost decreased. The results imply that people prefer to use RH for shorter and cheaper trips. Also, full-time students and those who have barriers to conventional transportation modes showed a higher probability of choosing RH.
4.4.2.4. Car-Sharing Services

The utility for choosing car-sharing services (CS), such as Zipcar, included four significant factors. First, for the in-vehicle time variable, with an estimated parameter mean of -0.108 and a standard deviation of 0.073, 93.1% of respondents were more likely to choose CS if the in-vehicle time decreased. Also, respondents who hold graduate or professional degrees were more likely to choose it.

4.4.2.5. Bike-Sharing Services

For bike-sharing services (BS), four factors were statistically significant in their utility function, with no factors showing heterogeneous effects across individuals. Specifically, if out-of-pocket costs increased, respondents were less likely to choose bike-sharing services. Also, non-Hispanic white showed a lower possibility to choose bike-sharing services. Also, as respondents got older, the possibility of choosing them decreased.

4.4.2.6. Conventional Personal Car

For conventional personal cars (CAR), trip-specific attributes, including in-vehicle time, out-of-pocket cost, and wait time, were negatively associated with choosing CAR. Specifically, 71.3% of respondents were more likely to choose CAR if the cost increased. Also, people who own a bike or people in the high-income group had a higher probability of choosing CAR.
4.4.2.7. **Carpool**

For carpool (CP), four factors were statistically significant in their utility functions, with one with random parameters. Specifically, a majority of respondents (77.8%) were more likely to choose CP if wait time decreased. Also, in-vehicle time was negatively associated with the probability of choosing CP. Interestingly, non-Hispanic whites showed a higher probability of choosing CP than people of color.

4.4.2.8. **Public Transportation**

Utility for choosing public transportation (PT), with an estimated parameter mean of -0.141 and a standard deviation of 0.159, 81.2% of respondents was likely to choose PT if walk time decreased. For those who enjoyed driving, PT was not an appealing transportation mode (parameter estimates of -0.692). Interestingly, if the trip purpose was for meal-out and recreation, the probability of choosing PT increased.

4.4.2.9. **Active Transportation**

Finally, for active transportation (AT), including walking and biking, if the respondent had a barrier to using conventional transportation modes, including a personal car, public transportation, and active transportation, the possibility of choosing AT significantly decreased (parameter estimates of -2.715). Also, those
who had a positive attitude toward alternative transportation modes showed a higher probability of choosing AT.

Table 9 Best Fit Mixed Logit Model (Random Parameter Logit Model) Specifications

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter estimates</th>
<th>Standard Error</th>
<th>Z-statistics</th>
<th>P-value</th>
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**Active Transportation (AT)**

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<td>Meal-out</td>
<td>-0.672**</td>
<td>0.313</td>
<td>-2.14</td>
<td>0.032</td>
</tr>
<tr>
<td>Recreation</td>
<td>1.018**</td>
<td>0.456</td>
<td>2.23</td>
<td>0.025</td>
</tr>
<tr>
<td>White</td>
<td>-0.626**</td>
<td>0.303</td>
<td>-2.07</td>
<td>0.038</td>
</tr>
<tr>
<td>Pro-Alt</td>
<td>0.947***</td>
<td>0.212</td>
<td>4.46</td>
<td>0.000</td>
</tr>
<tr>
<td>Enjoy-Driving</td>
<td>-0.466***</td>
<td>0.141</td>
<td>-3.29</td>
<td>0.001</td>
</tr>
<tr>
<td>Barriers</td>
<td>-2.715***</td>
<td>0.469</td>
<td>-5.79</td>
<td>0.000</td>
</tr>
<tr>
<td>Bike ownership</td>
<td>0.507*</td>
<td>0.278</td>
<td>1.82</td>
<td>0.068</td>
</tr>
</tbody>
</table>

**Model Statistics**

<table>
<thead>
<tr>
<th>Number of Observation</th>
<th>7,872</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log-likelihood function</td>
<td>-4,872.829</td>
</tr>
<tr>
<td>Restricted log likelihood</td>
<td>-17,015.307</td>
</tr>
<tr>
<td>McFadden Pseudo R-squared</td>
<td>0.714</td>
</tr>
</tbody>
</table>

### 4.4.3. Marginal Effect Estimations

This subsection simulates the consequences of potential policy scenarios primarily by changing four alternative-specific attributes: out-of-pocket cost (COST), in-vehicle time (IV), wait time (WAIT), and walk time (WALK). The analysis of marginal effects reveals the elasticity of the covariates by calculating the change in probability of given transportation modes corresponding to a one-unit increase in alternative-specific attributes while holding all other variables equal to their means.
4.4.3.1. Out-of-Pocket Cost

As shown in Table 10, a one-dollar increase in COST of PAV led to a decrease in the predicted probability of choosing PAV by 0.055. In terms of cross-marginal effects, due to the cost increase, the predicted probability of choosing CAR increased by 0.028, while that of choosing other modes increased by around 0.005. A one-dollar increase in COST of SAV resulted in a decrease in the predicted probability of choosing SAV by 0.044, while that of choosing a personal car increased by 0.022. However, a one-dollar increase in COST of using CAR led to a decrease of CAR by 0.028 and an increase in the predicted probability of PAV SAV, RH, and CS by 0.008, 0.010, 0.006, and 0.005, respectively.

4.4.3.2. In-Vehicle Time

A one-minute increase in IV for a PAV trip can be negligible (marginal effect of -0.001). However, a one-minute increase in IV of SAV led to the decrease in the predicted probability of choosing SAV by 0.009, while that of choosing CS, CAR, CP, and PT increased by 0.001, 0.005, 0.001, and 0.001, respectively. Whereas a one-minute increase in IV of RH caused the decrease in the predicted probability of choosing RH by 0.005, the increase of CS declined that of choosing CS by 0.018. The predicted probability of choosing CAR decreased by 0.040 for a one-minute increase in IV of CAR, and an increase in the predicted probability of choosing PAV, SAV, RH, and CS by 0.014, 0.017, 0.005, and 0.005, respectively.
4.4.3.3.   Wait Time

In contrast to IV, the marginal effects of WAIT were much more prominent in magnitude. Specifically, a one-minute increase in WAIT of PAV decreased the predicted probability of choosing PAV by 0.023 and increased that of choosing CAR by 0.013. Also, the increase in WAIT of SAV led to the decrease in the predicted probability of choosing SAV by 0.017 and an increase in that of choosing CAR by 0.007. Reversely, the predicted probability of choosing CAR decreased by 0.025 for a one-minute increase in WAIT of the mode.

4.4.3.4.   Walk Time

The direct marginal effects of WALK of CP, PT, and AT on each mode were -0.010, -0.012, and -0.004, respectively. The predicted average probability of choosing PAV and SAV increased by roughly 0.003 if the walk time of CP, PT, and AT increased by one minute.

Table 10 Selected marginal effect estimations

<table>
<thead>
<tr>
<th></th>
<th>PAV</th>
<th>SAV</th>
<th>RH</th>
<th>BS</th>
<th>CS</th>
<th>CAR</th>
<th>CP</th>
<th>PT</th>
<th>AT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Out-of-pocket cost (unit: dollar)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PAV</td>
<td>-0.055</td>
<td>0.000</td>
<td>0.008</td>
<td>0.002</td>
<td>0.005</td>
<td>0.028</td>
<td>0.004</td>
<td>0.007</td>
<td>0.002</td>
</tr>
<tr>
<td>SAV</td>
<td>0.000</td>
<td>-0.044</td>
<td>0.007</td>
<td>0.002</td>
<td>0.005</td>
<td>0.022</td>
<td>0.003</td>
<td>0.006</td>
<td>0.002</td>
</tr>
<tr>
<td>RH</td>
<td>0.005</td>
<td>0.005</td>
<td>-0.021</td>
<td>0.000</td>
<td>0.002</td>
<td>0.007</td>
<td>0.001</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td>BS</td>
<td>0.002</td>
<td>0.002</td>
<td>0.000</td>
<td>-0.007</td>
<td>0.000</td>
<td>0.002</td>
<td>0.000</td>
<td>0.001</td>
<td>0.000</td>
</tr>
<tr>
<td>CAR</td>
<td>0.008</td>
<td>0.010</td>
<td>0.006</td>
<td>0.001</td>
<td>0.005</td>
<td>-0.028</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>PAV</th>
<th>SAV</th>
<th>RH</th>
<th>BS</th>
<th>CS</th>
<th>CAR</th>
<th>CP</th>
<th>PT</th>
<th>AT</th>
</tr>
</thead>
<tbody>
<tr>
<td>In-vehicle time (unit: minute)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PAV</td>
<td>-0.001</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>SAV</td>
<td>0.000</td>
<td>-0.009</td>
<td>0.001</td>
<td>0.000</td>
<td>0.001</td>
<td>0.005</td>
<td>0.001</td>
<td>0.001</td>
<td>0.000</td>
</tr>
<tr>
<td>RH</td>
<td>0.002</td>
<td>0.002</td>
<td>-0.005</td>
<td>0.000</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000</td>
<td>0.001</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>CS</td>
<td>0.003</td>
<td>0.004</td>
<td>0.002</td>
<td>0.000</td>
<td>-0.018</td>
<td>0.006</td>
<td>0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>-------</td>
<td>------</td>
<td>--------</td>
<td>--------</td>
<td>--------</td>
<td>--------</td>
<td>---------</td>
<td>--------</td>
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</tr>
<tr>
<td>CAR</td>
<td>0.014</td>
<td>0.017</td>
<td>0.005</td>
<td>0.001</td>
<td>0.005</td>
<td>-0.040</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>CP</td>
<td>0.002</td>
<td>0.002</td>
<td>0.001</td>
<td>0.000</td>
<td>0.001</td>
<td>0.000</td>
<td>-0.005</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>AT</td>
<td>0.003</td>
<td>0.003</td>
<td>0.001</td>
<td>0.000</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>PAV</th>
<th>-0.023</th>
<th>0.000</th>
<th>0.002</th>
<th>0.001</th>
<th>0.002</th>
<th>0.013</th>
<th>0.002</th>
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<tbody>
<tr>
<td>SAV</td>
<td>0.000</td>
<td>-0.017</td>
<td>0.003</td>
<td>0.001</td>
<td>0.002</td>
<td>0.007</td>
<td>0.001</td>
<td>0.003</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td>CAR</td>
<td>0.010</td>
<td>0.010</td>
<td>0.003</td>
<td>0.001</td>
<td>0.003</td>
<td>-0.025</td>
<td>0.000</td>
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<td>0.000</td>
<td>0.000</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>CP</th>
<th>0.003</th>
<th>0.004</th>
<th>0.002</th>
<th>0.000</th>
<th>0.001</th>
<th>0.000</th>
<th>-0.010</th>
<th>0.000</th>
<th>0.000</th>
</tr>
</thead>
<tbody>
<tr>
<td>PT</td>
<td>0.004</td>
<td>0.004</td>
<td>0.002</td>
<td>0.000</td>
<td>0.002</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.012</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>AT</td>
<td>0.002</td>
<td>0.002</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.004</td>
</tr>
</tbody>
</table>

Note:
The effect of a one-unit change in each attribute (Out of pocket cost, in vehicle time, wait time, walk time) of the alternative in the row on the average probability change that individual would choose alternative at the aggregate level in the column choice.

Abbreviation: active transportation (AT), autonomous vehicle (AV), bike-sharing (BS), carpool (CP), car-sharing (CS), public transportation (PT), ride-hailing (RH), shared autonomous vehicle (SAV), and personal car (CAR).

4.5. Discussion

The market share forecast offers several notable implications. First, the predicted market shares of private and shared AVs in the stated choice experiments were within the range of previous literature. However, the estimation was relatively conservative than others in previous studies (Litman, 2021). Second, a conventional personal car would be still a dominant transportation mode in the AV era, suggesting the potential benefits that AVs may bring (Fagnant & Kockelman, 2015; Carrese et al., 2019), such as a significant reduction in car ownership, traffic volume, parking spaces, and traffic congestion, may be exaggerated. Third, given a certain proportion of people would still choose currently available alternative transportation modes, including shared mobility.
services, public transportation, and active transportation, planning efforts to effectively manage infrastructures for multimodal transportation and implement strategies to support them. Fourth, given that those who have barriers to currently available transportation modes showed a higher probability of adopting PAV and SAV than other groups, AVs may assist those excluded from the current automotive-dominant market in gaining access to destinations and expanding opportunities (Becker & Axhausen, 2017).

Furthermore, combined with parameter estimation and marginal effect estimates in the mixed logit model, this study provides additional implications. First, the fundamentals of transportation economics seem to hold for PAV and SAV, given the negative association between alternative-specific attributes and probability of choosing them. Second, people in the era of AVs would be responding primarily to financial incentives compared to other three factors, such as in-vehicle time, wait time, and walk time. Third, the decreased probability due to the increased alternative-specific attributes of PAV and SAV mainly led to the increase in the predicted probability of choosing CAR, suggesting that people in the era of AVs would prefer CAR if cost, in-vehicle time, and wait time of PAV and SAV would increase. However, the decreased probability due to the increased attributes of choosing other available transportation modes would spread out across others. Fourth, PAV and SAV users seem to be more cost-conscious than CAR drivers. In terms of direct out of pocket costs, it is interesting because for car trips, the marginal costs tend to be very low compared to other modes due to
the high fixed costs. Fifth, SAV users were slightly less cost-sensitive than PAV users. Moreover, PAV users had a lower value of time and were not as sensitive to increased in-vehicle travel because they could put time riding an AVs for other use. Sixth, there may be a strategy for future SAV operators to pick up passengers as soon as possible (shorter wait time), even the cost of a slightly longer detour for passengers already on board (longer in-vehicle time).

4.6. Conclusion

Consumers in the era of autonomous vehicles (AVs) would be able to choose from a variety of modes of transportation that would be highly likely to co-exist, including private AVs, conventional automobiles, and shared mobility services. The ongoing supply-side advancement in transportation modes may radically reshape travel behavior from the demand-side perspective (Singleton, 2019). The potential demand-side response needs to be studied to provide essential implications for the potential impacts of AVs to planners and policymakers and insights on who would use and how the market would react to these emerging modes.

Therefore, using the Mixed (Random Parameter) Logit Model with the U.S. nationwide stated choice experiments, this research addressed three questions: (1) what are the predicted market shares of each transportation mode available in the era of AVs? (2) what factors influence mode choices? and (3) what are the estimated marginal effects? This study contributes to offering
insights into future travel demand, influential factors in transportation mode choice behavior, and marginal effect estimations to help develop robust mid- to long-term transportation strategies that have been challenging due to the uncertainties surrounding consumer reactions.

There are limitations to this study. First, it is crucial to acknowledge the limitations of the stated choice experiment research design. One of the most significant constraints is that stated preferences may not be compatible with actual behavior (Holmes et al., 2017). Also, since the public may not be very knowledgeable about AVs at the time of the experiment, the results of this paper may alter when they will be well-aware (J. Zmud et al., 2016). Thus, there are inherent limitations of stated choice experiments, as the method may not provide accurate prediction, especially for technologies like AVs with which the public has no first-hand experience. Second, the SC experiments in this study did not include all transportation modes available in the era of AVs. For example, micro-mobility, including e-scooters, which emerged over the last few years, was nascent at the time of the data collection for this research. Electronic bikes were another neglect of this study framework. Third, the collected sample of the SC experiments may not fully represent the study area and the U.S., given the discrepancy in age between respondents and the actual population.
5.1. Introduction

The supply-side advancement in the transportation field has recently developed emerging transportation modes, including autonomous vehicles (AVs) and shared mobility services. They can potentially disrupt and redefine transportation mode choice behaviors (Singleton, 2019) since the new modes of transportation are emerging and becoming increasingly feasible alternatives to the existing modes of transportation. Although understanding and predicting mode choice behavior in the AV era has been challenging due to its uncertainty in nature, it is critical to have this type of information for transportation planning. For instance, understanding and anticipating traveler mode choice patterns are critical for appropriately implementing new transportation programs and strategies. Nonetheless, current transportation planning for the AV era has mostly depended
on speculative forecasts and expectations regarding travel demand that the emerging transportation modes will alter (Millard-Ball, 2018).

Therefore, the main objectives of this paper employing interpretable machine learning (ML) and the U.S. nationwide stated choice experiment survey data are to (1) develop an optimal ML algorithm to accurately predict transportation mode choice patterns in the era of AVs, (2) offer understanding of relative importance of various input features, such as in-vehicle time and gender, on the future choice behaviors, (3) gain insights on the non-linear relationship between the variables and choice probabilities. The findings will be transformed into essential information that the public and organizations can use, which holds true for the field of transportation planning and policy decision-making.

The remaining parts of this paper are organized into five parts. Section two reviews the literature and defines research gaps. Section three elaborates on the research approach, such as stated choice experiment survey data and methodology. Section four presents findings, and section five discusses them. The final section concludes this paper.

5.2. Literature Review

Since machine learning (ML) offers the potential to transform the domain of knowledge (H. Wang et al., 2009), it has become increasingly popular in the field of transportation mode choice modeling (Yan et al., 2020). Specifically, since ML is valuable in both practice and research for building models with better
predictability, it should serve as one of the baseline methodological approaches for transportation mode choice modeling (S. Wang et al., 2021).

In addition to improved prediction performance, it is necessary to provide information about the algorithm and data through interpretation (Knox, 2018) because end-users are more likely to embrace and comprehend models if systems are more transparent and interpretable (Bibal & Frénay, 2016; Mercado et al., 2016; Miller, 2019; Poursabzi-Sangdeh et al., 2021). Accordingly, the interpretability of ML models has drawn ever-growing attention in the research community (Tomsett et al., 2018).

Interpretable ML (also called explainable AI) (van Cranenburgh et al., 2022) aims to offer behavioral insights that are understandable to humans (Doshi-Velez & Kim, 2017; Gilpin et al., 2018; Zhao et al., 2020). However, few empirical studies in the transportation mode choice field (Hagenauer & Helbich, 2017; Golshani et al., 2018; Ali et al., 2021) have employed the interpretable ML. For instance, Wang and Ross (2018) investigated the Delaware Valley 2012 regional household travel survey. The feature importance in the algorithm revealed that travel time and distance were the top two critical input features. Also, Bas et al. (2021) evaluated the adoption of electric vehicles and found that residential location, intrinsic characteristics of the vehicles, and attitudinal factors were essential input features.

There are also a few attempts to investigate transportation mode choice behavior in the era of AVs using ML. Specifically, Ahmed (2021) analyzed
consumer intention to adopt AVs by only comparing algorithms regarding their prediction accuracy. Moreover, the Gradient Boosting Decision Tree algorithm developed by Lee et al. (2019) was used to predict and explain consumers' mode choice behavior while choosing between automobiles, private AVs, and shared AVs. This work employed the stated choice experiment distributed to car users in Israel and North America in 2014. They discovered that key input features were transportation costs, attitudinal factors, and travel time. Finally, partial dependence plots were used to depict non-linear relationships between inputs and the probability of selecting one mode among the three alternative options.

The literature review suggests several research gaps. First, despite the ongoing work on applying interpretable ML, many studies overly relied on black-box algorithms, although prediction accuracy is only one aspect of the original problem (Carvalho et al., 2019). Moreover, its application to transportation mode choice modeling, especially in the era of AVs, remains scarce. Second, not only is it necessary to gain knowledge about the adoption patterns of private and shared AVs, but it is also necessary to gain information about other available modes of transportation, such as conventional automobiles, shared mobility services, and public transit, that will still be available in the era of AVs. However, previous literature has not focused on the comprehensive transportation modes available in the proximate future. Third, a limited body of studies has examined the choice behavior using nationwide representative samples. Therefore, this study took a particular line of inquiry to understand the choice behavior involving eight
different modes of transportation using an interpretable ML approach with the U.S. nationwide stated choice experiments.

5.3. Research Design

5.3.1. Stated Choice Experiment Survey Data

This study used the stated choice (SC) experiment survey data collected in a project (L. Wang et al., 2018) funded by the National Institute for Transportation and Communities at Portland State University. The survey consisted of two parts: (1) SC experiments and (2) the survey questionnaires, including questions about respondents’ socio-demographic characteristics, their attitudes toward technology, and current travel pattern. The survey was disseminated through the Internet over two months in 2018. Each respondent was presented with ten experiments for the commute and non-commute trips with three alternatives (i.e., transportation modes) and their corresponding alternative-specific attributes (i.e., out-of-pocket cost, in-vehicle time, wait time, and walk time). Further details on the survey data can be found in the report (L. Wang et al., 2018).

5.3.2. Methodological Approach

This section describes the methodological approaches used in this study. The processes are implemented using libraries for the Python programming language, such as pandas, scikit-learn, tensorflow, and xgboost.
5.3.2.1. Output Target

The classifier algorithms had eight output classes (see Table 11): (1) private autonomous vehicles (PAV), (2) shared autonomous vehicles (SAV), (3) car-sharing (CS), (4) ride-hailing (RH), (5) personal car (CAR), (6) carpool (CP), (7) public transportation (PT), and (8) active transportation (AT). In further detail, one primary concern of the data-processing of the target classes is handling observations with a significantly small sample size, which may distort the outcomes in ML. Thus, this study incorporated walking, biking, and bike-sharing service in one category called AT. As a result, the valid number of complete experiments in the survey data was 7,872.

Table 11 Final set of alternatives used in the research

<table>
<thead>
<tr>
<th>Transportation Modes</th>
<th>Description</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private autonomous vehicle</td>
<td>Privately-owned self-driving car</td>
<td>988</td>
<td>12.6</td>
</tr>
<tr>
<td>Shared autonomous vehicle</td>
<td>Shared self-driving car with or without the passengers</td>
<td>912</td>
<td>11.6</td>
</tr>
<tr>
<td>Personal car</td>
<td>Drive a personal car</td>
<td>3,942</td>
<td>50.1</td>
</tr>
<tr>
<td>Ride-hailing service</td>
<td>Uber, Uber pool, Lyft, Lyft Line, and so on</td>
<td>457</td>
<td>5.8</td>
</tr>
<tr>
<td>Car-sharing service</td>
<td>Zipcar, Car2Go, and so on</td>
<td>272</td>
<td>3.5</td>
</tr>
<tr>
<td>Carpool</td>
<td>Carpool, vanpool, and get a ride</td>
<td>446</td>
<td>5.7</td>
</tr>
<tr>
<td>Public transportation</td>
<td>Transit, bus, and taxi</td>
<td>368</td>
<td>4.7</td>
</tr>
<tr>
<td>Active transportation</td>
<td>Walking, biking, and bike-sharing service</td>
<td>487</td>
<td>6.2</td>
</tr>
</tbody>
</table>

5.3.2.2. Input Features

Table 12 illustrates the 23 input features in five categories and their descriptive statistics. This study conducted an explanatory factor analysis to reduce the
dimensionality of 12 attitudinal questions collected in the survey into four factors, such as enjoy driving. The set of input features was used to train all classification ML algorithms.

Table 12 Descriptions of the variables used in the research

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Mean</th>
<th>S.D</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Alternative-Specific Attributes</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IV</td>
<td>In-vehicle time in minutes</td>
<td>14.61</td>
<td>14.36</td>
</tr>
<tr>
<td>WAIT</td>
<td>Wait time in minutes</td>
<td>8.74</td>
<td>9.82</td>
</tr>
<tr>
<td>WALK</td>
<td>Walk time in minutes</td>
<td>3.32</td>
<td>7.93</td>
</tr>
<tr>
<td>COST</td>
<td>Out of pocket cost in dollars</td>
<td>6.31</td>
<td>23.78</td>
</tr>
<tr>
<td><strong>Trip Purposes</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commute</td>
<td>1 if the trip purpose is commute-trip, 0 otherwise</td>
<td>0.41</td>
<td>0.49</td>
</tr>
<tr>
<td>Shopping</td>
<td>1 if the trip purpose is for shopping or errands, 0 otherwise</td>
<td>0.37</td>
<td>0.48</td>
</tr>
<tr>
<td>Recreation</td>
<td>1 if the trip purpose is recreational or social, 0 otherwise</td>
<td>0.17</td>
<td>0.37</td>
</tr>
<tr>
<td>Meal-out</td>
<td>1 if the trip purpose is for eating a meal out, 0 otherwise</td>
<td>0.16</td>
<td>0.36</td>
</tr>
<tr>
<td><strong>Socio-Demographic Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>1 if the respondent is female, 0 otherwise</td>
<td>0.42</td>
<td>0.49</td>
</tr>
<tr>
<td>Age</td>
<td>The age of the respondent in 2018</td>
<td>34.06</td>
<td>10.55</td>
</tr>
<tr>
<td>People-of-color</td>
<td>1 if the respondent is people-of-color, 0 otherwise</td>
<td>0.34</td>
<td>0.47</td>
</tr>
<tr>
<td>Low Income</td>
<td>1 if the household income of the respondent is below $44,999, 0 otherwise</td>
<td>0.36</td>
<td>0.48</td>
</tr>
<tr>
<td>Low Education</td>
<td>1 if the respondent attains high school, a high-school diploma, or GED, 0 otherwise</td>
<td>0.08</td>
<td>0.27</td>
</tr>
<tr>
<td>Student</td>
<td>1 if the respondent is a student, 0 otherwise</td>
<td>0.30</td>
<td>0.46</td>
</tr>
<tr>
<td>Rent</td>
<td>1 if the respondent rents a current residential place, 0 otherwise</td>
<td>0.47</td>
<td>0.50</td>
</tr>
<tr>
<td><strong>Attitudinal Factors</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Enjoy Driving</td>
<td>Factor 1 in factor analysis Questions: Do you agree that being a driver is an important part of who I am? Do you agree that I like driving? Do you agree that I need a car to do many of the things I like to do?</td>
<td>-0.01</td>
<td>0.87</td>
</tr>
</tbody>
</table>
Pro Attitude toward Tech
Factor 2 in factor analysis
Questions:
Do you agree that technology will provide solutions to many of our problems?
Do you agree that it is important to keep up with the latest trends in technology?
Do you agree that new technology makes life more complicated?
Do you agree that I am dependent on my technology?

Pro Attitude toward AVs
Factor 3 in factor analysis
Questions:
Has what you have seen or heard about AVs been mostly positive?
Has what you have seen or heard about AVs been mostly negative?

Pro Attitude toward ALTs
Factor 4 in factor analysis
Questions:
Do you agree that I like walking?
Do you agree that I like riding a bike?
Do you agree that I like taking public transportation?

Transportation-Related Features

<table>
<thead>
<tr>
<th>Feature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Driver’s License</td>
<td>1 if the respondent has a valid driver’s license, 0 otherwise</td>
</tr>
<tr>
<td>Car Ownership</td>
<td>1 if the respondent owns a car, 0 otherwise</td>
</tr>
<tr>
<td>Bike Ownership</td>
<td>1 if the respondent has a bike, 0 otherwise</td>
</tr>
<tr>
<td>Barriers</td>
<td>1 if the respondent faces barriers to driving a car, taking public transportation, or walking, 0 otherwise</td>
</tr>
</tbody>
</table>

5.3.2.3. Training and Test Data Split
This study used a stratified training-test data split, which preserves the exact proportions of instances in output target classes, given the highly unbalanced instances for each class (see Table 11). The training data used in this study comprised randomly selected 80% of the entire data, while the remaining 20% instances were then used as the test data.
5.3.2.4. **Classification Algorithm Selection**

This research trained twelve supervised ML classification algorithms, close to the complete list from previous studies that classify transportation mode choices. The twelve ML algorithms were multiclass logit model (MCL), naïve Bayes (NB), support vector machine (SVM), artificial neural network (ANN), decision tree (DT), random forest (RF), ada boosting decision tree (AdaBoost), logit boosting decision tree model (LogitBoost), gradient boosting decision tree (GBoost), stochastic gradient boosting decision tree (SGBoost), categories boosting decision tree (CatBoost), and extreme gradient boosting decision tree (XGBoost).

This subsection briefly illustrates the candidate ML algorithms. First, MCL is a family of Logit models that serve as a machine learning baseline classifier (Hagenauer & Helbich, 2017). MCL deals with the multi-class classification problem and cases where the decision boundaries are linear functions of the input features.

NB is a probabilistic method based on Bayes’ theorem (McCallum & Nigam, 1998). However, since NB assumes complete independence between all predictors, NB has a limitation when the model has highly correlated predictors due to a strict assumption (i.e., class conditional independence) (Singh et al., 2016; Zhao et al., 2020).

SVM is inherently a complex binary classifier (Cortes & Vapnik, 1995). SVM finds a separating linear decision boundary called hyperplane (optimal
decision surface) that maximizes the distance between data points of different classes (X. Zhou et al., 2019). Some approaches to handling a multiclass classification problem in SVM include the one-against-one and one-against-rest approaches (Weston & Watkins, 1998).

ANN mimics the neuronal network structure of the brain to make decisions in a human-like manner (Svozil et al., 1997). The complex structure allows researchers to handle strong assumptions of conventional techniques, such as normality, linearity, and class independence (Singh et al., 2016). ANN is composed of an input layer, hidden layers, and an output layer (Rojas, 2013).

DT predicts a classification outcome by splitting data based on a splitter for input features (Breiman et al., 2017). DT uses a sequential and hierarchical inquiry structure to make predictions based on feature values. However, DT is susceptible to overfit; in other words, the number of instances in the child (leaf) nodes may become too small, called the data fragmentation problem (Singh et al., 2016).

Ensemble models (EM) have been proposed to improve the prediction accuracy of simple predictors such as DT (Ardabili et al., 2020). EM techniques usually include bagging (also called bootstrap aggregating) and boosting (Assi et al., 2019). Bagging, such as RF, fits the same underlying algorithm to each bootstrapped copy of the original training data and then creates a final prediction by averaging the predictions from the different copies (Bi et al., 2019). Boosting trains multiple models with subsets of data in a sequential fashion. Boosting
algorithms include AdaBoost, LogitBoost, GBoost, SGBoost, CatBoost, and XGBoost.

5.3.2.5. **Hyperparameter Tuning**

Each ML algorithm has its own set of hyperparameters, such as the maximum number of splits in the DT model and the number of hidden layers or neurons in an ANN model (Hillel et al., 2021). Modelers should select them systematically through hyperparameter tuning, since the model performance is highly dependent on chosen hyperparameters (Jiménez et al., 2007). This study used the grid-search technique to find an appropriate set of hyperparameters to optimize the performance of different ML algorithms (Liashchynskyi & Liashchynskyi, 2019).

5.3.2.6. **Algorithm Validation and Comparison**

This study employed 10-fold cross-validation to evaluate the predictive capability of the twelve ML algorithms (Refaeilzadeh et al., 2016; Yan et al., 2020; Zhao et al., 2020). Regarding the performance measure, this study used a balanced accuracy score (García et al., 2009) and a micro F-1 score (Takahashi et al., 2021) due to the imbalance of the dataset. The two matrixes are appropriate for addressing the highly imbalanced distribution of the output classes (see Table 11) and avoiding inflated performance estimates on uneven class distributions (Mosley, 2013). Balanced accuracy \( BA \) can be formalized as (García et al., 2009):

\[
BA = \frac{TP + TN}{TP + TN + FP + FN}
\]
\[ BA = \frac{1}{2} \left( \frac{TP}{TP + FN} + \frac{TN}{TN + FP} \right) \]

The micro F-1 score \((miF)\), which is defined as the harmonic matrix of the micro precision and recall score, can be defined as (Takahashi et al., 2021):

\[ miF = 2 \left[ \frac{TP}{TP + FN} \times \frac{TP}{TP + FN} \right] \left/ \left( \frac{TP}{TP + FN} + \frac{TP}{TP + FN} \right) \right. \]

where \(TP\) denotes true positive in the confusion matrix, \(TN\) is true negative, \(FP\) is false positive, and \(FN\) is false negative.

5.3.2.7. **Optimal Algorithm Selection**

The Stochastic Gradient Boosting Decision Tree Model (SGBoost) was the optimal algorithm in this study (see Table 13). This subsection presents a more detailed explanation of SGBoost. Friedman (2002) proposed SGBoost; a hybrid supervised classification algorithm that takes advantage of bagging and boosting techniques to improve prediction accuracy (J. Zhou et al., 2016). The term "stochastic" means that a random percentage of training data points will be used for each iteration rather than using all of the data for training, resulting in improved performance (Nassif, 2016). A tree is constructed from the random subset of the dataset, with each iteration resulting in an incremental improvement in the model performance (Moisen et al., 2006; Chirici et al., 2013). The surrogate loss function of SGBoost can be expressed as (H. Ding et al., 2018; Shin, 2019):
\[
\psi(y_i, F_k(X)^k_i) = -\sum_{k=1}^{K} y_k \log [p_k(X)] \\
= -\sum_{k=1}^{K} y_k \log \left[ \frac{\exp (F_k(X))}{\sum_{k=1}^{K} \exp (F_k(X))} \right]
\]

where \( y_k = 1 \) (class = \( k \)) \( \in \{0,1\} \), \( X \) is the input features, and \( P_k \) denotes the estimated probability. Then, the following equation can be obtained:

\[
\bar{y}_i^k = -\left[ \frac{\partial \psi\{y_{ij}, F_j(x_i)\}^k_{j=1}}{\partial F_k(x_i)} \right]_{F_j(x) = F_{j,m-1}(x_i)}^k = y_i^k - p_k(x_i)
\]

where K-trees are induced, each of which predicts the corresponding current residuals \( \{y_i^k - p_k(x_i)\}^N_{i=1} \). This produces K-trees with L-terminal nodes at iteration \( m \), \( \{R_{k,lm}\} \). A separate line search is performed in each terminal node \( l \) of each tree \( k \), as shown in the following equation:

\[
Y_{klm} = \arg\min_{x_i \in Y_{klm}} \phi(y_i^k, F_{k,m-1}(x_i) + \gamma)
\]

where \( \phi_k = -\log [p_k(X)] \).

5.3.2.8. Interpreation of Machine Learning

This study employed two indicators to interpret the optimal ML algorithm: (1) permutation-based feature importance (PBFI) and (2) direct marginal effects.

First, this study calculated PBFI, which is the relative magnitude of the influence of input features on prediction performance (J. H. Friedman, 2001; Altmann et al., 2010; N. Huang et al., 2016). Unfortunately, PBFI did not offer crucial
information on statistical significance; specifically, although the variables with relatively small feature importance may be statistically insignificant, ML does not know the threshold for “small” in feature importance estimation (C. Ding et al., 2018; Jacobucci & Grimm, 2020; Yin et al., 2020). PBFI is a better metric than impurity-based feature importance (IBFI) since PBFI normalizes the biases of IBFI, such as the inflation of the values with many categories (Strobl et al., 2007). However, this study presented the findings of IBFI for comparison purposes.

PBFI (PBFI) is estimated following the equation below:

$$PBFI_j = s - \frac{1}{k} \sum_{k=1}^{K} s_{k,j}$$

where $PBFI_j$ represents PBFI for input feature $j$, and $s_{k,j}$ represents the score of the algorithm on a corrupted version of the data $D_{k,j}$ for repetition $k$.

Second, this study estimated the direct marginal effects of a particular input feature on the outcome target after marginalizing the influences of other input features. The marginal effect analysis helped understand the reaction mechanism of predicted probabilities due to the change in input features. The equation of direct marginal effects (ME) is as follows:

$$ME_k(Z_p) = p_k(Z_{-p}, Z_p + \Delta|\theta_k) - p_k(Z|\theta_k)$$

where $Z_p$ denotes feature $p$ of all input features $Z$, $Z_{-p}$ indicates all the features except $p$ of $Z$, $Z_p + \Delta$ is the change in $Z_p$ by constant $\Delta$, $\theta_k$ represents parameter vector for class $k$, $p_k(Z|\theta_k)$ is the average predicted probability for
class $k$ as a function of $X$ given $\theta_k$, and $p_k(Z_{-p},Z_{p+\Delta}|\theta_k)$ is aggregate-level average predicted probability for class $k$ due to the change in input feature $p$.

Additionally, this study conducted a hypothesis test (i.e., t-test) to examine if the averaged probability difference between $p_k(Z_{-p},Z_{p+\Delta}|\theta_k)$ and $p_k(Z|\theta_k)$ is statistically significant.

5.4. Findings

5.4.1. Model Performance

Table 13 indicates that the stochastic gradient boosting decision tree model (SGBoost) was the optimal ML algorithm in this study, given the balanced accuracy score of 0.849 and micro F-1 score of 0.894. Several advantages of SGBoost may explain the results. First, employing only a subset of the training data improves both the computing speed and the prediction accuracy while also avoiding over-fitting the data to the training data sets. Second, it is unnecessary to pre-select or transform predictor variables when using stochastic gradient boosting. Third, it is resistant to outliers because the steepest gradient method favors points close to their proper classification rather than points far from their correct categorization.

Additionally, the predictive accuracies of GBoost, SGBoost, CatBoost, and XGBoost were higher than other algorithms, and their differences in the two comparison matrixes were marginal. The result is consistent with previous
literature that ensemble models generally outperform other ML algorithms, including SVM and ANN, in transportation mode choice modeling.

Table 13 Prediction accuracy comparison between candidate algorithms

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Balanced Accuracy Score</th>
<th>Micro F-1 Score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev</td>
</tr>
<tr>
<td>MCL</td>
<td>0.362</td>
<td>0.023</td>
</tr>
<tr>
<td>NB</td>
<td>0.326</td>
<td>0.013</td>
</tr>
<tr>
<td>SVM</td>
<td>0.786</td>
<td>0.019</td>
</tr>
<tr>
<td>ANN</td>
<td>0.682</td>
<td>0.015</td>
</tr>
<tr>
<td>DT</td>
<td>0.273</td>
<td>0.012</td>
</tr>
<tr>
<td>RF</td>
<td>0.720</td>
<td>0.014</td>
</tr>
<tr>
<td>AdaBoost</td>
<td>0.415</td>
<td>0.015</td>
</tr>
<tr>
<td>LogitBoost</td>
<td>0.733</td>
<td>0.016</td>
</tr>
<tr>
<td>GBoost</td>
<td>0.836</td>
<td>0.013</td>
</tr>
<tr>
<td>SGBoost</td>
<td>0.849</td>
<td>0.016</td>
</tr>
<tr>
<td>CatBoost</td>
<td>0.822</td>
<td>0.015</td>
</tr>
<tr>
<td>XGBoost</td>
<td>0.841</td>
<td>0.017</td>
</tr>
</tbody>
</table>

Algorithms: Multiclass Logit Model (MCL), Naïve Bayes (NB), Support Vector Machine (SVM), Artificial Neural Network (ANN), Decision Tree Model (DT), Random Forest Model (RF), Ada Boosting Decision Tree Model (AdaBoost), Logit Boost Decision Tree Model (LogitBoost), Gradient Boosting Decision Tree Model (GBoost), Stochastic Gradient Boosting Decision Tree Model (SGBoost), Cat Gradient Boosting Decision Tree Model (CatBoost), and Extreme Gradient Boosting Decision Tree Model (XGBoost)

5.4.2. Feature Importance

Table 14 shows the permutation-based feature importance (PBFI) of SGBoost.

The table also presents impurity-based feature importance (IBFI) results for comparison purposes and indicates consistent results between PBFI and IBFI.

Table 14 reveals that in-vehicle time (IV), wait time (WAIT), walk time (WALK), and out-of-pocket cost (COST) were the input features of the outstandingly-high importance for the prediction of the transportation mode.
choice in the era of AVs. The four alternative-specific attributes account for nearly 66.2% of the importance that all independent variables have in the optimal algorithm. Interestingly, IV ranked at the 4th place with the importance of 6.6% in transportation mode choice in the AV era, which was considerably lower than the other three factors.

Furthermore, attitudinal factors, including enjoy driving, showed relatively higher ranks than others, which may support the arguments of technology acceptance theory (Davis et al., 1989; Venkatesh & Davis, 2000). Also, two input features found to be relatively crucial in transportation mode choice modeling included commute (2.6%) and driver’s license (1.7%). However, some socio-demographic characteristics, such as race/ethnicity, household income, and student status, considerably limited the choice behavior given their feature importance of 0.1%.

Table 14 Results of permutation-based feature importance

<table>
<thead>
<tr>
<th>Input Features</th>
<th>IBFI Mag (%)</th>
<th>PBTI Mag (%)</th>
<th>Std. Dev</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alternative-Specific Attributes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IV</td>
<td>6.6</td>
<td>9.0</td>
<td>0.008</td>
<td>4</td>
</tr>
<tr>
<td>WAIT</td>
<td>15.2</td>
<td>23.2</td>
<td>0.004</td>
<td>2</td>
</tr>
<tr>
<td>WALK</td>
<td>14.3</td>
<td>21.6</td>
<td>0.007</td>
<td>3</td>
</tr>
<tr>
<td>COST</td>
<td>30.1</td>
<td>28.5</td>
<td>0.004</td>
<td>1</td>
</tr>
<tr>
<td>Trip Purposes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commute</td>
<td>2.0</td>
<td>2.6</td>
<td>0.003</td>
<td>6</td>
</tr>
<tr>
<td>Shopping</td>
<td>0.5</td>
<td>0.0</td>
<td>0.001</td>
<td>23</td>
</tr>
<tr>
<td>Recreation</td>
<td>0.4</td>
<td>0.2</td>
<td>0.000</td>
<td>15</td>
</tr>
<tr>
<td>Meal-out</td>
<td>0.2</td>
<td>0.4</td>
<td>0.001</td>
<td>12</td>
</tr>
<tr>
<td>Socio-Demographic Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0.3</td>
<td>0.3</td>
<td>0.001</td>
<td>14</td>
</tr>
<tr>
<td>Age</td>
<td>2.9</td>
<td>0.6</td>
<td>0.002</td>
<td>11</td>
</tr>
<tr>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>--------</td>
<td>----</td>
</tr>
<tr>
<td>People-of-color</td>
<td>0.3</td>
<td>0.1</td>
<td>0.001</td>
<td>20</td>
</tr>
<tr>
<td>Low Income</td>
<td>0.3</td>
<td>0.1</td>
<td>0.000</td>
<td>20</td>
</tr>
<tr>
<td>Low Education</td>
<td>0.3</td>
<td>0.2</td>
<td>0.000</td>
<td>15</td>
</tr>
<tr>
<td>Student</td>
<td>0.2</td>
<td>0.1</td>
<td>0.001</td>
<td>20</td>
</tr>
<tr>
<td>Rent</td>
<td>0.5</td>
<td>0.2</td>
<td>0.001</td>
<td>15</td>
</tr>
<tr>
<td><strong>Attitudinal Factors</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Enjoy Driving</td>
<td>8.1</td>
<td>7.3</td>
<td>0.003</td>
<td>5</td>
</tr>
<tr>
<td>Pro Attitude toward Tech</td>
<td>3.8</td>
<td>1.7</td>
<td>0.002</td>
<td>8</td>
</tr>
<tr>
<td>Pro Attitude toward AVs</td>
<td>3.8</td>
<td>1.6</td>
<td>0.002</td>
<td>10</td>
</tr>
<tr>
<td>Pro Attitude toward ALTs</td>
<td>4.1</td>
<td>2.3</td>
<td>0.001</td>
<td>7</td>
</tr>
<tr>
<td><strong>Transportation-Related Features</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Driver’s License</td>
<td>1.6</td>
<td>1.7</td>
<td>0.002</td>
<td>8</td>
</tr>
<tr>
<td>Car Ownership</td>
<td>3.7</td>
<td>0.4</td>
<td>0.002</td>
<td>12</td>
</tr>
<tr>
<td>Bike Ownership</td>
<td>0.4</td>
<td>0.2</td>
<td>0.001</td>
<td>15</td>
</tr>
<tr>
<td>Barrier</td>
<td>0.6</td>
<td>0.2</td>
<td>0.001</td>
<td>15</td>
</tr>
</tbody>
</table>

Abbreviation: impurity-based feature importance (IBFI), permutation-based feature importance (PBFI), magnitude (Mag), and standard deviation (Std. Dev)

### 5.4.3. Direct Marginal Effect

This study presents selected findings of direct marginal effects of input features in Figures 18 to 24 that showed relatively higher importance for the prediction. The unit changes and their corresponding direct marginal effects on predicted probability are marked on the x-axis and y-axis. Moreover, the plots show the statistical significance of the t-test and polynomial trend lines for better visualization.

#### 5.4.3.1. Alternative-Specific Attributes

This subsection presents selected results of direct marginal effects of four alternative-specific attributes. Table 15 presents the average out-of-pocket cost in
dollars (COST), in-vehicle time in minutes (IV), wait time in minutes (WAIT), and walk time in minutes (WALK) of chosen transportation modes, which can help interpret the direct marginal effects.

Table 15 Average alternative-specific attributes of chosen transportation modes

<table>
<thead>
<tr>
<th></th>
<th>AV</th>
<th>SAV</th>
<th>RH</th>
<th>CS</th>
<th>CAR</th>
<th>CP</th>
<th>PT</th>
<th>AT</th>
</tr>
</thead>
<tbody>
<tr>
<td>COST</td>
<td>11.59</td>
<td>6.80</td>
<td>25.73</td>
<td>10.68</td>
<td>3.46</td>
<td>2.46</td>
<td>5.92</td>
<td>0.80</td>
</tr>
<tr>
<td>IV</td>
<td>17.86</td>
<td>18.39</td>
<td>18.19</td>
<td>21.52</td>
<td>12.30</td>
<td>6.64</td>
<td>21.68</td>
<td>14.30</td>
</tr>
<tr>
<td>WAIT</td>
<td>5.44</td>
<td>8.49</td>
<td>9.40</td>
<td>0.88</td>
<td>9.63</td>
<td>13.43</td>
<td>14.62</td>
<td>3.68</td>
</tr>
<tr>
<td>WALK</td>
<td>0.00</td>
<td>0.00</td>
<td>2.40</td>
<td>5.39</td>
<td>3.74</td>
<td>4.62</td>
<td>9.43</td>
<td>6.67</td>
</tr>
</tbody>
</table>

Abbreviations: out-of-pocket cost in dollars (COST), in-vehicle time in minutes (IV), wait time in minutes (WAIT), walk time in minutes (WALK), private autonomous vehicle (PAV), shared autonomous vehicle (SAV), car-sharing (CS), ride-hailing (RH), personal car (CAR), carpool (CP), public transportation (PT), and active transportation (AT).

First, the influence of change in COST on the predicted probability of a certain model showed a non-linear decrease, although the shapes of the slopes were different. For instance, the average predicted probabilities of choosing PAV significantly declined after increasing COST by 7 dollars (around 19 dollars on average), while the marginal increase in COST of PAV had no significant impact until 6 dollars increase (see Figure 18a). Figure 18b indicates that the increase in COST of SAV rapidly reduced the average predicted probabilities of choosing SAVs until the unit change reached 12 dollars (around 19 dollars). Following that, it became relatively stable with slight fluctuations. Figure 18c shows the downtrend of the predicted probability of choosing CAR due to the rise of its COST until around 12 dollars, despite wide fluctuations of the direct marginal effect estimations. In Figure 18d, a higher COST of PT resulted in a lower
estimated likelihood of selecting PT, particularly when the cost increased by more than 14 dollars.

Second, for the second critical input feature (WAIT) in Figure 19, a longer wait time for PAV resulted in a significant and sharp decrease in the average predicted probability of selecting PAV, especially between 5- and 10-minutes increase, but had little effect beyond that range (see Figure 19a). Figure 19b suggests the insignificant impacts between 1- and 15-minutes increases but a significant decline in the predicted probability of choosing SAV beyond the range. The magnitude and significance of the direct marginal effects suggest that those living in the era of AVs would be more susceptible to the change in WAIT associated with PAV than SAV. Also, the influence of WAIT on CS was significant (see Figure 19c), suggesting that individuals may not be tolerant of a slight increase in WAIT of CS. Moreover, Figure 19d reveals a negative and non-linear relationship between WAIT of CP and the predicted probability of choosing CP.

Third, the third influential element (WALK) showed a significant and negative impact on the predicted probability of choosing a certain transportation mode in the era of AVs. Figures 20a and 20b indicate that the average predicted probability of choosing PAV and SAV rapidly decreased if their associated WALK increased. The influence was pronounced, ranging between 1- and 5-minutes increase, while that became stable beyond the range. Figure 20c shows that a marginal increase in WALK of CAR insignificantly influenced the
predicted probability of choosing CAR. However, the impact became significant beyond 5 minutes increase, implying that people in the era of AVs would be willing to spend slightly more time walking to take CAR and exhibit a marginal change in their travel behavior.

Fourth, figure 21 depicts the direct marginal effects of IV. Notably, IV of PAV and SAV showed insignificant contribution to change predicted probability of choosing PAV and SAV, respectively (see Figures 21a and 21b). Interestingly, IV of SAV was positively associated with the predicted probability of choosing SAV, although its influences were found to be insignificant. In addition, IV of CAR was found to be significant and negative over specific ranges of unit changes (see Figure 21c).
Figure 18 Selected marginal effect estimation of out-of-pocket cost (unit: dollars)
Figure 19 Selected marginal effect estimation of wait time (unit: minutes)
Figure 20 Selected marginal effect estimation of walk time (unit: minutes)
Figure 21 Selected marginal effect estimation of in-vehicle time (unit: minutes)
5.4.3.2. Attitudinal Factors

This section presents direct marginal effect plots with three attitudinal factors that can offer implications, although their influences were statistically insignificant in t-tests. As expected, the relationship between positive attitude toward AVs and the predicted probability of choosing PAV and SAV was insignificant but positive (see Figure 22). Interestingly, the increase in positive attitude toward alternative transportation modes led to the increase in the predicted probability of choosing SAV, showing that individuals may currently perceive it as another form of alternative mode (see Figure 23). Moreover, as people enjoyed driving a car, the predicted probability of choosing PAV increased while choosing SAV decreased (see Figure 24).

Figure 22 Selected marginal effect estimation of pro-attitude toward AVs (unit: factor loading)
Figure 23 Selected marginal effect estimation of pro-attitude toward alternative transportation modes (ALTs) (unit: factor loading)

Figure 24 Selected marginal effect estimation of enjoy-driving (unit: factor loading)
5.5. Conclusion and Discussions

AVs have been on the horizon; specifically, automobile manufacturers have already provided semi-autonomous systems, and complete automation will be available in the near future (Thompson, 2016). Accordingly, governments have begun to support the newly emerging forms of transportation (Clark et al., 2016; Kim et al., 2022). Examples include publications from the United States Department of Transportation (USDOT) that set principles for preparing for the future of vehicle automation and basic implementation techniques for implementing those principles (National Highway Traffic Safety Administration, the United States, 2017; U.S. Department of Transportation, 2018).

However, although the technological advancement in the transportation mode would significantly disrupt and reshape travel behavior (Wiseman, 2018; Singleton, 2019), transportation planning efforts have depended on speculative predictions and expectations of travel demand that AVs will alter (Millard-Ball, 2018). As a result, developing robust mid- to long-term transportation strategies has been challenging due to the uncertainties surrounding consumer reactions and the magnitude of their overall impact on travel behavior.

Therefore, this study prioritized understanding and forecasting the demand for travel using reliable data and advanced modeling techniques that can produce accurate projections of travel behavior. Several notable findings in this study reinforce the conclusions of previous studies and add further understanding. First, the findings of permutation-based feature importance suggest that transportation
mode choice behavior in the era of AVs would be significantly influenced by the level of services of each transportation mode and individual attitudes toward driving, AVs, technology, and alternative transportation modes.

Furthermore, direct marginal effect estimations regarding the crucial factors reveal that the non-linear relationships indicate that the effects were generally noticeable within certain ranges across different transportation modes; specifically, many showed a threshold effect at a certain unit change. The findings imply that transportation planners who want to transform individual travel behavior need to consider them to develop planning frameworks. For instance, planners who may want to reduce automobile reliance in the era of AVs can use the findings to achieve the goal.

Moreover, in-vehicle time (IV) of AVs showed insignificant contribution to the predicted probability of choosing them. Since travel-based multi-tasking in PAVs would minimize values of travel time (Kockelman et al., 2017), changes in IV exerted insignificant effects when choosing the new modes of transportation. Also, IV of shared AVs was positively associated with the predicted probability of choosing SAVs, although its influences were insignificant. Since riders in PAVs alone may experience motion sickness and discomfort (Le Vine et al., 2015; Diels & Bos, 2016), individuals in SAVs would not only spend transition time and time out preparing for activities at their destination but also engage in more activity throughout the trips with other passengers including families and friends.
This study contributes to offering significant underlying knowledge to the decision-making process of transportation planning. The findings are intended to provide government policymakers with valuable insights into the dynamics of future travel demand, the influential factors, and the potentially effective strategies that will encourage more people to use a certain transportation mode in the era of AVs. Despite the valuable findings, this study acknowledged several limitations. First and foremost, the ML algorithm seems to work properly only with chosen alternatives (Xie et al., 2003; F. Wang & Ross, 2018; Zhao et al., 2020). However, dropping all the information on the non-chosen mode, especially regarding alternative-specific attributes, can be an issue since respondents chose travel mode accounting for relative differences in the attribute levels across alternatives in the experiments. Thus, future research is needed to develop a new customized ML algorithm to accommodate the non-chosen alternatives. Second, the stated choice experiments used in this study did not include all transportation modes available in the era of AVs, such as e-scooters and paratransit. Third, the public may not be very knowledgeable about AVs at the time of the experiment. Thus, the results of this paper may change when they are well aware.
Chapter 6. Machine Learning for Transportation Mode Choice Modeling: Limitations and Future Research Directions

6.1. Introduction

Discrete Choice Modeling (DCM) has been used to explore a decision maker’s transportation choice of one alternative from a finite set of alternatives over decades (Koppelman & Bhat, 2006). DCM has been the dominant method in transportation mode choice modeling research (F. Wang & Ross, 2018) for the following reasons. Its essential benefit is that its fundamental decision rule follows utility-based choice theory (also called utility maximization theory); in other words, an individual will choose an alternative j if the utility of the alternative j is more significant than other alternatives (Koppelman & Wen, 1998). Due to the connection with the crucial choice theory central in micro-econometrics (Samuelson, 1948; Mcfadden, 2001), the parameter estimations are
not just regression coefficients but give a richer behavioral interpretation of the representative decision-making process of the population (McFadden, 1980; Wild & Pfannkuch, 1999; Mullainathan & Spiess, 2017). More importantly, scholars have developed diverse methodological approaches to address a variety of limitations, including nested logit, mixed (random parameter) logit, and latent class choice models (Revelt & Train, 1998; McFadden & Train, 2000b; Wen & Koppelman, 2001; Greene & Hensher, 2003; Vij & Krueger, 2017). Accordingly, many empirical studies in transportation mode choice modeling have employed DCM (Blumenberg & Smart, 2010; Ermagun & Samimi, 2015; Fu, 2021; Dong et al., 2021). However, DCM has limitations because it follows strict statistical assumptions (e.g., IIA property and error distribution specification). Under certain circumstances, it may produce biased estimations and predictions (F. Wang & Ross, 2018).

In recent years, machine learning (ML) has shown significant potential to transform the domain in transportation mode choice modeling (Ran & Hu, 2017; Sidey-Gibbons & Sidey-Gibbons, 2019) for the following reasons. For instance, ML has more flexible modeling structures (Xie et al., 2003), which allows the data to speak for itself. ML is generally built for a reliable and accurate prediction (Golshani et al., 2018). Also, ML can draw complicated relationships between input features and output targets (Xie et al., 2003). Moreover, ML shows a promise to handle multicollinearity, outliers, noise data, and missing values more efficiently (Gupta & Lam, 1996). Additionally, after the optimal algorithm is
effectively trained, it can continuously learn from and make predictions about new instances as they occur without human intervention (Sidey-Gibbons & Sidey-Gibbons, 2019; Khanzode, 2020). Due to its strengths (L. Zhou et al., 2017; Simeone, 2018), empirical studies in the field of transportation mode choice modeling have increasingly used ML (Omrani, 2015; Hussain et al., 2017; Golshani et al., 2018; Yan et al., 2020; Truong et al., 2021).

However, while ML has been reaching a greater predictive performance with complexity, several limitations have been observed. For instance, its internal logic and inner working systems are usually hidden in the black-box to the user, which raises the interpretability issue (Paredes et al., 2017; Carvalho et al., 2019; D. Lee et al., 2019). As a result, recent studies have developed Explainable AI (XAI) techniques to handle the constraint of ML algorithms (Rodríguez-Pérez & Bajorath, 2020; Apley & Zhu, 2020; Sundararajan & Najmi, 2020; Burkart & Huber, 2021; Molnar et al., 2021). Also, empirical studies in transportation mode choice modeling have adopted XAI to offer understandable behavioral insights to humans, including transportation planners and scholars (Yan et al., 2020; Bas et al., 2021; Ali et al., 2021).

Furthermore, a limited body of research has explored the reasonableness of behavioral outcomes by comparing the results of ML and DCM. For instance, Lee et al. (2018) found that DCM is prone to unobserved biases and typically impracticable for detecting the complex relationships of explanatory variables. ML, however, is capable of capturing nonlinearity and biases in data, suggesting
that ML can be promising for the future of transportation mode choice modeling. However, Zhao et al. (2020) concluded that although ML captured non-linear relationships in marginal effects, ML showed unreasonable outcomes that imply tradeoffs between higher prediction accuracy and behavioral insights. Vovsha (2021) found similar findings that DCM offered sound elasticities and parameter estimation since DCM contains a strong microeconomic theory (i.e., utility maximization).

Despite the ongoing efforts to identify limitations and enhance ML algorithms, none of the studies have examined limitations on probability estimations of ML for transportation mode choice modeling. For instance, no studies have empirically explored how alternative-specific attributes of non-chosen alternatives, such as travel time and cost, play a role in the model performance of ML. Furthermore, a few studies have employed the ability of ML when connecting to stated choice experiment data since the remaining studies have used mainly revealed preference data (Hillel et al., 2021). Therefore, this study contributes to improving our understanding of the shortcomings of ML for transportation mode choice modeling, and suggesting future research directions for methodological improvements. This study conducted three experiments by comparing the model performance of ML to DCM since considerable efforts made in DCM to address its drawbacks can suggest vital insights into the limitations and future research directions of ML.
The remaining parts of this chapter are organized into four sections. Section two elaborates on data and methodological approaches. Section three presents the findings of this paper. Sections four and five discuss the findings, limitations of ML, and future research directions.

### 6.2. Methodological Approach

#### 6.2.1. Overview

This study attempts to identify limitations in machine learning (ML) by comparing it with discrete choice modeling (DCM). Figure 26 illustrates the research flow of this study. This section describes the first four steps regarding methodological approaches.

![Figure 25 Research flow](image)

#### 6.2.2. Step 1: Stated Choice Experiment Survey Data Collection

This study used the U.S. nationwide stated choice experiment survey data collected in a project supported by the National Institute for Transportation and Communities (L. Wang et al., 2018) for the following reasons.
First, one section of the survey consisted of stated choice (SC) experiments, while the other section comprised survey questionnaires, which questioned respondents' socio-demographic traits, their attitudes toward technology, and their current travel behaviors. Thus, the data enabled exploring the connection between ML and SC experiments. Second, the respondent was asked to choose one from a subset of alternatives (i.e., a set of three choices) corresponding to a mode with different qualities of alternative-specific attributes (e.g., out-of-pocket cost and in-vehicle time) shown in Figure 27. The choice experiment format offered an opportunity to explore the impact on model performance when considering alternative-specific attributes of chosen and non-chosen modes and a subset of alternatives from complete alternatives. Third, since each respondent was assigned ten experiments to complete, the data structure allowed for investigating the impact on model performance with the multiple-choice experiment (also called panel data) treatment. Additional detailed information can be found in Wang et al. (2018).
6.2.3. Step 2: Data Pre-Processing

6.2.3.1. Final Set of Variables

The final set of variables was 22 input characteristics used across all DCM models and ML algorithms (see Table 16). Specifically, alternative-specific attributes include in-vehicle time (IV), wait time (WAIT), and cost (COST). Moreover, regarding attitudinal factors, this study performed an explanatory factor analysis on twelve questions to reduce the dimensionality of the questions and improve interpretability through a simple structure. As shown in Table 17, this study defined the four latent factors: enjoy driving, pro-attitude toward technology, pro-attitude toward AVs, and pro-attitude toward alternative transportation.

Table 16 Descriptions of variables used in this study

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alternative-specific attributes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IV</td>
<td>In-vehicle time in minutes</td>
<td>7,872</td>
<td>14.61</td>
<td>14.36</td>
</tr>
<tr>
<td>WAIT</td>
<td>Wait time in minutes</td>
<td>7,872</td>
<td>8.74</td>
<td>9.82</td>
</tr>
<tr>
<td>COST</td>
<td>Out of pocket cost in dollars</td>
<td>7,872</td>
<td>6.31</td>
<td>23.78</td>
</tr>
<tr>
<td>Trip purposes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commute</td>
<td>1 if the trip purpose is commute-trip, 0 otherwise</td>
<td>7,872</td>
<td>0.41</td>
<td>0.49</td>
</tr>
<tr>
<td>Shopping</td>
<td>1 if the trip purpose is for shopping or errands, 0 otherwise</td>
<td>7,872</td>
<td>0.37</td>
<td>0.48</td>
</tr>
<tr>
<td>Recreation</td>
<td>1 if the trip purpose is recreational or social, 0 otherwise</td>
<td>7,872</td>
<td>0.17</td>
<td>0.37</td>
</tr>
<tr>
<td>Meal-out</td>
<td>1 if the trip purpose is for eating a meal out, 0 otherwise</td>
<td>7,872</td>
<td>0.16</td>
<td>0.36</td>
</tr>
<tr>
<td>Socio-demographic Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variable</td>
<td>Description</td>
<td>N</td>
<td>Factor 1</td>
<td>Factor 2</td>
</tr>
<tr>
<td>------------------------------</td>
<td>------------------------------------------------------------------------------</td>
<td>-----</td>
<td>-------------</td>
<td>-------------</td>
</tr>
<tr>
<td>Female</td>
<td>1 if the respondent is female, 0 otherwise</td>
<td>7,872</td>
<td>0.42</td>
<td>0.49</td>
</tr>
<tr>
<td>Age</td>
<td>The age of the respondent in 2018</td>
<td>7,872</td>
<td>34.06</td>
<td>10.55</td>
</tr>
<tr>
<td>People-of-color</td>
<td>1 if the respondent is people-of-color, 0 otherwise</td>
<td>7,872</td>
<td>0.34</td>
<td>0.47</td>
</tr>
<tr>
<td>Low income</td>
<td>1 if the household income of the respondent is below $44,999, 0 otherwise</td>
<td>7,872</td>
<td>0.36</td>
<td>0.48</td>
</tr>
<tr>
<td>Low education</td>
<td>1 if the respondent attains high school, a high-school diploma, or GED, 0</td>
<td>7,872</td>
<td>0.08</td>
<td>0.27</td>
</tr>
<tr>
<td>Student</td>
<td>1 if the respondent is a full-time student, 0 otherwise</td>
<td>7,872</td>
<td>0.30</td>
<td>0.46</td>
</tr>
<tr>
<td>Rent</td>
<td>1 if the respondent rents a current residential place, 0 otherwise</td>
<td>7,872</td>
<td>0.47</td>
<td>0.50</td>
</tr>
<tr>
<td>Enjoy driving</td>
<td>Factor 1 in factor analysis in Table 17</td>
<td>7,872</td>
<td>-0.01</td>
<td>0.87</td>
</tr>
<tr>
<td>Pro Attitude toward Tech</td>
<td>Factor 2 in factor analysis in Table 17</td>
<td>7,872</td>
<td>0.02</td>
<td>0.82</td>
</tr>
<tr>
<td>Pro Attitude toward AVs</td>
<td>Factor 3 in factor analysis in Table 17</td>
<td>7,872</td>
<td>-0.02</td>
<td>0.98</td>
</tr>
<tr>
<td>Pro Attitude toward ALTs</td>
<td>Factor 4 in factor analysis in Table 17</td>
<td>7,872</td>
<td>-0.02</td>
<td>0.77</td>
</tr>
<tr>
<td>Driver’s license</td>
<td>1 if the respondent has a valid driver’s license, 0 otherwise</td>
<td>7,872</td>
<td>0.93</td>
<td>0.24</td>
</tr>
<tr>
<td>Car ownership</td>
<td>1 if the respondent owns a car, 0 otherwise</td>
<td>7,872</td>
<td>0.77</td>
<td>0.41</td>
</tr>
<tr>
<td>Bike ownership</td>
<td>1 if the respondent has a bike, 0 otherwise</td>
<td>7,872</td>
<td>0.42</td>
<td>0.49</td>
</tr>
<tr>
<td>Barriers</td>
<td>1 if the respondent faces barriers to driving a car, taking public transportation, or walking, 0 otherwise</td>
<td>7,872</td>
<td>0.18</td>
<td>0.45</td>
</tr>
</tbody>
</table>

Table 17 Factor loadings in the explanatory factor analysis

<table>
<thead>
<tr>
<th>Questions</th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
<th>Factor 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1: Do you agree that technology will provide solutions to many of our problems?</td>
<td>0.05</td>
<td>0.73</td>
<td>0.11</td>
<td>-0.04</td>
</tr>
<tr>
<td>Q2: Do you agree that it is important to keep up with the latest trends in technology?</td>
<td>0.09</td>
<td>0.65</td>
<td>0.07</td>
<td>0.07</td>
</tr>
<tr>
<td>Q3: Do you agree that new technology makes life more complicated?</td>
<td>0.09</td>
<td>-0.30</td>
<td>0.00</td>
<td>0.28</td>
</tr>
<tr>
<td>Q4: Do you agree that I am dependent on my technology?</td>
<td>0.10</td>
<td>0.45</td>
<td>0.10</td>
<td>0.05</td>
</tr>
<tr>
<td>Q5: Do you agree that I like walking?</td>
<td>-0.01</td>
<td>0.07</td>
<td>-0.02</td>
<td>0.61</td>
</tr>
<tr>
<td>Q6: Do you agree that I like riding a bike?</td>
<td>0.11</td>
<td>0.02</td>
<td>0.05</td>
<td>0.57</td>
</tr>
<tr>
<td>Q7: Do you agree that I like taking public transportation?</td>
<td>-0.11</td>
<td>-0.03</td>
<td>0.10</td>
<td>0.51</td>
</tr>
<tr>
<td>Q8: Do you agree that being a driver is an important part of who I am?</td>
<td>0.80</td>
<td>0.00</td>
<td>0.03</td>
<td>0.07</td>
</tr>
<tr>
<td>Q9: Do you agree that I like driving?</td>
<td>0.68</td>
<td>0.06</td>
<td>0.00</td>
<td>0.10</td>
</tr>
<tr>
<td>Q10: Do you agree that I need a car to do many of the things I like to do?</td>
<td>0.52</td>
<td>0.14</td>
<td>-0.01</td>
<td>-0.14</td>
</tr>
<tr>
<td>Q11: Has what you have seen or heard about AVs been mostly positive?</td>
<td>0.05</td>
<td>0.05</td>
<td>0.99</td>
<td>0.13</td>
</tr>
<tr>
<td>Q12: Has what you have seen or heard about AVs been mostly negative?</td>
<td>0.01</td>
<td>-0.14</td>
<td>-0.36</td>
<td>-0.02</td>
</tr>
</tbody>
</table>

### 6.2.3.2. Final Set of Transportation Modes

Table 18 describes the final set of transportation modes in this research, including (1) private autonomous vehicle (PAV), (2) shared autonomous vehicle (SAV), (3) personal car (CAR), (4) ride-hailing service (RH), (5) car-sharing service (CS), (6) carpool (CP), (7) public transportation (PT), and (8) active transportation (AT).

Table 18 Final set of alternatives

<table>
<thead>
<tr>
<th>Modes</th>
<th>Description</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAV</td>
<td>Private autonomous vehicle (e.g., privately-owned self-driving car)</td>
<td>988</td>
<td>12.6</td>
</tr>
<tr>
<td>SAV</td>
<td>Shared autonomous vehicle (e.g., shared self-driving car with or without the passenger)</td>
<td>912</td>
<td>11.6</td>
</tr>
<tr>
<td>CAR</td>
<td>Personal car (e.g., drive a single-occupied vehicle)</td>
<td>3,942</td>
<td>50.1</td>
</tr>
<tr>
<td>RH</td>
<td>Ride-hailing service (e.g., Uber, Uber pool, and Lyft)</td>
<td>457</td>
<td>5.8</td>
</tr>
<tr>
<td>CS</td>
<td>Car-sharing service (e.g., Zipcar and Car2Go)</td>
<td>272</td>
<td>3.5</td>
</tr>
<tr>
<td>CP</td>
<td>Carpool (e.g., carpool and vanpool)</td>
<td>446</td>
<td>5.7</td>
</tr>
</tbody>
</table>
### 6.2.3.3. Further Details

Standardizing a data set is a common approach for many ML algorithms (D. Lee et al., 2018); specifically, continuous input features are normalized using scaling once the input features are selected. However, since non-normalized data is typically used to estimate the DCM model, this study did not normalize the input features.

Regarding missing data treatment, there are a few ways in ML: (1) elimination of incomplete instances (F. Wang & Ross, 2018; X. Zhou et al., 2019) and (2) imputation strategies, such as replacing missing data with the mean, mode, or median, and creating a predictive model to estimate the missing values (Bas et al., 2021). However, despite the advancement in the missing value treatment method in ML, the imputation approaches have not been typical DCM. Thus, this study discarded incomplete observations followed by previous literature (F. Wang & Ross, 2018; X. Zhou et al., 2019).

### 6.2.4. Step 3: Conditional and Full Model Development

#### 6.2.4.1. Conditional and Full Models

Using data from the SC experiment survey data, this study developed conditional 1 and 2 and full models for DCM and ML to uncover limitations in ML for
transportation mode choice modeling. Table 19 describes the differences between the models. Specifically, First, conditional model 1 did not consider any of the three aspects: alternative-specific attributes of both chosen and non-chosen alternatives and the subset of alternatives. However, conditional model 2 added alternative-specific attributes of only chosen alternatives to conditional model 1. Lastly, the full model considers all of the three aspects.

Table 19 Differences between conditional and full model specifications

<table>
<thead>
<tr>
<th>Considerations in models</th>
<th>Conditional model 1</th>
<th>Conditional model 2</th>
<th>Full model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alternative-specific attributes of chosen alternatives</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Alternative-specific attributes of non-chosen alternatives</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Treatment on a subset of alternatives</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

6.2.4.2. Candidate Models

Candidate models in this study included two DCM models and twelve ML algorithms. Table 20 briefly discusses each model. This research developed DCM models using NLOGIT software and ML algorithms using Python libraries, such as sklearn, tensorflow, catboost, and xgboost.

Table 20 Models developed in this study

<table>
<thead>
<tr>
<th>Models</th>
<th>Brief Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multinomial Logit Model</td>
<td>MNL is a widely-used discrete choice modeling (McFadden, 1974). It can explore why an individual uses a particular transportation mode from a set of modes under various factors (Stopher &amp; Mayburg, 1975). Its fundamental decision rule follows utility maximization theory; in other words, an individual will choose an alternative j if the utility of...</td>
</tr>
</tbody>
</table>
the alternative $j$ is more significant than other alternatives (Koppelman & Wen, 1998).

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mixed Logit Model</strong></td>
<td>MXL has been widely used due to its ability to relax strict assumptions (e.g., IIA property) of MNL and address random heterogeneity in panel data structures (McFadden &amp; Train, 2000a; K. E. Train, 2009).</td>
</tr>
<tr>
<td><strong>Machine Learning</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Multiclass Logit Model</strong></td>
<td>MCL deals with cases where the decision boundaries are linear functions of the input features. MCL usually serves as a baseline classifier in machine learning (Hagenaer &amp; Helbich, 2017).</td>
</tr>
<tr>
<td><strong>Naive Bayes</strong></td>
<td>NB is applied with conditional independence's &quot;naive&quot; assumption (McCallum &amp; Nigam, 1998). It is predicated on the assumption that the effect of a single feature in a class is independent of the effect of other features.</td>
</tr>
<tr>
<td><strong>Support Vector Machine</strong></td>
<td>SVM finds a separating linear decision boundary called hyperplane (optimal decision surface) that maximizes the distance between data points of different classes (Cortes &amp; Vapnik, 1995).</td>
</tr>
<tr>
<td><strong>Artificial Neural Network</strong></td>
<td>ANN mimics the neuronal network structure of the brain to make decisions in a human-like manner (Svozil et al., 1997). ANN is composed of an input layer, hidden layers, and an output layer (Rojas, 2013).</td>
</tr>
<tr>
<td><strong>Decision Tree Model</strong></td>
<td>DT is used to predict a classification outcome by splitting training data based on the splitter for input features (Breiman et al., 2017). DT runs a sequential and hierarchical decision based on features.</td>
</tr>
<tr>
<td><strong>Random Forest Model</strong></td>
<td>RF fits the same underlying algorithm to each bootstrapped copy of the original training data and then creates a final prediction by averaging the predictions from the different copies (Bi et al., 2019).</td>
</tr>
<tr>
<td><strong>Ada Boosting Decision Tree Model</strong></td>
<td>Boosting trains multiple models with subsets of data in a sequential fashion. AdaBoost begins by assigning equal initial weights to all training data for weak learning training and then adjusts the weight distribution based on the results of the prediction (Azmi &amp; Baliga, 2020).</td>
</tr>
<tr>
<td><strong>Logit Boost Decision Tree Model</strong></td>
<td>LogitBoost is an algorithm that fits a generalized additive model. It is similar to AdaBoost but applies a logistic loss function, while AdaBoost minimizes the exponential loss function (Sun et al., 2014).</td>
</tr>
<tr>
<td><strong>Gradient Boosting Decision Tree Model</strong></td>
<td>GBoost is a decision tree approach that is iterative. Its weak learners have strong dependencies between one another and are trained through progressive iterations based on the residuals. The ultimate result is calculated by adding up the results of all weak learners (T. Zhang et al., 2021).</td>
</tr>
<tr>
<td><strong>Stochastic Gradient</strong></td>
<td>SGBoost is a hybrid algorithm that takes advantage of bagging and boosting techniques to improve prediction accuracy (J. Zhou et al., 2017).</td>
</tr>
</tbody>
</table>
Boosting Decision Tree Model

2016). Using the term "stochastic" means that a random percentage of training data points will be used for each iteration rather than using all of the data for training (Nassif, 2016).

Cat Gradient Boosting Decision Tree Model

CatBoost introduces modified target-based statistics that allow for the utilization of the entire data set for training while avoiding the possibility of overfitting by performing random permutations (T. Wu et al., 2020).

Extreme Gradient Boosting Decision Tree Model

XGBoost is an upgraded version of the GBoost. It gets the residual by using second-order Taylor expansion on the cost function and incorporates a regularization term to regulate the complexity of the model simultaneously (T. Wu et al., 2020).

### 6.2.5. Step 4: Three Experiments

#### 6.2.5.1. Three Experiments

This study conducted three experiments. Table 21 lists DCM and ML models for each experiment.

**Table 21 Models developed in three experiments**

<table>
<thead>
<tr>
<th></th>
<th>Experiment 1</th>
<th>Experiment 2</th>
<th>Experiment 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>DCM Models</strong></td>
<td>CM1 of MNL</td>
<td>CM2 of MNL</td>
<td>CM2 of MNL</td>
</tr>
<tr>
<td></td>
<td>CM2 of MNL</td>
<td>CM2 of MXL</td>
<td>CM2 of MXL</td>
</tr>
<tr>
<td></td>
<td>Full of MNL</td>
<td>Full of MXL</td>
<td></td>
</tr>
<tr>
<td><strong>ML Models</strong></td>
<td>CM1 of MCL</td>
<td>CM2 of MCL</td>
<td>CM2 of MCL</td>
</tr>
<tr>
<td></td>
<td>CM2 of MCL</td>
<td></td>
<td>CM2 of NB</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CM2 of SVM</td>
<td>CM2 of MCL</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>CM2 of ANN</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>CM2 of DT</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>CM2 of RF</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>CM2 of AdaBoost</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>CM2 of LogitBoost</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>CM2 of GBoost</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>CM2 of SGBost</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>CM2 of CatBoost</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>CM2 of XGBoost</td>
</tr>
</tbody>
</table>
6.2.5.2. Comparison Matrix

This study used micro F-1 score and pseudo-R-squared for the model performance of the models in the three experiments. First, this study used an ML-driven way, the micro F-1 score with 10-fold cross-validation that has been widely used in the ML research community (Refaeilzadeh et al., 2016; Yan et al., 2020; Zhao et al., 2020). Micro F-1 score is appropriate due to the highly imbalanced distribution of the output classes shown in Table 18 (Takahashi et al., 2021). The equation of micro F-1 score \((miF1)\) in 10-fold cross-validation is as follows:

\[
miF = 2\left(\frac{TP}{TP + FP} \times \frac{TP}{TP + FN} / \frac{TP}{TP + FP} + \frac{TP}{TP + FN}\right)
\]

Where \(TP\) denotes true positive in the confusion matrix, \(TN\) is true negative, \(FP\) is false positive, and \(FN\) is false negative.

Furthermore, this study employed a DCM-driven way, pseudo-R-squared (Koppelman & Bhat, 2006; K. E. Train, 2009). The matrix \((Pseudo R^2)\) can be formalized as:

\[
Pseudo R^2 = 1 - \frac{LL_{model}}{LL_0}
\]

\[
LL = \sum_T \sum_f \sigma_{jt} \times ln(P_{jt})
\]
Where $LL_{model}$ denotes Log-likelihood of the estimated model and $LL_0$ is log-likelihood of the null (restricted) model when all the parameters are set equal to zero. $\sigma_{jt}$ denotes chosen indicator (1 if alternative j is chosen by individual t, 0 otherwise).

6.3. Results

6.3.1. Experiment 1

Table 22 displays the micro F-1 score in the 10-fold cross-validation and pseudo-R-squared results for models in experiment 1. This subsection has two notable findings. First, the findings reveal that conditional MNL and MCL models 1 and 2 produced nearly identical predictive performance. Although DCM and ML are two sister disciplines rooted in statistical theory and concerned with the same issue of discrete choices of transportation modes (Vovsha, 2021), DCM and ML have different approaches and aims, illustrated in Table 23 (Aboutaleb et al., 2021; van Cranenburgh et al., 2022). Even due to the benefits of ML, such as more flexible modeling structures (Xie et al., 2003), ML generally develops and finds an algorithm that is more accurate in predicting performance than any other methodological approach (Mohammed et al., 2016). However, the finding implies that the DCM and ML models can generate similar prediction accuracy as long as the probability estimation equations used by the two procedures are similar in the same data structure format (see Table 24).
Second, Table 22 reveals that the full MNL model produced a higher prediction accuracy (micro F-1 score of 0.710 and pseudo-R-squared of 0.657) than conditional MNL and MCL models. The fundamental rationale for the finding is that the full MNL model included both alternative-specific attributes of both chosen and non-chosen alternatives and considered a subset of alternatives in the modeling approach, whereas the conditional model did not. Therefore, the finding suggests that not taking into consideration the crucial information is not optimal and may even be problematic.

Table 22 Findings of experiment 1

<table>
<thead>
<tr>
<th>Models</th>
<th>Micro F-1 score</th>
<th>Pseudo-R-squared</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conditional Model 1</td>
<td>0.528</td>
<td>0.306</td>
</tr>
<tr>
<td>Conditional Model 1</td>
<td>0.529</td>
<td>0.307</td>
</tr>
<tr>
<td>Conditional Model 2</td>
<td>0.562</td>
<td>0.374</td>
</tr>
<tr>
<td>Conditional Model 2</td>
<td>0.564</td>
<td>0.373</td>
</tr>
<tr>
<td>Full Model</td>
<td>0.710</td>
<td>0.657</td>
</tr>
</tbody>
</table>

Abbreviations: discrete choice modeling (DCM), machine learning (ML), multinomial logit model (MNL), and multiclass logit model (MCL)

Table 23 Theoretical differences between discrete choice modeling and machine learning (Source: Aboutaleb et al., 2021; van Cranenburgh et al., 2022)

<table>
<thead>
<tr>
<th>Approach</th>
<th>Discrete Choice Modeling</th>
<th>Machine Learning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Approach</td>
<td>· Theory-driven modeling&lt;br&gt;· Knowledge-based model</td>
<td>· Data-driven modeling&lt;br&gt;· Black-box model</td>
</tr>
<tr>
<td>Aim</td>
<td>· Formalize understanding of how decision-makers make a choice&lt;br&gt;· Offer insights on the data and its relationship&lt;br&gt;· Produce unbiased parameter estimation</td>
<td>· Put data at the center and identify the best course of action&lt;br&gt;· Provide an efficient representation of the data in terms of accuracy and computation cost and predict the phenomenon under study&lt;br&gt;· Develop learning optimization via error minimization</td>
</tr>
</tbody>
</table>
Table 24 Probability estimation of multinomial logit model in discrete choice modeling and multiclass logit model in machine learning (Source: Train, 2009)

<table>
<thead>
<tr>
<th>Multinomial logit model (MNL)</th>
<th>Multiclass logit model (MCL)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{r_n}(j) = \frac{\exp(\beta_i X_i)}{\sum_{i=1}^{t} \exp(\beta_k X_{ik})}$</td>
<td>$\sigma_i(Z) = \frac{\exp(W_i X_i)}{\sum_{i=0}^{t} \exp(W_i^T X_{ik})}$</td>
</tr>
</tbody>
</table>

Where
- $i$: alternative (also called class)
- $t$: individual
- $\beta_k$: the coefficients (parameter estimations) of the attribute $k$ of an alternative
- $X_{ik}$: the value of attribute $k$ for alternative $i$

6.3.2. Experiment 2

The findings of experiment 2 in Table 25 indicate that conditional MXL model 2 outperformed comparable MNL and MCL models mainly because MXL accounts for random heterogeneity in multiple-choice SC experiments in the survey data (also called panel data structure). Interestingly, the finding contradicts those in previous literature (Cherchi & Cirillo, 2010; Zhao et al., 2020). The previous research concluded that MXL underperformed models without introducing random parameters (i.e., MNL), due to possible over-fitting issues in MXL. However, this study implies that the prediction accuracy of ML can be enhanced if ML considers panel data structure within its probability estimation function, as MXL did.
Moreover, similar to experiment 1, the comparison of model performance between conditional MXL model 2 and full MXL model suggests that ML algorithms may have better prediction accuracy when considering alternative-specific attributes of chosen and non-chosen alternatives as well as a subset of alternatives.

### Table 25 Findings of experiment 2

<table>
<thead>
<tr>
<th>Models</th>
<th>Micro F-1 score</th>
<th>Pseudo R-squared</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conditional Model 2 MCL ML</td>
<td>0.562</td>
<td>0.374</td>
</tr>
<tr>
<td>Conditional Model 2 MNL DCM</td>
<td>0.564</td>
<td>0.373</td>
</tr>
<tr>
<td>Conditional Model 2 MXL DCM</td>
<td>0.578</td>
<td>0.380</td>
</tr>
<tr>
<td>Full Model MXL DCM</td>
<td>0.762</td>
<td>0.683</td>
</tr>
</tbody>
</table>

Abbreviations: discrete choice modeling (DCM), machine learning (ML), multinomial logit model (MNL), mixed logit model (MXL), and multiclass logit model (MCL)

### 6.3.3. Experiment 3

This subsection now turns to prediction accuracy comparison of conditional DCM and ML models 2. First, the results in Table 26 show consistent patterns with previous literature in transportation mode choice modeling using revealed preference survey data that ML generally outperforms DCM, and the best performing models are ensemble models, such as GBoost, SBoost, CatBoost, and XGBoost.

The result may suggest a fairly good connection between ML and the stated choice (SC) experiment. Specifically, a discussion paper by van Cranenburgh et al. (2022) stated that “machine learning and SC experiments are a less natural fit (p. 10).” The paper argued that this issue occurs because the SC
experiment generally has relatively small sample sizes and limited explanatory variable observations. However, this study finds that ML algorithms using the SC survey data with more observations (7,872) and higher scope of explanatory variables (21) can perform well.

Moreover, the discussion paper contended that the simplified experimental environment of SC studies offers limited potential for ML to outperform theory-driven models (i.e., DCM) in terms of prediction accuracy. However, Table 26 reveals that ML can be helpful in exploring choice behavior under highly stylized hypothetical conditions controlled by the researchers. Therefore, this study can reject the claim that data-driven choice models (i.e., ML) and SC experiment data are less natural fits than theory-driven and parametric models (i.e., DCM), given most ML algorithms except for NB and DT performed better than comparable MNL and MXL models.

Table 26 Findings of experiment 3

<table>
<thead>
<tr>
<th>Models</th>
<th>Micro F-1 score</th>
<th>Pseudo R-squared</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conditional Model 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MNL DCM</td>
<td>0.564</td>
<td>0.373</td>
</tr>
<tr>
<td>MXL DCM</td>
<td>0.578</td>
<td>0.380</td>
</tr>
<tr>
<td>MCL ML</td>
<td>0.563</td>
<td>0.373</td>
</tr>
<tr>
<td>NB ML</td>
<td>0.480</td>
<td>0.116</td>
</tr>
<tr>
<td>SVM ML</td>
<td>0.827</td>
<td>0.830</td>
</tr>
<tr>
<td>ANN ML</td>
<td>0.721</td>
<td>0.643</td>
</tr>
<tr>
<td>DT ML</td>
<td>0.554</td>
<td>0.423</td>
</tr>
<tr>
<td>RF ML</td>
<td>0.793</td>
<td>0.735</td>
</tr>
<tr>
<td>AdaBoost ML</td>
<td>0.615</td>
<td>0.450</td>
</tr>
<tr>
<td>LogitBoost ML</td>
<td>0.795</td>
<td>0.643</td>
</tr>
<tr>
<td>GBoost ML</td>
<td>0.877</td>
<td>0.918</td>
</tr>
<tr>
<td>SGBBoost ML</td>
<td>0.882</td>
<td>0.930</td>
</tr>
<tr>
<td>CatBoost ML</td>
<td>0.859</td>
<td>0.928</td>
</tr>
</tbody>
</table>

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6.4. Discussion

This section mainly discusses limitations observed in the three experiments and future research directions for methodological improvements of machine learning (ML) when applied to transportation mode choice modeling. This study identified three points for ML algorithm development to make it a more promising tool for mode choice modeling.

6.4.1. Alternative-specific Attributes of Non-chosen Alternatives

First, it is crucial to include alternative-specific attributes of non-chosen alternatives (e.g., travel cost and time) in the transportation mode choice modeling since the information carries significant implications, particularly for the interpretation of the outcomes, which have been long acknowledged in DCM. Since ML algorithms have not incorporated the alternative-specific attributes of non-chosen alternatives (Omrani et al., 2013; Zhao et al., 2020), a new customized ML algorithm should be developed to accommodate the crucial information in transportation mode choice modeling.

<table>
<thead>
<tr>
<th>Conditional Model 2</th>
<th>XGBoost</th>
<th>ML</th>
<th>0.876</th>
<th>0.929</th>
</tr>
</thead>
</table>

Abbreviations: discrete choice modeling (DCM), machine learning (ML), multinomial logit model (MNL), mixed logit model (MXL), multiclass logit model (MCL), naïve bayes (NB), support vector machine (SVM), artificial neural network (ANN), decision tree (DT), random forest (RF), ada boosting decision tree (AdaBoost), logit boosting decision tree model (LogitBoost), gradient boosting decision tree (GBoost), stochastic gradient boosting decision tree (SGBoost), categories boosting decision tree (CatBoost), and extreme gradient boosting decision tree (XGBoost)
6.4.2. Subset of Alternatives

The stated choice (SC) experiment in the survey data used in this study showed a unique situation that the number of alternatives exposed to the respondents in each SC experiment was three instead of all eight transportation modes. Therefore, more complicated estimation processes should be employed in the data structure to derive the probability that the respondent chooses one alternative conditional on a subset of alternatives from a larger range of alternatives (K. E. Train, 2009). The argument is also valid in ML, given the difference in model performance between conditional and full models in experiments 1 and 2. Therefore, further methodological improvement in ML is needed to estimate conditional probability.

6.4.3. Multiple-choice Experiment Structure

Advanced DCM models, such as MXL (Hensher & Greene, 2003), were developed to address the issue (i.e., random heterogeneity) that the multiple-choice experiment design structure raises. However, previous studies in ML, including algorithms developed in this study, have partitioned the panel dataset by treating all observations as independent choices (Xie et al., 2003; Hagenauer & Helbich, 2017; Zhao et al., 2020). Since there can be a significant issue without handling the multiple experimental designs, further methodological improvements in ML are needed to handle the aspects of multiple-choice stated choice experiments.
6.4.4. Blending Discrete Choice Modeling and Machine Learning

In addition to developing a new customized ML algorithm that accommodates the three limitations mentioned above, the research direction that incorporates ML into the DCM framework innately assists in addressing the limitations. A limited body of methodological studies has engaged in pursuing this research avenue. For instance, Han et al. (2020) developed the integrated model, TasteNet-MNL, that embedded the neural network algorithm into a multinomial logit model. Also, Sfeir et al. (2022) proposed the Latent Class Choice Model with a flexible class membership component by employing Gaussian Mixture Model. That is, a methodologically new way of thinking has to be developed to incorporate the strengths of DCM and ML and, more importantly, alleviate the limitations.

6.5. Summary

While discrete choice modeling (DCM) has been dominant in transportation mode choice modeling over the past decades (Hess & Daly, 2014), machine learning (ML) has been recently used to explore the mode choice behavior with benefits, such as a high prediction accuracy (Ran & Hu, 2017; Sidey-Gibbons & Sidey-Gibbons, 2019). Although methodological research has been devoted to finding and addressing existing limitations of ML, some limitations have not been observed with empirical findings in previous literature. Therefore, this study conducted three experiments by comparing the model performance of ML and
DCM since considerable efforts made in DCM to address its drawbacks can suggest vital insights into the limitations and future research directions of ML. This study contributes to improving our understanding of the shortcomings of ML when applied to transportation mode choice modeling and suggesting future research directions for methodological improvements.
7.1. **Background**

Whether you are ready or not, autonomous vehicles (AVs) have been on the horizon; specifically, automobile manufacturers have already offered semi-autonomous systems, and complete automation will be available in the near future (Thompson, 2016). Moreover, shared mobility services, in particular, ride-hailing, car-sharing, and bike-sharing, have recently emerged as transportation options across the globe. Given the rapid advancement of new mobility technologies from the supply-side, it is vital to understand how travelers adopt new modes of transportation and continue to use traditional modes of transportation because the supply-side innovations are expected to disrupt and transform travel behavior and result in the creation of a new paradigm of transportation mode choice behaviors. However, since there has been little demand-side discussion about the transportation mode choice behaviors once AVs become commercially available,
it is unclear to what extent consumer reactions to the new mode of transportation and other available modes will differ from one another. Therefore, this dissertation employed discrete choice modeling (DCM) and machine learning (ML) using the U.S. nationwide stated choice experiment to offer and expand the demand-side understanding.

7.2. Summary of Works

The three papers that make up this dissertation are as follows: The first paper in Chapter 4 examines future market shares of each available mode of transportation in the era of AVs, factors influencing the mode choice, and their marginal effects using mixed (random parameter) logit model. The second paper in Chapter 5 used interpretable ML to investigate the optimal algorithm (stochastic gradient boosting decision tree model) with a higher prediction accuracy in greater depth, including feature importance and non-linear marginal effects. The final paper in Chapter 6 assesses the limitations of ML when applied to transportation mode choice modeling and suggests future research directions for methodological improvements by comparing it with the widely-used modeling approach over decades (i.e., DCM).
7.3. **Contribution**

The dissertation contributes to three major parts of the current understanding of transportation mode choice behavior in the era of AVs and choice modeling, which are as follows: First, consumers in the era of AVs would be able to choose from a variety of modes of transportation that would be likely to coexist, including private AVs, shared mobility services, and conventional transportation modes. This dissertation makes a significant contribution to examining more comprehensive transportation mode choice behaviors and expanding the demand-side discussion, given that none of the studies has placed them next to each other in an experiment for future travel behavior. Second, since current transportation planning efforts have been based on speculative estimates and expectations, this dissertation contributes to the decision-making process by providing crucial underlying knowledge that is not currently available. The third contribution of this dissertation is in the area of methodology, where it assesses the limitations of ML for transportation mode choice modeling and makes recommendations for potential future avenues of methodological improvement.

7.4. **Limitation**

This dissertation acknowledges several limitations. First, it is crucial to acknowledge the limitations of the stated choice experiment research design. One of the most significant constraints is that stated preferences may not be
compatible with actual behavior (Holmes et al., 2017). Also, since the public may not be very knowledgeable about AVs at the time of the experiment, the results of this paper may alter when they will be well-aware (J. Zmud et al., 2016).

The second limitation component is regarding the survey data used in this dissertation. The experiments in the survey did not include all transportation modes that would be available in the era of AVs. For example, micro-mobility, including e-scooters, which emerged over the last few years, was nascent at the time of the data collection for this research. Electronic bikes were another neglect of this study framework. Also, the collected sample of the experiments may not fully represent the study area and the U.S., given the discrepancy in age between respondents and the actual population.

Lastly, although this study identified a few limitations of ML for transportation mode choice modeling, this study did not develop a new customized algorithm to accommodate the limitations.
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