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A Review of Improving Trip Generation in Traffic Impact Assessments Using Machine Learning for Effective Land Use Planning

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Abstract: A Traffic Impact Assessment (TIA) is crucial in urban and transportation planning, especially in densely populated areas. Key components of a TIA include trip generation, trip distribution, modal split, and assignment. Among these, trip generation forecasting is the most significant because it influences land-use decisions and supports sustainable transportation strategies. This study conducted a Systematic Literature Review (SLR) following the Reporting Standards for Systematic Evidence Syntheses (ROSES) protocol. A total of 21 peer-reviewed articles were selected from the Scopus and Web of Science databases. The review focused on how machine learning (ML) techniques are used to enhance the accuracy of trip generation. Thematic analysis revealed five main themes: prediction model development, urban planning decisions, urban sustainability, forecasting challenges, and innovative ML applications. Standard models include Artificial Neural Networks (ANNs), Support Vector Machines, and Random Forests. Incorporating ML in trip generation forecasts improves the accuracy and reliability of TIA processes. These techniques help identify key variables that affect travel behavior, supporting more effective and sustainable urban transportation planning and decision-making.

Keywords: Trip generation forecasting models; TIA; Machine learning; Urban planning; Sustainability; Transportation planning

1 Introduction

Reviewing existing research helps identify the main gaps that require further study. Identifying these gaps leads us to the key research question: How can machine learning improve trip generation forecasting, and what added value do these improvements provide to TIA practices? Recently, transportation planners and engineers have begun using advanced ML techniques considering various factors, such as land use, demographics, travel behavior, and socioeconomic conditions. By evaluating the impact of each variable and connecting them through nonlinear equations, these techniques enhance the performance of trip generation forecast models [1–4].

Urban mobility in developing countries is often hampered by diverse land-use patterns that strain transportation infrastructure, causing congestion and environmental damage. These problems are severe in areas with uncoordinated planning and high travel demand. Urban and transportation planners should customize forecasting models to reflect local urban conditions. These models support TIA by analyzing how new developments influence infrastructure capacity and service quality. Consequently, they assist planners in developing sustainable mobility strategies and optimizing land use.

The novelty of this study lies in developing a ML-based trip generation model that incorporates context-sensitive variables, such as land-use characteristics, socioeconomic data, and travel behavior. These inputs come from traditional surveys and emerging data sources, enabling the model to outperform conventional regression methods. Algorithms like ANNs and Random Forests enhance forecasting accuracy and assess the model's transferability across cities with various urban forms and infrastructures [5–11].

Practically, incorporating ML into trip generation forecasting improves the reliability of TIA, helping planners avoid both under- and overestimation of traffic volumes. This leads to more cost-effective infrastructure planning and congestion management. A key technical contribution of this SLR is identifying ML models that use non-traditional data, such as mobile phone records and GPS traces, which can significantly reduce predictive errors when applied correctly [7].

This study also links ML applications to global sustainability goals, especially Sustainable Development Goals (SDGs) 11-sustainable cities and communities, and 13-climate action, emphasizing their potential to support data-driven, environmentally responsible urban development [12, 13]. However, limited model transferability due to different local conditions remains a significant challenge [3, 4], emphasizing the need for further research in other urban settings, particularly in developing countries.

2 Methodology

This study employs an SLR to explore the relationship between trip generation and ML and their influence on TIA results. SLR is a structured and transparent approach for reviewing literature, using predefined protocols to minimize bias and ensure reproducibility [14–16]. Unlike traditional reviews, it utilizes clearly defined search strategies, inclusion and exclusion criteria, and quality assessment procedures. To ensure rigor and clarity, this SLR follows the Reporting Standards for Systematic Evidence Syntheses (ROSES) protocol [17].

2.1 Review Protocol-ROSES

ROSES guided each stage of the review process: identification, screening, eligibility, and quality assessment. Researchers created a detailed search strategy using Boolean operators, wildcards, phrase searches, and field codes during identification. They searched six databases: Scopus and Web of Science (primary), ScienceDirect, Springer, Taylor & Francis, and Google Scholar (secondary). The screening stage involved removing duplicates and excluding irrelevant articles based on titles and abstracts. In the eligibility stage, researchers reviewed full texts using predefined inclusion and exclusion criteria. A quality assessment was conducted using a structured checklist aligned with ROSES. The team resolved disagreements during the assessment process by reaching a consensus [17].

2.2 Research Question Formulation

Using the PICo framework—Population (trip generation), Interest (ML), and Context (TIA)—the researchers formulated the research question: How can ML improve trip generation forecasting, and what added value do these improvements provide to TIA practices [15, 18]?

2.3 Search Strategy

The researchers conducted the document search in three stages: identifying relevant studies, screening them, and evaluating their eligibility. They emphasized Scopus and Web of Science for their extensive indexing and analytical capabilities. Keyword selection relied on previous literature, expert input, and synonym tools. Core terms included: trip generation, TIA, and ML, with expanded terms such as trip production, ANN, and AI.

Table 1. Search strings used for selected databases

Database	Search String
Springer	With all of the words: trip generation OR trip production AND traffic impact assessment OR traffic impact study AND machine learning OR artificial neural networks OR artificial intelligence
Web of Science	TS = ((trip generation OR trip production *) AND (traffic impact assessment* OR traffic impact study *) AND (machine learning OR artificial neural networks OR artificial intelligence *))
Taylor and Francis	[All: trip generation] OR [All: trip production] AND [All: traffic impact assessment] OR [All: traffic impact study] AND [All: machine learning] OR [All: artificial neural networks] OR [All: artificial intelligence]
Scopus	TITLE-ABS-KEY ("trip generation*" OR "trip production*") AND ("traffic impact assessment*" OR "traffic impact study*") AND ("machine learning*" OR "artificial neural networks*" OR "artificial intelligence*")
ScienceDirect	("trip generation" OR "trip production") AND ("traffic impact assessment" OR "traffic impact study") AND ("machine learning" OR "artificial neural networks" OR "artificial intelligence")
Google Scholar	All in title: ("trip generation" OR "trip production") AND ("traffic impact assessment" OR "traffic impact study") AND ("machine learning" OR "artificial neural networks" OR "artificial intelligence")

Advanced search techniques, such as Boolean logic, truncation, and phrase searches, were used to refine the results. Researchers collected a total of 2,483 articles from the databases. Table 1 shows the search strings used for each database.

2.3.1 Screening

The screening phase used inclusion and exclusion criteria to identify relevant studies on ML applications in trip generation modeling [15, 19]. Researchers included studies on trip generation, TIA, and integrated ML or artificial intelligence methods. Only empirical articles published between 2019 and 2023 were selected to reflect recent advancements [20]. Exclusions comprised studies using only traditional statistical approaches, those unrelated to urban transport modeling, and non-peer-reviewed or non-English publications. As a result, we excluded 2,175 articles, leaving 308 for the eligibility stage (Table 2).

Table 2. Screening criteria

Criteria	Inclusion	Exclusion
Timeline	2019–2023	2018 and earlier
Language	English	Non-English
Document type	Article journal only	Article review, chapters in a book, book series, book, conference, proceeding

2.3.2 Eligibility

Eligibility involved a manual review of titles, abstracts, and full texts to ensure they aligned with the research focus on ML in trip generation [15]. Researchers excluded two hundred forty articles for several reasons: they lacked relevance to trip generation, did not incorporate ML elements, presented general discussions without modeling, or were mismatched types such as editorials or newsletters. After this review, we retained 21 studies for quality appraisal. Figure 1 shows the full search and selection process.

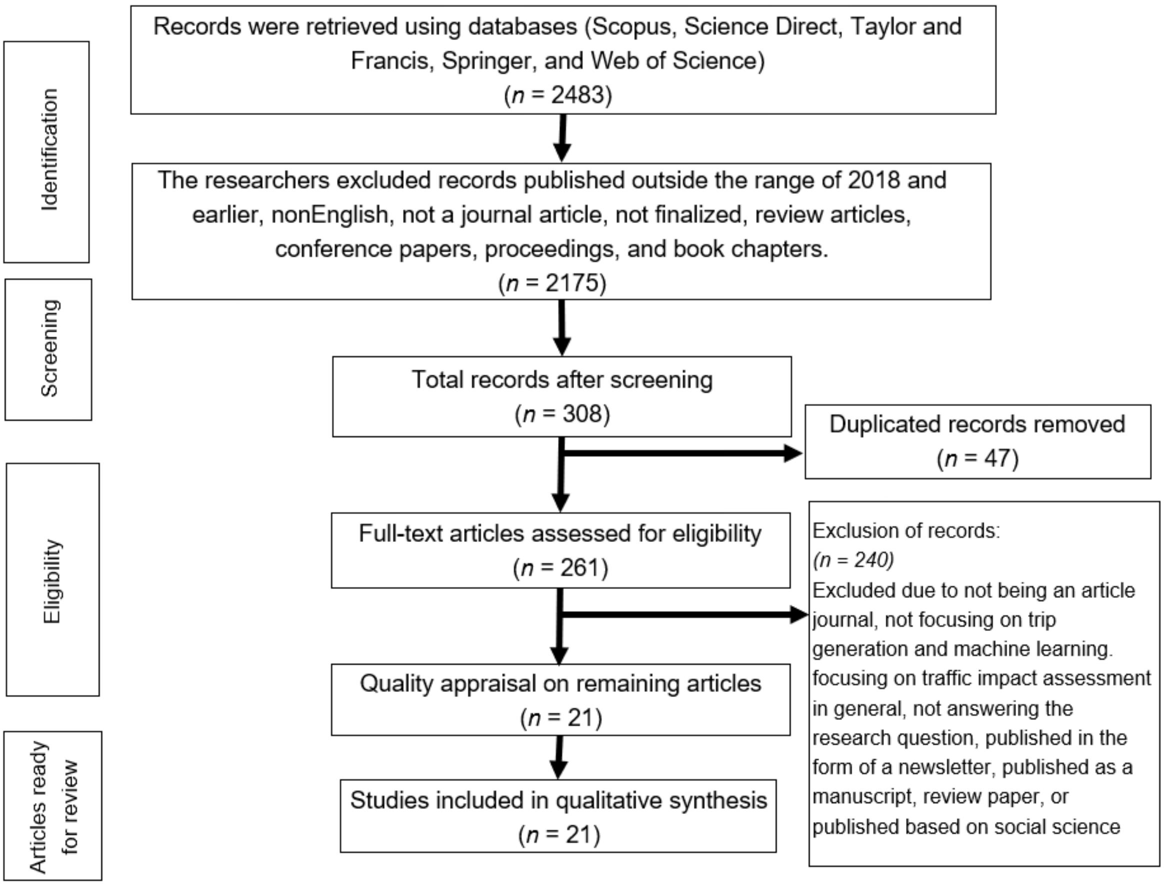

Figure 1. Searching process flow diagram adapted from the study [15]

2.3.3 Quality appraisal

The reviewers used the mixed methods appraisal tool (MMAT) to evaluate the methodological rigor of the articles. They classified the articles into five study types: qualitative, quantitative descriptive, randomized, non-randomized, and mixed methods. Each article underwent evaluation based on five relevant criteria [21], as shown in Table 3. The team included an article if it met at least three criteria. Two reviewers conducted the appraisal independently and resolved any disagreements through discussion. This method reduced subjectivity and enhanced consistency. Table 4 summarizes the results: 14 articles met all criteria, 3 met four, and 4 met three. We used a structured review and consensus-based decision process to mitigate potential biases from known limitations, ensuring a reliable evidence base for this SLR. We then conducted data extraction and analysis for 21 articles.

Table 3. Criteria applied to assess the rigor of research and analysis in selected articles [21]

Research Design	Assessment Criteria
Qualitative	QA1: Is the qualitative approach appropriate to answer the research question?
	QA2: Are the qualitative data collection methods adequate to address the research question?
	QA3: Are the findings adequately derived from the data?
	QA4: Is the interpretation of results sufficiently substantiated by data?
	QA5: Is there coherence between qualitative data sources, collection, analysis, and interpretation in the study?
Quantitative (descriptive)	QA1: Is the sampling strategy relevant to address the research question?
	QA2: Is the sample representative of the target population?
	QA3: Are the measurements appropriate?
	QA4: Is the risk of nonresponse bias low?
	QA5: Is the statistical analysis appropriate to answer the research question?
Quantitative (randomized controlled trials)	QA1: Is randomization appropriately performed?
	QA2: Are the groups comparable at baseline?
	QA3: Are there complete outcome data?
	QA4: Are outcome assessors blinded to the intervention provided?
	QA5: Did the participants adhere to the assigned intervention?
Quantitative (non-randomized)	QA1: Are the participants representative of the target population?
	QA2: Are measurements appropriate regarding both the outcome and intervention (or exposure)?
	QA3: Are there complete outcome data?
	QA4: Are the confounders accounted for in the design and analysis?
	QA5: During the study period, is the intervention administered (or exposure occurred) as intended?
Mixed method	QA1: Is there an adequate rationale for using a mixed methods design to address the research question?
	QA2: Are the different components of the study effectively integrated to answer the research question?
	QA3: Are the outputs of the integration of qualitative and quantitative components adequately interpreted?
	QA4: Are divergences and inconsistencies between quantitative and qualitative results adequately addressed?
	QA5: Do the different components of the study adhere to the quality criteria of each tradition of the methods involved?

Table 4. Quality assessment results [15]

Research	Research Design	QA1	QA2	QA3	QA4	QA5	Number of Criteria Matches	Inclusion in Review
[1]	QN-DC	√	√	√	√	√	5/5	√
[2]	MX	√	√	√	√	√	5/5	√
[5]	QN-DC	√	×	√	×	√	3/5	√
[11]	QN-DC	√	√	√	√	√	5/5	√
[12]	MX	√	√	√	√	√	5/5	√
[13]	QN-DC	√	√	√	√	√	5/5	√
[22]	QN-DC	√	√	√	√	√	5/5	√
[23]	QL	√	√	√	√	√	5/5	√
[24]	QL	√	√	√	×	×	3/5	√
[25]	QL	√	√	√	√	√	5/5	√
[26]	MX	√	√	√	√	√	5/5	√
[27]	QN-DC	√	C	√	C	√	3/5	√
[28]	MX	√	√	√	√	√	5/5	√
[29]	MX	√	√	√	√	√	5/5	√
[30]	MX	√	√	√	√	√	5/5	√
[31]	QN-DC	√	√	√	√	√	5/5	√
[32]	QN-DC	√	√	√	C	√	4/5	√
[33]	MX	√	√	√	√	√	5/5	√
[34]	QN-DC	√	√	√	C	√	4/5	√
[35]	QN-DC	√	√	√	×	√	4/5	√
[36]	QN-DC	√	C	√	C	√	3/5	√

QA: Quality assessment; QL: qualitative; QN-DC: Quantitative descriptive; QN-RC: Quantitative randomized control trials; QN-NR: Quantitative non-randomized; MX: Mixed method; CN: Can't tell

2.3.4 Data extraction and analysis

The study employed an improved integrative review method to ensure rigor and reduce bias in data handling [37]. The researchers analyzed the dataset through thematic analysis, a widely accepted technique for identifying and organizing patterns in qualitative reviews [14, 19, 20].

Using Braun and Clarke's research [38], the process started with familiarizing oneself with studies on trip generation and ML, especially from developing countries, then continued by coding key elements such as ML, trip generation, TIA, ANNs, and artificial intelligence.

Researchers identified five main themes, refined them through discussions, and validated them with two transportation and qualitative synthesis experts. The experts confirmed that these themes are relevant to the research objective [39].

3 Results

3.1 Background of Chosen Articles

This SLR reviewed 21 peer-reviewed articles (2019–2023) focused on applying ML in trip generation forecasting and TIA. A global distribution was observed, with the highest contributions from the USA (6 studies), followed by Thailand (3), and other countries including Malaysia, Portugal, Canada, Australia, China, Qatar, Bangladesh, South Korea, Iraq, and India. This result indicates a growing international interest in using ML for urban mobility solutions, as shown in Figure 2 and Figure 3.

Studies in developed countries like the USA, Australia, and Canada focus on improving TIA accuracy using deep learning and real-time data integration. In contrast, research in developing countries like Thailand, India, Malaysia, and Iraq demonstrates the limitations of traditional models. It promotes ML methods customized to local land use and socioeconomic conditions. These differences emphasize the importance of adapting ML methods to specific contexts.

Chronologically, interest in urban mobility solutions increased significantly after 2019, reaching its peak in 2021, as shown in Figure 4. This growth resulted from changes in mobility patterns caused by the pandemic. During this period, the rising use of ML tools reflected a shift toward data-driven urban planning, emphasizing the need for sustainability-focused models. This trend underscores the importance of integrating artificial intelligence into transportation planning to create more sustainable and context-aware urban mobility solutions through advanced modeling.

Regarding methodology, eleven studies used quantitative methods, seven utilized mixed methods, and three employed qualitative approaches (Figure 5).

The prevalence of quantitative designs underscores ML's reliance on structured data, while mixed-method studies indicate a rising recognition of incorporating policy, planning, and human behavior in model development. This distribution emphasizes measurable and computational solutions in the field while reflecting a growing shift toward more comprehensive methodologies.

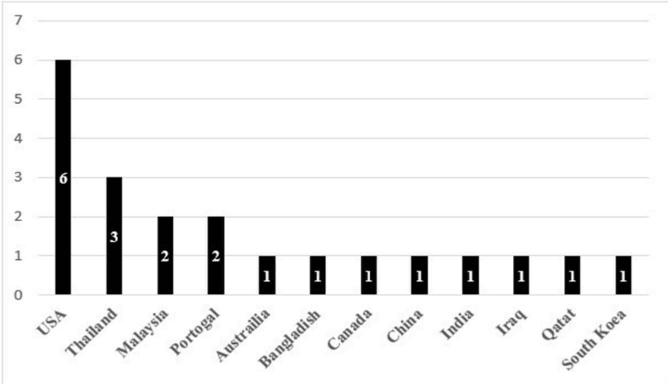

Figure 2. The countries of the selected compiled articles

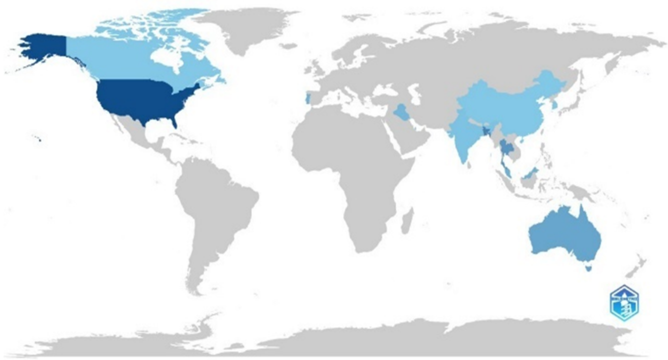

Figure 3. Authors appeared by country

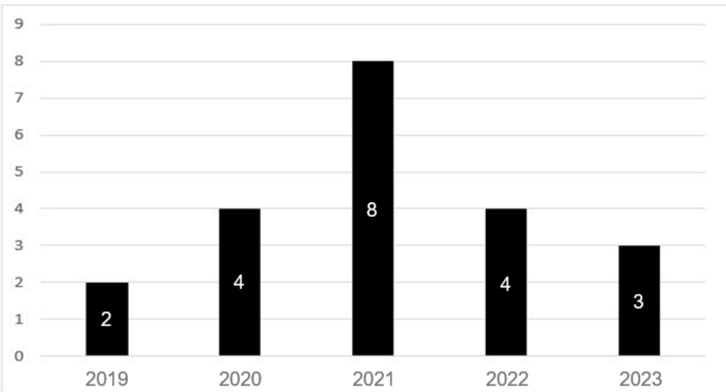

Figure 4. Published years of selected articles

The review highlights the publication outlets, featuring high-impact journals such as Cities, Transport Policy, and Transportation Research Part D. These journals are indexed in Scopus and Web of Science, typically holding Q1-Q2 rankings as shown in Table 5. This evidence confirms the academic quality and relevance of the literature reviewed.

The interpretation of the above results highlights two main paths—one emphasizing technological advances in data-rich settings and another on modifying models for underrepresented urban systems. However, the study does not fully represent other environments, such as African and Latin American contexts, and it lacks long-term evaluations

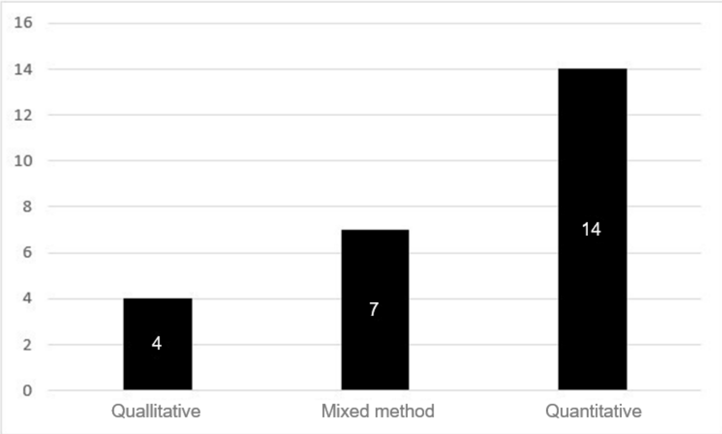

Figure 5. Research design of selected articles

Table 5. Chosen journals and their rankings

Journal	Total Number of Articles	Indexed by Scopus	Scopus Quartile (Latest)	Indexed by WoS	WoS Quartile (Latest)
Journal of Transport and Land Use	1	√	Q2	√	Q4
Journal of Planning Literature	2	√	Q1	√	Q1
Sustainability	1	√	Q1	√	Q3
ITE Journal (Institute of Transportation Engineers)	1	√	Q3	√	Q4
ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering	1	√	Q1	√	–
Transport Policy	1	√	Q1	√	Q1
Transportation Research Part D: Transport and Environment	1	√	Q1	√	–
Transportation Research Record	1	√	Q2	√	Q3
Iranian Journal of Science and Technology, Transactions of Civil Engineering	1	√	Q2	√	–
Scientific Reports	1	√	Q1	√	Q1
Transportation Planning and Technology	2	√	Q2	√	Q3
Cities	1	√	Q1	√	Q1
European Transport Research Review	2	√	Q1	√	Q1
International Journal of Management Science and Engineering Management	3	√	Q1	√	Q2
Journal of Intelligent Systems	1	√	Q1	√	Q3
International Journal of Transportation Science and Technology	1	√	Q1	√	Q2

of ML models in practice. Understanding how flexible and reliable these models are amid ongoing urban changes is crucial.

3.2 Developed Article Themes

The researchers analyzed 21 selected articles thematically to address the SLR research question: "How can ML improve trip generation forecasting, and what added value do these improvements provide to TIA practices?" They identified five themes: prediction model development, urban planning decisions, urban sustainability, forecasting challenges, and innovative ML tools, as shown in Table 6 and Figure 6. These themes illustrate how ML enhances trip generation forecasting by improving model accuracy, supporting planning decisions, and promoting sustainability. They also align with global efforts to modernize TIA practices while highlighting the need for adaptable models that reflect changing urban conditions.

Table 6. The main themes in the reviewed articles

Ref.	Prediction Model Development	Urban Planning Decisions	Urban Sustainability	Trip Generation Forecasting Challenges	Innovative Tool - Machine Learning
[1]	√			√	√
[2]	√			√	
[5]	√			√	
[11]	√	√	√	√	√
[12]	√	√	√	√	√
[13]	√			√	√
[22]	√	√		√	
[23]		√	√	√	
[24]		√		√	
[25]		√		√	
[26]	√	√		√	
[27]	√	√	√	√	√
[28]		√	√	√	
[29]		√		√	
[30]				√	
[31]	√	√		√	
[32]				√	
[33]				√	
[34]	√			√	
[35]				√	
[36]				√	

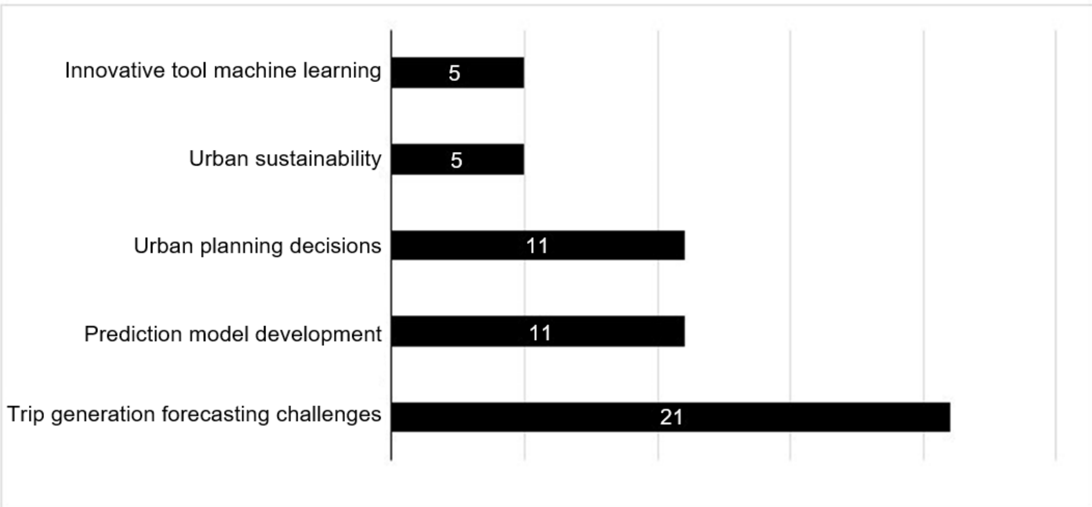

Figure 6. The main themes in the reviewed articles

3.2.1 Prediction model development

Studies on ML-based prediction models highlight trip generation's importance by overcoming traditional traffic analysis limitations. These models deliver more precise, data-driven forecasts that reflect actual travel behavior, improving the reliability of TIA results.

Eight articles highlighted key factors influencing model development, such as location, land use type, parking availability, socioeconomic features, and transportation options. For example, Hammadi and Miller [22] developed a model that combines population and employment data to estimate travel demand for significant urban developments. Likewise, Lin and Yang [23] pointed out that economic conditions greatly affect trip generation forecasts—especially in densely urbanized areas—highlighting the importance of using dynamic and context-aware models.

Studies show that including demographic and economic factors enhances trip predictions, emphasizing TIA's need for context-aware approaches.

3.2.2 Urban planning decisions

Trip generation modeling is essential for urban planning, especially in TIAs, which manage traffic impacts of land development to improve mobility and safety. Studies [2, 24, 25, 30, 34] demonstrate that accurate trip generation forecasts help align infrastructure investments with actual demand, reducing unnecessary expansions and improving road network efficiency. However, overestimating trip rates in congested areas can lead to resource misallocation and poor planning.

Researches [12, 23, 26–29] highlight the need for flexible tools that reflect evolving urban conditions. Incorporating artificial intelligence and ML into trip generation models lets planners consider variables like land use changes and population shifts, creating realistic scenarios for current and future urban growth.

Researches [1, 7–11, 31–33] show that trip generation modeling is vital in urban planning and TIA, especially when applying ML to develop flexible, data-driven tools that adapt to changing urban conditions and prevent resource waste.

3.2.3 Urban sustainability

Urban sustainability is becoming more crucial in transportation planning, especially for TIA in densely populated areas. Studies indicate that trip generation from new developments often leads to traffic congestion, which harms environmental quality and mobility. To address this, these authors [1, 5, 7–11, 31–33] point out that integrating artificial intelligence and multimodal traffic data into trip generation models is recommended, improving their ability to capture traffic patterns and encouraging sustainable planning by reducing congestion-related emissions.

Additionally, Ewing et al. [28] show that transit-oriented developments (TODs) provide greater sustainability benefits than transit-adjacent developments (TADs), such as reduced vehicle trip generation and parking demand, making them a more environmentally friendly alternative to traditional planning models.

3.2.4 Forecasting challenges

The literature highlights challenges in creating effective trip generation forecasting models for TIA. These authors [2, 5, 13, 22, 29, 32, 35, 36] illustrate that the key limitations include a lack of technical tools and difficulties in validating models across different urban settings. Studies stress the need for better model flexibility to capture land use's complex effects on transportation and support sustainable urban growth. There is also a call for advanced estimation techniques, such as ML, to improve predictive accuracy. Successful implementation depends on urban planners and decision-makers adopting technological innovations rather than relying solely on traditional methods.

3.2.5 Innovative ML tools

Machine learning allows models to identify nonlinear relationships in complex datasets, facilitating continuous updates and improving realism. This results in more responsive and reliable TIA results.

Researches [1, 7–12, 26, 31–33] highlight that these findings demonstrate the potential of ML to improve accuracy, support sustainable planning, and address practical forecasting problems, while also pointing out ongoing limitations related to its adoption, validation, and integration into real-world practices.

4 Discussion

4.1 Prediction Model Development and Machine Learning

Applying ML in trip generation modeling under TIA has revealed significant flaws in traditional methods, particularly the consistent overestimation noted in the ITE Trip Generation Manual. Goh et al. [2], Lemonde et al. [27], and Ewing et al. [28] highlight these inaccuracies in urban, mixed-use, and transit-oriented developments, often leading to unnecessary infrastructure expenses. Anam et al. [30] demonstrated an average forecasting error of 40% across 39 cases, underscoring the limitations of conventional models.

Several researchers have developed locally calibrated models to fill this gap. For instance, McDonald and Combs [29] demonstrate that localized forecasting adjustments better reflect land-use diversity and behavioral differences. This supports our finding that ML-based models offer a more flexible and context-sensitive method for predicting trips.

Integrating dynamic behavioral data also proves effective. Lee and Ki Eom [31] note that mobile device-based spatial-temporal data, as used in recent studies, reduces dependence on large-scale surveys and enhances prediction accuracy. Complementary methods, such as those proposed by McDonald and Combs [29], recommend using field-based observations to clarify trip purposes in mixed-use areas, which improves model reliability. These trends support the shift toward ML techniques, incorporating real-world behavior into forecasting systems.

Regarding model performance, ML algorithms consistently outperform traditional regression-based approaches. These authors [1, 11, 13, 27] illustrated that classifiers such as Random Forests and ANNs have demonstrated higher prediction accuracy across various urban contexts. These results align with our findings and support the broader trend in research toward nonlinear, data-driven forecasting methods.

Finally, considering socioeconomic variables and land use characteristics has become increasingly important. Researchers [5, 13, 31] find that studies using both regression and ML models show that variables such as population density, employment levels, and gross floor area significantly enhance model performance. Goh et al. [2] added an adjustment factor 0.63 to the Malaysian Trip Generation Manual, effectively correcting overestimated trip rates in dense urban areas.

In summary, our findings support and reinforce the expanding research promoting data-driven, behaviorally informed, and ML-enhanced forecasting models that better address the complexities of contemporary urban environments.

4.2 Urban Planning and Sustainability

Integrating ML into trip generation prediction models within TIA is crucial for promoting sustainable urban planning. This method allows for more accurate, adaptable, and responsive decision-making across land use developments.

Firstly, ML-based forecasting aligns with the broader shift toward data-driven urban mobility models. Consistent with prior studies [28–31], our findings confirm that including land use, socioeconomic data, and mobile activity patterns significantly enhances model responsiveness, especially in high-density areas. Similar to the dynamic models proposed by recent researches [1, 2, 7–12, 31, 32] that adapt to commercial, residential, and mixed-use typologies, our results emphasize the importance of context-specific, hourly-level predictions. Researches [25, 29, 30] demonstrates that ML-enhanced TIA has proven to be practical and scalable in large-scale applications, such as planning for mega-events.

Secondly, our findings support previous conclusions that empirical modeling approaches outperform fixed guideline values, such as those in the ITE Trip Generation Manual. Cerqueira et al. [12] and Anam et al. [30] advocate for replacing static estimates with localized decision intervals, and our analysis supports that this approach is crucial in dynamic urban environments. The lack of localized decision intervals in traditional manuals highlights that these manuals often lack the adaptability required in modern cities.

Thirdly, several reviewed studies identify random model error and uncertainty as significant barriers to reliable forecasting. Our findings support these conclusions, emphasizing that ML models can reduce uncertainty and improve policy responsiveness when trained on historical and real-time contextual data. Researchers [1, 12, 24, 27, 30] have integrated ML into urban traffic management in cities like Lisbon. Our research highlights the benefits of flexible forecasting tools that use artificial intelligence, providing a distinct advantage over traditional methods. They offer more accurate and customized insights, rather than a one-size-fits-all approach. Fourth, incorporating multimodal transport data and policy-driven variables further improves the sustainability of TIA. Our results align with recent case studies [22, 23, 26], demonstrating that ML models can better support urban mobility by considering a wider range of transportation effects, including pedestrian flows and environmental factors. In contrast, studies [23, 26] show that traditional models tend to focus too heavily on vehicle traffic and underestimate new travel patterns, which can lead to flawed infrastructure decisions.

In summary, our findings support the growing body of research highlighting ML-enhanced TIA as a vital tool for tackling urban mobility's complexity and sustainability issues. Compared to earlier studies, our work also shows how these models can be tailored to specific urban environments, addressing a significant gap in traditional forecasting methods.

4.3 Study Gaps and Recommendations for Future Research

This review highlights significant gaps in current trip generation forecasting literature.

First, many models lack accuracy for complex land uses, especially mixed-use developments, due to limited integration of contextual variables like socioeconomic data, traveler behavior, and environmental factors. This limitation reflects challenges discussed in earlier studies, emphasizing the need for more adaptable, machine-learning-based forecasting frameworks in densely urbanized areas.

Second, the geographic specificity of most models limits their broader use. Since previous research stresses the importance of transferable models, future studies should develop generalized frameworks that can adapt to various urban environments.

Third, automation in data collection—such as drones, sensor networks, and pedestrian counters—remains underused despite its potential to enhance multimodal datasets and boost ML performance. Fourth, current forecasting tools often ignore large-scale, trip-generating facilities like stadiums. This oversight highlights earlier calls for more flexible models that include land use diversity and changing urban contexts. To address these gaps, future research should:

• Explore stakeholder perspectives on TIA practices to enhance model implementation and reduce mitigation costs.

• As suggested by earlier studies, incorporate experiential decision intervals into ML models to enhance planning accuracy.

• Integrate sustainability by combining multimodal data (walking, cycling) with ML, promoting greener urban mobility.

• Apply advanced ML techniques—deep learning, fuzzy logic, ANN, and reinforcement learning—and Geographic Information Systems (GIS) tools to increase model flexibility and improve spatial accuracy.

These directions build on and expand previous work while promoting more precise, context-aware, and sustainable methods for urban transport planning.

5 Conclusions

This systematic review analyzed 21 studies to explore how trip generation forecasting can be improved using ML, especially in the context of TIA. Five key themes emerged: the development of forecasting models, urban planning decisions, sustainability, forecasting challenges, and innovative ML applications. A notablefinding is that traditional trip generation models—particularly those based on the ITE manual—often overpredict future trip rates in developing countries. This overestimation is especially common in dense or mixed-use developments, leading to inflated infrastructure costs and ineffective planning decisions.

The study uncovered a significant lack of research on combining ML with sustainability goals and urban behavior patterns, pointing out significant gaps in current practices. The findings emphasize the potential of ML models, especially those that use contextual and multimodal data, to offer more adaptive, precise, and sustainable forecasting methods. However, substantial knowledge gaps remain, especially in areas like variable selection, mixed-use modeling, and automating data collection.

The limitations of this SLR include its focus on studies published in English, which may limit the range of insights collected. Additionally, the chosen time frame and reliance on specific databases could exclude relevant research that is not indexed. Furthermore, the researchers did not thoroughly examine urban environments' cultural and technological differences. Recognizing these limitations is essential for a more comprehensive analysis.

Future research should concentrate on these areas:

• Testing ML-powered trip generation models in real-world urban projects.

• Exploring experiential decision intervals to minimize uncertainty in infrastructure planning.

• Incorporating variables such as socioeconomic context, pedestrian counts, and weather data using automated tools like drones and GIS.

• Evaluating ML models, including deep neural networks (DNN), reinforcement learning, and fuzzy logic, to improve forecasting accuracy.

• Developing adaptive routing and simulation tools to support dynamic TIA decision-making processes.

Finally, effective collaboration among governments, planners, and developers is essential for integrating these tools into sustainable urban planning policies that can adapt to the complexities of data-driven urban environments.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Author Contributions

Conceptualization—N.S.A.S.; L.S.A.; Methodology—L.S.A.;Formal analysis—L.S.A.; Investigation—Lubna Sami Amireh; Writing—original draft preparation: L.S.A.; Writing—review and editing: L.S.A.; Visualization—L.S.A.; All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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