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Mapping Five Decades of Trip Generation Research: A Bibliometric Review for Sustainable Transportation Planning (1972–2024)

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ABSTRACT

This study explores the development of trip generation research, highlighting key themes, trends, and future directions. Using the Scopus database, 394 documents published between 1972 and 2024 were analyzed with BiblioMagika, VOSviewer, and BiblioShiny. The analysis included examining publication and citation patterns, keyword co-occurrence, thematic mapping, and co-authorship networks. Data was cleaned by removing duplicates and irrelevant documents. The results indicate an increasing focus on innovative methods, sustainability, and urban transportation planning. Five main clusters emerged: advanced modeling techniques, sustainability in travel demand forecasting, trip generation as a planning foundation, land use and accessibility factors, and urban freight modeling. Contributions mainly come from the USA and China, with frequent use of terms like "trip generation modeling," "transportation planning," "land use," and "artificial neural networks." This bibliometric review clarifies achievements, identifies research gaps, and highlights future needs, offering insights to enhance sustainable urban mobility planning.

1. INTRODUCTION

Background — Trip generation estimates the trips produced or attracted by land use, which is vital for transportation planning, guiding infrastructure, and policies [1]. Originally focused on passenger transport, recent studies now include freight, land use, and multimodal travel, shifting from static models to context-sensitive forecasts [2-4]. The field has progressed from regression to AI techniques, but it still lacks a comprehensive synthesis. Researchers increasingly use bibliometric methods to identify trends and influential contributors [5-8].

This study employs Kuhn's theory to trace the evolution of trip generation from traditional models to machine learning and sustainability frameworks, indicating a paradigm shift [9]. Existing reviews often lack geographic diversity, especially from Asia and Latin America. While Scopus is a key source, broader inclusion recommends using Web of Science, Dimensions, and Google Scholar.

Problem Statement — Despite the increasing body of trip generation research, existing reviews often lack global coverage, theoretical depth, and methodological rigor, especially regarding sustainability and multimodal transportation. This study addresses these gaps through a systematic, theory-driven bibliometric analysis to map the field's evolution and guide future research.

Objectives — This study aims to explore, explain, and forecast the trajectory of trip generation research by answering these questions:

1). What are the publication trends in trip generation research, and how have they evolved over decades?
2). Who are the most prolific authors, and what are their main contributions?
3). Which institutions lead in publication output, and how have they shaped the field?
4). Which countries and regions are most active, and how has their participation changed over time?
5). Which journals are key sources for disseminating trip generation research?
6). What are the most highly cited documents, and what explains their academic influence?
7). What are the dominant themes and keywords, and how have they evolved?
8). What new research directions are emerging, particularly?

This study provides the first comprehensive bibliometric analysis of trip generation research (1972–2024), offering an overview of past work, guidance for future studies, and practical insights for planners and researchers.

2. METHODS

A Scopus search for bibliometric studies on "trip generation" found no results. This paper offers a bibliometric analysis to reveal publication trends and key themes. Using BiblioMagika, VOSviewer, and BiblioShiny, the study provides insights into major trends to guide future research.

2.1 Data collection

Data were collected from Scopus in November 2023 using the query TITLE ("trip generation") to find relevant literature. This search retrieved 394 publications with 1,027 authors. Scopus is popular for bibliometric research because of its extensive peer-reviewed coverage, but it has limited coverage of Asia and Latin America, which could bias trip generation analysis. This study uses only Scopus to maintain consistency with tools such as BiblioMagika, VOSviewer, and BiblioShiny. Future studies should include Web of Science, Dimensions, or Google Scholar for broader global coverage.

2.2 Data cleaning and harmonization

The initial 1195 documents from the Scopus database were reviewed for duplicates and those unrelated to trip generation topics, resulting in 394 relevant documents after eliminating 801 irrelevant ones. They were exported in RIS and CSV formats to ensure compatibility with bibliometric tools and allow flexible preprocessing [10, 11]. OpenRefine was used to clean and standardize key metadata, including author names, institutional affiliations, and keywords. Clustering techniques helped identify and merge inconsistent entries, followed by manual review for validation [12, 13]. After cleaning, the dataset was recombined for further bibliometric analysis, such as author productivity, institutional collaboration, and keyword co-occurrence, as described in Sections 2.3–2.5.

2.3 Bibliometric measures

A bibliometric analysis of Scopus data (1972–2024) was conducted using metrics such as Number of Cited Publications (NCP), Number of Contributing Authors (NCA), Total Publications (TP), Total Citations (TC), average citations per cited publication (C/CP), average citations per publication (C/P), and h-, g-, and m-indices. Tables, figures, and density/scatter maps were generated with BiblioMagika. Co-occurrence analysis, keyword clustering, trending topic detection, and research hotspot mapping were performed using BiblioShiny and VOSviewer, with a minimum keyword frequency of 2, association strength normalization, a LinLog layout, and Louvain clustering [3, 10, 13, 14].

2.4 Data analysis

To address the research questions, patterns, trends, and gaps in trip generation literature were examined. The study includes: (1) Descriptive profiling of citations, subjects, and core indicators; (2) Productivity analysis of publications, authors, institutions, countries, and journals; and (3) Thematic and co-occurrence mapping of keywords, research hotspots, and thematic shifts. The analysis covers three periods—1972–1999 (Foundational), 2000–2010 (Expansion), 2011–2024 (Innovation)—following Kuhn's model to track conceptual and methodological changes, including sustainability and machine learning. The literature search was conducted in Scopus using the TITLE ('trip generation') query. The initial search retrieved 1,195 documents. After applying the screening criteria, 394 relevant documents were retained for the bibliometric analysis. The overall search and screening process is illustrated in Figure 1.

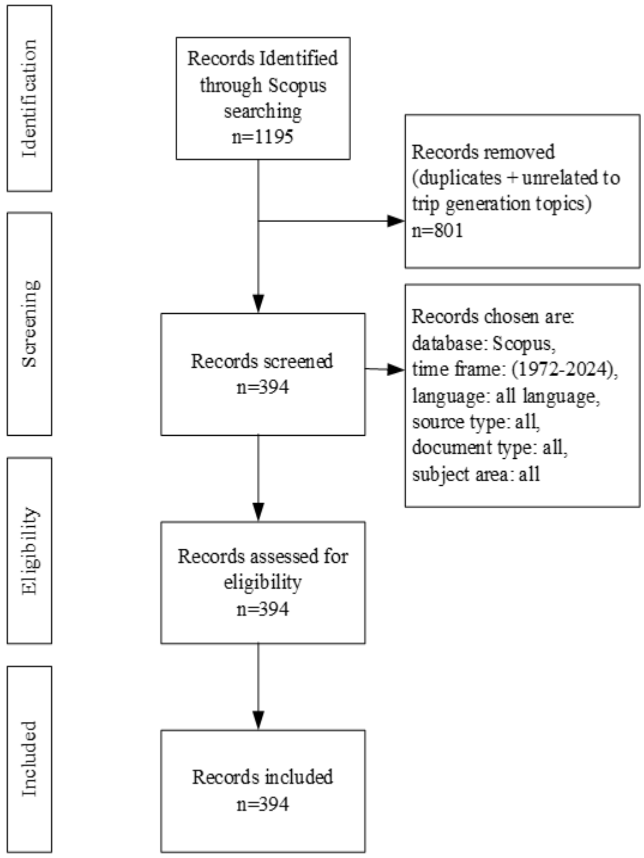

Figure 1. Flow diagram of the search strategy used for the bibliometric analysis [15]

2.5 Tools

A combination of bibliometric software tools was used for precise, reproducible analysis: Excel for data organization; BiblioMagika for bibliometric indicators, document classification, and keyword extraction; OpenRefine to standardize names and affiliations; BiblioShiny for advanced visual analytics; and VOSviewer for co-authorship, collaboration networks, and keyword clustering. Consistent visualization employed the Lin Log layout, modularity clustering, fractional counting, and association strength normalization. These tools provided macro and micro perspectives, tracked keywords such as Artificial Neural Network (ANN) and regression over time, and mapped regions such as the United States, the UK, China, Malaysia, India, and Jordan.

3. RESULTS

3.1 Document profiles

This section examines 394 documents from 1972 to 2024, focusing on productivity metrics, subject area distribution, publication formats, and language trends to highlight key development patterns in the field.

3.1.1 Citation and productivity metrics

Table 1 summarizes key indicators for 394 trip generation publications. Of these, 283 were cited, with a total of 3,900 citations (average 9.90 per paper; 13.78 for cited papers). Papers had an average of 2.61 authors and 3.80 citations per author. The h-index is 31, meaning 31 papers have at least 31 citations each; the g-index is 49, indicating that citation impact is concentrated in a few highly cited articles; and the m-index is 0.574, showing a gradual increase in academic influence over time. Overall, the field maintains steady interest but has room to improve its visibility through increased collaboration and interdisciplinarity.

Table 1. Citation metrics

Main Information	Data
Publication years	1972-2024
Total publications	394
Citable year	54
Number of contributing authors	1027
Number of cited papers	283
Total citations	3,900
Citation per paper	9.90
Citation per cited paper	13.78
Citation per year	75.00
Citation per author	3.80
Author per paper	2.61
Citation sum within h-core	3,627
h-index	31
g-index	49
m-index	0.574

Source: Generated by the author(s) using BiblioMagika® [16]

3.1.2 Subject area distribution

Table 2 presents subject areas; most studies (68.53%) focus on engineering, followed by social sciences (40.36%), environmental science (13.45%), and computer science (8.63%). The social and environmental contributions indicate a growing interest in the sustainability of trip generation. The limited presence of computer science highlights a gap in advanced data analytics and machine learning, which will guide future research.

Table 2. Subject area

Subject Area	TP	%
Engineering	270	68.53%
Social sciences	159	40.36%
Environmental science	53	13.45%
Computer science	34	8.63%
Earth and planetary sciences	24	6.09%
Business, management, and accounting	22	5.58%
Mathematics	21	5.33%
Decision sciences	20	5.08%
Economics, econometrics, and finance	13	3.30%
Multidisciplinary	8	2.03%
Energy	7	1.78%
Physics and astronomy	7	1.78%
Materials science	5	1.27%
Medicine	4	1.02%
Arts and humanities	3	0.76%
Agricultural and biological sciences	2	0.51%
Chemical engineering	1	0.25%
Undefined	1	0.25%

Source: Generated by the author(s) using BiblioMagika® [16]

3.1.3 Document types and source outlets

Table 3 shows that most publications are journal articles (74.87%), followed by conference papers (20.56%) and others (4.56%). Table 4 indicates that 78.17% appeared in journals, 17.50% in conference proceedings, and a few in other outlets. These patterns are strong in journals and reveal opportunities for expanding to other platforms.

Table 3. Document type

Document Type	TP	%
Article	295	74.87%
Conference paper	81	20.56%
Book chapter	6	1.52%
Review	5	1.27%
Note	3	0.76%
Letter	2	0.51%
Report	1	0.25%
Short survey	1	0.25%
Total	394	100%

Source: Generated by the author(s) using BiblioMagika® [16]

Table 4. Source type

Source Type	TP	%
Journal	308	78.17%
Conference proceeding	69	17.51%
Book series	9	2.28%
Book	5	1.27%
Trade journal	2	0.51%
Report	1	0.25%
Total	394	100%

Source: Generated by the author(s) using BiblioMagika® [16]

3.1.4 Language of publication

Table 5 shows the language distribution in publications. 90.61% are in English, emphasizing its importance in international academic communication. Other languages include Chinese (3.81%), Japanese (2%), Spanish (2%), and Persian (1%). This indicates the accessibility of global research and the underrepresentation of regional perspectives.

Table 5. Language

Language	TP	%
English	357	90.61%
Chinese	15	3.81%
Japanese	2	0.51%
Spanish	2	0.51%
Persian	1	0.25%
Undefined	17	4.31%
Total	394	100%

Source: Generated by the author(s) using BiblioMagika® [16]

3.1.5 Synthesis and implications

The bibliometric landscape shows growth in trip generation research, with numerous studies focused on engineering in English. Although citation metrics indicate progress, low h- and m-index totals highlight the need for more impactful, interdisciplinary work. Future research should adopt diverse methods, especially machine learning and spatial analysis, and increase regional representation to foster inclusivity.

3.2 Publication trends

Figures 2 and 3 address the first research question: "What are the publication trends in trip generation research, and how have they evolved over decades?" This section examines the increase in publication activity, author participation, citation patterns, and the thematic development of trip generation research from 1972 to 2024.

3.2.1 Annual growth in publications and citations

Figure 2 shows annual publications and citations, while Figure 3 depicts the growth of publications from 1972 to 2024.

A second-order polynomial model was chosen because it provided the best fit for cumulative publications over time. This is indicated by its high coefficient of determination (R^2 = 0.988), outperforming both the linear and exponential models. Early research was limited, but a steady increase began in the early 2000s. Publications peaked at 25 in 2022, indicating growing interest. Citations also increased, reaching a high of 388 in 2019. These metrics emphasize the importance of trip generation studies in urban development. Including mobility in these studies in urban planning, policy, and sustainable development is essential for building resilient communities.

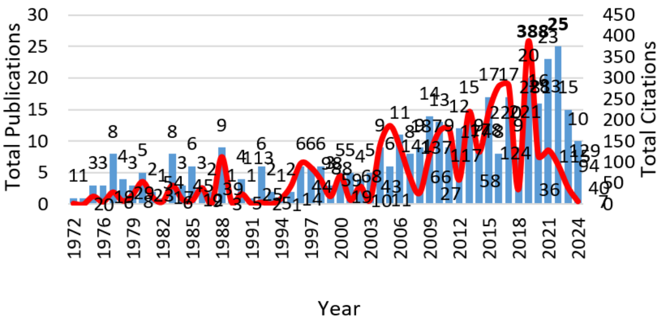

Figure 2. Total publications and citations by year
Source: Generated by the author(s) using BiblioMagika® [16]

X: represents the year index,
such as (1972=1,1973=2, …)

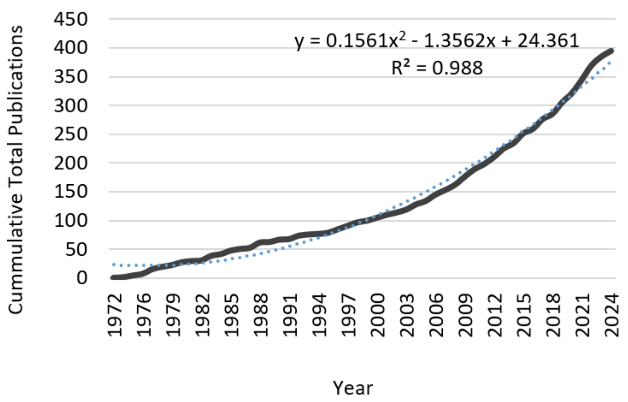

Figure 3. Publication growth
Source: Generated by the author(s) using BiblioMagika® [16]

3.2.2 Author contributions and citation metrics

Table A1 shows the full list of publications by year, displays the Number of Contributing Authors (NCA), Average Citations per Publication (C/P), and Average Citations per Cited Publication (C/CP). The NCA steadily increased, reaching 76 in 2022, indicating wider academic participation, but decreased to 29 in 2024, suggesting increased specialization. The peak values of C/P = 35.13 and C/CP = 40.14 correspond to years of major methodological breakthroughs, such as machine learning models, multimodal trip integration, and person-trip concepts, underscoring the influence of pioneering work.

3.2.3 Evolution of trip generation research

The fifty-three-year evolution of trip generation research can be divided into three phases.

Foundational Phase (1972–1999): Developed baseline models using cross-classification, regression, and household surveys. Focused on household size, vehicle ownership, and land use, with static, vehicle-based metrics mainly guided by ITE.

Transitional Phase (2000–2010): Integrated socio-economic and land-use factors using data-driven methods such as neural networks and decision trees. Focused on mixed-use developments and freight trip generation; however, models struggled with urban complexities.

Contemporary Phase (2011–2024): Highlights sustainability, multimodal transportation, and advanced tools like AI and GIS. Broadens research to include pedestrian trips, accessibility, and the impact of the built environment, supported by large datasets (CDR, GPS, mobile data) for real-time modeling.

COVID-19 Impact (2020–2022): The pandemic shifted focus to behavioral changes, remote work, and decreased public transportation. Existing studies highlight health risks, psychological factors, and lasting shifts in demand, underscoring the need for adaptable, resilient trip generation models [17-19]. Overall, research has advanced from static land-use estimates to dynamic, interdisciplinary approaches that reflect the complexity of urban mobility while prioritizing sustainability and resilience.

3.3 Publications by authors

This section addresses the second research question: "Who are the most prolific authors in trip generation publications?" Table A2 lists the top 26 authors based on publications, citations, and author-level indices (h, g, m). Currans Kristina (Portland State University, United States) leads with 8 publications, 6 citations, and 101 total citations (C/P = 12.63; C/CP = 16.83; h = 5; g = 8; m = 0.238), demonstrating consistent influence. Following is Clifton Kelly (Portland State University, United States) with 7 publications, 4 citations, and 28 total citations (C/P = 4; C/CP = 7; h = 4; g = 5; m = 0.098), indicating sustained relevance. Overall, the metrics highlight both productivity and impact, with contributions from Asia, the Middle East, and North America shaping the field's development.

3.4 Publications by institutions

To address the third research question: "What are the most influential institutions in trip generation publications, and how have they contributed to the development of the field?" Table A3 ranks the top 25 institutions by productivity and impact. Southeast University leads in both output and citations, supported by strong h- and g-indices. The University of California and Portland State University (United States) show consistent contributions with moderate impact. Parsons Brinckerhoff / WSP (Brazil), Institut Henri Fayol (France), and the University of Toronto (Canada) produce fewer publications but have high citation rates, reflecting quality-driven influence in areas such as multimodal mobility and machine learning. Others, including Tennessee Technological University, Rensselaer Polytechnic Institute, and Birla Institute of Technology and Science Pilani, demonstrate specialization, producing modest outputs but achieving strong citation impact. Overall, the data highlight a global research network with clusters in North America, Europe, and Asia, underscoring the need for greater collaboration and expanded research in developing countries on emerging themes such as non-motorized travel, pandemic effects, and AI in trip modeling.

3.5 Publications by countries

This section addresses the fourth research question: "What are the most active countries in trip generation publications, and how does this vary across different regions and periods?" Table A4 and Figure 4 rank the top 20 countries in trip generation research. The US leads with 157 publications and 1954 citations, supported by the highest h-index (23) and g-index (44). China (37 papers) and India (28) follow, reflecting growing research capacity despite lower citation impact. Several countries with fewer publications, including the UK, Canada, and Japan, achieve high citation efficiency (C/P = 11.77 – 20.28; C/CP = 13.91 – 31.69), indicating quality-driven influence. Germany and Sweden exhibit strong citation profiles, while Indonesia, Brazil, and Iran contribute moderate publication outputs with comparatively lower citation impact. Overall, research is concentrated in a few nations, but citation efficiency highlights broader global influence. Building collaboration between leading and emerging countries is essential to improve the adaptability and transferability of trip generation models across diverse contexts.

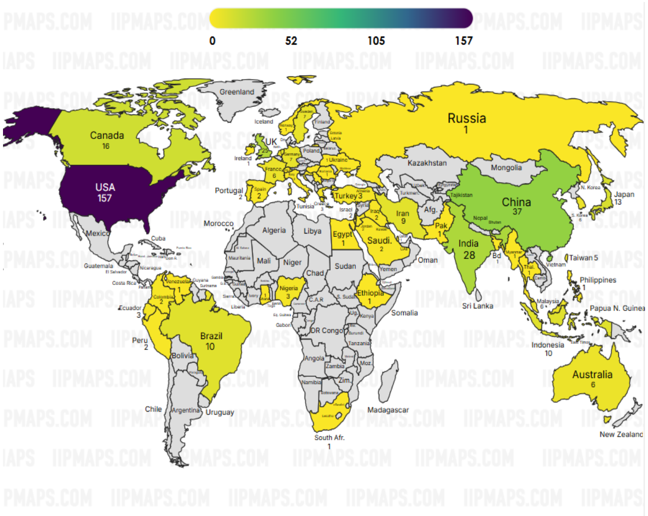

Figure 4. Most productive countries in trip generation research
Source: Generated by the author(s) using iipmaps.com

3.6 Publications by source titles

This section addresses the fifth research question: "Which journals are key sources for disseminating trip generation research?" Table A5 highlights the leading outlets in this field. Transportation Research Record (47 papers, 898 citations, h = 17, g = 28), ITE Journal (36 papers), and the Journal of Urban Planning and Development (10 papers) are the most prolific outlets, with the latter offering practice-oriented insights. High-impact journals such as Transportation and Transportation Research Part A: Policy and Practice publish fewer papers but achieve much higher citation efficiency (C/P = 35.56 – 39.75; C/CP = 35.56 – 39.75). This indicates a dual publishing pattern: technical and practitioner-focused outlets maintain steady output, while high-impact journals influence theoretical and methodological advances. Increasing publication in interdisciplinary venues could boost methodological diversity and support themes like sustainability, emerging mobility, and post-pandemic travel.

3.7 Highly cited documents

Table A6 addresses the sixth research question: "What are the most highly cited documents in trip generation publications?" The 20 top-cited studies focus on trip generation across several key areas, including under-studied or vulnerable groups, freight trip generation, disaster response, shared mobility, and multimodal systems, reflecting applications to emerging contexts. Future research opportunities include developing dynamic, context-sensitive trip generation models that integrate real-time geospatial and socio-demographic data, expanding the use of ML/AI methods, and linking passenger and freight modeling to support sustainable, digitally enabled transport systems.

3.8 Trend topics

Figure 5 displays a term frequency analysis from 2014 to 2024. VOSviewer categorizes the frequency into three categories: 90 for high-frequency terms, 60 for medium-frequency terms, and 30 for emerging but relevant terms. The analysis highlights trip generation modeling with 90 mentions, followed by transportation planning with 60 mentions, and freight/land-use studies with 30 mentions each. These trends indicate a growing interest in data-driven, multimodal, and sustainability-focused approaches. The increased focus on land use and freight emphasizes the need for flexible models that can accurately reflect diverse urban and logistical patterns to support sustainable mobility and effective demand forecasting.

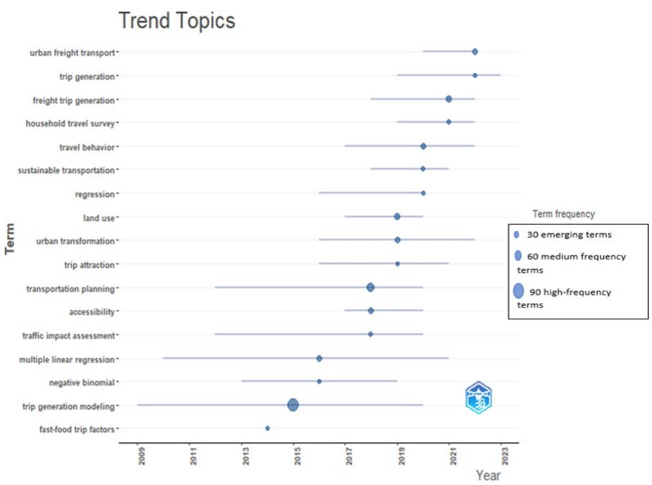

Figure 5. The trend topics in the trip generation field
Source: Generated by the author(s) using BiblioShiny

Figure 6 also illustrates the development of methodological groups within trip generation research across three periods (pre-2010, 2011–2014, and 2015–2024). The proportions of major methodological categories—Regression/Logit, ANN/ML, GIS, Simulation/Behavioral, and Trip Generation Modeling—change noticeably over time. Regression-based methods dominate early studies, while later periods show a gradual shift toward simulation/behavioral models and a modest rise in ANN/ML and GIS applications. The figure also highlights a clear gap: machine learning and GIS techniques remained limited for many years, only becoming more prominent in recent research.

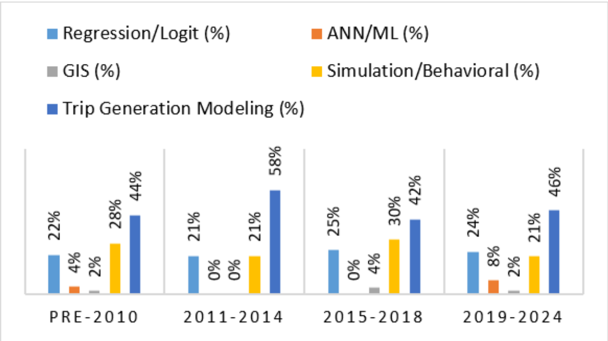

Figure 6. The evolution of methodological groups in trip generation research over time

3.9 Co-occurrence analysis

This analysis was conducted using VOSviewer by Van Eck and Waltman [7] to map relationships among keywords and terms, highlighting research trends and thematic clusters. A minimum occurrence of two, fractional counting, and modularity-based clustering with the LinLog layout were used, resulting in clear, color-coded clusters that reveal conceptual structures and reduce noise in groupings.

3.9.1 Author's keywords analysis

To answer the research question: "What are the most common author keywords in the literature on trip generation, and how have they evolved over time?", we analyzed 122 keywords that appeared at least twice using VOSviewer. Figure 7 displays the co-occurrence network of these keywords, with circle sizes indicating frequency and connections showing co-occurrence strength [6]. The map revealed five distinct semantic clusters, each representing a coherent subfield within the trip generation literature.

Trip Generation Modeling (Blue): planning, forecasting, traffic impact assessment, person-trip estimation, and developing-country studies (the field's traditional core).

Freight Trip Generation and Machine Learning (Red): freight/logistics, machine learning, simultaneous equations, and mode-choice analysis (data-driven and specialized).

Land Use and Mobility (Yellow): spatial analysis, accessibility, socio-demographics, and equity—linking built form to travel behavior.

Neural Networks and Simulation (Purple): demand prediction, micro-simulation, regression models, and operational traffic forecasting tools.

General Modeling (Green): trip forecasting, residential development, artificial neural networks, and data analysis—serving as a bridge between classic regression and advanced neural methods.

3.9.2 Temporal evolution of research focus

Figure 8 shows a timeline overlay of the co-occurrence network, emphasizing how research focus areas evolved across five distinct phases:

Pre-2010: Concentrated on early studies of disaggregated spatial interaction models and principal component analysis, laying the groundwork for trip generation research.

2013-2014: Transitioned toward mode choice and activity-based modeling, highlighting behavioral factors and person-trip interactions.

2015-2016: Trip generation became a central element in traffic impact assessment (TIA) studies, underscoring its growing importance in regulations and planning.

2017-2018: Focused on urban transformation, land use, and developing countries, with researchers exploring contextualized modeling methods amid rapid urban growth and logistics expansion.

2019–present: The field is shifting toward advanced analytics, such as freight trip generation, artificial neural networks, and machine learning, driven by the need for precision and scalability in demand forecasting.

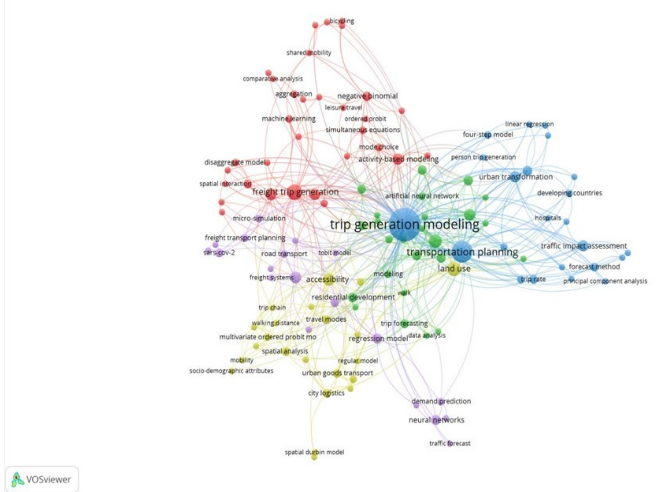

Figure 7. Co-occurrence network of the author's keywords in trip generation
Source: Generated by the author(s) using VOSviewer [7]

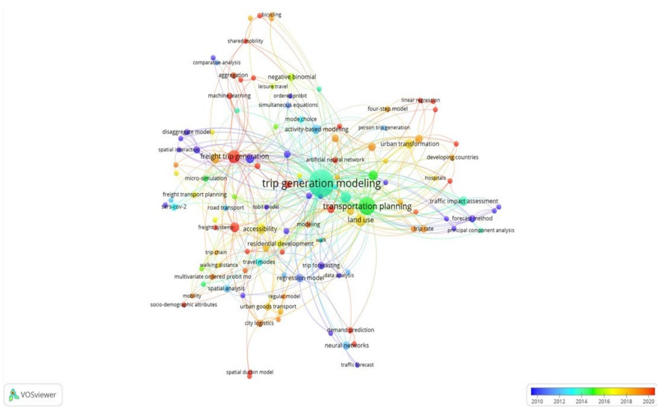

Figure 8. Co-occurrence overlay of the author's keywords in trip generation
Source: Generated by the author(s) using VOSviewer [7]

Figure 9 displays the temporal evolution of research themes across four periods (1972-1999, 2000-2011, 2012-2019, and 2020-2024). The earliest phase (1972-1999) is defined by foundational work focused on static trip rates and basic estimation methods. From 2000 to 2011, research shifts toward core trip-generation issues, reflecting growing interest in applying trip-generation techniques in practice. The period from 2012 to 2019 shows clear diversification, with studies addressing distribution centers, classification techniques, and advancements in data collection. In the most recent period (2020-2024), the thematic focus broadens to include land-use integration, improved estimation, and renewed regression-based refinements, aligning with broader trends toward behavioral, sustainability-focused, and multimodal perspectives highlighted by the thematic evolution map.

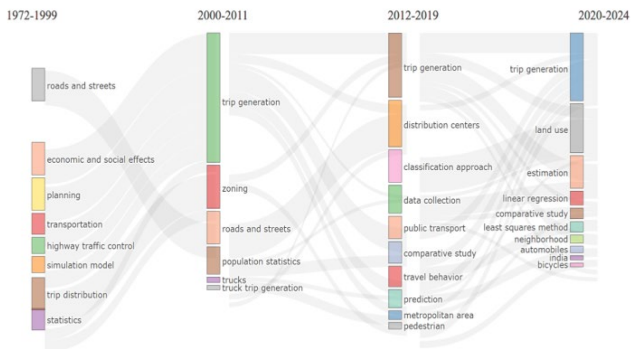

Figure 9. Thematic evolution map showing the progression of research themes across four periods
Source: Generated by the author(s) using BiblioShiny

3.9.3 Themes analysis

To address the research question, "What are the key themes and topics emerging from co-occurrence analyses of author keywords and title/abstract terms in the literature on trip generation research?", Figure 10 shows the co-occurrence clusters of author keywords in trip generation. These clusters are organized into five groups using modularity-based clustering to highlight common terms and their semantic connections.

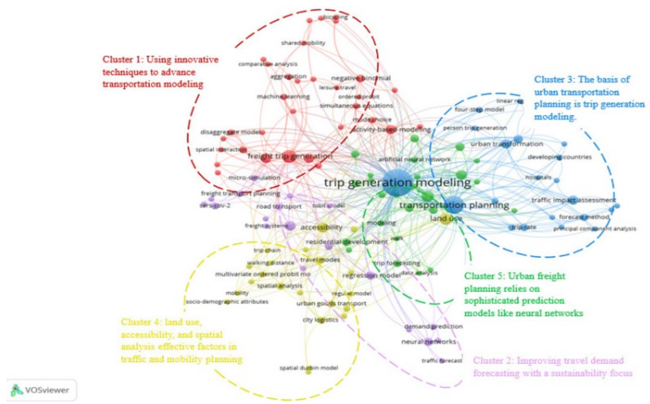

Figure 10. Co-occurrence clusters of the author's keywords in trip generation
Source: Generated by the author(s) using VOSviewer [7]

Trip generation research can be categorized into five thematic groups, highlighting both methodological evolution and policy requirements.

Cluster 1: Innovative Techniques marks a shift from traditional models to data-driven tools such as machine learning, simulations, and spatial econometrics. Applications include freight and evacuation trips, as well as micromobility, with an emphasis on sustainable and resilient transportation.

Cluster 2: Sustainable Demand Forecasting focuses on low-carbon and equitable travel policies. Methods have evolved from regression and logit models to AI-based approaches that link land-use patterns, lifestyles, and emissions.

Cluster 3: Core Modeling for Urban Planning establishes the foundation for trip estimation through surveys, four-step models, and mobile data. It highlights the need for localized, behavior-sensitive models, especially in regions with limited data.

Cluster 4: Land Use and Accessibility studies how urban form, demographics, and accessibility influence mobility. Advanced spatial methods uncover equity gaps and support multimodal, neighborhood-scale planning.

Cluster 5: Freight and Logistics is an emerging area that addresses freight flows, last-mile delivery, and disruptions such as pandemics. It increasingly uses synthetic data, micro-simulation, and sustainable freight strategies. Together, these clusters shift from static models toward sustainability, technological integration, and spatial equity—signaling a maturing field that responds to contemporary urban challenges.

4. DISCUSSIONS

This bibliometric review of 394 documents over 53 years traces the evolution of trip generation research, highlighting shifts in theory, methodological advances, and emerging themes.

4.1 Framing the evolution

The field has evolved from static rate-based models to include regression, logit, and neural networks, with increasing adoption of machine learning and sustainability-oriented frameworks. This signifies a Kuhnian shift toward more adaptable, data-driven approaches.

4.2 Key findings

The United States and China lead in output and citations, while contributions from India, the United Kingdom, Canada, Japan, Indonesia, Brazil, and Iran are increasing. Influential authors are mainly based in the United States, Sweden, and China. Most publications are in English, accounting for over 90%, and universities lead three-quarters of collaborations. Key outlets include the Transportation Research Record, the ITE Journal, and the Journal of Urban Planning and Development. Disciplinary patterns emphasize the field's broad reach across engineering, social sciences, environmental science, and computer science.

4.3 Thematic structures

Co-occurrence and citation mapping reveal five main clusters:

Trip Generation Modeling – the methodological foundation, covering planning, forecasting, and traffic impact assessment.

Freight & Machine Learning – highlighting AI and simulation in logistics forecasting.

Land Use & Mobility – connecting accessibility, demographics, and spatial equity.

Neural Networks & Simulation – reflecting data-driven approaches for demand prediction.

Traditional Modeling – regression-based methods bridging historical and current practices.

These clusters demonstrate how themes once treated separately, such as "urban transformation" and "accessibility," now converge under the umbrella of sustainable and equitable mobility.

4.4 Research gaps, limitations, and future

Trip generation research is expanding into freight, evacuation, and active mobility planning, but many studies still depend on fixed trip rates. More predictive, context-aware models that account for demographic, spatial, and behavioral diversity are necessary. Four key priorities emerge for future research: (a) technological innovation using AI, deep learning, and real-time data; (b) promoting sustainability and equity by including environmental impacts and underserved populations; (c) adapting models for developing countries for localization and transferability; and (d) addressing crisis mobility for disaster and disruption planning. This review focuses only on Scopus, highlighting the need for broader database coverage and semantic methods. Data scarcity and inconsistent sharing also hinder model robustness, underscoring the importance of increased international collaboration and open data frameworks.

5. CONCLUSIONS

Trip generation research has shifted from static trip rates to adaptive, technology-driven methods that better reflect the complexity of urban mobility. Five thematic clusters define the field, with increasing focus on sustainability, equity, and machine learning. The United States and China lead in output, but contributions from developing countries remain limited, underscoring the need for greater global participation. Overall, the field is progressing toward more interdisciplinary, context-aware, and sustainable models that tackle current urban challenges.

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NOMENCLATURE

AI	artificial intelligence
ANN	artificial neural network
C/CP	average citations per cited publication
C/P	average citations per publication
g-index	metric giving more weight to highly-cited papers; the top g papers have together at least g^2 citations
GIS	Geographic Information System
h-index	metric representing the number of papers (h) that have received at least h citations
m-index	h-index divided by the number of years since the first publication (productivity-adjusted impact measure)
NCA	number of contributing authors
R^2	coefficient of determination
TP	total publications
TC	total citations

APPENDIX

Supplementary Appendix A. Extended Bibliometric Tables

Table A1. Publications by year

Year	TP	%	Cumm. TP	Cumm. %	NCA	NCP	TC	C/P	C/CP
1972	1	0.25%	1	0.25%	2	1	2	2.00	2.00

1973	1	0.25%	2	0.51%	1	0	0	0.00	0.00
1975	3	0.76%	5	1.27%	6	2	19	6.33	9.50
1976	3	0.76%	8	2.03%	5	2	6	2.00	3.00
1977	8	2.03%	16	4.06%	12	4	29	3.63	7.25
1978	4	1.02%	20	5.08%	10	1	8	2.00	8.00
1979	3	0.76%	23	5.84%	5	2	23	7.67	11.50
1980	5	1.27%	28	7.11%	7	4	54	10.80	13.50
1981	2	0.51%	30	7.61%	3	1	17	8.50	17.00
1982	1	0.25%	31	7.87%	2	1	6	6.00	6.00
1983	8	2.03%	39	9.90%	15	3	45	5.63	15.00
1984	3	0.76%	42	10.66%	6	1	12	4.00	12.00
1985	6	1.52%	48	12.18%	9	3	9	1.50	3.00
1986	3	0.76%	51	12.94%	6	3	39	13.00	13.00
1987	2	0.51%	53	13.45%	3	1	3	1.50	3.00
1988	9	2.28%	62	15.74%	15	6	113	12.56	18.83
1989	1	0.25%	63	15.99%	2	1	5	5.00	5.00
1990	4	1.02%	67	17.01%	7	2	25	6.25	12.50
1991	1	0.25%	68	17.26%	1	1	2	2.00	2.00
1992	6	1.52%	74	18.78%	14	2	5	0.83	2.50
1993	2	0.51%	76	19.29%	3	1	1	0.50	1.00
1994	1	0.25%	77	19.54%	2	1	14	14.00	14.00
1995	2	0.51%	79	20.05%	4	2	44	22.00	22.00
1996	6	1.52%	85	21.57%	15	5	98	16.33	19.60
1997	6	1.52%	91	23.10%	11	5	88	14.67	17.60
1998	6	1.52%	97	24.62%	12	5	59	9.83	11.80
1999	3	0.76%	100	25.38%	8	3	19	6.33	6.33
2000	5	1.27%	105	26.65%	17	4	68	13.60	17.00
2001	5	1.27%	110	27.92%	9	4	10	2.00	2.50
2002	4	1.02%	114	28.93%	10	4	43	10.75	10.75
2003	5	1.27%	119	30.20%	9	3	11	2.20	3.67
2004	9	2.28%	128	32.49%	21	6	141	15.67	23.50
2005	6	1.52%	134	34.01%	15	5	187	31.17	37.40
2006	11	2.79%	145	36.80%	29	9	137	12.45	15.22
2007	8	2.03%	153	38.83%	22	7	66	8.25	9.43
2008	9	2.28%	162	41.12%	27	6	27	3.00	4.50
2009	14	3.55%	176	44.67%	30	7	117	8.36	16.71
2010	13	3.30%	189	47.97%	31	10	174	13.38	17.40
2011	9	2.28%	198	50.25%	21	8	178	19.78	22.25
2012	12	3.05%	210	53.30%	37	11	58	4.83	5.27
2013	15	3.81%	225	57.11%	46	12	220	14.67	18.33
2014	9	2.28%	234	59.39%	31	8	124	13.78	15.50
2015	17	4.31%	251	63.71%	51	17	221	13.00	13.00
2016	8	2.03%	259	65.74%	20	7	281	35.13	40.14
2017	17	4.31%	276	70.05%	54	17	283	16.65	16.65
2018	9	2.28%	285	72.34%	22	7	36	4.00	5.14
2019	20	5.08%	305	77.41%	60	13	388	19.40	29.85
2020	16	4.06%	321	81.47%	61	11	115	7.19	10.45
2021	23	5.84%	344	87.31%	71	18	129	5.61	7.17
2022	25	6.35%	369	93.65%	76	16	94	3.76	5.88
2023	15	3.81%	384	97.46%	42	7	40	2.67	5.71
2024	10	2.54%	394	100.00%	29	3	7	0.70	2.33
Grand Total	394	100.00%			1027	283	3900	9.90	13.78

Notes: TP = total number of publications; NCA = number of contributing authors; NCP = number of cited publications; TC = total citations; C/P = average citations per publication; C/CP = average citations per cited publication.

Source: Generated by the author(s) using BiblioMagika® [16]

Table A2. Most productive authors

Full Name	Current Affiliation	Country	TP	NCP	TC	C/P	C/CP	*h*	*g*	*m*
Currans, Kristina M.	Portland State University	United States	8	6	101	12.63	16.83	5	8	0.238
Clifton, Kelly J.	Portland State University	United States	7	4	28	4.00	7.00	4	5	0.098
Holguín-Veras, José	Rensselaer Polytechnic Institute	United States	6	4	45	7.50	11.25	3	6	0.061
Sánchez-Díaz, Iván	Pennoni Associates	Sweden	6	2	5	0.83	2.50	2	2	0.048
Chen, Xuewu	Parsons Brinckerhoff / WSP	China	6	5	177	29.50	35.40	4	6	0.148
Gonzalez-Feliu, Jesus	Institut Henri Fayol	France	5	4	7	1.40	1.75	2	2	0.041
Badoe, Daniel A.	Tennessee Technological University	United States	5	3	26	5.20	8.67	3	5	0.158
Ewing, Reid	University of Utah	United States	4	3	32	8.00	10.67	3	4	0.136
Schneider, Robert	University of Wisconsin-Milwaukee	United States	4	2	9	2.25	4.50	2	3	0.154

Huntsinger, Leta	consulting firm	United States	4	3	55	13.75	18.33	2	4	0.118
Handy, Susan	University of California	United States	4	2	11	2.75	5.50	2	3	0.200
Jaller, Miguel	Rensselaer Polytechnic Institute	United States	4	2	8	2.00	4.00	2	2	0.080
Venkadavarahan, Marimuthu	Vellore Institute of Technology (VIT)	India	4	2	22	5.50	11.00	1	4	0.022
Pani, Agnivesh	Birla Institute of Technology and Science Pilani	India	4	0	0	0.00	0.00	0	0	0.000
Sahu, Prasanta K.	Birla Institute of Technology and Science Pilani	India	4	2	26	6.50	13.00	2	4	0.040
Marisamynathan, Sankaran	National Institute of Technology	India	4	4	103	25.75	25.75	3	4	0.065
Morency, Catherine	École Polytechnique	Canada	4	3	216	54.00	72.00	2	4	0.045
Wang, Wei	Southeast University	China	4	3	59	14.75	19.67	2	4	0.118
Yang, Min	Southeast University	China	4	4	32	8.00	8.00	3	4	0.079
Henson, Jamie	government agency	United States	3	2	20	6.67	10.00	2	3	0.095
Dock, Stephanie	government agency	United States	3	2	43	14.33	21.50	2	3	0.111
Noland, Robert B.	Imperial College London	United Kingdom	3	3	7	2.33	2.33	2	2	0.143
Shafizadeh, Kevan	California State University	United States	3	2	15	5.00	7.50	2	3	0.087
Lawson, Catherine	State University of New York	United States	3	3	33	11.00	11.00	2	3	0.111
Wilmot, Chester G.	Louisiana State University	United States	3	3	39	13.00	13.00	2	3	0.041

Note: TP = total number of publications; NCA = number of contributing authors; NCP = number of cited publications; TC = total citations; C/P = average citations per publication; C/CP = average citations per cited publication; h = h-index; g = g-index; m = m-index.
Source: Generated by the author(s) using BiblioMagika® [16]

Table A3. Most productive institutions with a minimum of five publications

Institution Name	Country	TP	NCA	NCP	TC	C/P	C/CP	*h*	*g*	*m*
Southeast University	China	11	29	8	47	4.27	5.88	4	6	0.190
University of California	United States	8	9	8	159	19.88	19.88	7	8	0.412
Portland State University	United States	7	15	7	133	19.00	19.00	6	7	0.429
Parsons Brinckerhoff / WSP	Brazil	5	8	2	66	13.20	33.00	1	5	0.143
Institut Henri Fayol	France	5	6	5	86	17.20	17.20	4	5	0.400
University of Toronto	Canada	4	9	3	120	30.00	40.00	3	4	0.103
Tennessee Technological University	United States	4	8	3	16	4.00	5.33	3	4	0.136
Rensselaer Polytechnic Institute	United States	4	13	4	235	58.75	58.75	4	4	0.267
Birla Institute of Technology and Science Pilani	India	4	8	4	79	19.75	19.75	3	4	0.429
Metropolitan Transportation Commission	Brazil	4	5	1	65	16.25	65.00	1	4	0.143
Louisiana State University	United States	4	5	3	128	32.00	42.67	3	4	0.097
University of Utah	United States	4	9	4	59	14.75	14.75	3	4	0.231
Massachusetts Institute of Technology	United States	3	4	3	13	4.33	4.33	2	3	0.053
McMaster University	Canada	3	6	3	160	53.33	53.33	3	3	0.103
Universidad San Francisco de Quito USFQ	Ecuador	3	4	3	30	10.00	10.00	3	3	0.375
College Station	United States	3	6	3	114	38.00	38.00	2	3	0.050
North Carolina State University	United States	3	4	3	27	9.00	9.00	3	3	0.100
Erfurt University of Applied Sciences	Germany	3	4	2	8	2.67	4.00	2	2	0.182
Tongji University	China	3	5	1	3	1.00	3.00	1	1	0.059
University of Maryland	United States	3	6	3	40	13.33	13.33	2	3	0.143
California State University	United States	3	3	3	54	18.00	18.00	3	3	0.214
University of Arizona	United States	3	3	3	8	2.67	2.67	2	2	0.067
Morgan State University	United States	3	3	2	70	23.33	35.00	1	3	0.059
National Institute of Technology	India	3	5	3	18	6.00	6.00	3	3	0.600
North Dakota State University	United States	3	8	3	15	5.00	5.00	2	3	0.100

Note: TP = total number of publications; NCA = number of contributing authors; NCP = number of cited publications; TC = total citations; C/P = average citations per publication; C/CP = average citations per cited publication; h = h-index; g = g-index; m = m-index.
Source: Generated by the author(s) using BiblioMagika® [16]

Table A4. The top 20 countries contributed to the publications

Country	TP	NCA	NCP	TC	C/P	C/CP	*h*	*g*	*m*
United States	157	372	117	1954	12.45	16.70	23	44	0.426
China	37	114	31	533	14.41	17.19	11	23	0.524
India	28	63	21	351	12.54	16.71	9	18	0.184
United Kingdom	25	44	16	507	20.28	31.69	9	22	0.176
Canada	16	44	15	265	16.56	17.67	8	16	0.174
Japan	13	31	11	153	11.77	13.91	5	12	0.119
Indonesia	10	25	8	28	2.80	3.50	4	5	0.250
Brazil	10	29	7	29	2.90	4.14	4	5	0.143
Iran	9	17	8	42	4.67	5.25	4	6	0.138

Germany	7	14	5	119	17.00	23.80	3	7	0.158
Sweden	7	10	5	68	9.71	13.60	4	7	0.160
South Korea	6	11	6	62	10.33	10.33	4	6	0.190
Malaysia	6	16	4	46	7.67	11.50	2	6	0.167
Australia	6	16	2	32	5.33	16.00	2	5	0.100
France	6	10	4	24	4.00	6.00	4	4	0.190
Netherlands	5	9	4	20	4.00	5.00	3	4	0.083
Taiwan	5	10	3	36	7.20	12.00	2	5	0.100
Hong Kong	3	9	3	51	17.00	17.00	3	3	0.176
Palestine	3	7	1	21	7.00	21.00	1	3	0.125
Nigeria	3	5	3	106	35.33	35.33	3	3	0.130
Turkey	3	6	2	10	3.33	5.00	2	3	0.200
Greece	3	10	2	8	2.67	4.00	1	2	0.040
Ecuador	3	4	1	8	2.67	8.00	1	2	0.125
Portugal	2	3	1	9	4.50	9.00	1	2	0.071
Spain	2	4	1	1	0.50	1.00	1	1	0.111

Note: TP = total number of publications; NCA = number of contributing authors; NCP = number of cited publications; TC = total citations; C/P = average citations per publication; C/CP = average citations per cited publication; h = h-index; g = g-index; m = m-index.
Source: Generated by the author(s) using BiblioMagika® [16]

Table A5. Most active source titles that published two or more documents

Source Title	TP	NCA	NCP	TC	C/P	C/CP	*h*	*g*	*m*
Transportation Research Record	47	159	44	898	19.11	20.41	17	28	0.354
ITE Journal (Institute of Transportation Engineers)	36	70	30	90	2.50	3.00	5	6	0.122
Journal of Urban Planning and Development	10	22	8	55	5.50	6.88	4	7	0.154
Transportation	9	26	9	320	35.56	35.56	8	9	0.163
Transportation Research Part A: Policy and Practice	8	28	8	318	39.75	39.75	6	8	0.207
Transportation Research Procedia	7	26	6	24	3.43	4.00	3	4	0.300
Journal of Transport and Land Use	6	15	6	117	19.50	19.50	5	6	0.455
Traffic Engineering and Control	6	11	4	33	5.50	8.25	2	5	0.039
Transportation Planning and Technology	6	12	5	44	7.33	8.80	5	6	0.102
ITE Journal	5	7	5	11	2.20	2.20	2	3	0.043
IOP Conference Series: Earth and Environmental Science	5	15	0	0	0.00	0.00	0	0	0.000
Journal of Transportation Engineering	5	9	5	94	18.80	18.80	5	5	0.161
Travel Behaviour and Society	4	12	4	62	15.50	15.50	4	4	0.500
Wuhan Ligong Daxue Xuebao (Jiaotong Kexue Yu Gongcheng Ban)/Journal of Wuhan University of Technology (Transportation Science and Engineering)	4	12	2	4	1.00	2.00	2	2	0.111
Journal of Transport Geography	4	12	4	157	39.25	39.25	4	4	0.250
Traffic Engineering & Control	4	4	2	2	0.50	1.00	1	1	0.023
Case Studies on Transport Policy	4	10	4	41	10.25	10.25	4	4	0.667
Transportation Research Part D: Transport and Environment	4	10	4	175	43.75	43.75	4	4	0.200
AIP Conference Proceedings	4	10	1	22	5.50	22.00	1	4	0.111
Journal of Advanced Transportation	4	9	4	57	14.25	14.25	4	4	0.200

Note: TP = total number of publications; NCA = number of contributing authors; NCP = number of cited publications; TC = total citations; C/P = average citations per publication; C/CP = average citations per cited publication; h = h-index; g=g-index; m = m-index.
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Table A6. The most cited trip generation documents

No.		Author(s)	Title	Source Title	TC	Cited per Year	DOI
1	[20]	Noland R.B.; Smart M.J.; Guo Z. (2016)	Bikeshare trip generation in New York City	Transportation Research Part A: Policy and Practice	208	20.80	10.1016/j.tra.2016.08.030
2	[21]	Holguín-Veras J.; Jaller M.; Destro L.; Ban X.J.; Lawson C.; Levinson H.S. (2011)	Freight generation, freight trip generation, and perils of using constant trip rates	Transportation Research Record	108	7.20	10.3141/2224-09
3	[22]	Wilmot C.G.; Mei B. (2004)	Comparison of alternative trip generation models for Hurricane evacuation	Natural Hazards Review	107	4.86	10.1061/(ASCE)1527-6988(2004)5:4(170)
4	[23]	Schmöcker J.D.; Quddus M.A.; Noland R.B.; Bell M.G.H. (2005)	Estimating trip generation of elderly and disabled people: Analysis of London data	Transportation Research Record	107	5.10	10.3141/1924-02
5	[24]	Safwat K.Nabil Ali; Magnanti Thomas L. (1988)	Combined trip generation, trip distribution, modal split, and trip assignment model	Transportation Science	103	2.71	10.1287/trsc.22.1.14

6	[25]	Roorda M.J.; Páez A.; Morency C.; Mercado R.; Farber S. (2010)	Trip generation of vulnerable populations in three Canadian cities: A spatial ordered probit approach	Transportation	89	5.56	10.1007/s11116-010-9263-3
7	[26]	Wang L.; Abdel-Aty M.; Lee J.; Shi Q. (2019)	Analysis of real-time crash risk for expressway ramps using traffic, geometric, trip generation, and socio-demographic predictors	Accident Analysis and Prevention	87	12.43	10.1016/j.aap.2017.06.003
8	[27]	Ewing R.; DeAnna M.; Li S.C. (1996)	Land use impacts on trip generation rates	Transportation Research Record	81	2.70	10.3141/1518-01
9	[28]	Noland R.B.; Quddus M.A. (2006)	Flow improvements and vehicle emissions: Effects of trip generation and emission control technology	Transportation Research Part D: Transport and Environment	78	3.90	10.1016/j.trd.2005.06.003
10	[29]	Truong L.T.; De Gruyter C.; Currie G.; Delbosc A. (2017)	Estimating the trip generation impacts of autonomous vehicles on car travel in Victoria, Australia	Transportation	70	7.78	10.1007/s11116-017-9802-2
11	[30]	Holguín-Veras J.; Sánchez-Díaz I.; Lawson C.; Jaller M.; Campbell S.; Levinson H.; Shin H.S. (2013)	Transferability of freight trip generation models	Transportation Research Record	69	5.31	10.3141/2379-01
12	[31]	Cheng L.; Chen X.; Yang S.; Wu J.; Yang M. (2019)	Structural equation models to analyze activity participation, trip generation, and mode choice of low-income commuters	Transportation Letters	65	9.29	10.1080/19427867.2017.1364460
13	[32]	Pettersson P.; Schmöcker J.-D. (2010)	Active ageing in developing countries? - trip generation and tour complexity of older people in Metro Manila	Journal of Transport Geography	61	3.81	10.1016/j.jtrangeo.2010.03.015
14	[33]	Calvo F.; Eboli L.; Forciniti C.; Mazzulla G. (2019)	Factors influencing trip generation on metro system in Madrid (Spain)	Transportation Research Part D: Transport and Environment	51	7.29	10.1016/j.trd.2018.11.021
15	[34]	Gonzalez-Feliu J.; Sánchez-Díaz I. (2019)	The influence of aggregation level and category construction on estimation quality for freight trip generation models	Transportation Research Part E: Logistics and Transportation Review	50	7.14	10.1016/j.tre.2018.07.007
16	[35]	Kitamura R. (2009)	A dynamic model system of household car ownership, trip generation, and modal split: Model development and simulation experiment	Transportation	47	2.76	10.1007/s11116-009-9241-9
17	[36]	Zhou Z.; Chen A.; Wong S.C. (2009)	Alternative formulations of a combined trip generation, trip distribution, modal split, and trip assignment model	European Journal of Operational Research	44	2.59	10.1016/j.ejor.2008.07.041
18	[37]	Pani A.; Sahu P.K.; Chandra A.; Sarkar A.K. (2019)	Assessing the extent of modifiable areal unit problem in modelling freight (trip) generation: Relationship between zone design and model estimation results	Journal of Transport Geography	42	6.00	10.1016/j.jtrangeo.2019.102524
19	[38]	Agyemang-Duah K.; Hall F.L. (1997)	Spatial transferability of an ordered response model of trip generation	Transportation Research Part A: Policy and Practice	41	1.41	10.1016/S0965-8564(96)00035-3

20	[39]	Jiao J.; Bischak C.; Hyden S. (2020)	The impact of shared mobility on trip generation behavior in the US: Findings from the 2017 National Household Travel Survey	Travel Behaviour and Society	39	6.50	10.1016/j.tbs.2019.11.001

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