



Xgboost Modeling To Predicting Land Use-Based Trip Generation: Literature Review

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Abstract

Reliable trip generation prediction is essential for transportation planning, traffic forecasting, and sustainable urban development. However, conventional statistical models may struggle to capture nonlinear relationships between land-use characteristics and travel demand. This study systematically reviews research published between 2019 and 2025 on XGBoost applications in land-use-based trip generation and related travel-demand prediction. A total of 25 studies were analyzed based on data characteristics, land-use and built-environment variables, modeling approaches, validation techniques, evaluation metrics, and research findings. The review indicates that XGBoost can capture complex nonlinear relationships and interactions among explanatory variables, making it a promising approach for modeling travel patterns. However, predictive performance varies across datasets, geographical contexts, target variables, and evaluation methods, limiting direct comparisons among studies. Key challenges include model interpretability, data quality and availability, spatial transferability, and integration with Geographic Information Systems (GIS) and real-time transportation data. This review synthesizes methodological developments, identifies limitations in the existing evidence, and highlights opportunities for improving model explainability, validation, and cross-context generalization. The findings provide a basis for developing more reliable and context-sensitive trip generation models to support evidence-based transportation planning and smart city applications.

Keywords: XGBoost, Trip Generation, Land Use, Machine Learning, Systematic Literature Review

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INTRODUCTION

Trip generation has long been recognized as a fundamental component of transportation planning because it provides an estimate of the number of trips generated and attracted by different land-use activities [1]. Reliable trip generation estimates are required to support decisions related to traffic impact analysis, transport infrastructure provision,

public transport services, and urban development planning. As the first stage of the conventional four-step travel demand model, inaccuracies at this stage may propagate to subsequent analyses and reduce the reliability of planning outcomes. Previous research has shown that factors such as residential density, commercial land use, employment concentration, building floor area, and accessibility significantly influence travel demand and trip generation patterns [2], [3].

For several decades, regression-based models and conventional trip-rate manuals have been

widely adopted to estimate trip generation because they are relatively straightforward to implement and interpret [4]. Nevertheless, these approaches are generally developed under the assumption that the relationship between explanatory variables and travel demand follows a linear pattern. Such an assumption is often difficult to satisfy in real urban environments where travel behavior is simultaneously affected by land-use composition, socioeconomic conditions, accessibility, and characteristics of the built environment. As a consequence, conventional models frequently experience a decline in predictive performance when they are applied to complex and heterogeneous urban areas [5]

The increasing availability of spatial information, transportation databases, and Geographic Information Systems (GIS) has encouraged researchers to explore data-driven approaches for travel demand prediction [6], [7], [8], [9], [10]. Unlike conventional statistical techniques, machine learning algorithms are capable of identifying nonlinear relationships and complex interactions without relying on restrictive assumptions regarding data distribution. Among these algorithms, Extreme Gradient Boosting (XGBoost) has received considerable attention because it combines strong predictive capability with computational efficiency while reducing the risk of overfitting. In addition, the algorithm enables researchers to evaluate the relative contribution of explanatory variables, making the prediction process more transparent and informative [11].

Recent studies have increasingly adopted XGBoost to address the limitations of conventional trip generation models, particularly when travel demand is influenced by complex interactions among land-use characteristics [12], [13], [14], [15], [16]. Compared with traditional regression techniques, XGBoost is capable of accommodating diverse predictor variables, including land-use composition, development intensity, employment distribution, accessibility, population density, parking availability, and other built-environment attributes [17], [18]. Another important advantage is its compatibility with explainable artificial intelligence methods, such as SHAP, which enables researchers to interpret the contribution of individual variables rather than relying solely on prediction accuracy.

These capabilities make XGBoost an attractive tool for supporting transportation planning, urban policy evaluation, and data-driven decision making [19], [20].

Previous reviews have examined trip generation models based on land-use characteristics and the broader application of machine learning in trip generation and traffic impact assessment [3], [21]. These studies provide important foundations for understanding existing modeling approaches and their applications in transportation planning. However, differences in data sources, spatial units, explanatory variables, validation strategies, and evaluation metrics across the literature make it difficult to compare reported model performance directly [22], [23], [24], [25], [26]. In addition, the interpretability and spatial transferability of XGBoost-based models remain important considerations when assessing their applicability to different urban environments [21], [27]. Therefore, a focused comparative synthesis is needed to examine the methodological characteristics, reported predictive performance, and limitations of XGBoost applications in land-use-based trip generation and closely related transportation prediction tasks.

To address this research gap, this study conducts a systematic literature review of publications from 2019 to 2025 concerning the application of XGBoost to land-use-based trip generation and related transportation prediction tasks [17], [21]. The review examines the characteristics of the datasets, the types of explanatory variables employed, model development and validation procedures, evaluation metrics, and reported predictive performance [22], [23], [24], [25], [26]. It also synthesizes methodological limitations related to model interpretability, data availability, and spatial transferability, with the aim of identifying research opportunities for developing more reliable and practically applicable prediction models [18], [27]. Studies addressing related transportation outcomes are considered in terms of their methodological relevance, while their differences from direct trip generation prediction are recognized in the synthesis.

The contribution of this review lies in its comparative synthesis of methodological characteristics and reported findings across XGBoost-related transportation prediction studies [17], [21], [22], [23], [25], [28]. Rather than proposing a new prediction algorithm or assuming that XGBoost is universally superior to other modeling approaches, this study examines how data characteristics, explanatory variables, validation procedures, and evaluation metrics influence the interpretation of reported predictive performance [11], [17]. The review further considers model interpretability and spatial transferability as important methodological challenges for the practical application of prediction models in transportation planning [27], [28]. By synthesizing these aspects, the study aims to identify limitations in the existing evidence and research directions toward more reliable, interpretable, and spatially transferable trip generation models.

METHOD

A Systematic Literature Review (SLR) was employed to examine how Extreme Gradient Boosting (XGBoost) has been utilized for land-use-based trip generation prediction. Rather than evaluating a single case study, this review synthesized findings from previous studies to identify current research trends, methodological developments, and remaining research challenges [27], [29]. Relevant publications published between 2019 and 2025 were identified through comprehensive searches in three major scientific databases, namely Scopus, Web of Science, and ScienceDirect. The search strategy combined several keywords related to trip generation, land use, XGBoost, machine learning, and travel demand prediction to capture studies directly associated with the research topic.

The screening and selection process followed the PRISMA 2020 framework. Duplicate records were removed before titles and abstracts were evaluated against predefined inclusion criteria. Publications that did not specifically discuss land-use-based trip generation, lacked sufficient methodological information, or did not report quantitative model evaluation were excluded from further assessment. Only studies that fulfilled all eligibility criteria were retained for

detailed analysis. Each selected article was examined by considering its research objectives, data characteristics, explanatory variables, prediction models, validation procedures, evaluation metrics, and principal findings. The synthesized evidence was then compared to identify similarities, methodological differences, current limitations, and opportunities for future research regarding the application of XGBoost in trip generation modeling [25], [28], [30], [31]. Figure 1 presents the overall research methodology, covering the literature search, study selection, data extraction, comparative analysis, and synthesis of research findings. Figure 2 provides a detailed PRISMA 2020 flow diagram of the study selection process, including the number of records identified, duplicates removed, studies screened, full-text articles assessed, and studies included in the final review. Thus, the two figures serve complementary purposes: Figure 1 outlines the overall methodological framework, whereas Figure 2 documents the systematic selection of studies.



Figure 1. Research Methodology

Figure 1 summarizes the workflow adopted in this systematic literature review. The review process began with a comprehensive search of publications indexed in Scopus, Web of Science, and ScienceDirect. After duplicate records had been removed, the remaining articles were screened according to predefined inclusion and exclusion criteria. Publications satisfying all eligibility requirements were subsequently reviewed in detail and synthesized to examine methodological characteristics, prediction performance, and current research trends related to the application of XGBoost in land-use-based trip generation modeling. The initial search identified 186 records. After eliminating 38 duplicate entries, 148 publications remained for title and abstract screening. During this stage, 96 articles were excluded because they were not directly related to land-use-based trip generation or the application of XGBoost in transportation research. Subsequently, 52 full-text articles were assessed against the predefined eligibility criteria. Twenty-seven studies were excluded due to insufficient methodological information, the absence of quantitative model evaluation, a primary focus on transportation topics other than trip generation, or incomplete conference publications. Consequently, 25 peer-reviewed articles satisfied all selection criteria and were included in the qualitative synthesis. These publications formed the basis for comparing research approaches, predictive performance, and the contribution of XGBoost to land-use-based trip generation modeling.

RESULT AND DISCUSSION

The review was designed to provide a comprehensive understanding of recent developments in applying XGBoost to land-use-based trip generation prediction. The overall procedure consisted of four consecutive stages: literature identification, article screening, eligibility assessment, and qualitative synthesis. Each stage was conducted systematically to ensure that only studies closely related to the research objective were included in the review. Following article selection, the retained publications were compared from several perspectives, including research objectives, data sources, land-use variables, prediction algorithms, validation methods, performance indicators, and practical applications. This comparative approach made it possible to recognize common research patterns, evaluate methodological differences, and identify research gaps that remain open for future investigation [32].

Rather than focusing solely on predictive accuracy, this review also considered model interpretability, data quality, transferability across different urban contexts, and the practical implications of applying XGBoost in transportation planning. These aspects were incorporated to provide a broader understanding of both the strengths and the current limitations of the reviewed studies. The selected articles were subsequently reviewed using a comparative approach to identify similarities and differences in research objectives, modeling techniques, explanatory variables, validation procedures, predictive performance, and practical applications. This process enabled the identification of current research trends, methodological limitations, and potential directions for future studies in trip generation modeling.

Table 1 provides an overview of the studies selected for this review after the screening and eligibility assessment process. Rather than presenting only bibliographic information, the table highlights the diversity of research objectives, datasets, land-use characteristics, prediction methods, and practical applications reported in the literature. This overview serves



Figure 2. Prisma flow diagram

as the basis for identifying methodological trends and evaluating how XGBoost has been implemented in land-use-based trip generation studies.

Table 1. Synthesis of the 25 Reviewed Article

No	Author(s)	Title	Model/Method
1	Naseralavi et al., 2025 [17]	Machine Learning of Household Trip Generation Across the United States	CatBoost, Random Forest, Linear Regression
		A Review of Improving Trip Generation in Traffic Impact Assessments Using Machine Learning for Effective Land Use Planning	SLR / ML review
		Advancing Urban Transportation Planning: A Comparative Analysis of Machine Learning and Conventional Regression-Based Trip Generation Models	SVM, Regression
		A Comparative Study of CatBoost and Artificial Neural Networks in Enhancing Trip Generation Modelling for Ilorin City	CatBoost, ANN
		Developing Massachusetts-Specific Trip Generation Models for Land Use Projects	LBS data, regression model
		A Comprehensive Review of Trip Generation	Literature review
2	Amireh, Abdul Sukor, & Sadullah, 2025 [21]		
3	Kumar, Kumar, & Sinha, 2024 [33]		
4	Biala et al., 2024 [34]		
5	Xie et al., 2023 [35]		
6	Mukherjee & Kadali, 2022 [3]		
7	Yang et al., 2020 [36]	Models Based on Land Use Characteristics A Data-Driven Approach to Trip Generation Modeling for Urban Residents and Non-local Travelers	Random Forest / data-driven model
8	Parishwad et al., 2023 [36]	A Data-Driven Approach to Trip Generation Modeling for Urban Residents and Non-local Travelers	XGBoost
9	Yusuf et al., 2025 [23]	Data-Driven Predictive Modelling of Stop-Level Public Transit Patterns	XGBoost, SHAP
10	Liu, Wang, & Xiao, 2021 [37]	Non-linear Associations Between Built Environment and Active Travel for Working and Shopping: An Extreme Gradient Boosting Approach	XGBoost
11	Liu et al., 2024 [38]	Non-linear Relationship Between Built Environment and Active Travel: A Hybrid Model Considering Spatial Heterogeneity	XGBoost, MGWR, SHAP
12	Lei et al., 2024 [39]	How Does the Built Environment Affect Intermodal Transit Demand Across Different Spatiotemporal Contexts?	XGBoost, SHAP
13	Zhang et al., 2024 [19]	Analyzing Spatial Heterogeneity of	XGBoost

No	Author(s)	Title	Model/Method
		Ridesourcing Usage	
14	Shkera et al., 2025 [40]	Applying Machine Learning to Decode Built Environment Thresholds for Public and Active Transport Distances in the Global South	ML, SHAP
15	Çolak et al., 2025 [27]	Predictive Modeling of Urban Travel Demand Using Neural Networks and Statistical Methods	ANN, statistical models
16	Wang et al., 2024 [18]	Investigating the Nonlinear Effect of Land Use and Built Environment on Public Transportation Choice Using a Machine Learning Approach	XGBoost
17	Zang et al., 2025 [41]	A Scheduling-Optimization Model with Multi-Objective Constraints for Low-Carbon Urban Rail Transit Considering the Built Environment and Travel Demand: A Case Study of Hangzhou	XGBoost, BE-TCN
18	Long et al., 2025 [20]	The Influence of Neighborhood Environments on Children's Travel Mode Choices	XGBoost, SHAP
19	Sun et al., 2025 [42]	Nonlinear Effects of Built Environment on Ridesplitting Ratio: Discrepancies Across Sharing Motivations	XGBoost, PDP
20	Shen et al., 2025 [43]	Exploring the Nuanced Correlation Between Built Environment and the Integrated Travel of Dockless Bike-Sharing and Metro at Origin-Destination Level	XGBoost, SHAP
21	Chen et al., 2025 [44]	Examining nonlinear causal relationship between the built environment and VKT using RF-XGBoost	RF-XGBoost
22	Zhang et al., 2025 [45]	Nonlinear and Interactive Effects of Complex Built Environment on Travel-Related CO ₂ Emissions	XGBoost
23	Lee et al., 2025 [46]	Travel efficiency in urban space: the role of built environment in shaping excess travel distance across transport modes	MLR, XGBoost, PDP
24	Uddin et al., 2024 [47]	Exploring the Effects of Population and Employment Characteristics on Truck Flows: An Analysis of NextGen NHTS Origin-Destination Data	XGBoost, SHAP
25	Nourmohammadi et al., 2025 [48]	Spatial Transferability of Pedestrian Trip Generation Models	Bayesian Ridge, Random Forest

The reviewed publications demonstrate that research on trip generation prediction has evolved considerably over the last few years. Earlier studies predominantly relied on conventional regression models, whereas more

recent investigations increasingly employ machine learning techniques to capture the nonlinear relationships between land-use characteristics and travel demand. This transition reflects the growing availability of large transportation datasets together with advances in computational methods.

The titles of the 25 included studies were examined to identify recurring research themes. The results indicate that the built environment was the most frequently represented theme, appearing in 11 studies, followed by trip generation and travel demand or flows, each appearing in 8 studies. Other themes included transit or public transportation and land use, each appearing in 5 studies, and travel behavior or mode choice, appearing in 4 studies. These frequencies provide a descriptive overview of the main themes addressed in the literature rather than an assessment of the statistical significance or predictive importance of individual variables.

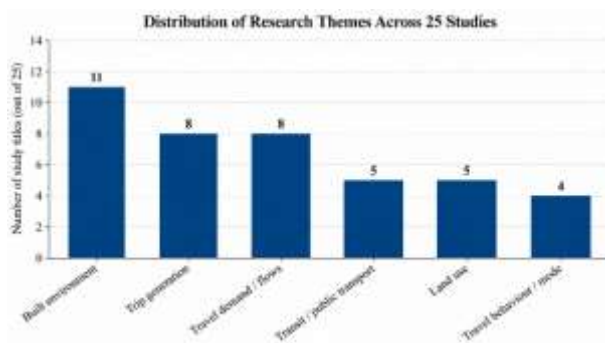


Figure 3. Title-Level Research Themes Across the 25 Reviewed Studies.

Although the reviewed studies share a common objective of improving prediction accuracy, substantial differences remain in terms of spatial scale, explanatory variables, data sources, and validation strategies. Several investigations emphasize household trip generation, while others examine public transport demand, active travel, ridesourcing, freight movement, or multimodal travel behavior. Such variation illustrates the broad applicability of machine learning within transportation planning while also making direct comparison between studies more challenging.

The variation in spatial scale is an important characteristic of the reviewed literature. The studies examine different transportation

contexts, including household trip generation, urban travel, public transportation demand, and other travel-related outcomes. Differences in geographical coverage and spatial units may influence the characteristics of the input data and the relationships captured by prediction models. Consequently, the spatial context should be considered when interpreting model performance and assessing whether a model developed in one setting can be transferred to another.

Figure 4 presents the preliminary classification of the spatial scales and study contexts identified in the reviewed studies. The distribution provides a descriptive overview of the spatial diversity represented in the literature. However, the classification should be interpreted in light of differences in the level of geographical detail reported by individual studies.

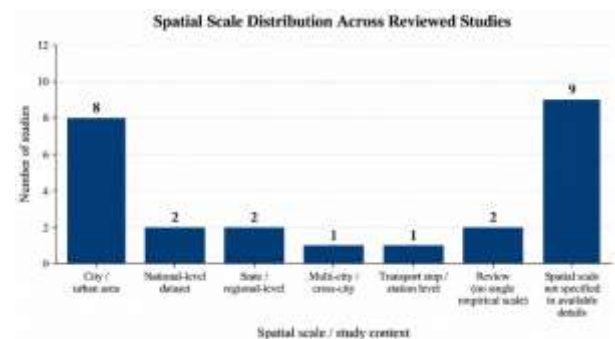


Figure 4. Spatial Scale of the 25 Studies Included in the Review

Most studies evaluated model performance using statistical measures such as R^2 , RMSE, MAE, and MAPE, while several recent publications incorporated explainable artificial intelligence techniques, including SHAP, to improve model interpretability. Although XGBoost consistently achieved competitive predictive performance, the literature also indicates that issues related to data availability, model transferability, and practical implementation remain important challenges requiring further investigation.

To complement the qualitative comparison, the reported model evaluation metrics were summarized to illustrate the range of predictive performance documented in the selected studies. The analysis considers R^2 , RMSE, and

MAE, which provide complementary information about model fit and prediction error. Nevertheless, differences in prediction targets, data sources, spatial units, and validation procedures limit direct comparisons across studies. Therefore, the reported values should be interpreted as a descriptive overview rather than as evidence of a definitive ranking of the reviewed algorithms.

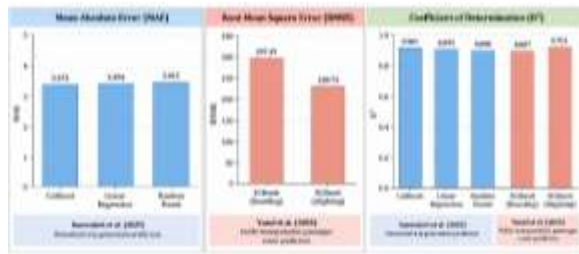


Figure 5. Reported Model Evaluation Metrics Across Selected Studies

The comparison of evaluation metrics must account for differences in the measurement scales and prediction tasks used in the reviewed studies. In particular, RMSE and MAE should not be compared directly when the target variables or their units differ. Similarly, R^2 values obtained from different datasets do not necessarily establish the superiority of one algorithm over another. These considerations reinforce the need for transparent reporting of data characteristics, validation procedures, and prediction targets when evaluating the practical applicability of trip generation models.

Despite these advantages, several challenges remain. Many studies rely on relatively small datasets collected from individual cities, limiting the generalizability of the developed models.

Spatial transferability is a critical challenge in the application of XGBoost-based trip generation models because the relationships between land-use characteristics, socio-demographic attributes, and travel demand may vary substantially across cities. Differences in population density, household structure, income distribution, employment patterns, land-use diversity, public transportation accessibility, and urban development can produce different distributions of predictor variables and different relationships between these variables and trip generation. Consequently, a model trained on

data from one city may learn patterns that are specific to its original spatial context rather than relationships that remain consistent across different urban environments. When applied to another city, these differences may result in distributional shifts, systematic prediction errors, and reduced predictive accuracy. The ability of XGBoost to capture nonlinear relationships and interactions does not automatically guarantee spatial generalization, particularly when the characteristics of the target city fall outside the range of conditions represented in the training data.

Recent transportation research has demonstrated that transferability depends on the compatibility of urban characteristics, the spatial scale of analysis, the availability of local data, and the modeling approach. For example, studies of pedestrian trip generation have reported differences in transferability between aggregate and disaggregate models across cities, while research on ride-hailing demand prediction has investigated knowledge-transfer approaches to improve cross-city model performance [48], [49]. These findings indicate that predictive performance within the training city should not be treated as sufficient evidence of applicability in other geographical settings.

Several methodological strategies can help address this challenge. First, models should be evaluated through external spatial validation, such as training on one or more cities and testing on a geographically separate city, or using leave-one-city-out validation when data from multiple cities are available. Second, training datasets should incorporate diverse urban contexts and harmonized definitions of land-use, socio-demographic, and accessibility variables to improve representation of cross-city heterogeneity. Third, transfer learning or domain adaptation can be considered to adjust a source-city model to the characteristics of a target city. Where a limited amount of target-city data is available, local calibration or fine-tuning can further reduce systematic prediction errors. Finally, model performance should be assessed separately across cities and relevant spatial or socio-demographic subgroups rather than relying exclusively on overall performance metrics. These strategies provide a more rigorous basis for determining whether

an XGBoost model can be transferred directly, requires local adaptation, or must be retrained for a new urban context.

In addition, model interpretability remains an important issue, particularly for transportation planners who require transparent decision-making processes. The integration of XGBoost with Geographic Information Systems (GIS), real-time traffic data, and explainable artificial intelligence (XAI) techniques has also received limited attention. Overall, the findings suggest that XGBoost is a promising approach for land-use-based trip generation prediction because of its high predictive accuracy, computational efficiency, and capability to model complex interactions among urban variables. Future research should focus on integrating multi-source spatial data, explainable machine

learning methods, and intelligent transportation systems to develop more reliable and transferable trip generation models for sustainable urban planning.

To better understand the relative strengths of different prediction approaches, the reviewed machine learning algorithms were compared according to their predictive capability, methodological characteristics, advantages, and practical limitations. This comparison provides a broader perspective on the position of XGBoost among other techniques that have been applied in transportation demand prediction.

Table 2. Comparison of Machine Learning Models for Land-Use-Based Trip Generation Prediction

Model	Strengths	Limitations	Typical Evaluation Indicators	Key Land-Use / Built-Environment Variables	Suitability for Trip Generation	References
Linear Regression (LR)	Simple, interpretable, and computationally inexpensive.	Assumes a specified functional form and may not capture nonlinear relationships or complex interactions.	R ² , RMSE, and MAE are reported in comparative trip-generation studies; performance varies by dataset and target.	Variables reported across cited studies include land-use type/intensity and household or development characteristics; the exact set depends on the study.	Useful as a transparent baseline, especially where relationships are approximately linear.	Clifton et al. (2015); Xie et al. (2023); Naseralavi et al. (2025) [5], [17], [35]
Decision Tree (DT)	Can represent nonlinear splits and is relatively easy to interpret.	May overfit and can be sensitive to changes in the training sample.	Use the metrics reported in each study (commonly R ² , RMSE, or MAE); no single performance level should be assumed across studies.	Potential inputs in the reviewed field include land-use mix/intensity, population or household characteristics, and accessibility; confirm the exact variables against each cited article.	Useful for interpretable exploratory models, with pruning or validation to control overfitting.	Breiman (1984); Amireh et al. (2025); Hassan et al. (2025) [21], [50], [51]
Random Forest (RF)	Captures nonlinear patterns and interactions;	Less transparent than a single tree and can	R ² , RMSE, and MAE are among the metrics	Study-dependent variables may include land-use/development	Appropriate for medium-to-large datasets and as	Breiman (2001); Naseralavi et al. (2025);

	generally robust to varied predictor sets.	require more computation.	used in reviewed predictive studies; values are not directly comparable across different targets and datasets.	characteristics, population or household attributes, and accessibility measures.	a benchmark against boosting methods.	Hassan et al. (2025); Amireh et al. (2025) [17], [21], [50], [51]
Support Vector Machine (SVM)	Kernel methods can model nonlinear relationships and may perform well on moderate-sized datasets.	Sensitive to kernel and parameter selection; scaling and tuning are important.	R ² , RMSE, and MAE may be used in model comparisons ; consult the individual study for the reported metric and value.	Exact predictor sets are study-specific; do not infer that all land-use or built-environment variables were included in every SVM study.	Suitable for moderate-sized datasets when preprocessing and hyperparameter tuning are carefully performed.	Kumar et al. (2024); Hassan et al. (2025); Amireh et al. (2025) [8], [21], [51]
Artificial Neural Network (ANN)	Can approximate complex nonlinear relationships in sufficiently informative datasets.	Requires careful tuning; can overfit and is less directly interpretable than simpler models.	R ² and error-based measures such as RMSE or MAE are commonly used in predictive comparisons ; the exact measures differ by article.	The specific land-use, household, and built-environment inputs vary by study; Biala et al. (2024) compares ANN with CatBoost for trip modelling in Ilorin.	Potentially useful where enough training data are available and model validation is rigorous.	Goodfellow et al. (2016); Biala et al. (2024); Hassan et al. (2025); Amireh et al. (2025) [21], [34], [51], [52]
Extreme Gradient Boosting (XGBoost)	Captures nonlinear relationships and interactions; can be paired with SHAP or other explainability methods.	Requires hyperparameter tuning; interpretation needs additional tools and spatial transferability must be tested.	The manuscript's reviewed literature mentions R ² , RMSE, MAE, and MAPE. Report only metrics actually provided by each individual article; no pooled range is implied here.	Across the review, candidate predictor families include land-use intensity/mix, population and employment density, floor area/development characteristics, road accessibility, and public-transport availability. Their use and significance must be confirmed study by study.	Promising for nonlinear trip-generation and related travel-demand tasks, provided external validation and transferability are assessed.	Chen & Guestrin (2016); Uddin et al. (2023); Hassan et al. (2025); Amireh et al. (2025) [11], [21], [47], [51]

The comparison confirms that no single prediction model is universally applicable to every transportation problem because model performance depends on the characteristics of the available data and the objectives of the

analysis. Conventional regression techniques remain useful when interpretability is prioritized, whereas tree-based ensemble methods generally perform better when relationships between explanatory variables become increasingly nonlinear. Among the reviewed algorithms, XGBoost consistently demonstrates competitive performance across different transportation applications. Its ability to handle heterogeneous datasets, reduce prediction errors through boosting, and estimate the relative importance of explanatory variables makes it particularly suitable for land-use-based trip generation prediction. Furthermore, the integration of XGBoost with explainable artificial intelligence methods, such as SHAP, allows researchers to better understand the influence of individual land-use variables, thereby improving both prediction accuracy and model transparency.

CONCLUSION

This systematic literature review demonstrates that XGBoost has become one of the most promising machine learning approaches for land-use-based trip generation prediction. Across the reviewed studies, the algorithm consistently achieved strong predictive performance by capturing complex nonlinear relationships that are often difficult to represent using conventional statistical models. Its ability to process heterogeneous datasets while supporting variable importance analysis also strengthens its value for transportation planning and urban policy evaluation.

The review further shows that prediction accuracy alone is no longer sufficient when selecting an appropriate modeling approach. Issues such as model interpretability, data quality, spatial transferability, and integration with Geographic Information Systems (GIS) and emerging transportation data have become equally important considerations. These aspects will influence how effectively prediction models can be adopted in practical planning environments.

Although the number of studies applying XGBoost continues to increase, several research opportunities remain open.

Future investigations may explore hybrid modeling approaches, incorporate real-time transportation data, examine broader urban contexts, and further improve model transparency through explainable artificial intelligence techniques. Addressing these challenges is expected to enhance the reliability and practical usefulness of trip generation prediction models for supporting sustainable transportation planning and smart city development.

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