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Advancing Travel Behaviour Modelling: A Systematic Literature Review

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Abstract

People's daily travel choices collectively shape traffic patterns, land-use efficiency, and broader urban systems. Traditional travel-behaviour models (TBMs) have long supported congestion management, infrastructure planning, and policy analysis. However, their adaptability to rapidly evolving technologies such as autonomous vehicles, connected transport, and smart mobility remains insufficiently explored. This study presents a systematic literature review of TBM research published between 2016 and 2025, adopting a PRISMA-guided and reproducible methodology to synthesise 41 peer-reviewed studies. The review analyses modelling paradigms, data sources, analytical techniques, and application contexts to identify dominant trends and structural limitations in the field. The synthesis reveals persistent gaps, including limited capacity to process real-time, high-granularity data, insufficient treatment of behavioural heterogeneity, and challenges in integrating emerging autonomous mobility scenarios within policy-relevant frameworks. Cross-cutting concerns related to privacy, equity, interpretability, and transferability are also evident across modelling approaches. Based on a structured qualitative and frequency-based synthesis, the study outlines priority research directions, including hybrid behavioural–machine learning models, dynamic calibration using crowd-sensed and multi-source data, explicit modelling of behavioural diversity in autonomous mobility adoption, and the development of standardised, privacy-aware multimodal datasets to enhance robustness and policy relevance.

Keywords
Travel behaviour; travel behaviour modelling; Mode Choice Modelling, Travel Data

1. Introduction

Travel behaviour modelling (TBM) has evolved from a predictive support tool into a critical analytical framework for understanding the complex interactions between human decision-making, transport systems, and urban form. As cities become increasingly dynamic and mobility systems become more interconnected, the need to interpret and predict travel behaviour has grown significantly. Travel decisions are shaped by accumulated behavioural patterns influenced by socio-economic conditions, infrastructure availability, spatial constraints, and individual preferences, making them inherently context-dependent and temporally variable. Empirical evidence indicates that daily travel patterns not only influence transport system performance but also affect broader socio-economic outcomes such as productivity and quality of life (Ma & Ye, 2019). Similarly, policy acceptance, particularly for measures such as congestion pricing, reflects the behavioural complexity underlying individual travel choices (Marazi et al., 2022).

Traditionally, TBM has relied on econometric and theory-driven approaches, particularly discrete choice models grounded in utility maximisation. While these models have provided strong interpretability and policy relevance, their ability to capture emerging complexities in travel behaviour has become increasingly limited. Contemporary mobility systems are shaped by rapid technological transformation, including the proliferation of real-time data, connected transport systems, and digital mobility platforms. These developments have introduced new dimensions of uncertainty, behavioural adaptation, and data availability, challenging the assumptions of static and homogeneous decision-making embedded in conventional models.

Recent research demonstrates that travel behaviour is influenced not only by observable socio-economic variables but also by behavioural, perceptual, and contextual factors. For instance, reliability and uncertainty in transport systems significantly affect travel decisions, as evidenced by modelling approaches that capture travel time variability under congestion conditions (Afandizadeh et al., 2023). Similarly, behavioural constructs such as risk perception, distraction, and compliance, particularly in the context of mobile phone use while driving, highlight the importance of incorporating psychological dimensions into modelling frameworks (Parishad et al., 2022). These insights underscore a shift toward behaviourally enriched models that move beyond aggregate assumptions to reflect individual decision processes better.

Spatial and contextual characteristics further complicate travel behaviour. Urban form, terrain, and accessibility conditions play a significant role in shaping route choice, activity participation, and modal preferences. Studies in geographically constrained environments, such as hill cities, illustrate how topography and connectivity influence travel patterns (Lalramsangi et al., 2025). At the same time, user-centric modelling approaches emphasise the importance of service quality, comfort, and reliability in determining public transport usage (Lodhi et al., 2024). These findings reinforce the need for TBMs that account for heterogeneity across individuals, locations, and socio-economic groups.

Parallel to these behavioural advancements, TBM has undergone a methodological transformation driven by developments in data and computational techniques. The increasing availability of high-resolution data from GPS devices, smart cards, mobile applications, and sensor networks has enabled more detailed and dynamic analysis of travel behaviour. Machine learning and artificial intelligence techniques have further expanded the analytical capabilities of TBM by capturing nonlinear relationships and complex interactions within large datasets. However, these data-driven approaches often introduce trade-offs, particularly related to interpretability, transparency, and policy applicability.

In addition, the integration of land use and transport systems has become a central theme in contemporary TBM research. Land use–transport interaction (LUTI) models and transit-oriented development (TOD) frameworks increasingly incorporate accessibility, density, and first- and last-mile connectivity as key determinants of travel behaviour (Sharma & Dehalwar, 2025; Yadav et al., 2025a). Emerging technologies such as generative artificial intelligence and digital twins are further enabling real-time, adaptive modelling environments capable of simulating dynamic responses to policy interventions and infrastructure changes (Sharma, 2025). These developments reflect a broader transition toward integrated, data-rich, and system-oriented modelling paradigms.

Despite these advances, significant challenges persist. Travel behaviour modelling continues to face issues related to unobserved heterogeneity, endogeneity between variables, temporal instability of preferences, and the limited ability to account for structural disruptions such as those observed during the COVID-19 pandemic. Furthermore, the growing reliance on large-scale and passive data sources raises concerns regarding privacy, equity, and data governance. These challenges highlight the need for a systematic and critical synthesis of the TBM literature better to understand current capabilities, limitations, and future directions.

In this context, the present study conducts a systematic literature review of travel behaviour modelling research published between 2016 and 2025. The review adopts a PRISMA-guided and reproducible methodology to synthesise developments across modelling paradigms, data sources, analytical techniques, and application domains. Rather than focusing on a single modelling approach, this study provides an integrative assessment that enables cross-paradigm comparison and deeper analytical insight.

The following research questions guide the review:

• RQ1: What modelling paradigms and behavioural theories dominate TBM research between 2016 and 2025?
• RQ2: How have data sources and technological tools (e.g., big data, real-time data) influenced TBM development?
• RQ3: What algorithms and analytical techniques are most commonly used, and what are their strengths and limitations?
• RQ4: How do TBMs address key challenges such as heterogeneity, endogeneity, and temporal instability?

• RQ5: What systematic research gaps and future directions emerge from the reviewed literature?

These research questions inform the screening criteria, data extraction framework, and analytical structure of the review, ensuring methodological transparency and reproducibility. By organising findings along analytical dimensions rather than narrative description, the study facilitates systematic comparison across diverse modelling approaches and contexts.

This review contributes to the literature in several important ways. First, it provides a comprehensive and systematic synthesis of recent TBM research, integrating behavioural theory, data ecosystems, modelling approaches, and application contexts within a unified analytical framework. Second, it moves beyond descriptive categorisation by explicitly examining core methodological challenges such as endogeneity, unobserved heterogeneity, temporal instability, and post-disruption behavioural change. Third, it adopts a structured and evidence-based approach to identifying research gaps, grounded in frequency analysis and recurring limitations across studies.

Importantly, this study does not position emerging data-driven approaches as replacements for traditional behavioural models. Instead, it highlights complementarities and trade-offs across modelling paradigms, demonstrating that improvements in predictive performance may come at the expense of interpretability, transferability, or policy relevance. By systematically linking modelling choices to their implications for inference and decision-making, the review provides a balanced and policy-oriented perspective on the current state of TBM.

This study offers an integrative and critically grounded synthesis that clarifies the evolution of travel behaviour modelling, identifies unresolved methodological challenges, and outlines a coherent roadmap for advancing research and practice in this field. Unlike prior reviews, this study integrates methodological, behavioural, and policy dimensions within a single analytical framework, enabling cross-paradigm evaluation.

2. Research Methodology

This study adopts a systematic literature review (SLR) approach to evaluate recent developments in travel behaviour modelling (TBM). The methodology follows a structured, PRISMA-guided process comprising five stages: (1) formulation of research objectives and questions, (2) literature search and selection, (3) application of inclusion and exclusion criteria, (4) data extraction and thematic classification, and (5) synthesis and gap identification. The methodology flowchart has been provided below in Figure 1.

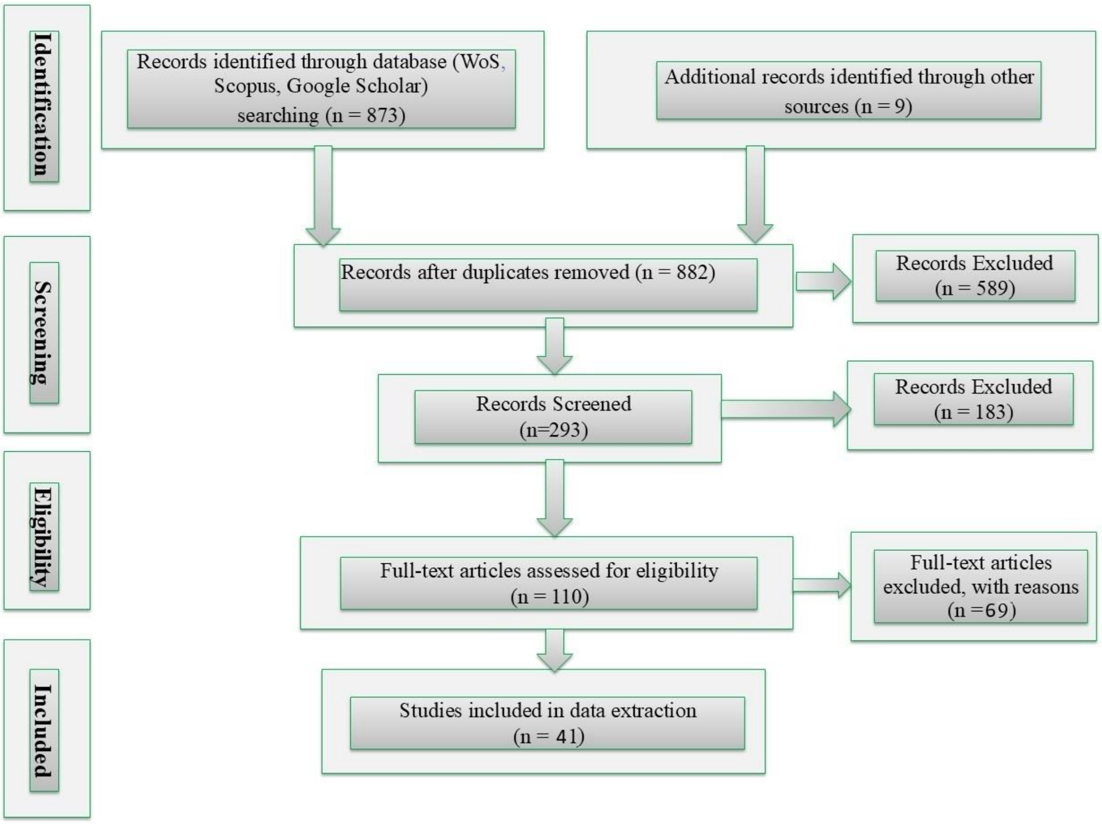

Figure 1 PRISMA Flowchart for the Systematic Literature Review

A comprehensive literature search was conducted across three major academic databases, Scopus, Web of Science, and Google Scholar, to ensure broad coverage of peer-reviewed transport research. The search was limited to studies published between 2016 and 2025, reflecting a period of rapid methodological and technological evolution in TBM. Keywords and Boolean operators such as "travel behaviour modelling," "mode choice modelling," "discrete choice model," "agent-based model," and "machine learning" were applied using database-specific syntax. Additional studies were identified through reference chaining and snowball sampling. The search yielded 873 records, with 9 additional sources identified through other means, resulting in 882 records after duplicate removal.

Explicit inclusion and exclusion criteria were applied to ensure analytical relevance and methodological rigour. Studies were included if they focused on empirical or methodological aspects of TBM and employed established or emerging modelling frameworks such as discrete choice models (DCM), structural equation models (SEM), machine learning (ML), or agent-based models (ABM). Only peer-reviewed publications in English were considered. Studies were excluded if they were descriptive without behavioural modelling, non-peer-reviewed, duplicated, or lacked accessible full texts. Following screening, 41 studies were retained for detailed analysis.

A structured data extraction protocol was used to systematically capture key attributes of each study, including publication details, geographic scope, modelling approach, data sources, application domain, and main findings. Modelling techniques were categorised into econometric, behavioural, machine learning, agent-based, and hybrid approaches, while data sources were classified as survey-based, revealed or stated preference, GPS/mobile data, smart card data, or integrated big-data systems. The studies were subsequently grouped into thematic clusters to support comparative analysis.

Given the substantial heterogeneity across studies, a qualitative and frequency-based synthesis was adopted. Variations in dependent variables, behavioural constructs, modelling techniques, and evaluation metrics precluded meaningful statistical aggregation. Specifically, outcomes ranged from discrete mode choices to continuous performance indicators, while modelling approaches spanned econometric, simulation-based, and machine learning frameworks with incompatible assumptions and validation measures. As a result, meta-analysis was deemed inappropriate, and patterns were instead identified through structured comparison of modelling approaches, data usage, and application contexts.

Finally, research gaps were identified based on recurring limitations and underrepresented themes. These include the limited representation of Global South contexts, insufficient integration of behavioural and environmental variables, lack of dynamic modelling of disruptive events, and emerging challenges related to data governance and interpretability. At the same time, the methodology ensures transparency and reproducibility, limitations remain, including database and language restrictions and the exclusion of grey literature. This approach provides a robust foundation for synthesising diverse TBM research and identifying future research priorities.

3. Findings

The findings are structured across key analytical dimensions, including modelling paradigms, geographic distribution, data sources, technologies, and behavioural analysis, rather than narrative description. This approach enables systematic comparison, highlighting methodological diversity, dominant trends, and critical gaps in contemporary TBM research.

3.1 Keywords Analysis

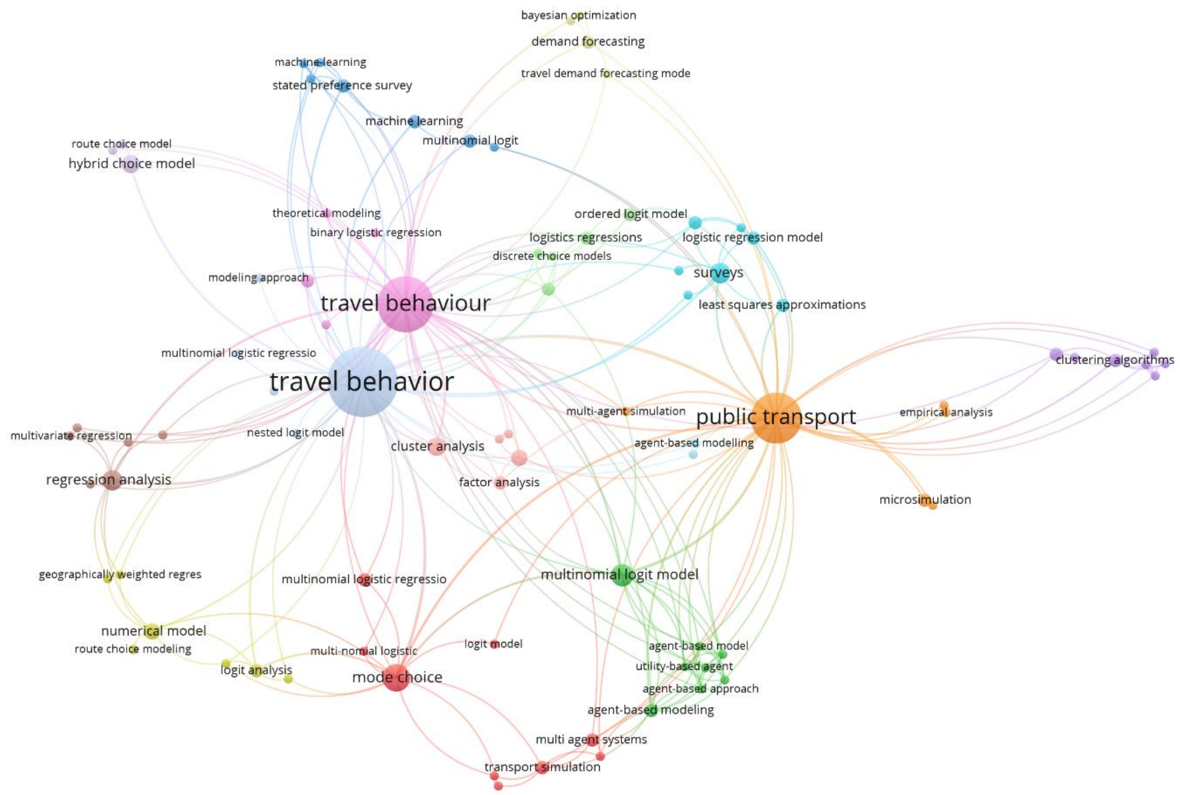

Figure 2 Keywords Analysis Network for the Travel Behaviour

Figure 2 illustrates the keyword co-occurrence network, revealing the conceptual structure and dominant themes in travel behaviour modelling (TBM). The network highlights the coexistence of multiple modelling paradigms rather than the dominance of a single approach. Traditional frameworks such as discrete choice models remain central due to their theoretical grounding in utility-based decision-making, while agent-based models enable dynamic analysis of interactions among heterogeneous travellers (Zhou et al., 2025; Wörle et al., 2021). In parallel, latent variable approaches incorporate psychological factors, improving behavioural realism (Kamargianni et al., 2015). More recent trends show a growing emphasis on machine learning techniques, which enhance predictive performance but raise concerns regarding interpretability and policy relevance (Cao & Tao, 2023; Zheng et al., 2021). The network reflects a clear shift toward hybrid and integrative modelling approaches that combine behavioural theory with data-driven methods.

This methodological diversity is further reflected in the widespread use of complementary modelling tools. Traditional econometric approaches, particularly multinomial and logistic regression models, remain central due to their interpretability and theoretical grounding (de Oliveira & Lima, 2023). At the same time, agent-based models enhance behavioural realism by simulating individual-level interactions (Diallo et al., 2023; Karolemeas et al., 2024), while microsimulation frameworks extend analysis to long-term land-use interactions (Basu & Ferreira, 2020; Cordera et al., 2021). More recently, machine learning and hybrid approaches have gained prominence for capturing nonlinear relationships and context-specific patterns (Tamim Kashifi et al., 2022; Zhou et al., 2024). This convergence reflects a shift toward integrated, multi-paradigm TBM frameworks.

3.2 Geographical Distribution

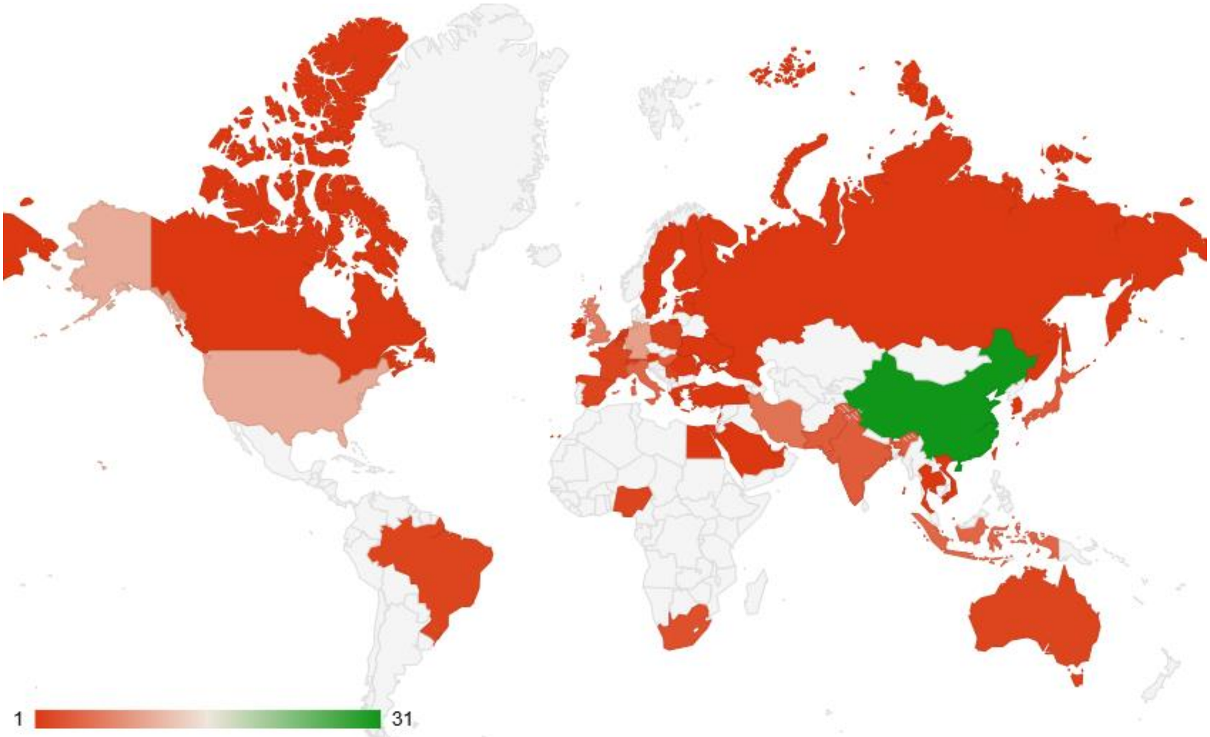

Figure 3 Geographical Distribution of selected papers on travel behaviour modelling

Figure 3 presents the geographical distribution of studies included in the review, highlighting clear spatial imbalances in travel behaviour modelling (TBM) research. The evidence shows a strong concentration of studies in a few countries, with China leading in publication output, followed by the United States and several European nations such as Germany, the United Kingdom, and Italy. This dominance is largely associated with advanced data infrastructure, strong institutional capacity, and sustained investment in smart mobility research. In contrast, contributions from developing regions, including India, Iran, Indonesia, and parts of Africa, remain limited but are gradually increasing, often focusing on context-specific challenges such as informal transport systems and rapid urbanisation. The distribution indicates that TBM research is still skewed toward developed economies, highlighting the need for greater inclusion of Global South contexts to improve the equity and transferability of modelling frameworks.

3.3 Technologies that include travel behaviour, models

Travel behaviour modelling (TBM) is increasingly integrated with emerging transport technologies, marking a shift from standalone analytical tools toward data-driven and system-level mobility frameworks. Autonomous vehicles and smart mobility platforms introduce new behavioural uncertainties and demand dynamics, where TBM supports the analysis of adoption patterns, induced demand, and policy impacts (Jászberényi et al., 2022). High-resolution data from GPS-based systems and large-scale mobility tracking further enable precise modelling of activity patterns, trip chaining, and route choice behaviour (Eom et al., 2024; Mwesigwa et al., 2024). In parallel, transit-oriented development (TOD) frameworks emphasise the integration of land use and transport systems in shaping travel demand (Tan & Li, 2022).

Within these technology-enabled environments, structural equation modelling (SEM) and latent variable frameworks play an important role in capturing unobserved behavioural factors such as perceptions, attitudes, and preferences that influence technology adoption and travel decisions. This enhances the ability of TBM to interpret behavioural responses to emerging mobility systems alongside purely data-driven predictions.

Emerging mobility services, including ride-sourcing and dynamic ride-sharing, require advanced demand modelling frameworks capable of capturing spatial–temporal dependencies and user heterogeneity (Wali et al., 2023). Optimisation-based approaches, such as multimodal routing and personalised trip-planning systems, further enhance TBM's capacity for real-time and user-centric decision support (Wins et al., 2024). Additionally, technologies such as automated fare collection and real-time traffic management systems enable dynamic modelling through continuous behavioural and network data streams (Chen & Fan, 2020), while applications such as park-and-ride optimisation demonstrate TBM's role in infrastructure planning and system resilience (Henry et al., 2022).

Although these technological integrations improve predictive capability and scalability, they also introduce challenges related to data governance, privacy, and interpretability. As such systems increasingly function as high-frequency data generators, ensuring ethical data use, representativeness, and alignment with behavioural realism remains essential.

3.4 Comparative Synthesis of Modelling Approaches, Data Sources, and Applications

To move beyond narrative description and enable structured comparison, this subsection presents a comparative synthesis of representative travel behaviour modelling (TBM) studies reviewed in this paper. The synthesis cross-tabulates modelling approaches, primary data sources, application domains, and key methodological limitations. By explicitly aligning models with their empirical foundations and policy contexts, Table 1 highlights both dominant methodological patterns and recurring constraints in contemporary TBM research. This structured comparison supports a clearer understanding of where specific approaches perform well, where they face limitations, and how methodological choices shape applicability across diverse mobility contexts.

Table 1: Comparative synthesis of travel behaviour modelling approaches, data sources, application domains, and key limitations

Modelling approach	Representative studies	Primary data sources	Application domain	Key limitations identified
Discrete Choice Models (MNL, NL, LC)	de Oliveira & Lima (2023); Lodhi et al. (2024); Zhou et al. (2025); McCarthy et al. (2025)	Household surveys, stated/revealed preference data	Mode choice, public transport satisfaction, scheduling behaviour	Assumption of rational choice; limited ability to capture real-time adaptation and unobserved heterogeneity
Latent Variable & Behavioural Models (SEM, hybrid DCM–LV)	Kamargianni et al. (2015); Parishad et al. (2022)	Surveys with attitudinal and perception variables	Behavioural realism, risk perception, compliance, safety	Increased data requirements; subjectivity in latent construct measurement

Agent-Based Models (ABM)	Diallo et al. (2023); Karolemeas et al. (2024);	Synthetic populations, travel diaries, and GPS traces	Intermodal policies, shared mobility, and AV adoption	High computational cost; calibration and transferability challenges
Machine Learning Models	Afandizadeh et al. (2023). Cao & Tao (2023); Kumar et al. (2024); Merikhipour et al. (2025); Zhou et al. (2024)	GPS data, traffic sensors, air quality data, and social media	Travel time reliability, congestion forecasting, and nonlinear behaviour	Limited interpretability; weak theoretical grounding for policy use
Hybrid ML–Behavioural Models	Wang et al. (2021); Tamim Kashifi et al. (2022); Zheng et al. (2021)	Survey + GPS + smart card data	Equity-aware prediction, mode detection	Complexity in model integration; higher data and skill requirements
LUTI & Integrated Urban Models	Basu & Ferreira (2020); Cordera et al. (2021); Sharma & Dehawar (2025)	Land-use data, transport networks, census data	Long-term urban growth, TOD, AV impacts	Coarse behavioural resolution; limited short-term dynamics
Big Data and Crowdsourced Models	Chaniotakis et al. (2022).	Smartphone sensors, social media, and AFC data	Network monitoring, accessibility, pedestrian behaviour	Privacy concerns; sampling bias; data governance constraints

The diversity documented across outcome variables, behavioural constructs, and evaluation metrics in Table 1 further illustrates why quantitative pooling through meta-analysis was not methodologically defensible in this review. The comparative synthesis (Table 1) reveals that no single modelling paradigm adequately addresses the full complexity of travel behaviour across temporal, spatial, and social dimensions. Traditional discrete choice models remain dominant in policy-oriented applications due to their interpretability, while machine-learning approaches excel in predictive accuracy but face challenges related to transparency and behavioural realism. Agent-based and hybrid models offer promising avenues for capturing behavioural heterogeneity and system dynamics, yet their scalability and data demands remain significant barriers. Across approaches, recurring limitations include difficulties in handling real-time data, addressing unobserved heterogeneity, and ensuring equity and privacy in data-intensive models. These findings underscore the need for integrative frameworks that balance theoretical robustness, computational efficiency, and policy relevance, an issue further explored in the subsequent discussion and future research directions.

Travel behaviour modelling (TBM) integrates behavioural, spatial, and socio-demographic perspectives to explain and predict travel decision-making within urban systems. Beyond trip representation, TBM captures underlying behavioural mechanisms through four key analytical dimensions: (i) travel pattern analysis, which identifies spatial–temporal regularities shaped by accessibility and lifestyle (Chaniotakis et al., 2022); (ii) forecasting, which evaluates behavioural responses to policy, technological, and demographic changes (Lodhi et al., 2024); (iii) behavioural change analysis, which examines the impact of external triggers such as life events or environmental awareness; and (iv) travel choice modelling, which analyses mode, route, and destination selection under varying constraints.

In this context, structural equation modelling (SEM) and latent variable approaches play a critical role by incorporating unobserved psychological constructs such as attitudes, perceptions, and preferences, thereby enhancing behavioural realism and explanatory depth. Recent advances, including contextual feature fusion techniques, further strengthen the representation of latent behavioural patterns (Solomon et al., 2025).

Table 2: Temporal Evolution of TBM Research

Period	Modelling Shift	Data Transition	Key Focus	Key Limitation
2016	Discrete choice, SEM	Surveys (SP/RP)	Behavioural explanation	Static assumptions
2017–2019	Latent class, ABM, and SEM extensions	Surveys + GPS	Heterogeneity, route choice	Data sparsity
2020–2021	ABM, LUTI, early ML	GPS, smart cards	Shared mobility, COVID impacts	Limited adaptability
2022–2023	ML, hybrid (ML–DCM/SEM)	Big data, LBS, AFC	Prediction, congestion, equity	Low interpretability
2024–2025	Hybrid AI, digital twins	Multi-source, real-time	AVs, sustainability, fairness	Governance & privacy

The temporal progression (Table 2) indicates a transition from theory-driven, survey-based models including discrete choice and SEM frameworks toward data-intensive and hybrid approaches. While recent methods enhance predictive capability and real-time responsiveness, they also introduce challenges related to interpretability, equity, and data governance. Importantly, the continued coexistence of econometric, behavioural, and machine-learning paradigms suggests that TBM has evolved through methodological diversification rather than replacement, supporting the use of structured qualitative synthesis over meta-analysis.

4. Discussion

This section critically synthesises the review findings to evaluate travel behaviour modelling (TBM) beyond descriptive trends. It assesses modelling approaches based on interpretability, behavioural realism, robustness, and policy relevance, while examining issues of equity, privacy, and fairness. The discussion also links methodological limitations to their implications and highlights key challenges such as heterogeneity, endogeneity, and temporal instability.

4.1 Interpreting Methodological Popularity, Analytical Value, and Practical Trade-offs

To address concerns regarding the conflation of methodological popularity with analytical superiority, this section evaluates dominant travel behaviour modelling (TBM) approaches using qualitative criteria central to theory-informed and policy-relevant research. Rather than treating frequency of use as an indicator of methodological advancement, the analysis compares modelling approaches based on interpretability, behavioural realism, robustness, data dependency, and policy applicability. Table 3 presents a structured synthesis that integrates these dimensions to provide a balanced assessment across modelling paradigms.

Table 3: Comparative Evaluation of Travel Behaviour Modelling Approaches

Modelling Approach	Frequency of Use	Interpretability	Behavioural Realism	Robustness & Transferability	Data Dependency	Policy Relevance	Key Trade-offs	Representative References

Discrete Choice Models (MNL, NL, LC)	High	High	Moderate–High	High (theory-driven)	Low–Moderate	High	Limited ability to capture nonlinearities	Lodhi et al. (2024); Zhou et al. (2025); McCarthy et al. (2025)
Latent Variable / SEM Models	Moderate	Moderate	High	Moderate	Moderate	High	Increased model complexity, estimation challenges	Kamargianni et al. (2015); Parishad et al. (2022)
Agent-Based Models (ABM)	Moderate	Low–Moderate	High	Moderate–Low	High	Moderate	Calibration difficulty, computational intensity	Diallo et al. (2023); Karolemeas et al. (2024)
Machine Learning Models	Very High (recent)	Low	Low–Moderate	High (data-driven)	Very High	Low–Moderate	Limited interpretability, weak behavioural grounding	Afandizadeh et al. (2023); Kumar et al. (2024); Merikhipour et al. (2025)
Hybrid ML–Behavioural Models	Emerging	Moderate	High	Moderate	High	High (potential)	Complexity, integration challenges	Tamim Kashifi et al. (2022); Zheng et al. (2021)
LUTI / Integrated Urban Models	Low	Moderate	Moderate	High (long-term)	Moderate	High	Coarse behavioural representation	Basu & Ferreira (2020); Cordera et al. (2021); Sharma & Dehawar (2025)

The comparison (Table 3) highlights that while machine-learning approaches dominate recent TBM research due to their predictive performance and ability to process large datasets, they often lack behavioural interpretability and transparency. In contrast, traditional econometric and behavioural models continue to provide stronger explanatory power and policy relevance, particularly in regulatory and planning contexts.

Importantly, hybrid approaches are emerging as a promising direction by combining behavioural theory with data-driven capabilities, offering a more balanced trade-off between prediction and interpretation. The analysis demonstrates that no single modelling paradigm is universally superior; instead, the suitability of a model depends on the research objective, data availability, and policy context.

This synthesis reinforces the need to evaluate TBM approaches not by their popularity, but by their ability to deliver interpretable, behaviourally consistent, and policy-relevant insights.

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4.2 Equity, Privacy, and Fairness in Travel Behaviour Modelling

To systematically address concerns regarding equity, privacy, and fairness, this section presents a structured synthesis of reviewed studies that explicitly or implicitly engage with these dimensions. The purpose of this tabular analysis (as given in Table 4) is to distinguish empirically grounded findings from interpretive commentary and to clarify how different travel behaviour modelling (TBM) approaches operationalise or overlook these considerations. Rather than whether methodological advancement inherently improves equity or fairness, the synthesis evaluates evidence across modelling paradigms, data sources, and application contexts.

Table 4: Evidence on Equity, Privacy, and Fairness Considerations in Travel Behaviour Modelling

Study	Modelling Approach	Data Source	Equity Dimension Addressed	Privacy / Data Ethics	Fairness in Model Outcomes	Key Limitation
Jain & Tiwari (2019).	Discrete choice model	Household travel survey (India)	Income and socio-economic heterogeneity	Survey-based; low privacy risk	Not explicitly evaluated	Limited capture of informal travel
Chakrabarti & Joh (2019).	Econometric analysis	Household travel survey (USA)	Gender and life-stage differences	Survey-based; implicit consent	Not assessed	Static preference assumptions
Mwesigwa et al. (2024).	Accessibility and equity analysis	BRT network + GIS	Spatial and service equity	Not discussed	Distributional access evaluated	Context-specific applicability
Zheng et al. (2021).	Hybrid DCM–DNN	Large-scale revealed preference data	Equality of opportunity in prediction	Implicit (algorithmic focus)	Explicit fairness metrics used	Reduced behavioural interpretability
Meena et al. (2024).	Machine learning	Survey + air-quality awareness data	Environmental justice awareness	Not addressed	Predictive bias not assessed	Self-reported data bias
Lalramsangi et al. (2025).	Route choice modelling	Field survey + spatial data	Topographic accessibility equity	Not addressed	Not evaluated	Limited transferability
Parishad et al. (2022).	Behavioural validation (DBQ)	Structured surveys	Safety-related behavioural vulnerability	Explicit ethical survey design	Not applicable	No predictive modelling
Chaniotakis et al. (2022).	Transferability analysis	Social media mobility data	Spatial representativeness	Explicit discussion of data bias	Not evaluated	Platform dependency

Wang et al. (2021).	Theory-based DNN	Revealed preference + simulation	Implicit population heterogeneity	Implicit	Performance trade-offs examined	High data and computation demands
Sharma (2025)	AI & digital twin framework	Multi-source mobility data	Sustainability and inclusion (conceptual)	Explicit governance and privacy focus	Conceptual fairness framing	Limited empirical validation

The synthesis reveals that equity considerations in TBM are most commonly addressed through socio-economic disaggregation, spatial accessibility analysis, and vulnerability-focused case studies, particularly in public transport and developing-country contexts. In contrast, privacy and data governance are inconsistently addressed and remain largely implicit in studies relying on large-scale passive or crowdsourced data. Explicit fairness evaluation, such as equality of predictive performance across population groups, is rare and primarily confined to recent hybrid and machine-learning-based studies. Collectively, the table demonstrates that while normative discourse on equity and fairness is increasing, systematic empirical integration within TBM remains limited, underscoring the need for clearer methodological standards and transparent evaluation frameworks in future research.

4.3 Policy Relevance and Practical Implications of TBM

Travel behaviour modelling (TBM) has emerged as a critical decision-support tool for urban planners and policymakers, enabling the evaluation of interactions between transport systems, land use, and travel demand. Beyond traditional applications such as traffic forecasting, contemporary TBM supports scenario-based assessment of infrastructure investments, mobility accessibility, and behavioural responses to policy interventions. This expanded scope enhances its relevance for addressing complex urban challenges related to sustainability, equity, and system efficiency.

However, the practical application of TBM remains constrained by several limitations. Many conventional models rely on simplified assumptions, including static socio-demographic characteristics and homogeneous decision-making, which restrict their ability to capture dynamic behavioural responses under evolving policy, technological, and environmental conditions. Furthermore, TBM applications are often fragmented, focusing on isolated components such as mode choice or corridor performance, without adequately integrating broader systems such as land use, energy, and social equity. This limits their effectiveness in informing comprehensive and cross-sectoral policy decisions.

Recent research indicates a shift toward more integrated and adaptive modelling frameworks that combine behavioural theory with advanced computational methods. Approaches incorporating agent-based modelling, probabilistic inference, and real-time data integration offer greater flexibility in capturing context-sensitive and evolving travel behaviour. Nevertheless, increased adoption of machine learning techniques should not be interpreted as methodological superiority. While such models improve predictive performance, they often lack interpretability and transparency, which are essential for policy evaluation and regulatory decision-making.

Accordingly, TBM approaches should be assessed based on their theoretical consistency, behavioural realism, and policy applicability. Strengthening integration across systems, improving interpretability, and aligning modelling outputs with policy needs remain essential for enhancing the practical impact of TBM in contemporary urban planning.

4.4 Data Constraints, Ethics, and Future Modelling Directions

The quality, accessibility, and representativeness of available data fundamentally constrain the effectiveness of travel behaviour modelling (TBM). Traditional survey-based datasets remain prone to recall bias, sampling limitations, and respondent fatigue, while emerging data sources such as GPS traces, mobile applications, and platform-based mobility services often suffer from restricted access, proprietary limitations, and incomplete behavioural context. In addition, digital divides in data availability can introduce systematic biases, particularly in regions with limited technological infrastructure, thereby affecting the inclusiveness and generalisability of TBM outcomes.

These challenges are compounded by growing concerns related to privacy, data governance, and ethical use of location-based information. The increasing reliance on passive and high-resolution data necessitates robust frameworks for anonymisation, consent, and secure data handling. In this context, approaches such as privacy-preserving analytics, differential privacy, and transparent data governance mechanisms are essential for ensuring responsible use of mobility data.

From a methodological perspective, persistent challenges, including endogeneity, unobserved heterogeneity, and temporal instability, continue to limit the robustness of TBM. While advancements such as random-parameter models and hybrid frameworks partially address these issues, structural disruptions, including those induced by the COVID-19 pandemic, remain insufficiently incorporated into modelling approaches. Furthermore, although machine learning techniques enhance predictive performance, their limited interpretability constrains their policy relevance.

Future research should prioritise data fusion strategies, integration of behavioural and contextual variables, and development of adaptive modelling frameworks that balance predictive accuracy with interpretability, equity, and ethical accountability.

On the whole, advancing TBM requires balancing predictive performance with behavioural interpretability, ensuring that methodological innovation remains aligned with policy relevance and societal outcomes.

5. Conclusion and Future Direction

5.1 Conclusion

This review highlights the rapid transformation of travel behaviour modelling (TBM) from traditional, survey-based frameworks toward data-intensive, behaviourally enriched, and technologically integrated systems. The increasing availability of high-resolution datasets such as GPS traces, smart card transactions, and crowdsourced mobility data has significantly enhanced the ability to capture real-time, context-sensitive travel behaviour across diverse populations and geographies. Alongside these developments, structural equation modelling (SEM) and latent variable approaches continue to play a critical role in incorporating unobserved behavioural factors such as attitudes, perceptions, and preferences, thereby strengthening the explanatory depth of TBM. Together, these advances enable more accurate and dynamic modelling of travel decisions, supporting improved planning, policy evaluation, and system optimisation.

At the same time, the integration of multiple data sources through data fusion techniques has emerged as a key direction for improving model robustness and predictive performance. Context-aware modelling approaches that reflect local socio-economic conditions, infrastructure characteristics, and policy environments are increasingly necessary to ensure relevance and transferability. However, the growing reliance on large-scale and passive data sources raises important concerns related to privacy, data governance, and ethical use.

Despite these advancements, several limitations persist, including challenges in capturing behavioural heterogeneity, limited integration with land-use and policy systems, and difficulties in processing real-time, large-scale data streams. Biases in survey data and restricted access to proprietary datasets further constrain generalisability and reliability.

Based on the structured synthesis, four priority directions emerge: (i) advancing methods to capture behavioural variability and latent preferences, including SEM-based and hybrid approaches; (ii) developing real-time and adaptive modelling frameworks; (iii) strengthening integration between transport, land use, and policy systems; and (iv) incorporating emerging mobility technologies within behaviourally grounded models. Achieving these goals will require interdisciplinary collaboration and the development of standardised, privacy-aware data ecosystems.

In the long term, TBM is expected to evolve into a flexible, real-time decision-support system. By aligning methodological innovation, including SEM and hybrid frameworks, with behavioural realism, ethical data practices, and policy relevance, TBM can play a central role in shaping sustainable and resilient urban transport systems.

5.2 Future Research Directions

Based on the systematic synthesis, future TBM research should prioritise four interrelated directions. First, data development should focus on integrating longitudinal, multi-source, and privacy-preserving datasets capable of capturing multimodal and dynamic travel behaviour. Second, methods should advance hybrid behavioural–machine learning frameworks that balance predictive performance with interpretability and policy relevance. Third, tools must evolve toward scalable and real-time modelling platforms that support adaptive behavioural inference under uncertainty. Finally, applications should emphasise equity-aware, climate-sensitive, and resilience-oriented modelling, particularly in rapidly urbanising and post-pandemic contexts. Addressing these priorities will enhance the explanatory power, operational relevance, and societal value of future TBM research.

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Use of Language Models

A language model (Grammarly) was used to assist with proofreading and grammar checking of the manuscript. The final edited manuscript was read and verified by the authors before submission.

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