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REVIEW

Discrete Choice Models and Artificial Intelligence Techniques for Predicting the Determinants of Transport Mode Choice—A Systematic Review

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ABSTRACT

Forecasting travel demand requires a grasp of individual decision-making behavior. However, transport mode choice (TMC) is determined by personal and contextual factors that vary from person to person. Numerous characteristics have a substantial impact on travel behavior (TB), which makes it important to take into account while studying transport options. Traditional statistical techniques frequently presume linear correlations, but real-world data rarely follows these presumptions, which may make it harder to grasp the complex interactions. Thorough systematic review was conducted to examine how machine learning (ML) approaches might successfully capture nonlinear correlations that conventional methods may ignore to overcome such challenges. An in-depth analysis of discrete choice models (DCM) and several ML algorithms, datasets, model validation strategies, and tuning techniques employed in previous research is carried out in the present study. Besides, the current review also summarizes DCM and ML models to predict TMC and recognize the determinants of TB in an urban area for different transport modes. The two primary goals of our study are to establish the present conceptual frameworks for the factors influencing the TMC for daily activities and to pinpoint methodological issues and limitations in previous research. With a total of 39 studies, our findings shed important light on the significance of considering factors that influence the TMC. The adjusted kernel algorithms and hyperparameter-optimized ML algorithms outperform the typical ML algorithms. RF (random forest), SVM (support vector machine), ANN (artificial neural network), and interpretable ML algorithms are the most widely used ML algorithms for the prediction of TMC where RF achieved an R2 of 0.95 and SVM achieved an accuracy of 93.18%; however, the adjusted kernel enhanced the accuracy of SVM 99.81% which shows that the interpretable algorithms outperformed the typical algorithms. The sensitivity analysis indicates that the most significant parameters influencing TMC are the age, total trip time, and the number of drivers.

KEYWORDS

Machine learning techniques; AI; transport mode choice; discrete choice model; sustainable transportation

Glossary/Nomenclature/Abbreviations

ML	Machine Learning
TMC	Transport Mode Choice

DCM	Discrete Choice Model
BE	Built Environment
TB	Travel Behavior
GBT	Gradient Boosting Tress
XGB	Extreme Gradient Boosting
k-NN	k-Nearest Neighbors
RF	Random Forest
NB	Naïve Bayes
BN	Bayesian Network
NN	Neural Network
DT	Decision Tree
SVM	Support Vector Machine
FSVM	Fuzzy Support Vector Machine
GE	Gene Expression
GEP	Gene Expression Program
SEM	Structural Equation Modeling
PT	Public Transport

1 Introduction

The term “transport mode choice (TMC)” refers to the different transport options, which might include a private vehicle, a public vehicle, walking, bicycle, or other modes of transportation. TMC is frequently expressed as a discrete choice model with options that match the various trip modes. TMC refers to the individual choice of a specific transport mode for his/her activity participation at a different place [1]. The choice of travel mode for a certain journey is determined by many factors, both personal and contextual [2]. These factors can differ from one person to another and from one location to another, but they typically include infrastructure and accessibility [3], time [4], cost [5], and purpose of travel, as well as factors like health and physical ability [6], demographics, personal preference [7], built environment (BE) concerns, weather conditions [8], information and technology (IT), traffic congestion, safety, parking availability, and governmental policies. There is a strong association between the phrase’s “connectivity” and “accessibility”. Connectivity describes the link between areas and hubs of activity, whereas accessibility describes a person’s or a product’s ability to travel by different modes of transportation [9].

The factors influencing people’s choice of transport mode can be greatly impacted by changes to urban infrastructure and policies, which can change how people choose between using private vehicles, walking, cycling, and public transportation. It becomes critical to comprehend how machine learning (ML) models can capture these changing dynamics as these factors change over time. Abulibdeh studied the introduction of new metro lines using ML algorithms and concluded that urban infrastructure significantly affects TMC [10]. After comparing the urban infrastructure of Germany and America, Buehler concluded that TMC is greatly impacted by living in lower-density neighborhoods, further from public transportation, and with a more restricted mix of land uses [11]. Changes in the policy such as parking prices, raising fuel taxes, providing subsidies on public transport, and employee-paid parking significantly encouraged and affected the model shift from private cars to public transport, walking, and cycling [12–14]. Beckx et al. concluded that 64% of the car trips were less than 8 km which can be replaced with walking and cycling that compensate for 3% of the fuel consumption [15].

Numerous traditional discrete choice models and statistical analyses, including the nested logit model and linear and non-linear regression analysis, mixed logit model, binary logistic regression [16], multinomial logistic (MNL) model [17], bivariate statistical analysis [18], and Structural Equation Modeling (SEM) [11,19], were employed in both recent and prior studies to study the correlation among several independent variables, mediation variables, and TMC such as PT, private vehicle, and active transport as dependent variables [20]. The mutual information (MI) [21] test method, which calculates the relevance of the inputs, was utilized by various researchers to determine the most influential component and its impact on TMC [22]. Even though some regression models can estimate interaction and quadratic effects, they are prone to outliers and have trouble reflecting the complex interactions between various variables. Furthermore, due to the restricted tools available, spotting abnormalities in nonlinear regression is more difficult than in linear regression [23]. Researchers use machine learning (ML) approaches because they rarely rely on assumptions, can handle enormous datasets, outliers, and missing values, and have advantages over traditional statistical methods [24].

ML models are emerging as an intriguing compelling substitute to multinomial logit (MNL) models in TB research, where tree-based ensemble models—gradient boosting and random forest (RF) have shown effectiveness in accomplishing this objective. MNL [25], k-nearest neighbors (k-NN), neural networks (NNs), RF, decision trees (DT), gradient boosting trees (GBT) [26], support vector machines (SVM) [22], and Naïve Bayesian (NB) [27] are the most often used machine learning (ML) techniques used in recent studies. Comparing these models to more conventional statistical methods, the majority of them outperformed [24,28,29]. It should be mentioned that most of these researchers applied the ML models with default settings, which can result in less-than-ideal outcomes due to some of the ML algorithms being capable of binary classification. Qian et al. applied an adjusted kernel function to SVM to map complex datasets into high dimensional that makes the data point separation easier and concluded that the SVMAK gives higher accuracy than the typical SVM [22]. Most researchers that utilized strategies for optimization to adjust the hyperparameters did so by using random search or grid, both of which have drawbacks of their own [30]. As a tool for policy analysis, the optimized GBT is used to investigate and assess ways to enhance the usage of more environmentally friendly transportation options while decreasing the use of private vehicles.

To avoid the limitations of the ML-specific tools and techniques, the latest studies used interpretable ML techniques in which they combine several ML techniques for a good understanding of TMC decisions. Tamim Kashifi et al. predict the TMC using five diverse interpretable ML models (LR, RF, DT, Multilayer Perceptron, LightGBDT) [31]. Since it is challenging to find a sufficient description for the link between the output and input variables due to the nature of the ML black box, Kim suggests an interpretable ML strategy to increase the interpretability of ML in TMC modeling [32]. Zhao et al. used an interpretable ML approach to explore the heterogeneity in mode-switching behavior and concluded that a machine-learning classifier in conjunction with interpretation tools that are model-independent offers useful insights into the mode-switching behavior of travelers [33].

Based on sensitivity analysis and feature importance metrics, which identify the most predictive features for the target variable, some researchers have claimed that factors such as the reason for not walking [22], household drivers, total travel time [25], household vehicles [31], and the purpose of the trip [34] are the most influential. Conversely, other researchers have concluded that household income, socio-demographic factors (such as age and gender) [35], the number of stops, road infrastructure availability [17], and accessibility (the distance between the last stop and the resident location) [36] are the most significant contributors.

Numerous characteristics have a substantial impact on TB, which makes it important to consider while studying transportation decisions. Traditional statistical techniques frequently presume linear correlations, but real-world data rarely follows these presumptions, which may make it harder to grasp the complicated interactions. We conducted thorough systematic research to examine how ML approaches might successfully capture nonlinear correlations that conventional methods may ignore to get around these constraints. An in-depth analysis of several ML algorithms, datasets, model validation strategies, and tuning techniques employed in previous research is carried out in the current review. Besides, the current review aims to systematically review the limitations and findings of the recent literature for the prediction of TMC and its determinants that utilize DCMs, ML algorithms, and interpretable ML techniques and suggest the best predictive model for the prediction of TMC. Moreover, based on the sensitivity analysis of the ML models, the most influential factors for the TMC are investigated to help policymakers in planning and forecasting TMC demands. The two primary goals of our study are to establish the present conceptual frameworks for the factors influencing the TMC chosen for daily activities and to pinpoint methodological issues and limitations in previous research. Our findings shed important light on the significance of considering factors that influence the TMC. For accurate analysis and efficient policy creation to promote sustainable transportation systems, it is essential to comprehend this complexity.

The review pattern is as follows: Section 2 provides an overview of the latest five-year studies in the field of modern techniques used for TMC, the methodology such as the methods of reviewing recent and past studies that are using PRISMA rules and Kitchenham and Charters Approach are discussed in Section 3, whereas Section 4 highlights the results and discussion of the selected 39 studies, and the conclusion is presented in Section 5 followed by the future direction in Section 6.

2 Literature Review

Using diverse transport modes has a substantial effect on individual health outcomes, subjective well-being, and the global environment [37–39]. However, on the other side, van Wee and Ettema, and Zhang studied that health is a capability constraint that influences transport options [40,41]. Besides, past studies concluded that planes, ships, cars, and heavy-duty vehicles are the main contributors to CO_2 emissions from the transportation sector [42]. According to a 2023 survey, 73% of American respondents chose the car, underscoring the car's crucial importance in daily life in the country which negatively contributes to GHG emissions [43], that households are responsible for 72% of global GHG emissions in which car and plane mobility is the most dominant component. European Union and the US aim to neutralize CO_2 emissions from the transportation sector by 2050. To achieve this aim, Zhang et al. concluded that active and public transport is encouraged in urban areas to reduce GHG emissions [34], whereas Xu et al. claimed that electric vehicles (EVs) in Europe significantly reduce GHG emissions [44]. Moreover, Aijaz et al. studied environmental sustainability through EVs and concluded that EVs have the potential to drastically decrease emissions from the transport sector and enhance sustainability [39]. However, the GHG emissions from the transportation sector are still questionable. Therefore, it is vital to predict TMC used for daily activities to promote green and sustainable transportation systems and a healthier society.

People are more inclined to switch modes if they are well-informed, yet mode choice behavior is an important subject when it comes to improving the overall sustainability of transportation networks [18]. Therefore, it is crucial to grasp and investigate what are the most effective variables for TMC to develop a more sustainable transport system [45]. Several factors such as BE, socio-demographic and economic variables, travel behaviors, availability, accessibility, and connectivity, time, weather conditions, purpose of travel, information and technology (IT), traffic congestion, safety, parking availability, and governmental policies describe by many researchers that influence TMC. Several studies are listed around the globe that highlight travel behavior, BE, factors, and TMC to work, school, and daily commuting. Besides, most researchers performed the comparison between different countries and provided interpretations about their transportation system, TMC or travel behaviors, and determinants of TMC.

The factors influencing the TMC are greatly impacted by changes in urban infrastructure and policies [46]. These dynamics can be well captured by ML models, particularly when temporal, geographical, and policy data are included [47]. Through the incorporation of dynamic elements like travel duration, expenses, and ease of use into flexible models, ML techniques can assist city planners in forecasting how transportation patterns will change in reaction to upcoming policy changes and infrastructure enhancements [29]. Insightful, data-driven transport planning is made possible by the combination of sophisticated ML techniques with solid datasets, despite obstacles like data availability and model interpretability [24,48].

Buehler conducted a comparative analysis of Germany and the USA for the determinants of TMC and concluded that the USA is more car-dependent than Germany, whereas Germans are more prone to cycle, walk, and use PT [11]. Besides, Bresson et al. performed a comparative analysis of England and France and studied the determinants of demands for PT. They concluded that the fare charges for PT are relatively sensitive and the main determinants for individuals to choose PT over a car. The reduction (subsidization) in the fare charges played a substantial role in encouraging the individual to choose PT, thus reducing the use of private cars [49]. Papaioannou et al. investigated how connectivity and accessibility affected PT. They concluded that while a system's accessibility might stimulate PT use, a particular trip's lack of connectivity could discourage it. Moreover, it seems that using PT instead of a private vehicle requires greater accessibility and trip-specific connectivity [50]. In addition, Wolday 2023 studied the effect of BE attributes on active transport in small cities and concluded that the frequency of walk/bike trips is significantly influenced by accessibility and attitude toward active travel [51].

Moreover, Harbering et al. studied the determinants of TMC for Mexico and concluded that although slow modes like cycling and walking are affected by distance from the city center, mass rapid transits are affected by infrastructure. In addition, based on their socioeconomic characteristic, women and younger people are more inclined to use PT despite the private vehicle. Moreover, higher education individuals are more dependent on cars and negatively influenced, whereas the availability of cars is negatively associated with all other transport modes [17]. Using binary logistic regression models, Szymon Wójcik studied possible factors impacting the decisions made by Łódź, Poland, citizens about the TMC they choose to utilize for everyday travel. He concluded that respondents' sociodemographic traits and household car ownership had the greatest impact on TMC. Furthermore, a statistically significant correlation was seen between geographic distances and subjective evaluations of PT. The factors influencing the decision to choose private or PT differed [35].

Convery and Williams studied the determinants of TMC for non-commuters by considering land use, the role of transport, and socio-demographic characteristics using bivariate statistical analysis. They concluded that vehicle ownership and income are recognized as key influences on TB patterns. Additionally, the comparatively low use of cars outside of the inner city core suggests initiatives offer alternatives to driving [18]. Using Tobit regression for efficiency and data envelopment analysis, Matulova and Tomes investigated the factors influencing urban PT efficiency in the Czech Republic. They concluded that certain factors, such as the average vehicle age, total vehicle kilometers, the tramlines existence in the city, percentage of drivers, and population density, increase efficiency while other factors, such as the percentage of revenue subsidies, ticket prices, and the existence of a two-city system, decrease efficiency [16]. Sharmin Sultana investigated the variables influencing parents' selection of active transportation options for their kids' school-related commutes. He chose 13 explanatory variables and concluded the Binary Logistic Regression Model results that gender, age, the distance between school and home, household size, home ownership status, household drivers, household vehicle ownership, and population density all play a significant role in parents' decisions to send their kids to school on foot [52].

Due to the technological advancement for the Prediction of work TMC to accurately forecast travel demand and achieve sustainability goals, ML techniques are interesting and are widely used by researchers over conventional techniques such as MNL models. For instance, Aghaabbasi et al. employed the ideal setting of the hyperparameters (which has an immediate impact on the model's performance). To forecast the TMC for work, ML methods utilizing a Bayesian Optimization (BO) algorithm are investigated. These methods include SVM, k-NN, single DT, ensemble DT, and NB. They concluded that BO is more effective than other models for enhancing the performance of the k-NN model [30]. With a focus on GBT, RF, and MNL models, Pineda-Jaramillo et al. analyze various logit and ML models to forecast TMC and identify the factors that influence TB in an urban setting. They concluded that GBT models outperformed the other models that were compared and that the factors that explain the TMC include age, gender, travel time, household motorized vehicles (cars and motorcycles), and availability of parking type at the destination [26]. Wang et al.'s research on TMC performance shows that when the dataset is unbalanced, the XGB model outperforms the MNL model in terms of prediction accuracy. Furthermore, they reported that although mode-specific travel time is the primary determinant of TMC, people's TMC is found to be substantially correlated with other trip characteristics, sociodemographic factors, and BE variables [25].

The performance of ML models is accessed using the classification metrics which are area under the curve (AUC), accuracy, precisions, F1-score, and recall. The model's actual and anticipated values serve as the basis for the classification. As illustrated in Eq. (1), accuracy is defined as the ratio of the correctly predicted class over all classes. Precision shows how much of a true positive class there is compared to the total number of true positive and false positive categories. Qian et al. studied the classification of imbalance TMC to work using an Adjustable kernel SVM model. They compared their results with the recent and past studies using simple SVM models as shown in Table 1 and concluded that the Adjustable kernel SVM model outperforms and enhances the model accuracy to 99.81%. From the Sensitivity Analysis mutual information (MI) test method, they concluded that household drivers and age are the most influential factors for TMC [22]. Aghaabbasi et al. investigated the impact of an employee's sociodemographic and living environment on active transportation using DT techniques, and they came to the conclusion that the availability and coverage of bike lanes, sidewalks, and transit stations were the most crucial factors in how frequently employees used AT modes to travel to work, shop, and enjoy themselves [53].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{1}$$

where TP, TN, FP, FN are the true positive, true negative, false positive, and false negative.

Besides several ML techniques, recent studies applied interpretable ML models for the prediction of TMC and travel behaviors. Kashifi et al. predicted the TMC using five different interpretable ML models (LR, RF, DT, Multilayer Perceptron, LightGBDT). They used 3-years of Dutch National

Travel Survey data and concluded that LightGBDT outperformed other models. In addition, they carried out analyses of variable importance and SHAP dependency to address the issue of ML models being a "black box" and enhance their interpretability. The investigation revealed that factors such as travelers' age and annual income, trip distance, trip density, and the number of vehicles or bicycles they possess are major determinants of their TMC [31]. Kim's research indicates that the interpretability of ML concerning TMC modeling is hindered by its opaque character, making it challenging to find a plausible explanation for the relationship between input and outcome variables. Consequently, he suggests an interpretable ML technique to address this issue. After using the XGB model, he concluded that, when it came to variable importance, variable interaction, and accumulated local effects (ALE), XGB performed better than the other ML models. Furthermore, he asserted that the number of tour trips taken and age had been demonstrated to be major factors in determining the TMC, whereas the connected trip and tour-related variables had a substantial impact on predicting TMC [32]. Zhao et al. employed an interpretable ML technique to explore the heterogeneity in mode-switching behavior. They first create a high-accuracy classifier that naturally captures the individual heterogeneity included in the data to forecast mode-switching behavior under a hypothetical Mobility-on-Demand Transit system. To study response heterogeneity, they proposed two novel model-independent ML interpretation tools, namely conditional individual partial dependence plots and conditional partial dependence plots. They concluded that using a machine-learning classifier in conjunction with interpretation tools that don't depend on a particular model might provide important information about mode switching in travel. Besides, the existing transit users are normally willing to share rides but unwilling to take any extra transfers, and the present drivers are more cautious about more collections than individuals employing other means of transportation [33]. The summary of the articles that utilize conventional techniques to study the determinants of TMC are presented in Table 2. However, those studies which utilize modern techniques for TMC predictions are depicted in Table 3.

Table 1: Accuracy of support vector machine-based models for imbalanced data

Authors	Models	Accuracy (%)
Wang et al. [54]	Boosting-SVM	83.29
Batuwita et al. [55]	Fuzzy-SVM	93.01
Wu et al. [56]	SVM	93.91
Qian et al. [22]	SVM_{AK} (adjusting kernel)	99.80

Table 2: Utilization of conventional techniques for TMC predictions

Authors	Country	Findings	Methods	Outcomes
[35]	Łódź, Poland	Potential factors influencing the decisions	Binary logistic regression models	– Socio-demographic characteristics – Household access to a car – Geographic distance

(Continued)

Table 2 (continued)

Authors	Country	Findings	Methods	Outcomes
[17]	Valley of Mexico	Influence of transportation supply, spatial characteristics, and socio-economic factors on TMC	Multinomial logistic regression	– Mass Rapid Transit (MRT) service use is being encouraged by road infrastructure rather than driving – The likelihood of walking and bicycling instead of driving a car increases with distance from the city center, which is the primary factor influencing slow modes
[11]	Germany and USA	Determinants of TMC	– Bi-variate analysis – Explanatory factors – SEM	– Higher population density – A greater mix of land uses – Household proximity to public transport – Fewer cars per household – (lower share of trips by automobile)
[18]	Dublin, Ireland	Determinants of TMC for non-commuters	– Bivariate analysis – Regression modeling	– Income and car ownership – Car use outside the inner-city core is relatively low
[16]	Czech Republic	Determinants of urban public transport efficiency	– Data envelopment analysis – Tobit regression	– Increasing efficiency—the proportion of drivers, average vehicle age, the presence of tramlines in the city, total vehicle kilometers, and population density – Decreasing efficiency—ticket price, proportion of subsidies in revenues, and presence of a two-city system
[51]	Norway	Influence of BE and attitudes on active travel behavior in small cities	– Descriptive statistics – ANOVA test – Negative binomial regression	– The frequency of walk/bike trips is greatly influenced by accessibility and attitudes toward active travel – Changes in the layout of small cities have a significant impact on active transportation, though the impact differs depending on the kind of facility

Table 3: Utilization of ML techniques for determinants of TMC predictions

Authors	Modeling methods	Main determinants used	Significance
[25]	XGB and MNL models	Multiple trip characteristics, socio-demographic traits, BE variables, and travel-specific time	− ve influence TMC
[22]	SVM, NN, XGBoost, BN, SSVM	Number of drivers in the household, age, infrastructure, safety, traffic congestion, and insufficient night lighting	− ve influence TMC
[53]	DT	Transit station conditions, sidewalk availability and coverage, and bike path availability	+ ve influence TMC
[52]	Binary logistic regression model	Age, gender, the distance between home and school, home ownership status, household size, the number of vehicles in the household, the number of drivers in the household, and population density	− ve influence TMC
[26]	GBT, RF, and MNL	Travel time, age, cars, motorcycles, trip purpose, parking, home type, income, workers, and geographical coordinates	+ ve influence TMC
[30]	SVM, KNN, DT, NB	Age, education, race, gender, workers, house ownership, income, household size, vehicles, travel time, urban area size, vehicle owned	+ ve influence TMC

3 Methodology

There are two different approaches for conducting a systematic literature review which are (1) Kitchenham and Charters (2007) and (2) the PRISMA approach. However, the current literature study mainly used the PRISMA approach due to its established reputation and extensive usage in various fields to conduct a systematic literature review. Both methods are briefly described.

3.1 Kitchenham and Charters Approach

This approach addresses the three stages of a systematic literature review: preparation, execution, and reporting. It is a generally acknowledged and approved procedure for carrying out systematic reviews, offering a strict and organized process for locating, assessing, and combining research findings. Furthermore, the technique has complete rules and checklists that guarantee a thorough and transparent review process. This allows for the replication of the review methodology, hence augmenting the study's credibility. The review mainly focuses on the methodological aspect of the recent and past studies rather than interfering with the outcome of the study, nor do they specify the detailed mechanisms performed in metadata [57]. Therefore, the quality of the research is not assessed and out of ten steps, the remaining nine steps were considered for the review process as shown in Fig. 1.

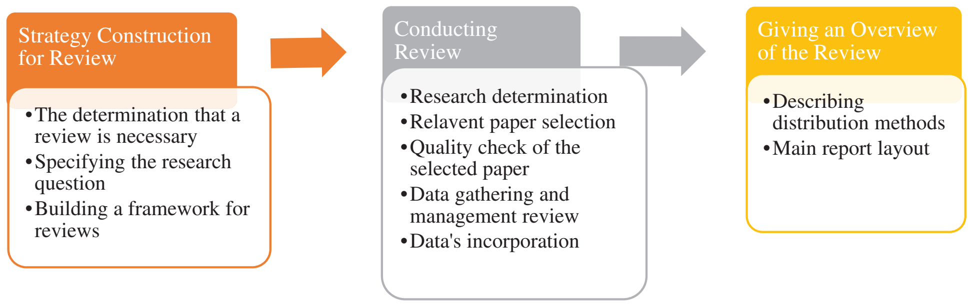

Figure 1: Kitchenham and charters review process for a systematic literature review

3.2 PRISMA Approach

Many researchers globally perform systematic literature reviews using the PRISMA (preferred reporting items for systematic reviews and meta-analyses) approach, which is easy to use and includes a four-phase flow diagram and a 27-item checklist [58]. The 27-item checklist is mainly composed of title (1), abstract (1), introduction (2), methods (12), results (7), discussion (3), and findings (1), whereas the for-phase diagram contains identification, screening, eligibility, and final inclusion as shown in Fig. 2. Following the 27-checklist and four-phase flow diagram makes it easier for the researchers to retrieve the important information from the research articles to conduct a convenient systematic review.

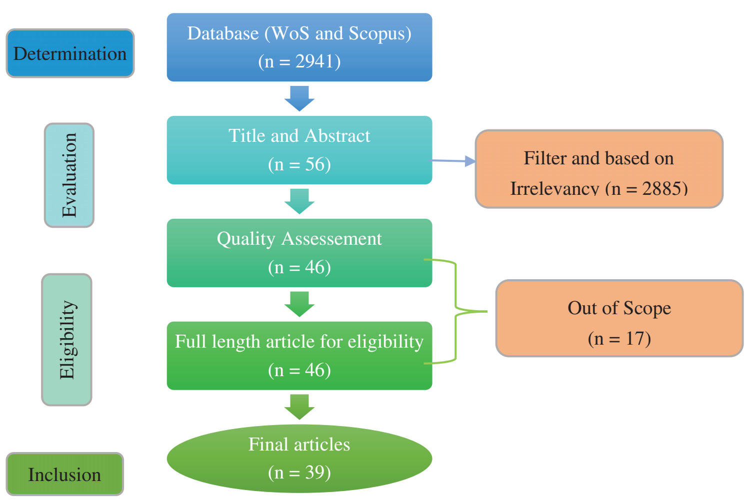

Figure 2: PRISMA statement for the systematic literature review

The primary subject of the current review is to review and summarize the study that mainly focuses on the determinants of TMC using conventional and ML techniques. The following review questions are the focus of the review.

Review Question # 1: Do machine learning algorithms outperform the conventional techniques for predicting the determinants of TMC?

Review Question # 2: Which ML techniques have been used to determine the determinants of TMC?

Review Question # 3: What are the characteristics of the datasets used to determine the determinants of TMC?

Review Question # 4: How are ML models' performances evaluated?

3.3 Procedure for Review

Throughout the review process, the four phases were used. The search approach so-called the identification, criteria for inclusion such as the screening and eligibility, and procedure for data retrieval are utilized for the review process and are presented here.

3.3.1 Search Approach

For the search engine, several databases including Scopus and Web of Science (WoS) with the utilization of Google Scholar are considered. Academic articles such as journals and conferences written in English were considered. Indeed, it was a challenging task to well-structured the search function as ML, TMC, and TBs are vast areas. To obtain specific, relevant, and up-to-date articles for the analysis, the current systematic review adopted the following procedure; initially, the phrases or keywords from Table 4 were used to conduct a comprehensive search in a Scopus and WoS database. Secondly, the keys from the table combined such TMC and ML algorithms, modern and conventional techniques, transport and environment, transport and health, DCMs, and TMC that search within article title, abstract, and keywords through which we got 2941 articles. The final dataset of 2941 articles is narrowed down to limited studies by using the filter option in the search engine. For instance, the filter applied to choose those articles using ML techniques, the latest five years publications, English version only. In addition, through the physical examination, the irrelevant publications were discarded, leaving 56 articles. The objectives, suggested methods, real contributions, findings, and recommendations for the future of the 56 papers that were gathered via the search engine were carefully examined by hand, going over the complete contents of the publications. In the end, after carefully assessing of article by reading its abstract, methods, results, and conclusions, 46 most recent articles (2017–2023) were collected for the study, whereas 39 of the articles were chosen for review after a manual review of the publications.

Table 4: Keywords used for the search at the initial stage

Transport mode choice	Travel; trip; trip purpose; travel purpose; travel mode; travel behavior; mode choice; travel demand; mode shift; travel distance; journey distance; travel pattern; trip distance; travel time; trip time; journey time; commute time; commute distance; usage; use; ridership, transport and health, environment
Built environment	Infrastructure; availability; accessibility; urban area; neighborhood; distance from city center, CBD, school, university, workplace, supermarket; basic amenities
Artificial intelligence	ML algorithms, discrete choice models

3.3.2 Inclusion Procedure and Requirements

Several criteria were set for the inclusion of the articles in the review process after the query search that is (1) only articles that are published in conferences and journals with English editions from the year 2018–2023 were considered in which one article, mostly relevant to the topic from 2017 were also considered because of its relevancy to the scope of the study; (2) studies modeling TMC and examine the correlation between several endogenous and exogenous variables; (3) studies that determine the determinants of TMC; and finally (4) those studies which used ML techniques for the prediction, modeling, and correlation of TMC. The PRISMA approach was used to choose the paper for the final inclusion using the four phases.

To effectively compare the performance of ML models across different datasets for predicting transport mode choice (TMC), a systematic approach should be adopted that ensures the evaluation is consistent, transparent, and meaningful. The specific variables such as socio-demographic data (age, income, occupation), geographic data or quantitative (distance, origin, destination), real-time data or qualitative variables (traffic, weather, public transport availability), TMC for different purposes, and different ML algorithms are looked in the different dataset for the model comparison. It's common to test all models and compare their performance using cross-validation and metrics like accuracy, precision, recall, and F1-score to decide which model is optimal. Therefore, the performance of several ML models is compared using performance evaluation metrics and k-fold, 2-fold, 3-fold, 5-fold, and 10-fold cross-validation metrics to suggest the best predictive model. This process ensures a fair and thorough comparison of machine learning models across different datasets for TMC prediction.

3.3.3 Data Retrieval Approach

Based on the research questions, the data are retrieved from the articles and compiled in Table 5 to gather the information and avoid biases during the data collection that are concrete, measurable, and well-defined. After a thorough review of the paper, it was accessed with which research question it was allied to gather specific information.

Table 5: Collection of research articles for systematic literature review based on the review questions

Review question	Description
RQ1	Where had ML techniques been used to determine the determinants of TMC?
RQ1.a	Application domains
RQ2	Which ML techniques have been used to determine the determinants of TMC?
RQ2.a	Utilization of ML algorithms in research
RQ2.b	Interpretable ML techniques
RQ3	What are the characteristics of the datasets used to determine the determinants of TMC?
RQ3.a	Characteristics and size of the dataset
RQ3.b	Data availability statements—freely available?
RQ3.c	TMC variables
RQ3.d	TMC dataset
RQ4	How are ML models' performances evaluated?

(Continued)

Table 5 (continued)

Review question	Description
RQ4.a	Validation approach
RQ4.b	Criteria for performance evaluation

4 Results and Discussion

The summary of the particular 39 papers that are selected for the current study along with the references and identifications are presented in Table 6. In the next subheading, the source and the date (years of publication) are mentioned to easily assess the review process and understandable to the readers.

Table 6: Selection of 39 articles for a systematic literature review

No.	Authors	No.	Authors	No.	Authors
N1	[59] Yang et al. (2023)	N2	[60] Xia et al. (2023)	N3	[61] Noorbakhsh et al. (2023)
N4	[62] Murugan (2023)	N5	[63] Martín-Baos et al. (2023)	N6	[64] Liu et al. (2023)
N7	[65] Koushik et al. (2023)	N8	[66] Hatami et al. (2023)	N9	[67] Bei et al. (2023)
N10	[10] Abulibdeh (2023)	N11	[68] Barri et al. (2022)	N12	[31] Kashifi et al. (2022)
N13	[69] Salas et al. (2022)	N14	[26] Pineda-Jaramillo et al. (2022)	N15	[70] Naseri et al. (2022)
N16	[71] Momin et al. (2022)	N17	[72] Mohd Ali et al. (2022)	N18	[73] Hasan et al. (2022)
N19	[74] García-García et al. (2022)	N20	[75] Wong and Farooq (2021)	N21	[76] Sun et al. (2021)
N22	[32] Kim (2021)	N23	[77] Gao et al. (2021)	N24	[78] Buijs et al. (2021)
N25	[28] Ali et al. (2021)	N26	[79] Zhao et al. (2020)	N27	[80] Slik et al. (2021)
N28	[81] Koushik et al. (2020)	N29	[82] Jin et al. (2020)	N30	[83] Buijs et al. (2020)
N31	[84] Yan et al. (2019)	N32	[85] Haynes et al. (2019)	N33	[86] Cheng et al. (2019)
N34	[87] Chang et al. (2019)	N35	[88] Assi et al. (2019)	N36	[89] Zhu et al. (2018)
N37	[90] Wong and Farooq (2018)	N38	[25] Wang et al. (2018)	N39	[91] Hagenauer et al. (2017)

4.1 Articles Source

As can be seen in Table 7 the articles were included from different publishers such as Elsevier, Springers, SAGE, Hindawi, and MDPI and conferences. Among 39 articles, 36 articles are from different peer-reviewed journals consisting of 87% and 3 conference proceedings contributed 13%

in total after the search engine from Scopus and WoS as shown in Fig. 3. However, after the manual examination of the publications, the peer-reviewed journals contributed 92.30% and the conference proceedings contributed 7.69% in total. The most prominent, prestigious, and well-known journals; Travel Behavior and Society, IEEE Access, and Transportation Research Part C: Emerging Technologies contributed 27.10% in total.

Table 7: The number of articles from different sources and journals included for the systematic review

Journals	Publisher	Type	%	No.
Travel Behavior and Society	Elsevier	Journal	13.51%	5
IEEE Access	IEEE	Journal	8.10%	3
Transportation Research Part C: Emerging Technologies	Elsevier	Journal	5.40%	2
Expert Systems with Applications	Elsevier	Journal	5.40%	2
Transportation Research Interdisciplinary Perspectives	Elsevier	Journal	5.40%	2
International Journal of Transportation Science and Technology	Elsevier	Journal	2.70%	1
Land	MDPI	Journal	2.70%	1
Environment and Planning B: Urban Analytics and City Science	SAGE	Journal	2.70%	1
Transportation Letters	Taylor & Francis	Journal	2.70%	1
International Journal of Environmental Research and Public Health	MDPI	Journal	2.70%	1
Journal of Transport Geography	Elsevier	Journal	2.70%	1
KSCE Journal of Civil Engineering	Springer	Journal	2.70%	1
Journal of Transport & Health	Elsevier	Journal	2.70%	1
Journal of Urban Planning and Development	ASCE	Journal	2.70%	1
Communications	De Gruyter	Journal	2.70%	1
Transportation Research Procedia	Elsevier	Journal	2.70%	1
Knowledge-Based Systems	Elsevier	Journal	2.70%	1
Open Transportation Journal	Bentham	Journal	2.70%	1
Journal of Advanced Transportation	Hindawi	Journal	2.70%	1
Transport Reviews	Elsevier	Journal	2.70%	1
Procedia Computer Science	Elsevier	Conference	8.10%	3
Transportmetrica A: Transport Science	Taylor & Francis	Journal	2.70%	1
International Journal of Behavioral Nutrition and Physical Activity	Springer	Journal	2.70%	1
Sustainability	MDPI	Journal	2.70%	1
Transportation Research Record	SAGE	Journal	2.70%	1
Transportation	Springer	Journal	2.70%	1

4.2 Year and Country of Publication

The current systematic review considers the latest five-year articles that were published from 2018–2023 with only one article considered from 2017 that was highly cited and most relevant to the study as shown in Fig. 4. There was a gradual increase in the number of articles that used ML tools and algorithms for assessing travel behavior, TMC, and the determinants of TMC. The highest number of articles (10) were published in 2023 which shows the usage of ML algorithms for the prediction of determinants of TMC and outperforms the conventional models. Besides, the US shows the highest number of articles 11 articles as shown in Fig. 5 published for evaluating the determinants of TMC. China is the second highest after the US published 9 articles, whereas the UK published 6 articles in total of 39 articles related to the current review.

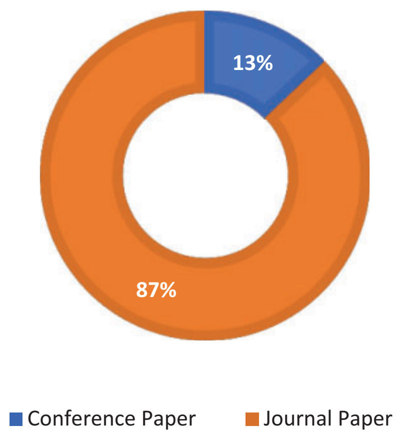

Figure 3: Number of articles from different sources

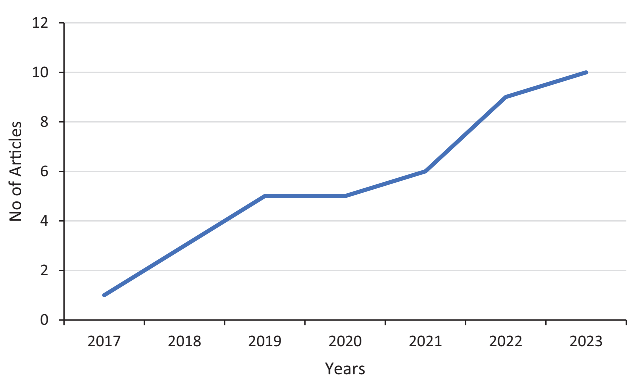

Figure 4: Yearly basis distribution of articles considered in the systematic review

4.3 Where Were ML Techniques Used to Determine the Determinants of TMC?

RQ1. a. ML application domains

ML techniques are used in several areas that outperform conventional statistical techniques and enhance TMC. In the current review of 39 articles, this study identified five different areas in which both ML and conventional techniques are used to investigate TMC as shown in Table 8. The application domains contained (1) TMC, (2) BE, (3) active transport, (4) shared mobility, and (5)

BE. Among five application domains, twenty-three ML-based investigations were used for the TMC and nine were used for the TB. However, four investigations were used for active transport such as women cyclists and travel to school by cycle, etc., two were used for BE, and two for shared mobility. Most of the ML approaches have been utilized for the prediction and determination of determinants of TMC and TB, that's the motivation behind conducting this systematic review based on the high number of studies in the field of TMC and TB utilizing ML techniques. Most of the studies claimed that ML techniques outperformed conventional techniques, whereas hyperparameter-optimized ML algorithms outperformed typical ML algorithms. Several ML algorithms were utilized for imbalanced TMC to work data while others were used to classify TMC prediction and feature the importance of input variables to investigate the most influential factors. Most of the studies claimed that total travel time, number of household vehicles, and income are the most influential factors, while others claim that age, gender, activity type, parking, and trip purpose were the most significant features.

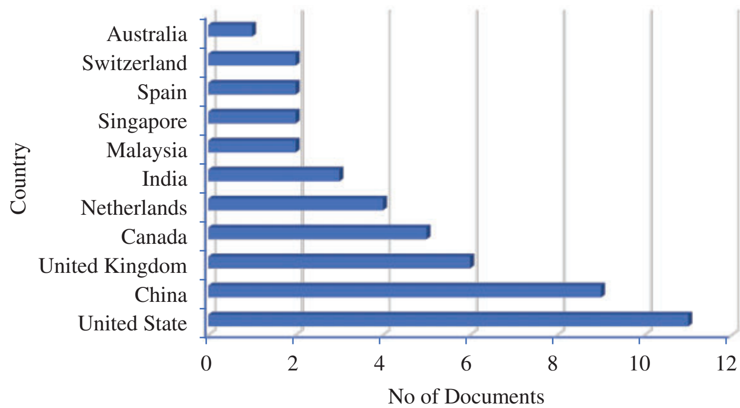

Figure 5: Number of articles distributed by Country

Table 8: Grouping of studies based on their applications and techniques

Application domain	Studies
Transport mode choice	N2, N5, N9, N10, N12, N13, N14, N15, N17, N18, N19, N20, N21, N23, N24, N25, N26, N29, N30, N33, N34, N38, N39
Built environment	N1, N8
Active transport	N3, N17, N32, N35
Shared mobility	N4, N31
Travel behavior	N6, N7, N11, N16, N22, N27, N28, N36, N37

4.4 RQ2. Which ML Techniques Have Been Used to Determine the Determinants of TMC?

In the following section, the synopsis of various ML approaches used in 39 studies will be discussed. Several different types of ML algorithms are utilized for the determination of TMC in diverse countries either for urban or rural areas in which different determinants influence TMC.

RQ2. a. Utilization of ML algorithms

Past studies were limited to conventional techniques such as structural equation modeling, bivariate and multivariate analysis, and regression analysis using SPSS, AMOS, and R [92–95]. Due to the recent development in modern techniques, recent studies utilize ML and AI techniques such as ANN, BN, k-NN, XGBT, GBT, DT, FT, SVM, GE, and GEP [96–98]. Due to the limitation of conventional techniques, ML algorithms, and data types such as linear or non-linear, recent and past studies utilize integrated and interpretable ML techniques for the factors affecting TMC and to enhance the model efficiency using deep and reinforcement learning [31,32,99]. Therefore, based on the current literature, the ML approaches are categorized into three groups—conventional techniques, ML algorithms, and interpretable ML as shown in Fig. 6. RF is one of the most widely used ML algorithms in TB research for TMC, BE, AT, and shared mobility followed by the ANN and interpretable ML algorithms. However, on the other side, conventional techniques are mostly utilized for the prediction of TMC and TB, whereas ML algorithms and interpretable approaches are widely utilized for the BE, active transport to promote sustainability, TB, shared mobility, and TMC. Moreover, Table 9 depicts the summary of several utilized ML techniques for TMC, TB, active transport, BE, and shared mobility in the selected studies. It can be seen that among all studies, only 10 studies utilized conventional techniques which contributed 25.6%, whereas 74.4% used ML algorithms in which random forest (RF) was the most frequently employed approach (18 studies) contributed about 47%; however, 20.5% studies applied interpretable ML algorithms. There was a gradual increase in the number of studies in 2022/2023 that utilize ML techniques with special attention to extreme gradient boosting trees (XGBT) and RF contributing a total of 19/39 in the scientific literature. The outcome of all these models shows that ML techniques outperformed conventional techniques, whereas interpretable ML algorithms outperform ML approaches due to the black box which turns out to white-box in integrated and interpretable ML approaches and enhances TMC decisions.

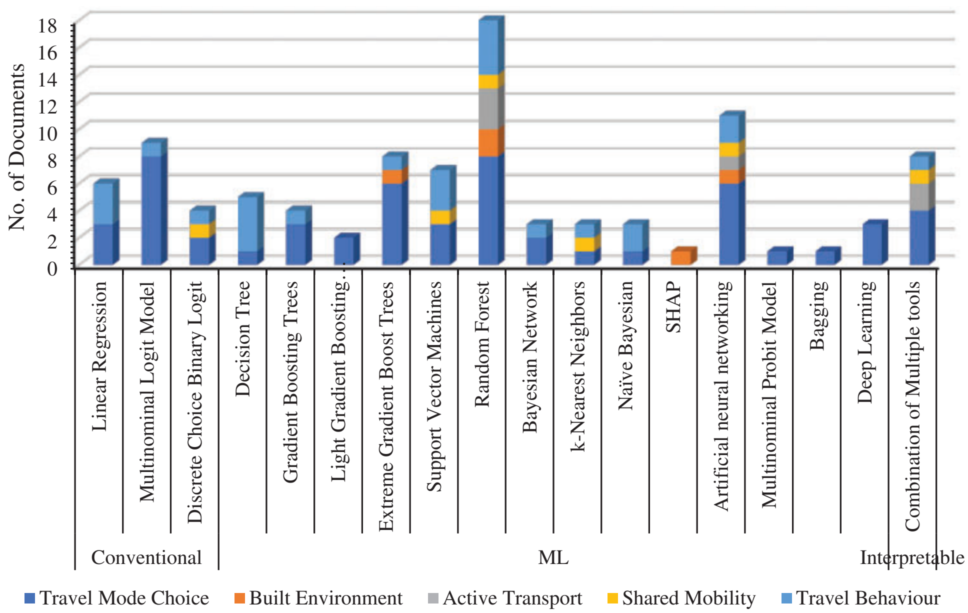

Figure 6: The number of studies used Conventional, ML, and interpretable techniques in selected studies

Table 9: Utilization of conventional, ML, and interpretable techniques used in selected articles

Study	ML classification			Study	ML classification		
	Conventional	ML	Interpretable		Conventional	ML	Interpretable
N1		√		N21			√
N2		√		N22	√		
N3		√		N23		√	√
N4	√	√		N24		√	
N5	√	√		N25	√	√	
N6		√		N26		√	
N7		√		N27	√	√	
N8		√	√	N28		√	
N9	√	√		N29			√
N10	√	√		N30		√	
N11	√	√		N31			√
N12	√		√	N32		√	
N13		√		N33		√	
N14		√		N34			√
N15		√		N35			√
N16		√		N36		√	
N17		√		N37	√	√	
N18		√		N38		√	
N19		√		N39		√	
N20		√					

RQ2. b. Interpretable ML techniques

Due to the nature of the dataset such as linear and non-linearity and the limitations of the ML techniques, most of the researchers applied interpretable ML techniques to solve the issue of black-box in the dataset and ML techniques. Interpretable ML techniques could resolve the issue of a black box and turn it into a white box considering the nature of the dataset. RF, GBT, XGBT, and SVM were the utmost commonly employed algorithms in the selected studies. The most popular machine learning algorithms for evaluating the impact of many independent variables on travel time and distance, including safety, BE, sociodemographic, and journey time, were RF and GBT. However, because GBT is trained sequentially rather than in parallel, it is prone to overfitting and inefficiency for the huge dataset. Nevertheless, if you use the RF technique for regression analysis, you can rely on orthogonal decision boundaries, which can produce less-than-ideal outcomes.

4.5 RQ3. What Are the Characteristics of the Datasets Used to Determine the Determinants of TMC?

This section contains the characteristics of the dataset that are used in 39 articles such as the description and size of the data that are gathered for the analysis and correlation between the variables. It mainly focuses on the targeted variables such as the determinants of TMC, ML techniques, and the

TMC in return. Besides, the unit of analysis, data size, and the data availability statement are also discussed in this section. Several studies used separate variables for the target variables and TMC; therefore, the data sources of the targeted variables and TMC variables are described separately.

RQ3. a. Characteristics and size of the dataset

Table 10 predicts the characteristics and the sample size of the selected 39 articles. During the entire review process of the selected 39 articles, it was noticed that for the TMC and its influencing variables, three types of data sources are used National, Local, and Departmental Data (NLDD), Academic Data (AD), and Company Data (CD) for the targeted variables. Among 39 studies, 24 studies which contributed circa 61% used NLDD data source type, whereas AD used 13 studies contributing 33.33%, and only 2 studies used CD which contributed the remaining 5.12% of the data source.

Table 10: Description and sample size of selected studies

No.	Outcome variable	Data type	Data availability	Sample size	Unit of analysis
N1	BE and mobility	NLDD	NE	546	Individuals
N2	Modes of transport	NLDD	DUa	167,717	Household
N3	Women cyclist	NLDD	DUa	52	Women
N4	Electric vehicle	NLDD	DUa	522	Individuals
N5	TB	NLDD	DA	1906	Individuals
	Travel modes			230,608, 69,918	Trips, individuals
				81,096, 17,616	Samples, participants
N6	Rail transit	NLDD	AoR	80,000, 28,000, 11,729	Individual, Household, Trips
N7	Netherlands daily travel pattern	NLDD	AoR	30,781	Travel diary
N8	BE	NLDD	DUa	546	Block groups
N9	Behavior analysis	NLDD	AoR	121,765, 69,208	Individuals, Household
N10	Trip conditions-Meto	NLDD	DUa	1247	Air travelers
N11	TB-Low-income	AD	DUa	22,213, 61,539	Individuals, trips
N12	Travel modes	NLDD	DA	230,608, 69,918	Trips, individuals
N13	TB	AD	NE	1000–5000	Individuals
N14	Determinants of TB	NLDD	DA	43,160	Household

(Continued)

Table 10 (continued)

No.	Outcome variable	Data type	Data availability	Sample size	Unit of analysis
N15	Child mode choice	AD	AoR	9597	Child trips
N16	Travel mode for long-distance	NLDD	NE	852	Respondents
N17	Active commuting behavior	AD	AoR	2316	Individuals
N18	Mode detection	AD	NE	120	Participants
N19	TMC	NLDD	DA	1906, 230,608	OPTIMA, NTS, Trips
N20	Data-driven choice model	NLDD	DA	60,365	Trips
N21	Smartphone recommend TMC	NLDD	DA	303,436	Transport routes
N22	Mode choice behavior	NLDD	AoR	76,190, 172,889	Individuals, Trips
N23	Travel decision making	NLDD	NE	2316, 386	Observation, Individuals
N24	TMC	NLDD	DA, DUa	106,647, 712	Trips, Users
N25	TMC	AD	AoR	1956	Individuals
N26	Behavioral analysis of TMC	AD	NE	8141, 1163	Observation, individuals
N27	TB	CD	NE	Over 1000	Employees
N28	Activity travel behavior	NLDD	NE	407 articles	Review
N29	Habitual travel modes	NLDD	DA	997	Household
N30	Public transportation	AD	NE	705	Trips
N31	Employee ridesharing	CD	NE	3370	Driver and passengers
N32	Active transport	AD	AoR	280	Individuals
N33	TMC	AD	NE	2991, 1435	Individuals, households
N34	TMC	AD	NE	361, 162, 5265	Individuals, households, trip
N35	Travel to school mode choice	AD	NE	1484	School students

(Continued)

Table 10 (continued)

No.	Outcome variable	Data type	Data availability	Sample size	Unit of analysis
N36	Travel decision	NLDD	NE	5213	Individuals
N37	Travel behavior	AD	NE	246	Observations
N38	TMC	NLDD	NE	51,910	Trips
N39	TMC	NLDD	DA	230,608, 69,918	Trips, Individuals

Note: DA = Data Available; DUa = Data Unavailable; AoR = Available on Request; NE = Not Exist in the article. Data Type—NLDD; National/Local/Departmental Data; AD = Academic Data; CD = Company Data.

The analyzed research in the reviewed study made use of multiple research units. In general, it was individuals, households, respondents, trips, travel (air, travel diary), adults, children, women, transport routes, employees, drivers, passengers, and school students. However, these research units are classified into individuals, households, trips, travels, and adults. Among 39 studies, 13 studies contributed 33.33% in total used individuals as a unit of analysis, 5 studies (12.82%) utilized household survey data as a unit of analysis, 7 studies employed trip as a sample unit, 5 studies (12.82%) used travel data, and the rest of 9 studies circa 23% employed adults as a unit of analysis.

Regarding the data size, there was only one study that used less than 100 sample size which was N3 (women cyclist), 4 articles that used less than 500 sample size which contained one review article, 6 studies that used less than 1000 samples, and the rest of 28 studies used over 1000 sample size.

RQ3. b. Data availability statements—freely available?

Throughout the selected articles, it was checked whether the data used in the current study is freely available to the public and users or not; therefore, the data availability is mainly categorized into four different sections that are data available (DA), data unavailable (Dua), available on request for the corresponding or any authors (AoR), and the availability statement didn't mention in the article (NE). It was noticed that most of the research data will not be freely available due to some institutional policies or confidentiality. Nine articles used data that are publicly available and accessible to all researchers. Besides, there were only two studies that used CD, whereas there were 16 studies that did not mention the data availability statement. However, eight studies mentioned that the data is AoR from the corresponding author(s). Four studies used the NLDD data and kept it available on request, which are:

- Chongqing Urban Resident Travel Survey from 2014.
- Onderweg in Nederland databy Centraal Bureau voor de Statistiek (CBS), Netherlands (Centraal Bureau voor de Statistiek (CBS), Rijkswaterstaat (RWS-WVL) 2019 and 2020.
- Annual National Travel Survey (NTS) data of the UK from 2005 to 2016, which are publicly provided by the Department for Transport.
- 2016 National Household Travel Survey (NHTS) dataset in Seoul, Korea.

RQ3. c. TMC variables

TMC was determined from several variables such as gender, income, distance, purpose, safety, time, household vehicle ownership, available transport mode, accessibility to public transportation, BE variables, and weather conditions. All these variables directly or indirectly influence TMC depending on the country, situation, and type of available data. For instance, safety and security have a significant impact on women cyclists, whereas the built environment has an impact on travel behavior with a higher degree of 5Ds such as design, density, destination accessibility, diversity, and short distance to transit.

RQ3. d. TMC dataset

As can be seen in past studies, the source of the targeted variables and TMC are different. 25 studies explain the TMC from three different transport modes such as private vehicles, public transport, and active transport. These studies gathered the data from public databases to determine TMC using statistical tools and ML techniques. Almost every study used different ML techniques and algorithms for the determination of TMC in different countries and compared the results with the conventional techniques in which the ML techniques always outperformed and enhanced the model efficiency which helped the policymakers to better develop the policy based on the ML outcomes. In most models, the coefficient of determination was over 0.95 (95%) which shows the high significance of the model.

4.6 RQ4. How Are ML Models' Performances Evaluated?

RQ4. a. Approach for validation

For the model validation in ML algorithms, several cross-validation (CV) methods such as the k-fold cross-validation method, 3-fold CV, 5-fold CV, 10-fold CV, and holdout validation methods are used by the past studies. Some of the studies also used both k-fold and holdout validation methods, whereas others used k-fold and 10-fold CV. Table 11 depicts the approach for model validation using several CVs in which nine studies used k-fold CV, two studies used 3-fold CV, four studies used 5-fold CV, and five studies used 10-fold CV. However, three studies used both k-fold and 10-fold CV, whereas two studies used k-fold and 5-fold CV. Most of the studies used an 80:20 ratio of train-test data whereas some of the studies used a 70:30 ratio and others used a 90:10 ratio of train-test data. Only one study was found (N35) which used three different ratios of train-test data which are 60:40, 70:30, and 80:20, and concluded that the 80:20 ratio train-test data provided higher accuracy than the rest of the train-test ratios. Out of all 39 selected studies, nineteen studies did not report their validation approach.

Table 11: Cross-validation methods of ML algorithms

Study	Cross validation				Study	Cross validation			
	k-fold	3-fold	5-fold	10-fold		k-fold	3-fold	5-fold	10-fold
N3	√	√	–	–	N19	√	–	–	√
N5	–	–	√	–	N22	–	–	√	–
N8	–	√	–	–	N23	–	–	–	√
N10	√	–	–	–	N25	–	–	√	–
N11	√	–	–	√	N26	–	–	–	√
N12	–	–	–	√	N27	–	–	√	–
N13	√	–	–	–	N33	–	√	–	–
N14	√	–	–	–	N34	√	–	√	–

(Continued)

Table 11 (continued)

Study	Cross validation				Study	Cross validation			
	k-fold	3-fold	5-fold	10-fold		k-fold	3-fold	5-fold	10-fold
N15	√	–	√	–	N38	–	–	–	√
N16	–	–	–	√	N39	√	–	–	√

RQ4. b. Model performance evaluations

The performance of the models in 39 selected studies is accessed using several evaluation techniques. The different performance criteria are used to assess the relationship among TB, BE, TMC, and its determinants. Table 12 depicts the model evaluation process in each study that is used to assess the model performance. The current review merely reviewed and considered the performance criteria and the analysis as shown in Tables 12 and 13; however, several other important measures that could be employed to assess ML models' performance are not covered in the current review as it wasn't presented in the selected studies. Only ten studies did not show their performance criterion and ML model performance.

Table 12: Model evaluation performance criteria used in the selected studies

Study	R/R^2	AUC	PRE	MAPE	MAE	MSE	RMSE	Study	R/R^2	AUC	PRE	MAPE	MAE	MSE	RMSE
N3	√	–	–	√	–	√	√	N19	–	√	–	–	–	–	–
N4	√	√	√	–	–	–	–	N20	–	√	–	–	–	–	–
N5	–	√	√	–	–	–	–	N22	–	√	–	–	–	–	–
N6	–	–	√	–	–	–	–	N23	–	√	√	–	–	–	–
N7	–	√	√	–	–	–	–	N24	–	√	–	–	–	–	–
N8	–	–	–	–	√	√	√	N25	–	√	√	–	–	–	–
N10	√	√	√	–	–	–	–	N26	–	√	–	–	–	–	–
N11	√	–	–	–	√	√	√	N27	–	√	–	–	–	–	–
N12	–	√	√	–	–	–	–	N33	–	√	√	–	–	–	–
N13	–	–	–	–	–	–	√	N34	–	√	–	–	–	–	–
N14	–	√	√	–	–	–	–	N35	–	√	–	–	–	–	–
N15	–	√	–	–	–	–	–	N36	–	√	–	–	–	–	–
N16	–	√	–	–	–	–	–	N38	–	√	–	–	–	–	–
N17	–	√	–	–	–	–	–	N39	–	√	–	–	–	–	–
N18	–	√	–	–	–	–	–								

The relationship between two variables was assessed using the linear correlation or coefficient of determination (R/R^2). The R^2 value of 10%–20% is considered satisfactory in travel behavior research. Furthermore, the Mean Absolute Percentage Error (MAPE) is used to quantify the deviation between the actual and anticipated values, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). As the name MAPE, it is a percentage-based measure while MAE, RMSE, and MSE are absolute measures. For the classification task, precision (PRE) and classification accuracy (AUC) are utilized to determine the anticipated positive cases among all actual positive cases. Among all 39 selected studies, nine studies (N4, N5, N7, N10, N12, N14, N23, N25, N33) used AUC and PRE, whereas fifteen studies used AUC for measuring the corrected positive predicted cases.

Besides, four studies (N3, N4, N10, N11) employed linear correlation or the coefficient of determination (R/R^2), whereas four studies (N3, N8, N11, N133) used absolute measure, RMSE, MSE, MAE. Only one study (N3) employed a percentage-based (MAPE) performance criterion. In addition, Table 13 presents the performance of several machine learning models employed in the chosen research. Several studies divided the data into training and testing through which they have different performance ML models and R^2 values. Sometimes the models achieved higher values such as 90%–99% (0.90–0.99), while in other cases, they achieved lower values ranging from 20%–30% (0.20–0.30). Several ML models such as SVM, DT, RF, XGBT, NB, MNL, ANN, NN, KNN, AdaBoost, XGBoost, LightGBM, etc., are used to demonstrate the accurate performance. The R^2 values for both training and testing in RF in two studies (N3 and N11) show the highest (0.91 and 0.58), whereas it was lower in one study (N4) in which the SVM R^2 values were higher than RF.

Table 13: Model performance of selected studies using ML

Study	Model performance
N3	**RF:** MSE: 0.30, **Training:** R^2: 0.91, RMSE: 0.08, MAPE: 5.94%, **Testing:** R^2: 0.67, RMSE: 0.08, MAPE: 9.74% **AdaBoost:** MSE: 0.35, **Training:** R^2: 0.66, RMSE: 0.19, MAPE: 12.45%, **Testing:** R^2: 0.59, RMSE: 0.19, MAPE: 11.55% **XGBoost:** MSE: 0.37, **Training:** R^2: 0.88, RMSE: 0.08, MAPE: 6.14%, **Testing:** R^2: 0.66, RMSE: 0.14, MAPE: 7.6% **LightGBM:** MSE: 0.31, **Training:** R^2: 0.86, RMSE: 0.09, MAPE: 7.14%, **Testing:** R^2: 0.66, RMSE: 0.14, MAPE: 8.1%
N4	**SVM:** Prediction: 84%, R^2: 0.53, AUC: 0.897, **ANN:** Prediction: 81%, R^2: 0.51, AUC: 0.765 **RF:** Prediction: 78%, R^2: 0.44, AUC: 0.654
N5	**MNL:** 0.65–0.75 (training), 0.44–0.51 (testing), **SVM:** 0.43–0.55 (training), 0.65–0.75 (testing), **RF:** 0.47–0.57(training), 0.69–0.78 (testing), **XGBoost:** 0.69–0.78 (training), 0.70–0.78 (testing), **NN:** 0.68–0.77 (training), 0.69–0.76 (testing), **DNN:** 0.67–0.77 (training), 0.68–0.75 (testing)
N6	**RF:** Precision = 0.858, **AdaBoost:** Precision = 0.733, **XGBoost:** Precision = 0.874, **DT:** Precision = 0.772, **LR:** Precision = 0.757
N7	**Nested Logit model:** AUC = 0.78, **ANN-based model:** AUC = 0.88
N8	**RF:** MAE = 0.023, MSE = 0.0019, RMSE = 0.038, R^2 = 0.319
N10	**BL:** AUC = 0.8089, PRE = 0.820, **XGBoost:** AUC = 0.825, PRE = 0.862, **MNL:** AUC = 0.8089, PRE = 0.823
N11	**DT:** R^2 = 0.523, RMSE = 0.694, MAE = 0.068, MSE = 0.690 **RF:** R^2 = 0.582, RMSE = 0.650, MAE = 0.0.116, MSE = 0.646 **XGB:** R^2 = 0.539, RMSE = 0.683, MAE = 0.121, MSE = 0.678 **NN:** R^2 = 0.553, RMSE = 0.672, MAE = 0.098, MSE = 0.668 **SVM:** R^2 = 0.530, RMSE = 0.689, MAE = 0.080, MSE = 0.685

(Continued)

Table 13 (continued)

Study	Model performance
	LR: R^2 = 0.467, RMSE = 0.734, MAE = 0.203, MSE = 0.729
N12	**LR:** AUC = 0.566, PRE = 0.62, DT: AUC = 0.563, PRE = 0.43, **RF:** AUC = 0.654, PRE = 0.73, **LightGBDT:** AUC = 0.675, PRE = 0.76
N13	**KNN:** RMSE = 0.030, AUC = 0.634, **NN:** RMSE = 0.030, AUC = 0.703, **RF:** RMSE = 0.027, AUC = 0.634, **SVM:** RMSE = 0.030, AUC = 0.652, **XGB:** RMSE = 0.031, AUC = 0.634
N14	**GBoost:** AUC = 0.953, PRE = 0.853, **RF:** AUC = 0.951, PRE = 0.853, **ANN:** AUC = 0.943, PRE = 0.856, **SVM:** AUC = 0.943, PRE = 0.843, **MNL:** AUC = 0.940, PRE = 0.834, **k-NN:** AUC = 0.912, PRE = 0.791, **DT:** AUC = 0.853, PRE = 0.808
N15	**AUC:** MOHPT = 0.765, RF = 0.728, Hyperparameter = 0.737, Grid = 0.752
N16	**AUC:** NB = 0.871, DT = 0.937, SVM = 0.937, KNN = 0.929, RF = 0.953
N17	**AUC:** LR = 0.654, NB = 0.669, DT = 0.665, SVM = 0.495, RF = 0.716
N18	**AUC:** RF = 0.972, XGBT = 0.969, ANN = 0.940, SVM = 0.804
N19	**AUC:** MNL = 0.713, SVM = 0.746, RF = 0.753, NN = 0.742, DNN = 0.757, CNN = 0.744
N20	**AUC:** MNL = 0.720, ResLogit = 0.767
N22	**AUC:** ANN = 0.985, RF = 0.990, XGB = 0.993
N23	**RF:** AUC = 0.686, PRE = 0.217
N24	**AUC = 0.84**
N25	**AUC:** ANN = 0.729, LR = 0.709, RF = 0.700, DT = 0.661, SVM = 0.542
N26	**AUC:** MNL = 0.647, NB = 0.584, BOOST = 0.850, RF = 0.856, SVM = 0.772, ANN = 0.646
N27	**AUC:** BL = 0.92, LR = 0.93, NN = 0.96, GBT = 0.91, RF = 0.96
N33	**AUC:** RF = 0.853, AdaBoost = 0.636, SVM = 0.834, MNL = 0.630
N34	**Single Predictor: AUC:** MNL = 0.637, NB = 0.539, SVM = 0.448, RF = 0.981, Adaboost = 0.636, GBDT = 0.746
	Fusion Model: AUC: MNL+RF+SVM = 0.974, NB+RF+SVM = 0.954, NB+SVM+GBDT = 0.985, Adaboost+RF+SVM = 0.987, GBDT+RF+SVM = 0.975
	Hybrid Model: AUC: PCA+RF = 0.943, DAE+RF = 0.982
N35	**AUC:** SVM = 0.895, ELM = 0.997, MLP-NN = 0.996
N36	**AUC:** NL = 0.447, DT = 0.454, BN = 0.47
N38	**AUC:** MNL = 0.949, XGB = 0.952
N39	**AUC:** MNL = 0.52, NB = 0.61, SVM = 0.85, ANN = 0.63, BOOST = 0.80, BAG = 0.92, RF = 0.95

5 Discussion

The classification matrix was checked through the coefficient of determinations (R^2), RMSE, MSE, MAE, and MAPE, and model performance through AUC, accuracy, precision, F1-score, recall, and MCC for both training and testing of the data. Some of the studies used 70% training and 30% testing data, while others used 80:20 and 90:10. Most of the studies claimed that 80% training and

20% testing data give the best performance. Besides, several cross-validations are used such as 3-folds, 5-folds, and 10-folds during the model analysis. Moreover, some studies utilized both conventional and modern techniques and compared the models based on statistical correlations between the variables such as R^2 and significance level. It was found that most of the conventional model R^2 was below 50%, whereas it was the opposite for modern techniques which gives sometimes over 95%.

Besides, several ML models were compared based on the classification matrix and model performance evaluations. Some of the ML models give an accuracy of over 90% while others are below 80%. Most of the models have over 80% precision values in which the RF outperformed the rest of the models. Besides, almost all studies claim that modern techniques outperform conventional techniques, where interpretable ML algorithms outperform the typical ML algorithms due to the binary classification and unable to handle imbalances or multidimensional datasets. Adjusted kernel SVM mapping the complex dataset into high dimensions makes the data point separations easier which simplifies the data boundaries for non-linear problems. The kernel SVM can handle optimized problems that have multiclass and variables.

Lack of interpretability is one problem with machine learning models, especially black-box methods like deep learning. Additionally, DCMs' great interpretability strength stems from their utility maximization foundation. DCMs may overlook complicated relationships between trip duration, cost, and convenience; ML models can see these relationships. Hybrid models can combine the prediction capacity of ML with the interpretability of traditional models by merging DCMs with ML models such as RF or GBMs. The utility function of a DCM can then receive the output from various ML models to improve prediction while preserving interpretability.

Moreover, the feature importance of the input variables over the output variables is studied to check the evaluate the individual input variable effect on the targeted variables. It was concluded that the total travel time [86], trip distance [87], income [10], waiting time [28], sociodemographic [66], age, and car ownership [32] are the most influential variables for the prediction of TMC. However, these factors were varying in different studies around the globe due to personal, geographical, and contextual factors in some studies, weather conditions are the most influential factors, whereas in other studies infrastructure availability and accessibility were the most influential factors. The primary socioeconomic characteristics that motivate passengers to transition to more environmentally friendly modes of transportation include age, nationality, employment, ownership of a vehicle, and income [10].

In addition to promoting environmentally friendly transportation options, reducing traffic, and mitigating the effects of travel mode choices on the environment, long-term policy recommendations also seek to improve community accessibility and mobility. For promoting sustainable transportation systems including walking, public transport, and cycling, the government should prioritize the investment of funding in infrastructure and maintenance and modernization of existing transit systems to ensure their reliability and efficiency. Besides, health is a part of capability constraints that influence transport options [100]; therefore, providing and enhancing accessibility for people with disabilities helps in the reduction of private cars and the promotion of a sustainable transportation system. Moreover, the implementation of road user charges based on factors, increment in parking fees in urban areas, providing subsidies on public transport tickets, and introduction of pricing charges scheme discourage private car users in peak days and hours. As one of the most significant factors is the distance between the last stop and individual residence location; therefore, the adoption of land use policies, and the development of affordable housing near the transit stations enhance the access to public transportation. However, in some cases, the residential areas closer to the basic amenities and public transport lines are more expensive than the other way around which encourages individuals to live far away and use private vehicles.

This study emphasizes the increasing importance of ML as a useful substitute for traditional statistical methods in the modeling of determinants of TMC used for daily activities. Nevertheless, a close look at the literature review indicates notable differences in the approaches used. Thus, more investigation is required to develop reliable and consistent scientific methods for using ML to analyze TMC and investigate its determinants. In 39 selected studies, the R^2 values and even the same algorithm values are changing, which might be due to the nature of the data and the variables used; however, standardized methods need to be developed for the prediction of TMC and its determinants. Moreover, in terms of data aggregation, it is crucial to assure consistency between both the input and the output variables to prevent problems with generalization and accuracy.

The practical application of DCMs and ML models is vital for urban planners and policymakers. By increasing prediction accuracy and result interpretability, DCMs and ML algorithms can be integrated into transportation planning tools or policy frameworks to greatly improve decision-making. Each approach has its own merits, and when combined, it can produce strong tools for policy evaluation, infrastructure development, and transportation demand modeling. Large, real-time data sets might be processed and analyzed using ML techniques in the first step of a hybrid model. Subsequently, pertinent factors (such as transport availability and congestion levels) could be fed into a DCM to predict how travel behavior would change in response to those conditions. This makes the results more valuable for making policy decisions by guaranteeing that predictions are not only accurate but also based on a solid theoretical framework. The data-driven policy that is effective in the near term and long-term sustainable is made possible by these integrated approaches.

Several factors need to be considered when discussing the issues of reproducibility of the results and generalizability of the ML techniques in diverse areas and countries. Transport options, urban infrastructures, weather conditions, and geographical factors vary from country to country and cannot be generalized. Reproducibility can be improved through open data, transparent methods, and standardized processes. In addition, the models trained on one dataset cannot be used for other datasets for the predictions due to cultural, behavioral, infrastructure, and policies.

ML models use real-time data from smart city infrastructure, mobility apps, and personal devices, which is crucial to address ethical considerations related to the use of personal data. While there are many advantages to integrating ML models into transportation planning, there are also serious ethical concerns about data privacy, fairness, openness, and monitoring. Planners and policymakers should implement best practices including data anonymization, bias audits, and open decision-making frameworks to reduce these risks. The preservation of people's privacy should come first in ethical data governance, and it should make sure that ML models improve transportation systems without escalating inequality or jeopardizing citizens' rights.

6 Conclusion

The current review provides a systematic evaluation of ML techniques that are used for predicting the determinants of TMC around the globe. The research develops four review questions that relate to the application domains, utilization of ML algorithms, the dataset used in the studies, and performance evaluation of the ML models. Using two main online publishing databases such as WoS and Scopus, 39 relevant studies were found related to determinants of TMC and its influence that were considered for the review.

This research systematically reviews the conventional (statistical tool) and modern techniques (ML algorithms), criterion, and model performance of the past studies and concludes that in most of the studies, RF outperforms SVM, GBT, DT, XGBT, and MNL. Besides, some studies used interpretable ML techniques in which they combined two different algorithms such as SVM + GBT or NB + RF + SVM as mentioned in the N34 study, and concluded that the accuracy of the model reached 99% (0.99). However, in some other studies, the accuracy of the RF model ranges from 95% to 99% (0.95–0.99) as shown in Table 13 studies N14, N16, N18, N22, N27, N34, and N39. Moreover, the coefficient of determination (R2) is also found higher in RF compared to other ML models. For instance, the value of R2 is 0.91 (91%) in study N3 is higher than Adaboost, XGBT, and LightGBM.

Several studies confirmed that socio-demographic characteristics, household vehicle ownership, and income status in the main determinants of TMC. Besides, other studies confirm that attitude, built environment, accessibility, and infrastructure influence TMC. Moreover, travel time, parking type, motorized vehicles, age, and gender explain TMC.

Given the prevalence of the problems this research describes, a deeper understanding of the methods utilized in ML modeling of nonlinear interactions between transport mode choice and built environment is needed. Even though more research is necessary to completely comprehend the implications of these limitations, it is already clear that some of the "matters of concern" violate the fundamental holdout validation principle of machine learning and ought to be disregarded in subsequent studies.

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