교통연구 제30권 제2호 pp.15-33

10.34143/jtr.2023.30.2.15

Understanding Travel Behavior in the Era of Autonomous Vehicles: A Machine Learning Approach

Lee, Sangwan (Research Associate, Korea Land and Geospatial Informatix Corporation)

자율주행시대의 교통수단선택 분석
- 기계학습을 활용하여 -

이상완*

2023년 2월 22일 접수, 2023년 4월 27일 최종수정, 2023년 5월 12일 게재확정

* 한국국토정보공사 공간정보연구원 선임연구원

Abstract

New mobility technologies, such as autonomous vehicles (AVs), continue to evolve. This paper employed machine learning (ML) using the U.S. nationwide stated choice experiment to understand how travelers adopt new transportation modes or continue to use conventional modes of transportation. Specifically, this study used 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. Several notable findings in this study 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. Moreover, 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 paper contributes to (1) exploring how people would react to a variety of transportation modes likely to coexist, including private AVs, shared mobility services, and conventional transportation modes, (2) supporting the decision-making process through crucial underlying knowledge not currently available, and (3) elaborating the limitations of ML for transportation mode choice modeling and suggests potential future avenues for methodological improvement.

■ Keywords: Transportation Mode Choice, Autonomous Vehicles, Interpretable Machine Learning, Stated Choice Experiment

자율주행차(AV)와 같은 새로운 모빌리티 기술은 계속 진화하고 있다. 이에 본 논문은 선호조사 데이터를 바탕으로 기계학습을 활용하여 AV가 상용화된 시점에 교통수단 선택 패턴을 분석하였다. 구체적으로, 해석 가능한 기계학습을 사용하여 변수 중요도 및 비선형 한계 효과를 포함하여 최적의 알고리즘(확률적 그래디언트 부스팅 의사 결정 트리 모델)을 깊이 분석했다. 주요 연구결과는 다음과 같다. 첫째, 순열 기반 특징 중요도 분석 결과는 AV 시대의 교통수단 선택 행동이 각 교통수단의 서비스 수준과 운전, AV, 기술 및 대체 교통수단에 대한 개인의 태도에 의해 크게 영향을 받을 것임을 시사한다. 더욱이, 결정적인 요인에 관한 직접적인 한계 효과 추정은 비선형 관계가 효과가 일반적으로 다양한 운송 모드에 걸쳐 특정 범위 내에서 눈에 띈다는 것을 보여준다. 특히 많은 사람들이 특정 단위 변화에서 교통 수단 변화 패턴을 보였다. 본 논문은 (1) 개인 AV, 공유 모빌리티 서비스 및 기존 교통 수단을 포함하여 미래에 공존할 가능성이 있는 다양한 교통 수단에 사람들이 어떻게 반응하는지 탐구하고, (2) 중요한 기본 지식을 통해 교통계획 의사 결정 프로세스를 지원하는 데 기여하며, (3) 교통수단선택 모델링에 대한 기계학습의 한계점을 제시하고 잠재적인 향후 방법을 제안한다.

■ 주제어: 교통수단선택, 자율주행, 해석가능한 기계학습, 선호조사

Ⅰ. Introduction

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. 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).

There have been a very limited attempts to investigate transportation mode choice behavior in the era of AVs using machine learning (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.

There are 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. 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 elaborates on the research approach, such as stated choice experiment survey data and methodology. Section three presents findings, and section five discusses them as well as limitations on machine learning when applied to transportation mode choice modeling. The final section concludes this paper.

Ⅱ. Methodological Approach

1. Stated Choice Experiment

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. This study employed the data set since the SC research is appropriate for this research that investigates hypothetical circumstances. However, the experiments can suffer from hypothetical bias in this study since respondents may have difficulties envisioning fully automated vehicles. 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.

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). Moreover, each respondent carried out five experiments, one for the commute and one for the non-commute trip, with ten experiments in total. Further details on the survey data can be found in the report (L. Wang et al., 2018).

2. Variables

2.1. Output Target

There were eight output classes (see Table 1): (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 1〉 Final Set of Output Classes(Transportation Modes)

Mode	Description	N	%
PAV	Private autonomous vehicle (e.g., privately-owned self-driving car)	988	12.6
SAV	Shared autonomous vehicle (e.g., shared self-driving car with or without the passenger)	912	11.6
CAR	Personal car (e.g., drive a single-occupied vehicle)	3,942	50.1
RH	Ride-hailing service (e.g., Uber, Uber pool, and Lyft)	457	5.8
CS	Car-sharing service (e.g., Zipcar and Car2Go)	272	3.5
CP	Carpool (e.g., carpool and vanpool)	446	5.7
PT	Public transportation (e.g., transit and bus)	368	4.7
AT	Active transportation (e.g., walking, biking, and bike-sharing service)	487	6.2

2.2. Input Features

Table 2 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.

3. Machine Learning Algorithm

3.1. 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 1). 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.

3.2. Classification Algorithm Candidates

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

〈Table 2〉 Descriptions of the Input Features

Name	Descriptions	Mean	S. D.
Alternative-Specific Attributes			
IV	In-vehicle time in minutes	14.6	14.3
WAIT	Wait time in minutes	8.7	9.8
WALK	Walk time in minutes	3.3	7.9
COST	Out of pocket cost in dollars	6.3	23.7
Trip Purposes			
Commute	1 if the trip purpose is commute-trip, 0 otherwise	0.4	0.4
Shopping	1 if the trip purpose is for shopping or errands, 0 otherwise	0.3	0.4
Recreation	1 if the trip purpose is recreational or social, 0 otherwise	0.1	0.3
Meal-out	1 if the trip purpose is for eating a meal out, 0 otherwise	0.1	0.3
Socio-Demographic Characteristics			
Female	1 if the respondent is female, 0 otherwise	0.4	0.4
Age	The age of the respondent in 2018	34.0	10.5
People-of-color	1 if the respondent is people-of-color, 0 otherwise	0.3	0.4
Low Income	1 if the household income of the respondent is below $44,999, 0 otherwise	0.3	0.4
Low Education	1 if the respondent attains high school, a high-school diploma, or GED, 0 otherwise	0.1	0.2
Student	1 if the respondent is a student, 0 otherwise	0.3	0.4
Rent	1 if the respondent rents a current residential place, 0 otherwise	0.4	0.5
Attitudinal Factors			
Enjoy Driving	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?	-0.1	0.8
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?	0.1	0.8
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?	-0.1	0.9
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?	-0.1	0.7
Transportation-Related Features			
Driver's License	1 if the respondent has a valid driver's license, 0 otherwise	0.9	0.2
Car Owner-ship	1 if the respondent owns a car, 0 otherwise	0.7	0.4
Bike Owner-ship	1 if the respondent has a bike, 0 otherwise	0.4	0.4
Barriers	1 if the respondent faces barriers to driving a car, taking public transportation, or walking, 0 otherwise	0.1	0.4

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.

3.3. 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).

3.4. 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 1) and avoiding inflated performance estimates on uneven class distributions (Mosley, 2013). Balanced accuracy can be formalized as (García et al., 2009):

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

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

$$miF = 2\left[\left(\frac{TP}{TP+FP}*\frac{TP}{TP+FN}\right)\Big/\left(\frac{TP}{TP+FP}+\frac{TP}{TP+FN}\right)\right] \tag{2}$$

where denotes true positive in the confusion matrix, is true negative, is false positive, and is false negative.

3.5. Optimal Algorithm Selection

The Stochastic Gradient Boosting Decision Tree Model (SGBoost) was the optimal algorithm in this study (see Table 3). 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):

$$\begin{aligned}\psi(y_k, F_k(X)_1^k) &= -\sum_{k=1}^{K} y_k \log \left[p_k(X)\right] \\ &= -\sum_{k=1}^{K} y_k \log \left[\exp(F_k(X)) \Big/ \sum_{k=1}^{K}\exp(F_k(X))\right]\end{aligned} \tag{3}$$

where, is the input features, and denotes the estimated probability. Then, the following equation can be obtained:

$$\begin{aligned}\bar{y}_i^k &= -\left[\frac{\partial_\psi\{y_{ij}, F_j(x_i)\}_{j=1}^k}{\partial F_k(x_i)}\right]_{\{F_j(x)=F_{jm-1}(x)\}_1^k} \\ &= y_i^k - p_k(x_i)\end{aligned} \tag{4}$$

where K-trees are induced, each of which predicts the corresponding current residuals . This produces K-trees with L-terminal nodes at iteration.

3.6. Interpretation 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; 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 is estimated following the equation below:

$$PBFI_j = s - \frac{1}{k}\sum_{k=1}^{K} s_{k,j} \tag{5}$$

where represents PBFI for input feature, and represents the score of the algorithm on a corrupted version of the data for repetition.

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 is as follows:

$$ME_k(Z_p) = p_k(Z_{-p}, Z_p + \Delta | \theta_k) - p_k(Z | \theta_k) \tag{6}$$

Ⅲ. Findings

1. Model Performance

Table 3 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 3〉 Prediction Accuracy Comparison between Candidate Algorithms

Algorithm	Balanced Accuracy Score		Micro F-1 Score	
	Mean	Std. Dev	Mean	Std. Dev
MCL	0.362	0.023	0.597	0.012
NB	0.326	0.013	0.445	0.028
SVM	0.786	0.019	0.841	0.012
ANN	0.682	0.015	0.761	0.012
DT	0.273	0.012	0.595	0.015
RF	0.720	0.014	0.826	0.009
AdaBoost	0.415	0.015	0.673	0.008
LogitBoost	0.733	0.016	0.826	0.011
GBoost	0.836	0.013	0.886	0.006
SGBoost	0.849	0.016	0.894	0.009
CatBoost	0.822	0.015	0.874	0.010
XGBoost	0.841	0.017	0.887	0.009

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)

2. Feature Importance

Table 4 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 4 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.

〈Table 4〉 Results of Permutation-based Feature Importance

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

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

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%.

3. Direct Marginal Effect

This study presents selected findings of direct marginal effects of input features in Figures 1 to 7 in the Appendix 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.

3.1. Alternative-Specific Attributes

This subsection presents selected results of direct marginal effects of four alternative-specific attributes. Table 5 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.

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 1a). Figure 1b 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 1c 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 1d, 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 2, 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 2a). Figure 2b 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 2c), suggesting that individuals may not be tolerant of a slight increase in WAIT of CS. Moreover, Figure 2d 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 3a and 3b 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 3c 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 4 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 4a and 4b). 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 4c).

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 5). 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 6). Moreover, as people enjoyed driving a car, the predicted probability of choosing PAV increased while choosing SAV decreased (see Figure 7).

Ⅳ. Discussions

1. Major Findings

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.

Lastly, 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.

2. Methodology

ML and discrete choice modeling can deal with a same problem, which is the transportation mode choice modeling, with several similarities and differences (see Table 5). More importantly, this study acknowledged limitations on ML when applied to transportation mode choice modeling (S. Lee, 2022). For instance, 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 discrete choice modeling (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.

Moreover, 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 (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.

Lastly, advanced DCM models, such as nested

〈Table 5〉 Similarities and differences between discrete choice modeling and machine learning

	Discrete Choice Modeling	Machine Learning
Similarity		
Shared concept	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		
Approach	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	a. Formalizing understanding of how decision-makers make a choice Offering insights on the data and its relationship b. Unbiased parameter estimation c. Testing using the goodness of fit and residuals examination	a. Putting data at the center and identifying the best course of action b. Providing an efficient representation of the data in terms of accuracy and computation cost and predicting the phenomenon under study c. Learning optimization via error minimization Testing using new data, comparison with other algorithms
Strengths	Interpretability	Prediction
Limitation	Assumptions (e.g., IIA)	Interpretability and explainability

logit or radom parameter logit models (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.

Ⅴ. Conclusion

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.

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. Forth, this study did not control for all factors influencing transportation mode choice in the era of AVs, such as climate, the level of knowledge on AVs, and trip chains.

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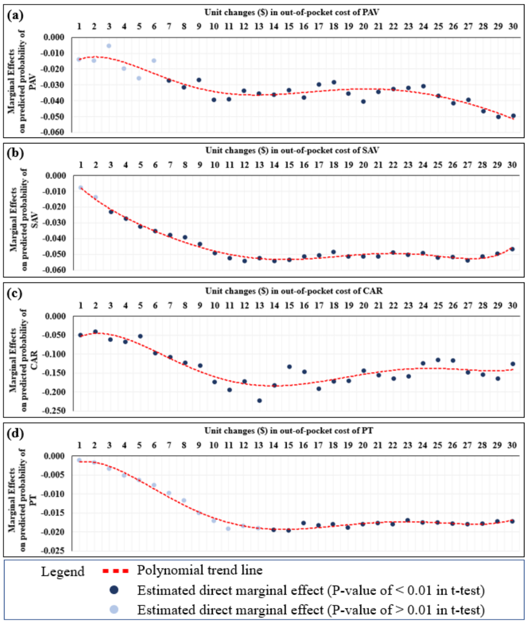
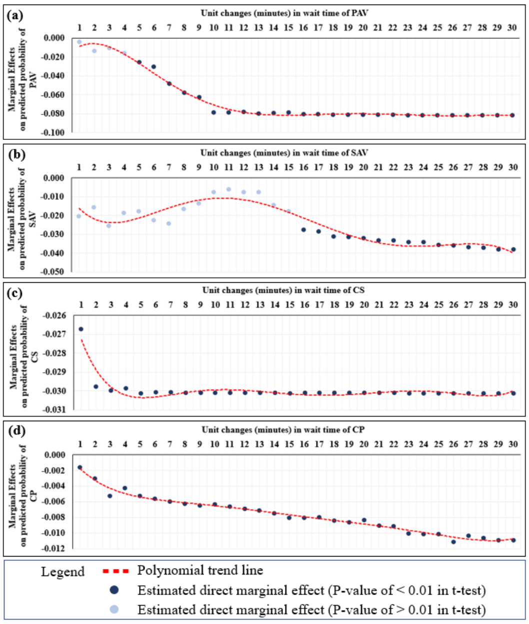
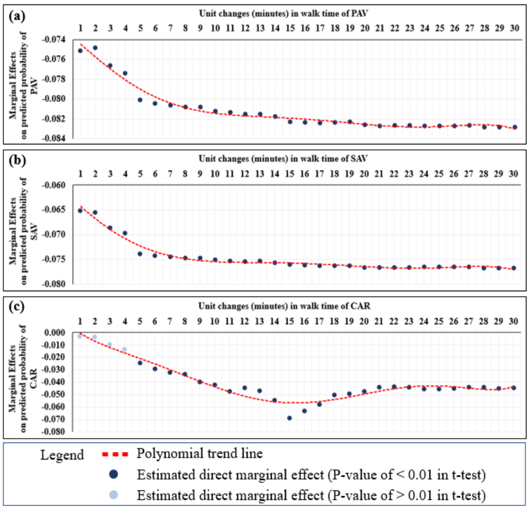
Appendix



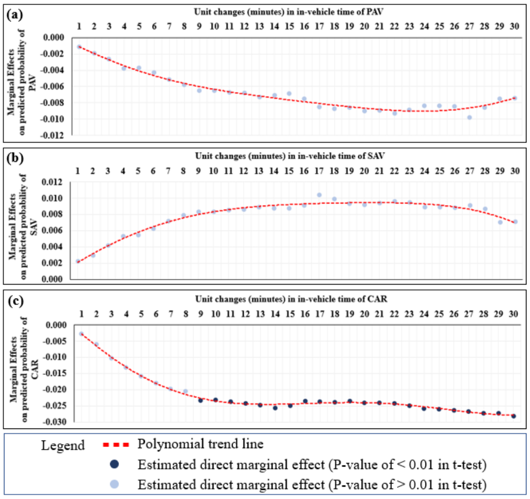
〈Figure 1〉 Selected Marginal Effect Estimation of Out-of-Pocket Cost (Unit: Dollars)



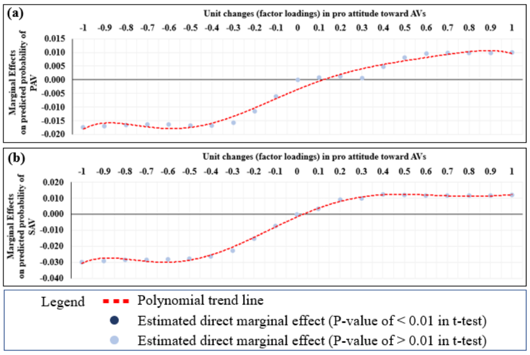
〈Figure 2〉 Selected Marginal Effect Estimation of Wait Time (Unit: Minutes)



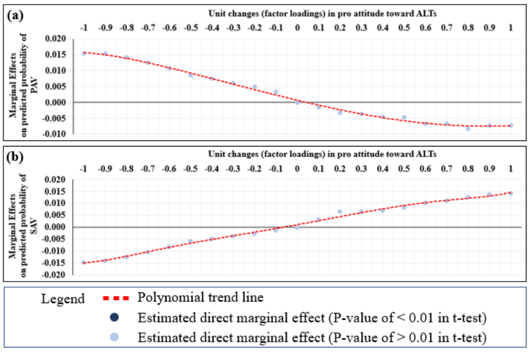
〈Figure 3〉 Selected Marginal Effect Estimation of Walk Time (Unit: Minutes)



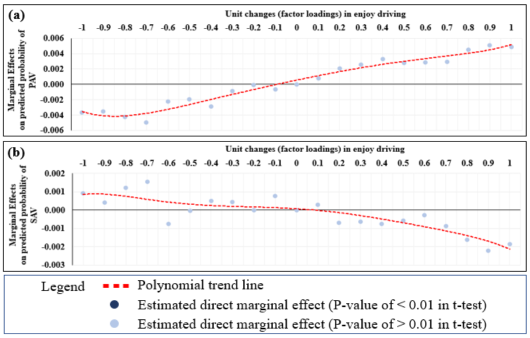
〈Figure 4〉 Selected Marginal Effect Estimation of In-Vehicle Time (Unit: Minutes)



〈Figure 5〉 Selected Marginal Effect Estimation of Pro-Attitude toward AVs



〈Figure 6〉 Selected Marginal Effect Estimation of Pro-Attitude toward Alternative Transportation Modes



〈Figure 7〉 Selected Marginal Effect Estimation of Enjoy Driving