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A decade of Mobility-as-a-Service research: A systematic review of modeling methods and future research agenda

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ABSTRACT:

Over the last decade (2015–2025), Mobility-as-a-Service (MaaS) has rapidly evolved from a visionary concept into a mature, user-centric socio-technical ecosystem. This paper marks a ten-year methodological milestone by conducting a PRISMA-guided systematic review of 92 peer-reviewed journal articles from Web of Science, Scopus, and Google Scholar. The existing body of quantitative modeling literature informing MaaS design, operations, and regulation remains fragmented across disciplines, assumptions, and decision-making layers. In response, we propose a unified framework that categorizes the literature into six methodological families: simulation models, optimization models, discrete choice models, other statistical methods, data-driven and predictive machine learning models, and game theory and mechanism design models. Using this framework, we map these modeling methods onto four core MaaS research themes: demand-side modeling, supply-side operations, MaaS ecosystem governance, and platform and subscription bundle design. Major findings indicate that existing demand studies have predominantly relied on stated-preference valuations of MaaS subscription plans and bundles, with only limited revealed-preference validation; optimization models have increasingly formalized allocation, matching, and assignment under operational constraints, albeit often assuming overly simplified traveler behavior; and machine learning techniques have expanded rapidly but are generally deployed as stand-alone prediction tools rather than integrated into policy-constrained decision support systems. In addition, the maturity levels of each methodological family reveal significant disparities: foundational areas such as revealed-preference modeling and choice-based optimization are well-established (extensively studied), while emerging fields like machine learning and game theory remain less studied or in early-stage exploration. To advance the field, we provide a forward-looking agenda of 20 research directions, prioritizing more data-driven behavioral modeling, tighter demand–supply integration in operational settings, new multi-sector partnerships, and the concept of Mobility-as-a-Feature. We emphasize planning for equity and long-term impacts and the responsible incorporation of emerging technologies into next-generation MaaS. This systematic methodological review provides evidence-based guidance and a structured roadmap for researchers, operators, and policymakers, addressing identified gaps and highlighting areas requiring further development to support robust, policy-aligned decision-making in MaaS.

KEY WORDS: ***Mobility-as-a-Service (MaaS), Multimodal urban mobility, Modeling methods, Systematic literature review***

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1. Introduction

MaaS has emerged as a significant transformation in urban mobility, shifting the emphasis from private car ownership to user-centric digital platforms that enable users to plan, book, and pay for multimodal bundles integrating various transport options, such as public transit, ride-sharing, bikes, and scooters. By lowering transaction costs, enabling cross-operator coordination, and improving information and payment interoperability, MaaS serves as a lever to reduce car dependence, accelerate decarbonization, and enhance accessibility and system efficiency (MaaS, 2022). These objectives align with Sustainable Development Goals (SDGs), including sustainable cities and communities (SDG 11), good health and well-being (SDG 3), reduced inequalities (SDG 10), and climate action toward net-zero targets (SDG 13).

The early MaaS literature (2014–2016) emphasized a seamless, app-based vision of "one-stop" access to multimodal travel (Hietanen, 2014; Sochor et al., 2015; Giesecke et al., 2016). Subsequent work (2017–2020) shifted from journey planning toward operational integration, including unified booking, ticketing, and payment across modes and operators (Li and Voege, 2017; Ho et al., 2018; Reyes García et al., 2019; Ho et al., 2020). More recent contributions conceptualized MaaS as a broader multi-service ecosystem, emphasizing collaboration among providers, cross-sector embedding of mobility within non-mobility platforms, electrified and car-inclusive portfolios, and governance arrangements that link MaaS performance to societal outcomes (Merkert et al., 2020; Hensher and Hietanen, 2023; Kandanaarachchi et al., 2025; Hensher et al., 2022, 2023). For example, Collaboration-as-a-Service (CaaS) was introduced as part of a "MaaS 2.0" model, leveraging collaborative alliances among transport operators rather than a single broker aggregator (Merkert et al., 2020). Mobility as a Feature (MaaF) (Hensher and Hietanen, 2023) reframed MaaS as mobility functionality delivered on platforms that need not be mobility-first, highlighting the role of non-mobility service providers (NMSPs) and multi-service offerings as potential levers for scalable and sustainable travel behavior change (Kandanaarachchi et al., 2025). Researchers also proposed extensions that incorporated (i) electric car sharing as a service (ECSaaS) as part of an emerging eMaaS proposition (Hensher et al., 2022); (ii) private assets as a service (PAaaS), private car as a service (PCaaS), Corporate MaaS (C-MaaS) (Hensher, 2022b), and community-based car-sharing clubs (CCC) (Xi et al., 2025b) to mobilize private and employer-managed assets and decision makers; and (iii) an idealized MaaS governance framework centered on tendering authorities and societal KPIs (Hensher et al., 2023).

1.1. Umbrella review

Over the past decade, the literature review on MaaS has evolved from clarifying its definition and reporting early pilot trials to structured thematic overviews and implementation frameworks. Early efforts investigated the definitional ambiguity, framing MaaS as a user-centric socio-technical system shaped by digital integration, traveler behavior, and sustainability goals (Giesecke et al., 2016). A complementary review addressed fundamental questions, i.e., the "Who, What, Where, When, Why, and How" of MaaS, and highlighted the roles of stakeholders and pilot experiences, while flagging unresolved issues around user behavior and sustainability impacts (Arias-Molinares and García-Palomares, 2020). Real-world pilots (notably UbiGo in Sweden) revealed the practical challenges of aligning user value, commercial viability, and societal objectives (Sochor et al., 2015, 2016), and scenario analyses sketched plausible MaaS development pathways, along with their implications for public transport (PT) agencies and regulators (Smith et al., 2018). Building on these foundations, later contributions sought to consolidate MaaS concepts and key attributes. For example, one review distilled common definitions and characteristics of MaaS and explicitly linked these features to implications for travel demand modeling, service operations, and business models (Jittrapirom et al., 2017). Likewise, Sochor et al. (2018) introduced a "MaaS topology" with an integration ladder ranging from no integration to full integration of societal goals, providing a shared vocabulary for comparing MaaS offerings and interpreting their behavioral, technical, and business significance. Other early reviews catalogued emerging findings by modal roles, lessons from pilot implementations, and anticipated system impacts (Utriainen and Pöllänen, 2017).

Another stream of MaaS reviews examined how MaaS implementations have unfolded, with a focus on governance and the public–private partnerships. Several broad reviews have traced the development of MaaS deployments, highlighting the institutional arrangements and governance conditions that shape rollout trajectories (Audouin and Finger, 2018; Hensher, 2017; Hensher and Nelson, 2025). (Hirschhorn et al., 2019) emphasized how issues of ecosystem integration and contract design can determine stakeholder roles and influence MaaS outcomes. Building on such insights, a policy-oriented European review (Pagoni et al., 2022) summarized literature and stakeholder perspectives to recommend enabling measures for MaaS, calling for multimodal passenger rights and robust personal-data governance in emerging MaaS markets.

Various systematic reviews have since mapped the thematic MaaS research and cataloged common opportunities and barriers (Tsouros et al., 2021; Alyavina et al., 2022; Zhang and Kamargianni, 2023; Anthony Jr, 2023). A recurring focus is the set of impediments to MaaS adoption such as city-level analyses distinguish supply-side challenges (e.g., limited cooperation among providers, service coverage gaps, data and cybersecurity concerns, or lack of a shared vision) from demand-side challenges (e.g., low platform attractiveness or uncertain WTP), linking these barriers to expected outcomes such as reduced private car use and improved equity (Butler et al., 2021). Many reviews adopted specific lenses, examining MaaS developments in the Global South (Hasselwander and Bigotte, 2023), factors influencing user adoption and acceptance (Lyons et al., 2019; Zhang and Kamargianni, 2023), mobility provision for vulnerable user groups (Dadashzadeh et al., 2022), or the integration of MaaS with paratransit in emerging markets (Dzisi et al., 2022). Others focused on the sustainability and equity implications of MaaS business models and service designs (Lindkvist and Melander, 2022; Loubser et al., 2021). This mapping-oriented literature has consolidated key themes (integration, adoption, equity, sustainability) and highlighted persistent cross-cutting challenges. Empirical benchmarking of MaaS offerings has helped ground these insights in practice, e.g., by clustering analyses of more than 30 operational MaaS services that identified archetypal service configurations and degrees of integration, providing an empirical view of how MaaS has materialized across different markets (Esztergár-Kiss et al., 2020). Beyond reviewing past deployments, some studies leveraged the growing evidence base to develop practical frameworks for MaaS. For example, a stakeholder-informed analysis produced a public policy and decision-support framework to help authorities evaluate and foster MaaS initiatives (Lajas and Macário, 2020). Krauss et al. (2022b) applied morphological analysis to characterize alternative MaaS business model configurations. These framework-oriented contributions shifted emphasis from describing what MaaS is toward prescribing how MaaS can be orchestrated, sharpening the focus on how MaaS might be governed, contracted, and made viable in practice.

A few studies have also examined quantitative modeling and the operational aspects of MaaS. For example, Cisterna et al. (2023) proposed a multi-actor modeling framework and identified agent-based simulation and advanced discrete-choice modeling as promising approaches for capturing heterogeneous user needs and the competing objectives of service providers and regulators. Daou and Leurent (2024) emphasized the need for integrated modeling platforms capable of representing multimodal journeys and financial flows between actors. While valuable, however, these reviews still lacked detailed modeling and addressed only individual subsystems or modeling traditions, each focused on a specific aspect or method.

The umbrella review above has clarified MaaS concepts, mapped key themes, benchmarked real-world offerings, and developed high-level governance, policy, and business frameworks. However, it remains challenging to offer an analytical framework for the multi-actor MaaS ecosystem, especially at the intersections of user demand, service operations, and platform and bundle design (Cisterna et al., 2023; Daou and Leurent, 2024). These gaps in the literature motivate our study.

1.2. Scope and contributions of the review

To address the lack of an integrated, method-first systematic review of MaaS modeling methods, we conduct a PRISMA-guided systematic review of 92 peer-reviewed journal articles published between 2015 and 2025 that operationalize MaaS through quantitative modeling, e.g., demand estimation, system simulation, operational optimization, platform design, and regulatory analytics. Focusing on studies with substantive modeling content, we examine how studies translated defining MaaS features, such as digital integration, subscription and bundling, and multi-actor coordination, into tractable assumptions, endogenous decision variables, data requirements, and evaluative outputs. Most early MaaS publications (2015–2017) focused on conceptual clarification, policy frameworks, and implementation narratives, summarized in the umbrella review above (Section 1.1), whereas modeling-oriented contributions accelerated after pilots and deployments expanded. Accordingly, the remainder of this paper is method-first and draws primarily on the post-2018 modeling evidence base. Figure 1 provides an overview of key research themes and modeling methods of MaaS research reviewed in this paper.

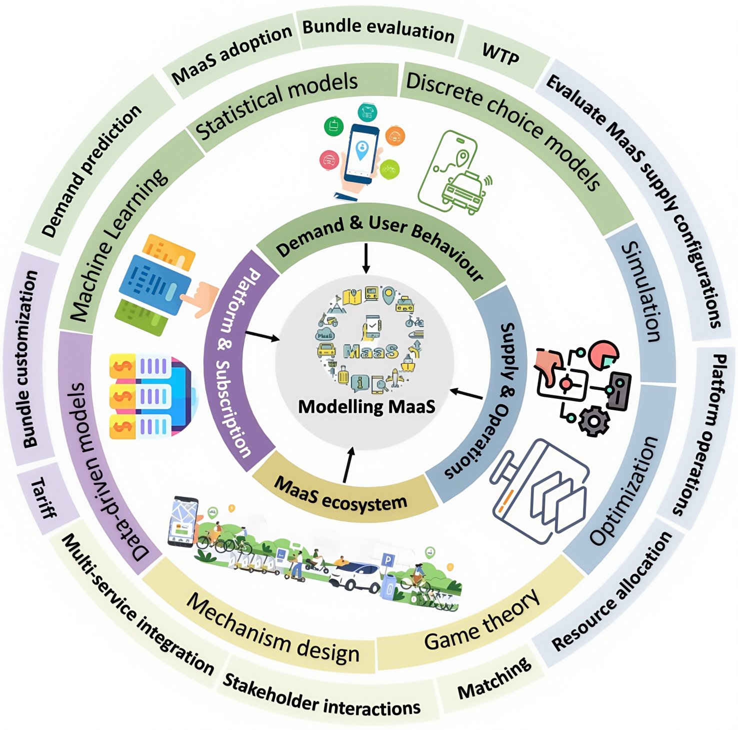

Figure 1: Key research themes and modeling methods of MaaS literature (2015–2025)

This paper presents the first method-focused systematic review of MaaS modeling literature from 2015 to 2025, marking a decadal milestone in the field. Our major contributions are threefold: (i) we develop a unified framework that organizes MaaS modeling into six methodological families, i.e., simulation models, optimization models, discrete choice models, other statistical methods, data-driven and predictive machine-learning models, and game theory and mechanism design, while linking each family to its input data samples, decision variables, and outputs; (ii) we map the application of these methods across the core MaaS research themes, i.e., demand and user behavior, supply and operations, MaaS ecosystem, and platform and subscription model, highlighting areas where evidence is concentrated and identifying policy-relevant gaps, especially in emerging areas; and (iii) we propose a forward-looking agenda that prioritizes 20 research directions, from data-driven behavioral modeling to emerging technologies for the next generation of MaaS. Additionally, we incorporate maturity levels to reflect the varying degrees of research advancement within each area, ranging from extensively studied domains like revealed preference modeling (RD1) and choice-based optimization (RD2) to less explored fields, including connected automated fleets (RD18) and privacy-preserving data sharing (RD5). This integrated view provides a roadmap for future MaaS research, emphasizing the need for dynamic, multi-sector frameworks that incorporate equity, long-term feedback loops, and cutting-edge methodologies such as deep learning and game theory.

1.3. Review methodology

In accordance with PRISMA 2020 guidelines (Page et al., 2021), we conduct a structured literature search across Web of Science, Scopus, and Google Scholar for the period 2015–2025. This comprehensive search yields 2,248 records (Web of Science: 632; Scopus: 356; Google Scholar: 1,260). We removed 420 duplicate entries and 38 records flagged through automated filtering. At this stage, we further exclude 620 records not published in SCI/SSCI-indexed journals and 670 records outside the transportation domain, leaving 500 unique records for screening. We screen titles and abstracts against four inclusion criteria: (a) the study is framed in the MaaS context; (b) it applies a quantitative modeling approach (e.g., discrete choice, hybrid choice, structural equation modeling, machine learning, agent-based simulation, game theory, optimization,

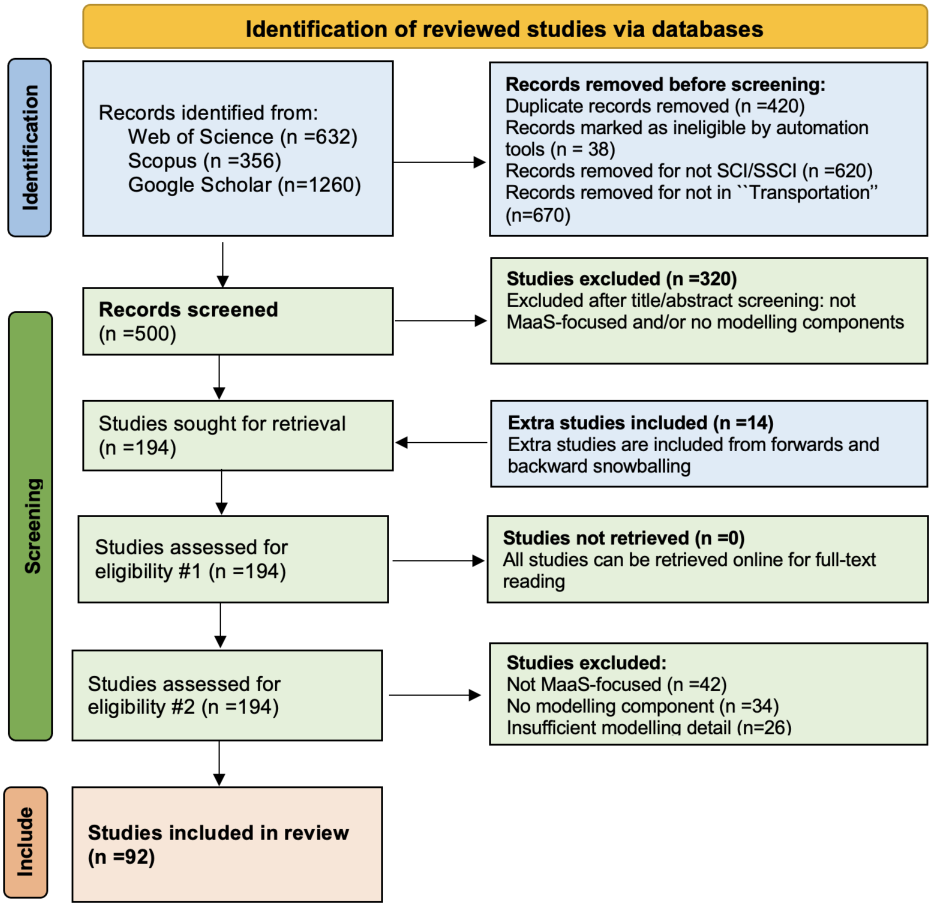

Figure 2: PRISMA 2020 (Page et al., 2021) flow diagram for systematic review

matching, or evaluation models); (c) it reports model structure, assumptions, and key endogenous outputs (e.g., adoption, pricing, service assignment, mode shift, emissions, equity impacts, or system performance); and (d) it provides sufficient detail on data sources and scenario design. This screening excludes 320 clearly ineligible records. We then conduct backward and forward snowball sampling of these eligible studies and identify an additional 14 relevant papers. The remaining 194 articles are retrieved for full-text review. Each full-text is then assessed using two eligibility gates: (i) the study is MaaS-focused and includes a quantitative modeling component, and (ii) the paper reports sufficient modeling details (model structure, assumptions, outputs, data sources, and scenario design). At the full-text stage, 102 studies are excluded: not MaaS-focused (n=42); no modeling component (n=34); insufficient modeling details (n=26). In total, 92 studies are included in the systematic review, as depicted in Figure 2.

1.4. Bibliographic review of MaaS modeling

The eligible quantitative modeling literature is concentrated after 2018. Early MaaS research (2015–2017) was predominantly conceptual, exploratory, and policy-oriented as summarized in the umbrella review, and relatively few peer-reviewed articles reported quantitative models with sufficient methodological detail to satisfy our inclusion criteria. As pilots and deployments expanded, modeling contributions accelerated from 2018 onward, reflecting MaaS maturation from conceptualization to operational integration and, more recently, ecosystem and governance modeling. Across 2015–2025, MaaS modeling broadened from adoption-focused quantification to a multi-layer body of work spanning traveler demand, service supply and operations, ecosystem governance, and platform and subscription design. Early studies primarily used stated-preference data and discrete choice models to quantify WTP, preference heterogeneity, and behavioral determinants of

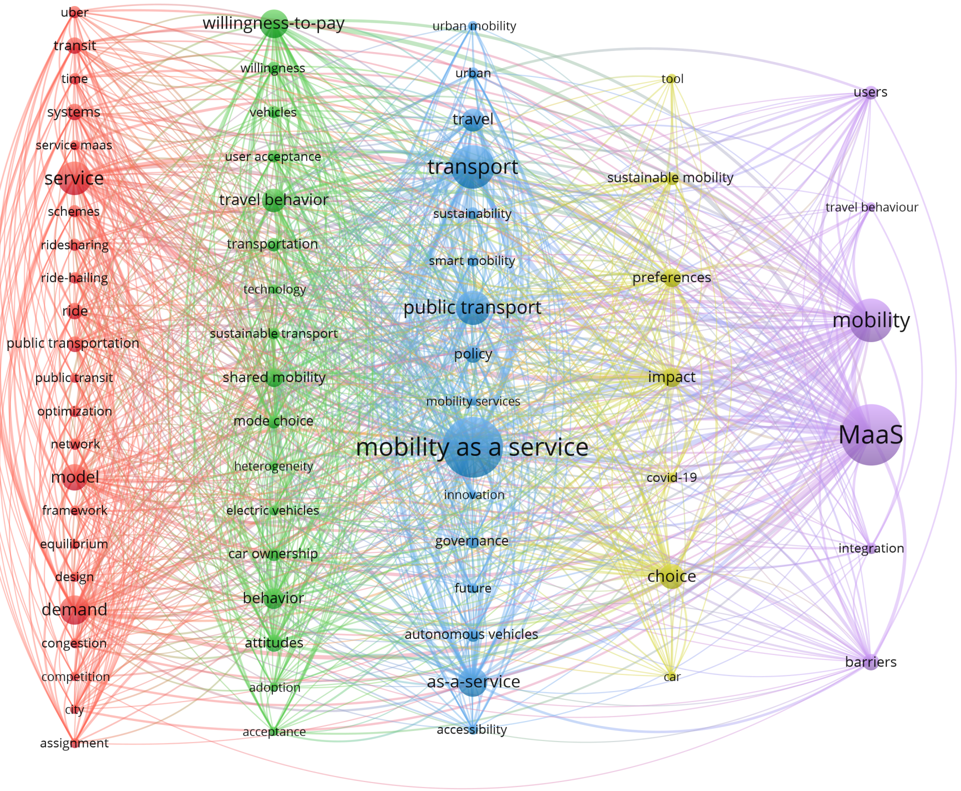

Figure 3: Keyword bibliographic-coupling network in MaaS modeling (2015–2025).

subscription and bundle uptake. With the growth of real-world deployments, attention increasingly shifted toward supply-side questions, operations, service design, and network performance, often using optimization and simulation to study ride-hailing-transit integration, fleet management, and impacts on congestion and reliability. More recent studies have framed MaaS as a multi-actor system and have applied game-theoretic and bilevel optimization to model strategic interactions among platforms, operators, and public agencies, e.g., pricing, revenue sharing, and regulation. In parallel, platform design models examined how bundling, incentives, and subscription schemes could reshape car ownership, mode choice, and travel patterns.

Figure 3 illustrates the keyword bibliographic-coupling network for MaaS modeling literature (2015-2025). A user-centric cluster, covering WTP, preferences, attitudes, acceptance, and travel behavior, reflects the early dominance of adoption and mode-choice research. An operations-oriented cluster links ride-hailing, ridesharing, optimization, network performance, equilibrium, and demand, capturing work on system performance and operational integration. A policy and public-sector cluster connects public transport, governance, policy, and sustainable mobility, reflecting the growing emphasis on regulation and societal outcomes. Core terms such as mobility as a service (MaaS) and transport bridge these communities, indicating increasing cross-fertilization: behavioral choice models are increasingly embedded in simulation and optimization studies, and governance questions are increasingly informed by empirical evidence on adoption and user responses. The dense linking around MaaS also signals methodological convergence, with recent work combining econometric and operations research with data-driven tools such as segmentation, clustering, latent class modeling, and machine learning.

Figure 4 clarifies how themes emerged and persisted over time. The period 2015–2017 was characterized by broad transport/travel framing and foundational MaaS conceptualization. Momentum accelerated in 2018–2020 alongside pilots, when MaaS-related terms and demand-focused concepts (e.g., choice, travel behavior, and WTP) became prominent. During 2021–2022, attention shifted from adoption feasibility to impacts, including sustainable mobility, public transportation, and barriers, signaling a move from “will

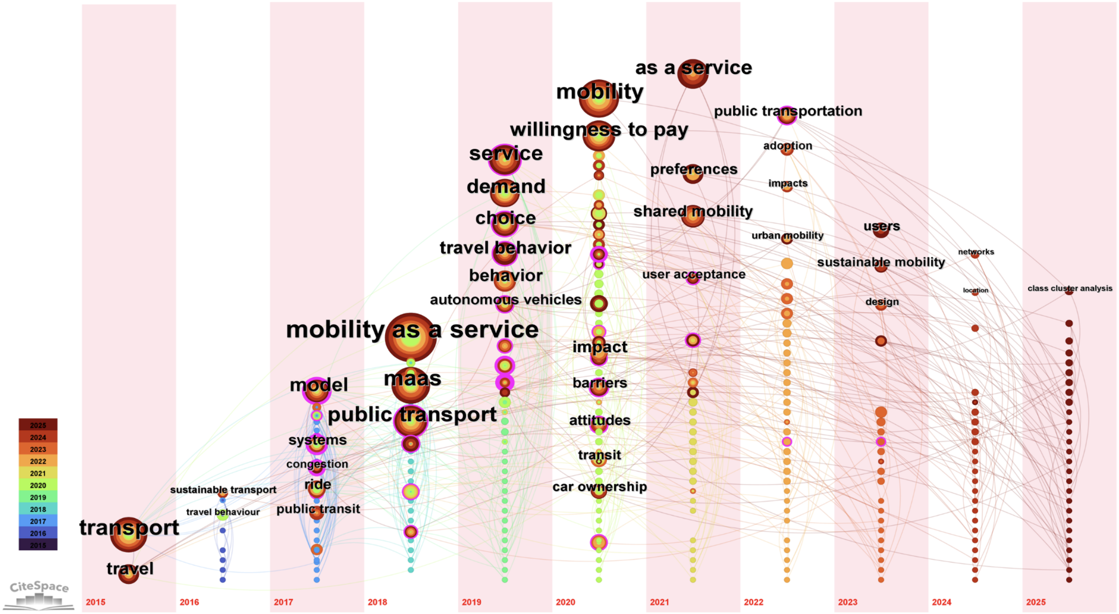

Figure 4: Timeline of keyword clusters in MaaS modeling literature (2015–2025).

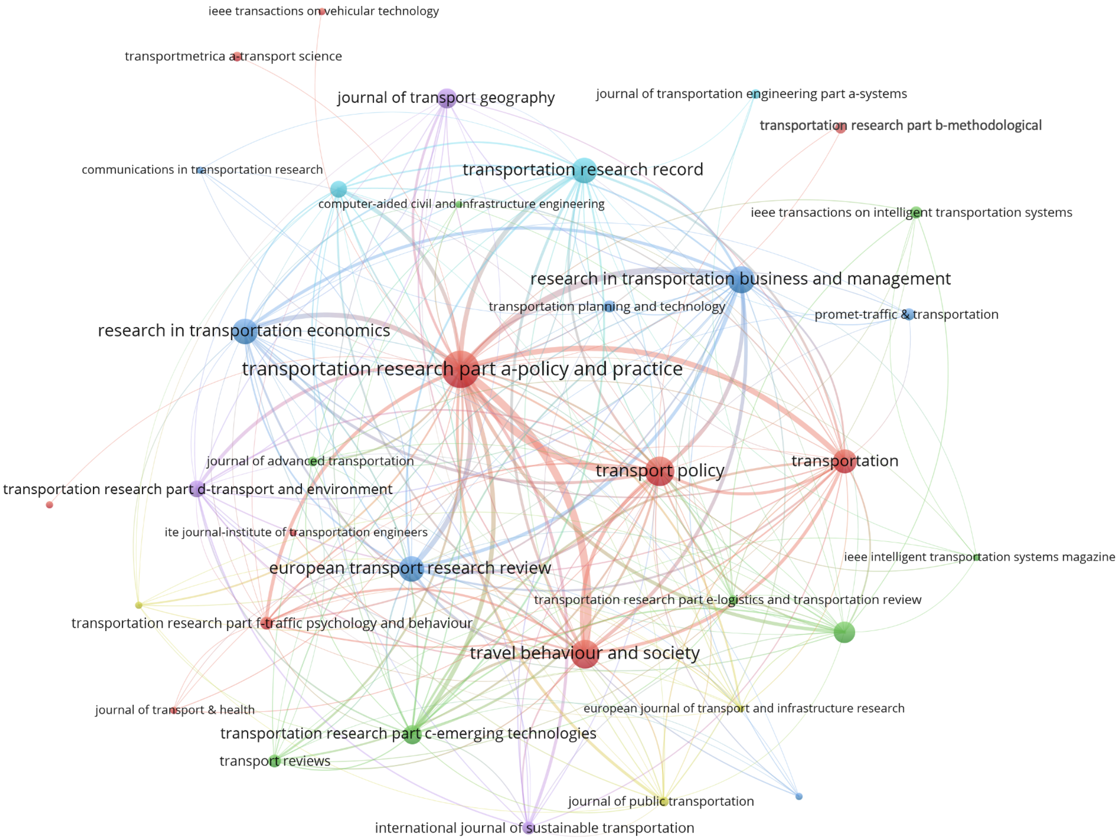

Figure 5: Journal co-citation network of MaaS modeling literature (2015–2025).

people adopt?" toward "what does MaaS do to systems and sustainability?" From 2023 to 2025, emerging directions became more visible, including algorithmic and market-design topics (e.g., matching and coordination), richer user segmentation (e.g., clustering and latent classes), integration challenges across operators and platforms, and a stronger emphasis on distributional outcomes. The timeline shows both long-running cores (e.g., public transport, transport policy, MaaS) and newer fronts such as stable matching and social inequality, while inter-cluster citation links suggest that earlier work on ride-hailing/transportation network company (TNC) integration and stated-preference adoption studies increasingly informed later platform-mechanism and governance research.

Figure 5 shows that MaaS modeling is interdisciplinary while remaining anchored in transportation science. A dense core of outlets (e.g., *Transportation Research Part A*, *Transport Policy*, *Transportation*) reflects the centrality of policy, behavioral, and system-level perspectives. More computational contributions cluster around *Transportation Research Part C* and ITS-oriented journals, whereas business and economics venues link work on business models and market structure, whereas behavior-focused journals support research on attitudes and adoption. Together, Figures 3–5 depict a decade-long shift from definition and adoption studies toward integrated modeling that couples user behavior with operational control and governance. The most visible emerging directions are (i) end-to-end MaaS models calibrated with real deployment data, (ii) dynamic and learning-enabled decision support, and (iii)incorporation of sustainability and equity objectives into platform design and policy, pointing to the need for unified spatio-temporal, multi-source modeling frameworks that operate at user and system levels.

The remainder of the paper is organized as follows. Section 2 categorizes MaaS modeling studies by four research themes, while Section 3 reorganizes them by six methodological families. Section 4 cross-maps methods to themes, Section 5 identifies six cross-cutting research gaps, Section 6 proposes a structured future agenda and practical implications, and Section 7 concludes the paper with insights and takeaways.

2. Key Research Themes of Modeling MaaS

This section organizes existing MaaS modeling research around four interdependent research themes: traveler demand, service supply, ecosystem governance, and bundle design. Specifically, we review modeling evidence on the demand side (Section 2.1), the supply side (Section 2.2), the multi-actor MaaS ecosystem (Section 2.3), and platform and subscription bundle design (Section 2.4).

2.1. Modeling the Demand Side: User Behavior & Adoption

Demand-side MaaS modeling has primarily asked (i) who adopts MaaS and under what subscription and bundle configurations, (ii) how heterogeneity, attitudes, habits, and risk perceptions shape adoption and WTP, and (iii) how demand and usage evolve once MaaS-like offerings are embedded in networks and platforms. Table 1 summarizes representative literature on demand-side modeling with respect to methodology, data sources, empirical scale, and whether the primary behavioral outcomes (e.g., adoption, subscription bundling, and travel-behavior) are examined.

2.1.1. Subscription uptake and valuation of MaaS bundles

A dominant stream in demand modeling quantified subscription uptake and the valuation of bundle attributes. Demand-side MaaS modeling was dominated by discrete choice models (DCMs), estimated primarily using SP data and, to a lesser extent, revealed-preference (RP) data. Most studies estimated multinomial logit (MNL), mixed logit (random-parameters), error-components models, or joint discrete–continuous formulations based on SP experiments in which respondents chose among hypothetical MaaS bundles, subscription tiers, or integrated trip alternatives (Ho et al., 2018, 2020, 2021a; Hensher et al., 2021; Matyas and Kamargianni, 2019; Polydoropoulou et al., 2020; Grau et al., 2025; Vij et al., 2020; Wang et al., 2024; Zhao et al., 2025; Reck and Axhausen, 2020; Militão et al., 2025; Caiati et al., 2020; Bushell et al., 2022; Li et al., 2023; Krauss et al., 2022a; Zhou et al., 2023; Yao et al., 2025). A recurring output was the valuation of individual components (e.g., included modes, caps, fare levels, discount structures), typically reported as WTP and used to benchmark MaaS subscriptions against existing services in largely pre-implementation settings (Matyas and Kamargianni, 2019; Guidon et al., 2020; Polydoropoulou et al., 2020). Evidence from MaaS trials extended this econometric core by linking plan choice to observed usage outcomes, including discrete-count models of monthly trips and revenue, and joint discrete–continuous specifications connecting subscription uptake to private-car impacts (Ho et al., 2021a; Ho, 2022; Hensher et al., 2021).

2.1.2. Heterogeneity and psychological drivers of MaaS adoption

Another stream increased behavioral realism by modeling heterogeneity and psychological drivers of adoption. Latent class models and related segmentation approaches were widely used to uncover segments with distinct sensitivities to MaaS attributes and systematically different adoption propensities (Vij et al., 2020; Yao et al., 2025; Wang et al., 2024; van't Veer et al., 2023; Lopez-Carreiro et al., 2021, 2024). Latent class cluster analysis and latent class choice models, in particular, differentiated groups by openness to sharing, technology orientation, or multimodality preferences (Alonso-González et al., 2020; Chen and He, 2023; Chen et al., 2023), while some contributions developed composite indicators of latent MaaS demand to characterize early-adopter profiles without tying results to a single fixed MaaS product design (Zijlstra et al., 2020). Hybrid choice models, especially integrated choice and latent variable (ICLV) frameworks, embedded psychological factors directly into utility by deriving latent attitudes from Likert-scale batteries and lifestyle surveys (e.g., perceived convenience, environmental concern, intermodal propensity, and MaaS-related perceptions) (Polydoropoulou et al., 2020; Kim et al., 2021b; Kim and Rasouli, 2022; Kriswardhana and Esztergár-Kiss, 2025; Bahamonde-Birke et al., 2023; Alyavina et al., 2024). More recent contributions treated uncertainty and risk as first-order determinants of subscription and mode decisions, for example via constant relative risk aversion (CRRA) calibration or Prospect Theory variants embedded in mixed logit structures (Liu et al., 2023, 2024a,b).

2.1.3. Intentions and post-adoption user experiences

User intention and experience have been examined to identify design levers and context-specific barriers. Exploratory and confirmatory factor analyses, regression specifications, and generalized ordered logit models were used to relate sociodemographics, mobility patterns, innovativeness, and technology affinity to latent MaaS demand, willingness-to-adopt, and intention-to-use outcomes (Zijlstra et al., 2020; Lopez-Carreiro et al., 2021; Alyavina et al., 2024; Lopez-Carreiro et al., 2024). Structural equation modeling and extended technology-acceptance-type frameworks further traced pathways from psychographic lifestyles and perceived attributes to MaaS intentions, often paired with cluster analysis to derive traveler typologies (Kim and Rasouli, 2022; Lopez-Carreiro et al., 2024). Several contributions targeted specific user groups and market niches (e.g., tourists, university communities, long-distance commuters), clarifying differentiated needs and adoption barriers that are easily obscured in aggregate models (Li et al., 2023; Coppola et al., 2025; Bruzzone et al., 2025). Post-adoption perspectives were increasingly addressed through approaches such as partial least squares structural equation modeling, finite-mixture segmentation, and necessary condition analysis to assess satisfaction, perceived seamlessness, experiential value, and heterogeneity in user experiences (Chen et al., 2025). This stream expanded demand-side modeling beyond adoption outcomes to include readiness, intention, satisfaction, and perceived value in MaaS (Chen and He, 2023; Chen et al., 2023).

2.1.4. Dynamic simulations and predictions of MaaS usage

Agent-based and activity-based transport models, often implemented in platforms such as MATSim, simulated multimodal demand under MaaS-like offerings using large-scale inputs (e.g., mobile network data) to generate realistic trip chains and activity patterns (Franco et al., 2020; Qiao and Yeh, 2023). Such frameworks support equity and spatial justice assessments by linking changes in accessibility to socioeconomic indicators, e.g., housing prices, under alternative service designs (Qiao and Yeh, 2023). Artificial neural networks were trained on survey and behavioral variables to predict MaaS usage across purposes and identify influential determinants (Duan et al., 2022), while neural-network-based bundle choice models combined with SHAP explainability and clustering were used to interrogate equity-efficiency trade-offs, emissions, and platform profits under alternative bundle and pricing designs (Liu et al., 2024b). Multi-task Transformer-based learning models were proposed to dynamically predict each user's mode-specific usage frequency class and expected travel fare for the next period (Xi et al., 2025c). Reinforcement learning was adopted for adaptive multimodal trip planning on integrated networks via double Q-learning formulations that updated route selection as network conditions and user preferences evolved (Yan et al., 2025).

Table 1

Representative MaaS literature modeling the demand-side.

Study (Year)	Methodology	Data Source	Scale	Adoption	Subscription/Bundling	Travel behaviour
Ho et al. (2018)	SP survey; DCM	SP survey	Individuals; Sydney	✓	✓	×
Matyas and Kamargianni (2019)	Mixed MNL with random coefficients	SP survey with randomized attributes	Individuals; SP sample	✓	✓	×
Alonso-González et al. (2020)	Attitudinal survey (Likert), EFA, LCCA	Netherlands Mobility Panel (MPN) online survey	Individuals; 1006 urban Dutch respondents	✓	✓	✓
Guidon et al. (2020)	SP DCE; mixed logit with repeated choices	Online survey with multiple DCEs	Individuals; online sample	×	✓	×
Ho et al. (2020)	SC survey (CAPI); DCM on bundles	SC/CAPI survey (Tyneside, UK)	Urban area (Tyneside, UK)	✓	✓	×
Reck and Axhausen (2020)	RP analysis; random-utility model with generalized cost	RP travel-stage data; DNTM	Denmark; national/urban sample	×	✓	✓
Vij et al. (2020)	Latent-class logit model	SP survey of travellers	Individuals, large national sample	✓	✓	×
Zijlstra et al. (2020)	Survey-based latent demand modeling: CFA-built latent demand for MaaS index	Netherlands Mobility Panel and questionnaire	Individuals; Netherlands	✓	×	✓
Hensher et al. (2021)	joint discrete–continuous (binary logit)	Sydney MaaS trial subscription records & Safer Journeys & surveys	Individuals; Sydney trial	✓	✓	✓
Ho et al. (2021a)	Mixed logit on revealed uptake; usage tracking	App logs & pre/post surveys	MaaS trial participants	✓	✓	✓
Kim et al. (2021b)	ICLV model (choice & latent attitudes); SP survey with current modes and MaaS plans; Likert attitude items	SP survey	Individuals, SP sample in Seoul	✓	✓	×
Lopez-Carreiro et al. (2021)	generalized ordered logit	Web-based survey (Madrid n=1000; Randstad n=418)	Individuals; Madrid (Spain) & Randstad (Netherlands) metropolitan areas	✓	×	✓
Bushell et al. (2022)	Random-parameters logit; integrated choice experiments	Integrated choice experiments	Individuals; repeated tasks	✓	✓	×
Duan et al. (2022)	Artificial Neural Network (MLP)	Survey with demographics, travel, attitudes	Individuals; N=331 (Australia)	✓	×	×
Ho (2022)	Discrete choice model of monthly bundle choice (PAYG vs. multiple bundles) & discrete-count models (e.g., Poisson/NegBin/ZINB)	MaaS trial Tripi app booking records, GPS-tracking, ticketing data	Sydney Greater Metropolitan Area; 93 participants & PAYG users	✓	✓	✓
Kim and Rasouli (2022)	Hierarchical latent-variable & latent-class model	SP & lifestyle/psychographic survey	Individuals; Netherlands (N=1,299)	✓	✓	×
Krauss et al. (2022a)	Mixed logit on SP mode-choice data	SP experiments & socio-demographics	Individuals; urban Germany (N=1,445)	×	×	✓

Table 1

Representative MaaS literature modeling the demand-side (Continued).

Study (Year)	Methodology	Data Source	Scale	Adoption	Subscription/Bundling	Travel behaviour
Bahamonde-Birke et al. (2023)	Hybrid choice model; two SC experiments	Online SC surveys (bundles vs car ownership)	Individuals, Utrecht (Netherlands)	✓	✓	×
Chen and He (2023)	SC experiment; LCCM; attitudinal EFA	Online/on-site SC surveys & attitudes	Individuals; Taipei sample	✓	✓	×
Li et al. (2023)	SP survey; segmentation into Strict/Weak/No Preference; random-parameter logit for mode choice	SP survey on tourists and MaaS products	Individual tourists; Beijing tourism context	✓	✓	×
Liu et al. (2023)	CRRA risk calibration & mixed logit for subscription and mode	SP survey	Individuals, N=997 (Hong Kong)	✓	✓	×
van't Veer et al. (2023)	Cross-sectional questionnaire; sample/population checks; duplicate control	Questionnaire in Netherlands	Individuals (N=339)	✓	×	×
Xi et al. (2023a)	Auction-based mechanism; IC, IR, budget balance; MILP	Simulation-based model	Platform/network level	×	×	✓
Zhou et al. (2023)	Activity-based demand model (ActivitySim) with tour-based multimodal mode-chain generation	travel survey (2013-2017) & synthetic population/LOS inputs	Individuals; Individual (tour-level); commuters in Netherlands	×	✓	✓
Liu et al. (2024a)	mixed logit / nonlinear risky-choice discrete choice models	SP survey (Hong Kong); weekly commute scenarios	Individuals; Hong Kong	✓	✓	✓
Liu et al. (2024b)	Neural network on SP data; SHAP explainability; user clustering; equity-aware system assessment	SP survey with socio-demographics, bundle attributes, derived emissions/profit metrics	SP survey with socio-demographics, bundle attributes, derived emissions/profit metrics	✓	✓	✓
Lopez-Carreiro et al. (2024)	extended TAM-based behavioural model with cluster analysis	Web-based survey	Individuals, Randstad metropolitan area (Netherlands)	✓	×	✓
Wang et al. (2024)	Mixed logit; group-wise heterogeneity (PT/car/other)	SP survey with ticket attributes and profiles	Individuals, user groups (PT, car, others)	×	✓	×
Xi et al. (2024a)	Game-theoretic SLMFG & Strong-duality B&B	simulated data in Australia	Sydney	×	×	✓
Alyavina et al. (2024)	PCA/EFA & ordinal logistic regression	Attitudinal & demographic survey	Individuals; survey sample	✓	×	×
Coppola et al. (2025)	Large survey (N=1,873); discrete-choice modeling; university case study	University travel survey; aggregate stats	Metro Milan; campus users	✓	✓	×
Grau et al. (2025)	SP-based logistic regression; alternative generation	SP survey; OTP times; tariffs, costs	Individuals; Thessaloniki	×	×	✓
Kriswardhana and Esztergár-Kiss (2025)	Hybrid choice with latent attitudes	Online SC/SP survey	Individuals; Hungary (N=519)	✓	✓	×
Militão et al. (2025)	Error-components random-parameter logit	Simulated choice sets and estimation data	Individuals; simulation-based datasets	✓	✓	✓
Yao et al. (2025)	Latent class model (habits, cross-scenario vars); socio-demographic controls	SP survey (Jan-Feb 2022); habits and socio-demographics	Individuals; Beijing megacity	✓	×	×
Zhao et al. (2025)	Mixed logit with error components	UAT SP survey	Individual SP samples	×	×	✓

Notes: Adoption indicates whether the study focuses on user adoption propensity; Subscription/Bundling indicates whether the study involves MaaS subscription plans, bundles, or pricing of packages; Travel behavior indicates whether the study examines travel behavior changes (modal shift, usage).

2.1.5. Demand responses under platform bundle design

Demand modeling has been embedded within MaaS platform and market-design settings, recognizing that allocation rules, pricing exposure, and governance constraints shape MaaS adoption and usage. Mechanism-design studies have framed MaaS as an auction marketplace in which travelers bid for trips, and the platform determines allocations and prices subject to user requirements and fleet availability (Xi et al., 2023a; Ding et al., 2023). Leader-follower games modeled MaaS providers as strategic leaders choosing prices and service levels, while travelers responded iteratively through equilibrium choice structures, which were solved using B&B and alternating direction method of multipliers (ADMM) algorithms (Xi et al., 2024a,b). Comparative analyses of business models (e.g., integrator, platform, intermediary) further examined how governance, contracting, and revenue-sharing arrangements shaped prices, profits, consumer surplus, and welfare (van den Berg et al., 2022). Domain-specific applications, including urban air taxi integration (Zhao et al., 2025), tourism-oriented MaaS (Li et al., 2023), campus-based schemes (Coppola et al., 2025), and long-distance systematic travel settings (Bruzzone et al., 2025), have illustrated how platform pricing strategies and bundle compositions interact with user preferences across distinct niches.

2.2. Modeling the Supply Side: Pricing & Operations

Supply-side MaaS modeling focused on the operational decisions faced by MaaS operators, such as (i) allocation, pricing, and infrastructure decisions; (ii) strategic-tactical planning for CMaaS; (iii) multimodal journey planning and recommendation; and (iv) MaaS supply-level evaluation. Table 2 summarizes representative MaaS literature modeling the supply side from the perspective of methodology, decisions, objectives, application context, and the operational and evaluation dimensions covered, i.e., whether the study addresses real-time control, pricing, fleet management, infrastructure planning, equity, and environmental outcomes.

2.2.1. Allocation, matching, pricing, and infrastructure decisions

Existing studies formulated mixed integer linear programming to allocate MaaS bundles (Xi et al., 2023a, 2024c), and bilevel optimization models to represent platform-network interactions where a MaaS integrator chose allocations while anticipating user behavior (Xi et al., 2024b; Cheng et al., 2022). Yao and Zhang (2024) proposed an intermediary MaaS platform design that jointly determined multimodal trip assignment and origin-destination pricing with wholesale capacity purchase prices via a many-to-many stable matching and bilevel traffic-assignment framework, established stability existence and pricing uniqueness under mild conditions, and demonstrated the approach on an extended Sioux Falls network. Rasulkhani and Chow (2019) developed a generalized market-equilibrium assignment-game model that jointly determined stable generalized-cost pricing and capacity-constrained route matches, yielding a convex set of stable outcomes with unique user- and operator-optimal solutions, and demonstrated its policy relevance on fixed-route examples and a NYC shared-taxi case with a one-block passenger walk-to-meet rule. Complementing these decision-focused formulations, (van den Berg et al., 2022) used stylized market models to compare MaaS business roles and their implications for prices, profits, and welfare.

2.2.2. Strategic-tactical supply planning and sustainability in CMaaS

Corporate MaaS (CMaaS)is a strategic-tactical planning problem where organizations coordinate private fleets with public transport access. Frank et al. (2024) minimized expected corporate mobility cost over a multi-week horizon by jointly selecting fleet size and composition for company-exclusive services (e.g., electric cars, bikes, scooters) and choosing public-transport tariffs; key structural elements included spatiotemporal demand, technical constraints, vehicle availability, and micromobility acceptance, demonstrated using driving profiles from 144 companies and ten mobility services. Building on this foundation, Klopfer et al. (2023) proposed a multi-objective framework that combined cost estimation with life-cycle assessment (LCA) to identify Pareto-efficient CMaaS designs trading off total cost against life-cycle emissions. These studies showed how fleet, tariff, and sustainability objectives were co-optimized subject to operational feasibility constraints. Feasibility also depended on institutional adoption conditions: Dzisi et al. (2023) employed SEM and content analysis to show that operators' intentions to adopt MaaS were driven by performance and effort expectancy, familiarity with ride-hailing, and social influence, while union leaders' concerns about job losses could constitute a binding barrier and suggested that MaaS should be introduced gradually and alongside existing paratransit, based on interviews with 181 informal minibus-taxi operators in Kumasi and five GPRTU union executives.

2.2.3. *Multimodal journey planning and recommendation*

Sequential decision models captured the fact that MaaS operations evolve as network conditions, supply availability, and user decisions change over time. Yan et al. (2025) proposed a Q_EDQ framework and formulated the real-time multimodal journey planning problem as a reinforcement learning problem on an integrated, graph-based transport network. Similarly, Chu and Guo (2023a) represented passenger decisions as a Markov process embedded within a deep reinforcement learning framework; the resulting multi-objective formulation aimed to maximize operator profit while satisfying user-oriented criteria (e.g., satisfaction and fairness), illustrating how data-driven control could couple operational performance with service-quality objectives. Song et al. (2021) adopted a dynamic discrete choice model coupled with hyperpath search to optimize whole-day multimodal itineraries. Travelers chose mode chains and departure times across the day; an expectation-maximization procedure estimated heterogeneous preferences, and a user-constrained shortest-hyperpath algorithm generated feasible multimodal plans. Using a 10,000-participant MaaS social experiment in Shanghai with discounted weekly passes and post-incentive tracking, Yu et al. (2025) showed that incentives boosted short-term usage but usage dropped sharply once discounts ended (with incentive-acquired users declining more than naturally acquired ones), and higher discount levels did not improve retention, implying that financial incentives alone were insufficient and should be optimized by favoring lower, broader discounts and selectively higher discounts for high-ROI segments. Bayliss et al. (2025) proposed a transfer-zone-sampling, decomposition-based MaaS journey-planning framework that augments shortest-path search with neural-network guidance to generate diverse, high-quality Pareto-optimal multimodal itineraries (e.g., trading off cost, time, emissions, and inconvenience) at real-time speeds on large-scale networks.

2.2.4. *MaaS supply-level evaluation*

Agent-based microsimulation and activity-based models were used to stress-test MaaS supply configurations and quantify system-wide outcomes that were difficult to represent in closed form. Becker et al. (2020) proposed an extended MATSim implementation for the Zurich metropolitan region integrated with car-sharing, bike-sharing, and ride-hailing with public transport; agents followed daily activity schedules while minimizing generalized travel costs, and scenarios varied supply-side levers, such as fleet sizes, service availability, and integration policies with public transport. Related studies supported distributional analyses. For example, Qiao and Yeh (2023) evaluated alternative MOD and MaaS supply, coverage, frequency, and pricing scenarios using a multi-agent simulation coupled with spatial justice analysis, linking operational choices to accessibility and social inequality metrics. At the urban-network scale, Labee et al. (2022) combined the activity-based model ALBATROSS with user-equilibrium traffic assignment and the COPERT emissions model to evaluate MaaS scenarios; a synthetic Amsterdam population was generated via iterative proportional fitting, and scenario parameters (e.g., assumed adoption rates, bundle attributes, mode shares) were propagated through the simulation to quantify impacts on demand, network performance, and emissions.

2.3. Modeling the MaaS Ecosystems

At the ecosystem scale, MaaS shifted from an individual bundle-choice problem to a multi-actor market in which platforms, mobility operators, public authorities, corporate buyers, and road-space managers strategically interacted and co-evolved. Correspondingly, the literature is organized around four research themes: (i) mechanism design and resource allocation; (ii) Matching, assignment, and multi-actor interactions; (iii) Competition, cooperation, and governance; (iv) ecosystem valuation and simulation. Table 3 summarizes modeling of the MaaS ecosystem from the perspectives of methodology, modeling scope, data sources, and the institutional dimensions addressed, namely whether the study explicitly represents the platform, competition, policy intervention, and dynamic behavior.

2.3.1. *Mechanism design and resource allocation*

MaaS has been modelled as a platform where access to mobility resources (e.g., multimodal vehicle fleets) was allocated and priced to meet user preferences and WTP. From the platform perspective, Xi et al. (2023a) proposed an incentive-compatible auction-based mechanism where users bid for trips; and

Table 2
Representative MaaS literature modeling the supply-side.

Study	Methodology	Decisions	Objectives	Application Context	Real-time	Pricing	Fleet	Infrastructure	Equity	Environment
Yan et al. (2025)	Double Q-learning on an integrated multimodal network	Routing actions/state–action values	Improve real-time multimodal routing efficiency and adaptability	Simulated integrated urban multimodal network	✓	×	×	×	×	×
Qiao and Yeh (2023)	Multi-agent MOD/MaaS simulation with spatial-justice analysis	Service type, coverage, frequency, and price scenarios	Evaluate accessibility and social inequality under alternative MOD/MaaS schemes	Chengdu city and neighborhoods; mobile phone and socioeconomic data	×	✓	×	×	✓	×
Becker et al. (2020)	Agent-based microsimulation (MATSim) with shared modes and PT integration	Fleet sizes/mixes; integration policies; pricing/availability settings	Assess system-level impacts and shared-mobility roles in MaaS schemes	Zurich multimodal network; synthetic population and supply scenarios	×	✓	✓	×	×	×
Klopfer et al. (2023)	Cost estimation & LCA & multi-objective MILP optimization (Pareto design)	Company-exclusive fleet size, tariff selection, trip-to-service assignment	Minimize total corporate mobility cost and lifecycle GHG emissions	428 driving profiles; 144 companies	×	✓	✓	×	×	✓
Song et al. (2021)	Whole-day multimodal path planning for MaaS recommendation	Daily mode-chain and departure-time choices	Optimize whole-day multimodal plans under time-cost trade-offs	Multimodal urban network case study	×	×	×	×	×	×
Cheng et al. (2022)	Bi-level bike-sharing infrastructure planning model	Station locations/capacities; bike-lane links; network assignment	Minimize construction cost and user travel time for bike integration	Multimodal network with new bike-sharing infrastructure design	×	×	×	✓	×	×

the proposed MaaS mechanism was formulated as an MILP solved with a polynomial-time primal-dual online algorithm. Similarly, Ding et al. (2023) developed an online auction-based allocation and pricing scheme benchmarked against an offline VCG mechanism and derived competitive-ratio bounds, emphasizing that valuations could be elicited without relying on survey data. Further, Pantelidis et al. (2020) modeled MaaS as a stable matching and bilevel optimization problem, in which an agency (leader) set prices and cost allocations and users and TSPs (followers) responded; tractability was achieved through a capacitated assignment reformulation and LP-based constraint generation.

2.3.2. Matching, assignment and multi-actor interactions

Assignment and stable-matching games formalized coalition stability, and agent-based frameworks captured day-to-day adaptation and network feedback that produced emergent congestion, service availability, and market shares (Djavadian and Chow, 2017; Franco et al., 2020). Pan and Sun (2024) analyzed equilibrium mode choice on an OD corridor linking a residential area to a CBD by highway and mass transit, incorporating MaaS fixed and inconvenience costs and a piecewise-linear parking access-time function that depended on occupancy; they derived conditions under which MaaS became competitive with private car use. Liu and Chow (2024) studied a many-to-many matching problem for mobility-on-demand by combining branch-and-bound with Frank-Wolfe and Lagrangian relaxation to obtain optimal assignments; they then proposed a stability-aware heuristic with subsidy design to recover globally or locally stable solutions. (Xi et al., 2023b) proposed a MaaS ecosystem where integrated mobility and delivery services are allocated to users and derived a two-class bundle-choice user equilibrium under a bilateral surcharge-reward scheme.

2.3.3. Competition, cooperation and governance

Studies modeling the MaaS ecosystem focused on strategic interactions among heterogeneous actors rather than on travelers' bundle choices alone; thus, game-theoretic formulations have been widely used to represent platform competition and strategic coupling with operators and regulators. Considering the competition among MaaS platforms, Xi et al. (2024b) formulated a multileader-multi-follower game (MLMFG) where multiple MaaS platforms (leaders) chose prices and service configurations while anticipating travelers' participation decisions (followers) in electric (traditional) MaaS bundles; a customized ADMM algorithm was proposed to solve the MLMFG. van den Berg et al. (2022) compared archetypal business structures (e.g., Integrator, Platform, Intermediary) and traced how welfare and surplus shifted across stakeholders under different parameter regimes. Extending this line of work, McHardy (2024) developed a game-theoretic frame-

Table 3
Representative literature modeling the MaaS ecosystem.

Study (Year)	Methodology	Modeling Scope	Data Sources	Platform	Competition	Policy	Dynamic
Wong and Hensher (2021)	Stated choice experiment, mixed logit with WTP estimates	Aggregator MaaS ecosystem: mobility-contract design and organizations' willingness to invest in	International SP survey of mobility-related organizations	✓	×	✓	×
Frank et al. (2024)	Strategic–tactical optimization; feasibility checks	Corporate MaaS design (fleet & tariffs)	Corporate mobility demand from real-world driving profiles (144 companies)	✓	×	×	×
Xi et al. (2023b)	Two-class bundle-choice user equilibrium under a BSRS scheme and bilevel optimization	MaaS ecosystem integrating mobility and instant delivery	Real-world OD demand data in Shenzhen China	✓	×	✓	×
Xi et al. (2024b)	MLMFG; ADMM solution	Competition among MaaS platforms and travellers	simulation	✓	✓	×	×
van den Berg et al. (2022)	Numerical market model; welfare comparison of business models	MaaS market structures (Integrator, Platform, Intermediary)	Scenario-based	✓	✓	✓	×
Pantelidis et al. (2020)	Stable matching; bilevel optimisation; capacitated assignment	Multimodal, multi-operator pricing & cost allocation	Model-based	✓	×	×	×
Chu and Guo (2023a)	Deep reinforcement learning; proportional-fairness objective	Supply-side journey planning/recommendation with feedback	Simulated MaaS scenarios	✓	×	×	✓
Pan and Sun (2024)	Analytical mode-choice equilibrium; stylised corridor model	MaaS vs private car competitiveness (mode shares, costs)	Stylised OD corridor; numerical	×	✓	×	×
McHardy (2024)	Game-theoretic platform model; Cournot-style interactions	Platform regimes, prices, outputs, and welfare	Calibrated elasticities; scenario analysis	✓	✓	✓	×
Liu and Chow (2024)	Many-to-many matching; network optimization; stability & subsidies	MaaS/MOD matching with congestion and operator interdependence	Synthetic networks; Sioux Falls testbed	✓	×	✓	×
Kraus et al. (2023)	Choice-based conjoint (CBC); MNL; market simulations	Competitive positioning of MaaS products/platform offerings	CBC survey responses; simulated markets	✓	✓	×	×
Djavadian and Chow (2017)	Agent-based, day-to-day adjustment model of two-sided FTS market	FTS/MOD market dynamics within MaaS context	Real-data-informed inputs; simulated day-to-day evolution	✓	×	✓	✓
Franco et al. (2020)	Agent-based simulation (MATSim); activity-based demand	Mobile network data, MODLE, network data	Bristol city/suburban corridors	×	×	✓	
Ding et al. (2023)	Online auction mechanism; learning vs greedy algorithms	Online market mechanism for MaaS with strategic travellers	Theoretical model; numerical simulations	✓	×	×	✓

work comparing an Integrator regime with a Free-Market regime, drawing on Cournot-style reasoning about strategic substitutes and complements and testing robustness across competitive configurations. Further, Frank et al. (2024) developed a decision-support tool for corporate mobility managers, where an optimization model jointly selected fleet size for company-exclusive services and a tactically optimal set of public-mobility tariffs under spatiotemporal demand, costs, technical restrictions, availability, and micromobility acceptance; the framework was validated using data from 144 companies and 10 services. Klopfer et al. (2023) proposed a multi-objective optimization model that yielded a Pareto-optimal Corporate MaaS configuration, as well as cost and emissions. Ren et al. (2024) proposed a random-effects error-component mixed logit model using a stated-choice experiment in the Netherlands; the results showed that the availability of MaaS and shared e-mobility services significantly reshaped household vehicle ownership decisions and revealed strong demand for pedelecs, highlighting complementarities between emerging and conventional modes. Xie et al. (2019) proposed a multi-stage discrete choice framework linking subscription, service access, and menu option choice for on-demand mobility services and demonstrated it using smartphone-based context-aware SP data for a real-time sustainability incentive system. At the city scale, Basu and Ferreira (2021) employed survey-based descriptive and inferential statistical analysis, combined with scenario-informed interpretation of mobility trends, to examine how COVID-19-induced risk perceptions and service uncertainty influenced traveler behavior, particularly transit avoidance and car purchase intentions, and to assess MaaS as a potential policy lever for sustainable mobility. Data-driven optimization and reinforcement learning extended these approaches to dynamic recommendation, real-time allocation, and adaptive pricing, where preferences and supply conditions evolved (Chu and Guo, 2023a). The MaaS ecosystem literature modeled MaaS as a multi-sided system shaped by platform rules, governance design, and long-run viability (Xi et al., 2023a, 2024b; van den Berg et al., 2022; McHardy, 2024; Pantelidis et al., 2020; Frank et al., 2024; Klopfer et al., 2023; Kraus et al., 2023).

2.3.4. Ecosystem valuation and simulation

Valuation and pre-deployment market simulations are crucial when empirical data on the MaaS ecosystem are scarce. Kraus et al. (2023) combined choice-based conjoint preference estimation with choice simulation to quantify the joint value of MaaS ecosystems under alternative public versus private orchestrator and discount settings. van den Berg et al. (2022) examined how alternative regimes redistributed welfare and surplus, while ecosystem-level matching and allocation formulations Pantelidis et al. (2020); Liu and Chow (2024) conducted counterfactual simulations of pricing, subsidy, and capacity policies. Using an international stated-choice survey of 202 organizations, Wong and Hensher (2021) estimated mixed logit models to quantify how mobility-contract attributes (e.g., modal revenue mix, government support, ROI risk, branding, equity) influenced firms' willingness to invest in or supply assets to a MaaS broker/aggregator, and derived WTP measures for these attributes.

2.4. Modeling Platform and Subscription Bundle Design

Research on MaaS platforms and subscription bundle design focused on MaaS bundle design, MaaS Subscription adoption and plan choice, and MaaS subscription fees. Table 4 summarizes representative literature on MaaS platforms and subscription bundle design from the perspectives of methodology, modeling scope, data sources, application domain, and whether the study considers subscription decisions and multi-actor interaction.

2.4.1. MaaS bundle design

Discrete choice modeling remained central for valuing MaaS products, bundle attributes, and emerging modes. For example, Guidon et al. (2020) employed discrete choice experiments estimated via mixed logit to compare standalone services with bundled MaaS offerings and then simulated WTP distributions that revealed substantial preference heterogeneity. Polydoropoulou et al. (2020) extended this approach by employing a hybrid choice model with a latent "Intermodaller" trait inferred from sociodemographics and current travel patterns; the latent construct was incorporated into the utility function and helped explain variation in plan adoption and WTP for package attributes. Zhao et al. (2025) estimated a random-parameter error-components logit model using a large SP experiment for urban air taxis (UAT) offered via a MaaS platform. Their design spanned 72 hypothetical configurations with high-dimensional attribute variation, enabling estimation of heterogeneous WTP for UAT-specific features such as price, waiting time, and safety. Further studies argued that MaaS bundles should be designed as context-sensitive products tailored to local supply conditions and heterogeneous user segments. Evidence from discrete choice and hybrid choice studies reinforced this need for customization: across settings, estimated preferences exhibited substantial heterogeneity in WTP and attribute trade-offs (Guidon et al., 2020; Polydoropoulou et al., 2020; Caiati et al., 2020), motivating segment-specific menus and targeted plan features. Trial-informed demand modeling also clarified how subscriptions could reshape realized mode choices and thus function as a policy-relevant lever (Militão et al., 2025).

In parallel, RP-based scenario simulation highlighted how subscription components and subscription length influenced plan viability in realistic usage settings (Reck and Axhausen, 2020). Together with reliability-oriented mechanisms (Zhou et al., 2024) and portfolio-aware pricing models (Hörcher and Graham, 2020; Ho et al., 2021a), these studies indicated that MaaS platforms and tariff design are inherently multi-level, spanning preference measurement, menu engineering, resource allocation, and strategic interaction among platforms and public authorities.

2.4.2. MaaS Subscription adoption and plan choice

Subscription adoption and plan choice were frequently represented as structured processes, e.g., whether to subscribe followed by conditional plan selection, to separate market-entry decisions from plan-level trade-offs. Caiati et al. (2020) employed a mixed logit structure in which the first stage captured the subscribe/not-subscribe decision and the second stage modeled conditional preferences over specific plans; random parameters and interactions with social and personal factors represented heterogeneity. Wang et al. (2024) applied mixed logit with random parameters to quantify differences across user groups in their valuation of bundle attributes, supporting segment-specific menu and ticket design.

Another body of studies embedded MaaS subscriptions within broader household or organizational mobility portfolios. For example, Hoerler et al. (2020) estimated binary logistic regression models of individuals' openness to using MaaS for commuting versus leisure trips and qualitatively coded open-ended responses to identify attributes motivating adoption, using data from the Swiss Household Energy Demand Survey. Evidence from real-world trials complemented these stylized models. Ho et al. (2021a) analyzed data from the Sydney MaaS trial using joint discrete–continuous mixed logit models, where travelers chose among four monthly bundles and a pay-as-you-go (PayG) option while simultaneously determining monthly private-car kilometers. Their results identified sociodemographic and attitudinal correlates of subscription uptake and indicated that enrollment in MaaS plans could reduce car use, consistent with the substitution mechanism proposed by Hörcher and Graham (2020). At the organizational level, Frank et al. (2024) developed an optimization-based design tool for Corporate MaaS that integrated strategic and tactical decisions on fleet size, fleet composition, and corporate access to public transport.

2.4.3. MaaS pricing and subscription fee

Most discrete choice models in MaaS bundle design treated the subscription fee as an exogenously specified attribute in the choice experiment. Although several optimization models did endogenize pricing as decision variables, e.g., Xi et al. (2024a); Ding et al. (2023), they typically focused on PayG or trip-level fares rather than subscription fees. Only a small subset of studies moved beyond evaluating predefined price points to modeling personalized MaaS subscription fees that adapt to heterogeneous demand and usage patterns. For example, Xi et al. (2025c) developed a multi-task Transformer model that periodically predicts each user's personalized fare for the upcoming week/month using more than one billion multimodal travel records, creating a practical pathway toward individualized subscription pricing. Xi et al. (2024c) proposed a "predict-then-optimize" framework where a Group Method of Data Handling (GMDH) neural network predicted individual WTP for subscription options using historical travel behavior and sociodemographic information; these personalized WTP estimates then informed a self-adaptive harmony search (SAHS) algorithm for pricing decisions. Hörcher and Graham (2020) proposed a microeconomic, three-level nested discrete choice model with endogenous car ownership and subscription choice as well as externalities such as congestion, crowding, and access, then optimized MaaS pricing (e.g., flat fares, subscriptions, differentiated pricing) and capacity to assess whether subscription-based MaaS could reduce car ownership and improve welfare. Zhou et al. (2024) proposed a reliability-based premium fare for multimodal public transport, in which travelers pay an extra fee for a travel-time reliability guarantee with compensation if delays exceed a threshold, and formulated the design as a two-stage optimization model that selects the premium and threshold via nonlinear programming and evaluates performance via dynamic programming on a multimodal network.

3. Methodological Modeling in MaaS

This section reviews methodological approaches used to model MaaS and organizes the literature into six families: simulation models (Section 3.1), optimization and prescriptive models (Section 3.2), discrete choice and econometric demand models (Section 3.3), other statistical modeling methods (Section 3.4), data-driven predictive and learning-based methods (Section 3.5), and game-theoretic and mechanism-design approaches for strategic interaction and governance (Section 3.6).

Table 4
Representative literature modeling MaaS platform and subscription bundle design.

Study (Year)	Methodology	Modeling Scope	Data Sources	Application Domain	Subscription	Multi-actor
Polydoropoulou et al. (2020)	Hybrid choice model with latent variable; menu-based SP	MaaS subscription plan/package choice with attitude–behavior links	SP survey with socio-demographics and attitudinal items (MaaS4EU)	MaaS subscription/package design and adoption	✓	×
Zhou et al. (2024)	Two-stage optimization (nonlinear programming & dynamic programming)	Reliability-oriented premium fare with delay-compensation service	Model-based numerical experiments	MaaS tariff design with reliability guarantees	×	×
Wang et al. (2024)	Mixed logit with random parameters; SP experiment	MaaS bundle/ticket choice with heterogeneous preferences	SP survey on bundle attributes and socio-demographics	MaaS bundle adoption and pricing/ticketing design	✓	×
Xi et al. (2024c)	redict-then-optimize: GMDH neural networks & metaheuristic optimization	MaaS subscription resource allocation and pricing across weekly, monthly, and annual subscription; optimize MaaS bundles	Simulated MaaS request dataset based on Australian multimodal PT context	Subscription bundle design and mobility resource allocation in MaaS	✓	✓
Zhao et al. (2025)	Mixed logit with error components; SP with experimental design	Urban air mobility alternative choice within MaaS offerings	Stated-choice survey with fractional factorial design	Urban air mobility as a component of MaaS	×	×
Hörcher and Graham (2020)	Microeconomic model with three-level nested discrete choice & optimization	Subscription-based MaaS pricing and policy evaluation with endogenous car ownership and network externalities	calibrated inputs from literature	Welfare/profit impacts of MaaS subscriptions and pricing design; car-ownership reduction	✓	×
Ho et al. (2021a)	Discrete–continuous mixed logit	MaaS bundle subscription vs PayG and car-km travelled	Real-world MaaS trial data (Sydney)	Drivers of subscription adoption and impact on car use	✓	×
Guidon et al. (2020)	DCE analyzed with mixed logit; WTP simulation	Choice between MaaS bundles and standalone transport services	Online SP survey with multiple embedded DCEs	WTP for MaaS bundles vs single-mode services	✓	×
Caiati et al. (2020)	Two-stage mixed logit (adoption and plan choice)	Decision to subscribe and choice among MaaS plans/bundles	Stated-choice survey data	Determinants of MaaS subscription adoption and bundle preferences	✓	×
Frank et al. (2024)	Optimization model (strategic–tactical) with case-study data	Corporate MaaS design: fleet sizing, composition and PT tariff setting	Corporate mobility and travel-profile data (Germany)	Corporate MaaS system design and cost minimization	×	×
Reck and Axhausen (2020)	RP-based scenario simulation vs monthly subscription	Viability of MaaS subscription plan components and sensitivity to subscription length	RP mobility traces from Copenhagen: 555 students over 13 weeks	MaaS plan/bundle design (PT, car-sharing, bike-sharing, taxi)	✓	×

3.1. Simulation models

Simulation has served as a pre-deployment "virtual laboratory" for MaaS, enabling counterfactual evaluation of integrated service designs, fare and tariff rules, and platform operating policies on realistic networks. Over the past decade, MaaS simulation studies have increasingly relied on agent-based and activity-based paradigms, complemented by corridor-level microsimulation, multi-scale urban simulation platforms, and subscription-aware tour-based demand simulators. The central methodological advantage of simulation is its ability to translate behavioral responses into system-wide outcomes through endogenous supply constraints and network feedback (e.g., congestion, waiting, vehicle availability, mode shifts, emissions, and welfare), which often dominate realized performance after deployment.

3.1.1. Simulation of MaaS demand, emissions, and accessibility

An initial stream of research used city- or region-scale simulations to quantify how MaaS-style integration reshapes travel demand, network performance, and environmental outcomes. Franco et al. (2020) developed an activity-based agent-based model in MATSim to simulate ride-shared mobility services in the Bristol area, using mobile phone network data to reconstruct activity–travel patterns and to represent trip chaining more realistically. Labee et al. (2022) coupled the activity-based demand model Albatross with mode choice components, user-equilibrium assignment, and the COPERT emission model to evaluate MaaS-induced changes in vehicle-kilometers traveled and emissions in Amsterdam under alternative adoption scenarios. Becker et al. (2020) used MATSim for Zurich to assess welfare and congestion impacts under different integration configurations (e.g., car sharing, free-floating e-bike sharing, ride-hailing), and to examine how fleet sizing and public-transport integration strategies affected system performance. Beyond aggregate indicators, Qiao and Yeh (2023) proposed a conceptual framework linking Mobility-on-Demand (MOD) accessibility to socioeconomic status in Chengdu and implemented a multi-agent simulation informed by mobile phone trajectories, geographic data (e.g., POIs and road networks), and housing price information. By comparing alternative MOD/MaaS configurations (e.g., stop-based versus floating fleets; different vehicle capacities), the study highlighted how operational choices translate into spatial equity outcomes, indicating where MaaS improved accessibility and where targeted interventions were likely needed.

3.1.2. *Simulation of MaaS operational performance*

A second stream used simulation to evaluate operational design choices, including fleet sizing, assignment and dispatch rules, curb and corridor management strategies, and multimodal coordination, under realistic demand streams. Nayeem et al. (2024) developed an intelligent MaaS simulation with traveler agents, MaaS Fleet Units (MFUs), and a central assignment module, using a two-level optimization structure to balance pickup time, empty mileage, idling, and profitability. At a finer corridor scale, El-Agroudy et al. (2022) employed a calibrated VISSIM microsimulation for International Drive (Orlando) and used experimental designs to vary modal shares and congestion conditions; regression analysis then linked MaaS-inspired modal mixes and curbside strategies to travel time, queueing, delay, and emissions. In a first/last-mile context, Bürstlein et al. (2021) used PTV MaaS Modeller (with Visum travel times) to test ridesharing designs feeding GO rail stations in Markham, quantifying trade-offs among waiting time, served demand, cost, and emissions, and identifying fleet and constraint settings consistent with service-quality targets. Across these studies, simulation is particularly valuable for representing operational frictions, such as vehicle availability, repositioning, and queue spillbacks, that are difficult to capture in closed-form analytical models.

3.1.3. *Multi-scale MaaS simulation platforms*

A third stream examined automation-enabled MaaS configurations using multi-scale simulation platforms, particularly when operator control policies (e.g., assignment, rebalancing, charging, and parking) interact with public transport performance. Using SimMobility, Nguyen-Phuoc et al. (2023) simulated scenarios ranging from partial to full automation to study interactions between Automated Mobility-on-Demand (AMOD) and public transport, embedding an AMOD controller for assignment, scheduling, rebalancing, and charging under specified pricing and parking strategies. Oh et al. (2020) also used SimMobility for Singapore and showed that unregulated AMOD could cannibalize public transport and increase vehicle-kilometers traveled and congestion, despite improved service convenience. Collectively, these platform-based simulations underscore that policy and governance levers (e.g., pricing, access rules, and the regulation of automation) can be decisive in determining whether MaaS integration supports system objectives.

3.1.4. *Simulation of two-sided market and subscription behavior*

MaaS is modeled as an adaptive market using simulation to represent day-to-day adjustment, platform policies, and longer-run behavioral changes (e.g., car ownership and subscription decisions). Djavadian and Chow (2017) modeled MaaS as a two-sided market in which travelers (buyers) and service operators (sellers) make decisions over repeated days while the platform sets policies and prices; the model converged to an agent-based stochastic user equilibrium and was benchmarked against a social optimum via Ramsey pricing. Hörcher and Graham (2020) developed a microeconomic framework with a three-level nested random-utility structure capturing long-run car ownership, medium-run MaaS tariff choice, and short-run trip-level mode choice, and then numerically optimized pricing and capacities under welfare and profit objectives. More recently, Zhou et al. (2023) embedded MaaS subscription ownership into a tour-based mode-chain model within ActivitySim by constructing tour-level mode-chain choice sets reflecting access and egress conditions, vehicle ownership, subscription ownership, and vehicle states.

Table 5
Overview of simulation models in MaaS studies.

Study	Agents & Decision Rules	Demand & Inputs	ABM	Traffic Sim.	Multi-modal	On-demand	AV	City-scale	Full-day	Pricing	Env.	Econ.
Nayeem et al. (2024)	Traveler agents submit on-demand trip requests, a central intelligent assignment module selects fleet units via bi-level multi-objective search	24-h trip requests from NovaTRAC & road network geodatabase; event-based congestion module; fleet size scenarios	✓	✓	×	✓	×	✓	✓	×	✓	✓
El-Agroudy et al. (2022)	Travelers choose route/mode/booking by cost/comfort/reliability; operators manage fleet/schedule/pricing; platform integrates; regulators set curbs.	2018 PM peak counts; Lynx/I-Ride; AADT, K/D factors; mode capacities.	×	✓	✓	✓	×	×	×	✓	✓	×
Nguyen-Phuoc et al. (2023)	Travelers: mixed-logit mode & PT access; AMOD controller assign/schedule/rebalance; vehicle energy/charging rules.	HITS 2012; LTA 2013 counts; taxi GPS; smart-card; BN 2030 synthetic population.	✓	✓	✓	✓	✓	✓	✓	✓	×	×
Oh et al. (2020)	Travelers follow activity-based daily schedules and choose mode/route/departure with day-to-day/within-day learning; AMOD operator assigns requests	Population & land use & road/PT networks; calibrated base-year (2012) with HITS/taxi GPS/smart-card/traffic counts	✓	✓	✓	✓	✓	✓	✓	✓	×	✓
Qiao and Yeh (2023)	Users (MOD bus/metro), vehicles, dispatcher (nearest); fleet expands when unmet within wait threshold.	Mobile traces (Dec 3, 2018) infer home/work; POIs, stops, OSM; Lianjia prices as SES proxy.	✓	✓	✓	✓	×	✓	×	×	×	×
Zhou et al. (2023)	Travelers choose tours, stops, times, mode-chains; MaaS subscribers relax constraints; one mode change/trip.	Population synthesizer; OViN/ODiN; LOS for 7 modes; assumed parking rates; fixed hub transfer times; MaaS free.	✓	×	✓	×	×	✓	✓	✓	×	✓
Djavadian and Chow (2017)	Users adapt mode/departure by perceived cost; operators adjust policies; drivers enter by profit threshold; regulator enforces.	Oakville TTS; H-W trips; utilities with time/fare; observed itineraries.	✓	×	×	✓	×	✓	×	✓	×	✓
Franco et al. (2020)	Agents: travelers with daily plans; DRT vehicles and PT; MATSim replanning guides route/time choices; DRT acts as feeder to PT.	Mobile phone network data with inferred purpose/mode; OSM roads; Traveline/GTFS PT; basic demographics.	✓	✓	✓	✓	×	✓	✓	×	×	×
Bürstlein et al. (2021)	Commuters submit first-mile trip requests, the operator dispatches a homogeneous car/van fleet via MaaS Modeller tour-planning under max-wait and detour constraints to pool riders to GO stations.	TTS-based first-mile car-trip demand projected to 2018 (AM peak); PUDO network (avg. ∼200 m walk); link travel times from calibrated Visum assignment.	×	✓	✓	✓	×	✓	×	✓	✓	✓
Qiao and Yeh (2023)	Agents: user and vehicle; MaaS users follow a door-metro-door rule, otherwise MOD.	Mobile phone trajectory data, departure/arrival times and metro vs non-metro mode; road network, neighborhood house prices	✓	✓	✓	✓	×	✓	✓	×	×	×
Labee et al. (2022)	Agents: travelers/households, daily activity–travel schedules generated by rule-based Albatross; MaaS adoption simulated via mixed logit	Dutch travel-diary survey & Amsterdam census; MaaS bundle attributes and stated adaptation variables, network for assignment	✓	✓	✓	✓	×	✓	✓	✓	✓	×

Notes: **Traffic Sim.** = within-day mobility simulation with network dynamics (e.g., micro-simulation, queue-based loading, MATSim-style event simulation), rather than only using exogenous LOS/skims. **Pricing** = explicit analysis of fare levels, pricing schemes or subsidies in the scenarios (e.g., MaaS tariffs, temporal pricing, fare integration). **Env.** = environmental performance indicators are reported as outputs (e.g., energy use, CO_2/GHG emissions). **Econ.** = economic indicators are reported as outputs (e.g., operator costs or profits, consumer surplus, welfare metrics, or users' monetary savings).

3.2. Optimization models

MaaS operational decision-support problems are typically formulated as optimization models subject to constraints, including capacity limits and operating rules. In MaaS, the optimization has been used for: (i) strategic and tactical operational decisions such as fleet sizing, zoning, timetables, and multimodal integration, (ii) platform clearing and implementable allocation across users and operators (assignment games and stable matching), (iii) hierarchical regulation and competition (bilevel and multi-leader formulations). The transferability of results depends critically on how user behavior is represented (e.g., exogenous demand, embedded choice models, or equilibrium response) and on whether the formulation assumes a centralized decision-maker or decentralized, strategic actors.

3.2.1. Strategic and tactical operational decisions

For strategic-tactical operations, MaaS decisions are jointly constrained by infrastructure, fleet, and timetable requirements. For example, in a corporate MaaS (CMaaS) setting, Frank et al. (2024) developed a time-dependent integer program that jointly selected public-transport tariff options and sized company-exclusive fleets across modes; spatiotemporal demand heterogeneity was captured through demand profiles and cost parameters, while practical limits on vehicle availability and technical restrictions were enforced. At the network scale, Liu and Ouyang (2021) introduced constrained nonlinear programming problems based on aspatial queuing networks to co-design service-region partitioning, a fixed-route backbone, and local demand-responsive operations, with decision variables spanning zoning, fleet sizing, repositioning, and backbone design parameters. Camargo et al. (2021) proposed an event-based dynamic dial-a-ride dispatch algorithm and an integration framework that converted conventional model outputs into time-stamped trips, then fed simulated level-of-service back into traditional forecasting models. For passenger-facing coordination in scheduled services, Lee et al. (2022) presented a path-oriented MILP to synchronize public-transport schedules while accounting for transfer times; by optimizing arrival, dwell, and departure times under transfer-feasibility constraints, the model reduced waiting, transfer, and deviation penalties.

3.2.2. Assignment, matching and allocation in MaaS systems

Beyond long-term design, MaaS platforms face an operational clearing task: translating heterogeneous user requests into implementable MaaS bundles (i.e., sets of integrated mobility options) and allocating limited mobility resources (vehicles, seats, service time, and purchased capacity) across users and operators. A typical modeling approach focused on assignment or matching problems between travelers and capacity-constrained service “sellers” (routes, links, or operators). Liu and Chow (2024) formulated MaaS assignment with fixed-route transit and MOD services under congestion as a nonlinear mixed-integer model, incorporating flows, service activation, fleet sizing, and fares under capacity constraints, and showed that stability may require additional design layers (e.g., stability-enforcing heuristics and subsidy mechanisms). From an intermediary-platform perspective, Yao and Zhang (2024) examined joint assignment and OD-based pricing on a multimodal network via a long-term bilevel optimization model with purchased capacities and congestion effects. Pandey et al. (2019) compared centralized, cooperative, and competitive brokerage settings by adapting dial-a-ride and linear assignment formulations and evaluating efficiency, waiting times, detours, and incentives using NYC taxi data. Cooperative-game formulations provide further structure: Rasulkhani and Chow (2019) modeled an assignment game with routes (sellers) and travelers (buyers), using linear programming with matching and fare variables to identify stable outcomes, again demonstrated on NYC taxi data. Extending to many-to-many settings, Pantelidis et al. (2020) proposed a multicommodity capacitated fixed-charge network design model with subsidies and prices, using constraint generation and lexicographic core allocations to characterize stable outcomes that could support negotiation by a public agency.

In real-world operations, resource allocation is often dynamic and must be updated online as requests arrive. Xi et al. (2023a) formulated an online mobility resource allocation problem, where users’ trip requests arrive dynamically, and the regulator solves a MILP model with a primal–dual online algorithm to allocate mobility resources to meet users’ MaaS requests in real time. Ding et al. (2023) proposed a resource allocation problem to assign travelers with multidimensional requirements to capacity-constrained multimodal paths, and a truthful, near-optimal auction-based mechanism that efficiently allocated scarce mobility resources even when travelers bid strategically. Pandey et al. (2019) studied real-time multi-company ridesharing assignment using a dynamic framework that estimates per-vehicle DARP costs and solves a matching step at each sampling window, highlighting how cooperation/competition and user/operator preferences affect system efficiency under binding vehicle-capacity and feasibility constraints. MaaS bundles may also embed reliability-related promises that directly consume scarce backup resources; for example, Zhou et al. (2024) considered a “premium fare with delay insurance” design in which the operator sets premium fares while allocating limited alternative-mode capacity to cover eligible delays, resulting in a nonconvex decision problem that couples pricing with constrained resource commitment.

3.2.3. Bilevel optimization models in MaaS systems

Leader-follower games (bilevel optimization models) are employed to capture the hierarchical decisions and strategic interactions among platforms and regulators in MaaS systems. For example, Pantelidis et al.

(2020) modeled MaaS as a stable matching and bilevel optimization problem in which an agency (leader) sets prices and cost allocations, and users and TSPs (followers) respond; tractability was achieved through a capacitated assignment reformulation and LP-based constraint generation. Xi et al. (2024a) proposed a single-leader multi-follower model for regulating two-sided MaaS markets with/without network effects, deriving MILP/MIQP bilevel formulations and solving them via a strong-duality-based branch-and-bound algorithm that improved computational performance on large instances. Xi et al. (2024b) modeled an electric MaaS ecosystem as a multi-leader-multi-follower game, where competing platforms chose EV acquisition ratios, unit prices, rewards, and bundle allocations while anticipating traveler participation; a tailored ADMM-based decomposition enabled efficient solution on real-world Australian transportation data and simulated MaaS requests. Xi et al. (2023b) formulated a bilevel program in which the regulator (upper level) chooses the surcharge and reward ratio to minimize total system equilibrium cost, while anticipating that mobility and delivery users (lower level) reach a two-class MaaS bundle-choice user equilibrium under the bilateral surcharge reward scheme (BSRS).

3.3. Discrete choice models

Discrete choice models are central to MaaS demand analysis, capturing decisions ranging from subscription uptake to the selection of specific plans or bundles. Common approaches include binary logit/probit models for the basic subscription decision, multinomial logit/probit for choices among multiple plans or travel options, and nested or mixed logit models for hierarchical decision processes that incorporate taste heterogeneity and more flexible substitution patterns. Advanced extensions, such as hybrid choice models (integrated choice and latent variable, ICLV) and latent class models, incorporate attitudinal or lifestyle factors, thereby explaining variation in WTP and identifying distinct user segments. Ordered response models are also employed when outcomes, e.g., willingness or agreement levels, are measured on ordinal scales.

3.3.1. Binary choice models (Logit/Probit)

Binary logit and probit models are widely used to represent the fundamental decision of whether to subscribe to a MaaS offering. For instance, Caiati et al. (2020) employed a binary mixed logit model in the first stage to explain MaaS subscription uptake based on service attributes, social influence, and socio-demographics, before modeling the subsequent choice of bundles. Field trials similarly analyze MaaS uptake with binary logits: in Australia's first MaaS trial, Hensher et al. (2021) examined the choice between a monthly MaaS bundle and PayG, finding that bundle adopters significantly reduced their private vehicle use. Binary choice models can even gauge interest in particular bundle types. Coppola et al. (2025), for example, estimated separate binary logits for university users' interest in different hypothetical bundle combinations, such as PT transport with micromobility or PT with car-sharing, and identified factors such as age, transit pass ownership, and car availability as significant predictors of interest. Post-pandemic analyses continue to utilize binary formulations. Soria et al. (2023) used a binary logit model to examine transit ridership lapse (whether individuals ceased using transit) and combined it with ordered logit models for the intention to return and willingness to ride more if MaaS-style fare integration with ride-hailing and micromobility were implemented. Binary choice models have also been applied at the trip level: using SP data, Grau et al. (2025) estimated the probability that travelers would select a MaaS-suggested trip option, based on the option's generalized cost components such as travel time, monetary cost, and transfers.

3.3.2. Multinomial choice models (MNL/MNP)

When multiple MaaS plans or travel alternatives are being evaluated, multinomial logit (MNL) and multinomial probit (MNP) models provide the standard framework for choice analysis. For example, Tsouros et al. (2021) applied an MNL to respondents' choices among hypothetical MaaS plans that differed in their PT allowances, bike-sharing access, taxi/car-sharing credits, and monthly price, highlighting the ease of obtaining intuitive WTP estimates for bundle attributes with a basic MNL, while noting that extensions such as mixed logit or ICLV models could be used to capture additional preference heterogeneity. Ho et al. (2020) estimated an MNL model on stated-choice data from Sydney and Newcastle, augmenting it with a scale function to account for individual-specific variability in choice consistency, thereby improving the realism of uptake predictions. Coppola et al. (2025) presented respondents with several MaaS plan options alongside a status quo, and used an MNL model to infer baseline demand for different bundle designs.

Table 6

Overview of optimization models in MaaS studies.

Study (year)	Problem	Model	Decision variables	Key constraints	Objective function	Bi-level	Dynamic?	Uncertainty	Heterogeneity	Solution method
Pandey et al. (2019)	Real-time multi-company ridesharing assignment under cooperation vs. competition	Dynamic assignment framework: per-vehicle DARP cost estimation &LA	vehicle-request match per time step, idle-vehicle-to-unserved-request assignment.	One new request per vehicle per sampling window; each request assigned to at most one vehicle; feasibility via DARP with capacity constraints.	Minimize total assignment cost; quantify efficiency loss under competition/preferences.	×	✓	✓	✓	Insertion heuristic for single-vehicle DARP & LAP solvers evaluated on NYC taxi data.
Liu and Chow (2024)	the matching problem is formulated as a convex multicommodity flow network design problem under congestion, capturing the cost of accessing MOD services.	a nonlinear mixed integer programming	link flow, whether a fixed-route link is chosen to be operated, whether a MOD node represents a MOD service zone; link fare.	fixed-route transit links have capacity constraints.	maximize operators' total profit and travelers' total social welfare by minimizing total costs.	×	×	×	×	Branch and Bound
Yao and Zhang (2024)	the assignment and OD-based pricing problem for a MaaS platform in a multi-modal transportation network.	a bi-level programming model	MaaS demand, link capacity purchased, and resulting link flows.	multi-modal network capacity, road congestion, and stable matching constraints.	minimize the total system cost and maximize the MaaS platform's profit.	✓	×	×	✓	Decomposition; gradient-based algorithm
Zhou et al. (2024)	"premium fare with delay insurance" problem proposed to evaluate and enhance travel time reliability within a multimodal transportation network.	a non-convex problem considering the interaction of the choice model with the decision variable	premium ticket fare for an OD pair; fixed or OD-specific multiplier of minimum travel time that qualifies the traveler to use the alternative mode free of charge.	capacity constraint for the alternative mode, limiting the number of premium tickets that can be sold based on available taxi resources; and limits on the premium fare.	maximize the public transport operator's total profit.	×	×	✓	✓	two-stage allocation strategy with a path-following method
Xi et al. (2024b)	efficient allocation of E(T)-MaaS bundles to meet heterogeneous requests, incentivizing travelers to use more E-MaaS bundles, and optimizing pricing, rewards, EV acquisition ratios.	a multi-leader multi-follower game model	MaaS platform's EV acquisition ratio for different modes; unit price for E(T) mobility resources; unit rewards; travelers' participation levels.	mobility resource capacity, investment budget, the government's funding budget, users' heterogeneous preferences.	each MaaS platform (leader) aims to maximize its profits, each traveler (follower) aims to minimize their total travel costs.	✓	×	×	✓	ADMM
Xi et al. (2024a)	an optimization framework for the regulation of two-sided MaaS markets considering network effects.	Two bilevel formulations: MILP (no network effects) vs MIQP (with network effects)	unit prices for travelers and TSPs; whether the platform offers; service time of each mode in the MaaS bundle; supply–demand gap; users'/TSPs' participation levels.	MaaS bundle composition constraints; travel delay budget; inconvenience tolerance; mobility resource capacity.	the MaaS regulator maximizes profit, each traveler minimizes total travel cost, and each TSP maximizes profit.	✓	×	×	✓	Branch and Bound
Rasulkhani and Chow (2019)	a many-to-one model where sellers are routes with line capacities and travelers are matched to segments of each route.	a linear program (LP) for a simple assignment game	binary variables for matching each buyer with a route segment, and fare.	flow feasibility; link capacity limits; non-negativity and integrality for flows and matching decisions.	maximize the total payoff from matching buyers (users) and sellers (routes).	×	×	×	✓	many-to-many assignment game with stable outcome algorithm
Pantelidis et al. (2020)	a many-to-many assignment game with user path and operator levels, formulated as a multicommodity capacitated fixed-charge network design problem.	a mathematical program with linear constraints	binary variables indicating if a match occurs on a link; binary variables for operating a link; continuous flow for each OD pair; link-level subsidies; prices; and path flows.	link capacity constraints; effective service capacity limits for systems.	minimize total costs, including passenger generalized travel cost and operator operating costs.	×	×	×	✓	constraint-generation algorithm with lexicographic core allocations
Frank et al. (2024)	a wide range of strategic and tactical decisions in a Corporate MaaS (CMaaS) system.	Integer Program (IP)	required fleet sizes for company-exclusive services; binary variables indicating selected price tariffs for public services.	spatio-temporal demand; costs; upper bounds on vehicle counts; technical restrictions (e.g., EV range, bike limits).	minimize expected total corporate mobility cost over the planning horizon.	×	✓	✓	✓	Gurobi 8.1.0 (MIP solver)
Liu and Ouyang (2021)	new aspatial queuing network models that optimize an integrated mobility service system that simultaneously considers service region partition, transit network design, and DRT operations.	constrained non-linear programming	zone partition, fleet size, repositioning operation for the local DRT service, spacing, headway of a grid transit network, expected number of vehicles, repositioning rate, and headway.	capacity constraints; minimum values for transit network spacing and DRT zone size for practical considerations; vehicle capacities.	minimize the system-wide total cost per passenger.	×	×	×	×	Python Scipy package
Lee et al. (2022)	the path-oriented scheduling problem considering path transfer time in multi-modal mobility.	mixed integer linear programming (MILP)	arrival, dwell, and departure times for vehicles, and binary indicators for transfer feasibility and passenger boarding.	synchronization constraints, and operational constraints such as allowable headway range and dwell time limits.	minimize the weighted sum of all time-related attributes to provide travelers with a seamless travel experience.	×	✓	×	✓	solver
Camargo et al. (2021)	Integrate pooled DRT/TNC dispatching into traditional regional forecasting/assignment models.	Event-based simulation-optimization; dynamic DARP/PDPRCTW	Request-to-vehicle assignment; pickup/dropoff sequence	Vehicle capacity, pickup time windows / max waiting time, absolute and relative detour constraints, and route/schedule feasibility.	Minimize marginal operating cost subject to LoS constraints.	×	✓	×	✓	Greedy vehicle preselection & CP solver
Song et al. (2021)	Multimodal path planning for MaaS that recommends feasible mode chains and corresponding shortest hyperpaths	shortest-hyperpath formulation coupled with dynamic DCM	Binary link-use variables	Time-window constraints; distance; cost budget; transfer limit; flow conservation; park-and-ride constraint	Min expected generalized tour disutility, producing a Pareto set	×	✓	✓	✓	EM-based estimation for dynamic DCM & label-correcting

3.3.3. Nested logit (GEV family)

For situations in which MaaS choices are made hierarchically, nested logit models from the generalized extreme value family are employed to relax the independence of irrelevant alternatives assumption by allowing correlated errors within nests. Hörcher and Graham (2020) proposed a three-level nested structure: households first decide on private car ownership, then choose whether to subscribe to MaaS (and if so, which subscription type), and finally select daily travel modes. This nesting structure captures shared unobserved factors among alternatives at each decision tier, e.g., between different MaaS subscription options, and enables policy scenario analysis (such as pricing or congestion charges) along with their welfare implications.

3.3.4. Mixed Logit (Random-parameters and error-components)

Mixed logit models, also known as random-parameters logit, have become a prominent approach in MaaS research because of their flexibility in capturing taste heterogeneity and relaxing the restrictive substitution patterns of simple logit. Many stated-preference studies employ mixed logit to estimate the distribution of preferences for MaaS bundle features. For example, Matyas and Kamargianni (2019) and Guidon et al. (2020) applied mixed multinomial logit models to discrete choice experiments, recovering heterogeneity in WTP for key attributes of mobility bundles. Mixed logit has also been used on revealed-preference trial data: Ho et al. (2021a) analyzed observed choices among PayG and various subscription plans in a Sydney MaaS trial, introducing random parameters, e.g., for discount effects, to reflect unobserved taste differences and seasonal effects. This approach can highlight segment-specific responses; for example, Wang et al. (2024) showed that current public transport users and habitual car users respond differently to MaaS bundle attributes, suggesting the need for segment-tailored bundle designs.

Further extensions of mixed logit broaden its application. Zhao et al. (2025) incorporated both random taste heterogeneity and error-component terms into a logit model of MaaS plans that include emerging modes such as urban air taxis, thereby capturing preference variation and correlation across alternatives. Ren et al. (2024) estimated a panel mixed logit model (with error components) to jointly model MaaS subscription adoption and long-term ownership decisions for e-bikes, electric cars, and conventional cars, thereby linking MaaS uptake to household vehicle ownership patterns. Beyond individual travelers, mixed logit has also been applied in business and tourism contexts. For example, Bushell et al. (2022); Wong and Hensher (2021) modeled organizations' stated preferences for MaaS-style corporate mobility contracts, demonstrating that the method can capture B2B decision factors. Similarly, Li et al. (2023) incorporated MaaS attributes (travel time, cost, walking distance) into a random-parameters logit for tourist mode choice, finding that these attributes significantly influenced mode selection only for a subset of "weak-preference" tourists. Militão et al. (2025) developed an error-components random-parameters logit to describe travelers' mode choices in the Sydney MaaS trial. These diverse applications underscore the versatility of mixed logit in accommodating complex preference patterns across different MaaS scenarios.

3.3.5. Hybrid choice and latent class models (ICLV and Latent Classes)

To incorporate travelers' attitudes and lifestyles, many MaaS studies have adopted hybrid choice models and latent class extensions. For example, Polydoropoulou et al. (2020) developed an ICLV model that introduced a latent "intermodality" propensity, derived from socio-demographics and travel habits, into the utility functions for MaaS package choices, thereby improving the explanation of WTP for more comprehensive multimodal bundles. On the segmentation side, Vij et al. (2020) estimated a latent class logit model on a large Australian sample, revealing distinct market segments with different preferences for integration features, ticketing/booking options, and subscription costs. This analysis identified groups ranging from those enthusiastic about fully integrated services to others more sensitive to price or less interested in MaaS subscriptions. In Taiwan, Chen and He (2023) applied a latent class choice model with attitudinal indicators informing class membership and identified two user segments, i.e., "cost-sensitive" vs. "service-quality-oriented", that value MaaS bundle attributes very differently. Likewise, Yao et al. (2025) found that in Beijing, only specific traveler segments (characterized by their lifestyles and attitudes) have a strong propensity to shift from current modes to MaaS options, whereas other segments remain reluctant. Attitudinal influences have also been observed in different contexts.

Table 7
Overview of discrete choice models in MaaS studies.

Study	Region	Sample size/ population	Data	Model	Sub./ bundle	Latent vars	Hetero.	Opt-out	Block	Adoption	Pricing/ WTP	Choice tasks
Zhao et al. (2025)	Beijing, China	467 commuters	SP	Mixed logit (RP-EC)	✓	×	✓	✓	✓	×	✓	alts=[Bike sharing&UAT, PT&UAT, Taxi/Ridesourcing&UAT, Car&UAT, No UAT]; attrs=[door-to-door travel time, walking & waiting time, shared UAT ride, travel cost, gov. support, monthly sub. fee, sub. discount/ride]
Yao et al. (2025)	Beijing, China	1,242 online respondents	SP	Hybrid choice (ICLV)	✓	✓	✓	×	×	✓	×	alts=[bus, taxi/ride-sourcing, private car, MaaS options (metro&bus/bike/taxi, ride-sharing)]; attrs=[in-vehicle time, waiting time, walk/ride distance, parking & fuel cost, travel time, travel cost]
Wang et al. (2024)	Nanjing, China	878 adults	RP	Mixed logit	✓	×	✓	✓	✓	×	×	alts=[MaaS bundles A,B,C with bus/metro, bike share, ride hailing, car share, carpool, on-demand bus]; attrs=[included modes, bundle price]
Vij et al. (2020)	Australia	3,985 representative adults	SP	Latent class logit	✓	×	✓	✓	✓	✓	✓	alts=[Scheme A,B]; attrs=[local/long-distance PT, taxis, car/car-/ride-/bikeshare, real-time info, personalisation, ticketing/booking integration, subscription model, monthly cost]
Tsouros et al. (2021)	Greater Manchester, UK	574 adults	SP	MNL / ICLV	✓	✓	×	✓	×	✓	✓	alts=[Your Plan, No]; attrs=[PT entitlement (none/bus/all), bike-sharing month, taxi trips, car-sharing hours, plan price]
Ren et al. (2024)	Netherlands	494 households	SP	Mixed logit & ICLV	✓	✓	✓	✓	✓	✓	×	alts=[buy pedelec/speed pedelec/conventional car/e-car, join e-bike/e-car sharing, subscribe to MaaS]; attrs=[purchase/maintenance cost, operating fuel cost, range, charging time, distance to fast charging, deposit, membership fee, unlocking cost, access distance, MaaS bundle]
Ho et al. (2020)	Tyneside (UK), Sydney	290 / 252 adults	SP	MNL (heteroscedastic)	✓	×	✓	✓	✓	✓	✓	alts=[current travel record, Plan A, Plan B, PAYG]; attrs=[monthly cost, NEXUS/PT trips, car hrs/miles, taxi discount, bike-share, credit, PT fare]
Ho et al. (2021a)	Sydney, Australia	93 trial participants	SP&RP	Mixed logit (RPL)	✓	×	✓	✓	×	✓	✓	alts=[PAYG, Fifty50, Saver25, GreenPass, SuperSaver25]; attrs=[monthly fee, Opal discount, Uber discount, Taxi discount, GoGet discount, Thrifty discount]
Ho et al. (2018)	Sydney, Australia	252 shoppers	SP	×nlinear mixed logit	✓	×	✓	✓	✓	✓	✓	alts=[current travel record, Plan A, Plan B, PAYG]; attrs=[PT trips/days, car hours/km, car-share booking/type, taxi/UberPOOL discount, unused credits, fortnightly cost]
Guidon et al. (2020)	Zurich, Switzerland	1,000 registered persons	SP	Mixed logit (RPL)	✓	×	✓	✓	×	✓	✓	alts=[option 1, option 2]; attrs=[cost, app, PT subscription, car-sharing km/month, bike-/e-bike-sharing hours/month, parking days/month, taxi subscription min/month]
Xie et al. (2019)	Boston-Cambridge, USA	202 (1,940 obs.)	SP&RP	Hybrid choice	×	✓	✓	✓	×	×	×	alts=[non-motorised (walk/bike/bikeshare), private motorised (car/carpool), on-demand (Uber/Lyft, carsharing, taxi), transit]; attrs=[travel time, waiting time, energy savings, tokens]
Wong and Hensher (2021)	28 countries	202 organizations	SP	Mixed logit (RPL)	✓	×	✓	✓	✓	✓	✓	alts=[mobility contract 1, mobility contract 2, mobility contract 3]; attrs=[mobility offering, government support, return on investment, business branding, equity contribution]
Polydoropoulou et al. (2020)	Manchester, UK	449 individuals	SP	Hybrid choice / ICLV	✓	✓	✓	✓	×	✓	✓	alts=[PT entitlement levels, bike-sharing month, taxi trips, car-sharing hours]; attrs=[mobility services in bundle, service levels, price]
Matyas and Kamargianni (2019)	Greater London, UK	1,068 web respondents	SP	Mixed MNL	✓	×	✓	×	×	✓	×	alts=[Plan A, Plan B, Plan C]; attrs=[PT, bike sharing, taxi, car sharing, cost]
Matowicki et al. (2024)	DE, UK, PL, CZ	6,405 urban commuters	SP	Latent-class mixed choice model	×	×	✓	✓	✓	✓	✓	alts=[PT, carsharing, bikesharing, micromobility, mobility-on-demand, intermodal routing]; attrs=[price, trip duration, walking time, distance to vehicle/bike/pick-up, route conditions, number of passengers]

Table 7
Overview of discrete choice models in MaaS studies (Continued).

Study	Region	Sample size/ population	Data	Model	Sub./ bundle	Latent vars	Hetero.	Opt-out	Block	Adoption	Pricing/ WTP	Choice tasks
Liu et al. (2024a)	Hong Kong	1,007 regular commuters	SP	Mixed logit	✓	×	✓	✓	✓	×	×	alts=[Driving, Taxi, Carpool, Bus, Rail, Rail&Bus]; attrs=[time saving per trip, fare discount, bundle price, perceived occasional activity probability, weekly travel expense, weekly travel time]
Li et al. (2023)	Beijing, China	1,945 tourists	SP	Mixed logit (RPL)	×	×	✓	×	×	×	×	alts=[tour bus, ride sharing, PT, car sharing]; attrs=[total travel time, in-vehicle cost, walking distance]
Kriswardhana and Esztergár-Kiss (2025)	Hungary	519 individuals	SP	Hybrid choice / ICLV	✓	✓	✓	✓	×	✓	×	alts=[Bundle A, Bundle B, Bundle C, Pay-as-you-go]; attrs=[PT, bike-sharing, car-sharing, e-scooter sharing, taxi, gym membership, online shopping voucher, price without MaaS, price with MaaS]
Kraus et al. (2023)	Ruhr area, Germany	10,782 (students, employees)	SP	MNL & hierarchical Bayes	✓	×	✓	✓	×	✓	✓	alts=[PT, CS, BS, ES]; attrs=[monthly sub. (city/tariff association), car-sharing contingents, bike/e-bike time contingents, trip-count contingents]
Krauss et al. (2022a)	83 cities, Germany	1,445 urban residents	SP	Mixed logit	×	×	✓	✓	×	×	×	alts=[e-scootersharing, bikesharing, walking, private car, carsharing, ridepooling, PT]; attrs=[travel, access, egress, parking-search, waiting, detour time, cost, availability, scheme, engine, range, crowding, transfers]
Kim et al. (2021b)	Seoul, South Korea	346 commuters	SP	ICLV	×	✓	✓	✓	×	✓	×	alts=[Private car, Carpool, PT, PT&Taxi, PT&Bike-sharing]; attrs=[travel time, walking time, travel cost, number of transfers]
Kim and Rasouli (2022)	×rth Brabant, Netherlands	1,299 residents	SP	Latent variable / latent class	✓	✓	✓	✓	×	✓	×	alts=[MaaS subscription]; attrs=[monthly subscription price, commitment period, service reviews, share among family, friends, colleagues]
Kim et al. (2021a)	Jeju Island, Korea	331 tourists	SP	Mixed logit	×	×	✓	×	×	×	×	alts=[bus, shared van, taxi]; attrs=[travel time, out-of-vehicle time, in-vehicle time, travel cost]
Coppola et al. (2025)	Milan, Italy	1,873 university community	SP	Binary logit / binary mixed logit	✓	×	✓	✓	×	✓	×	alts=[PT&bike/e-scooter sharing, PT&car/moped sharing, PT&reserved parking at interchanges]; attrs=[interest in bundle]
Chen and He (2023)	Taipei City, Taiwan	619 prospective users	SP	Latent class choice model	✓	×	✓	✓	✓	×	✓	alts=[Alternative A, Alternative B]; attrs=[PT (metro, bus, light rail), shared bike, shared e-scooter, taxi, price]
Caiati et al. (2020)	Amsterdam & Eindhoven, Netherlands	1,078 panel members	SP	Binary mixed logit & mixed logit	✓	×	✓	✓	✓	✓	✓	alts=[option 1, option 2]; attrs=[real-time alerts, app synchronisation, parking payment, mobility tracker, service area, free trial, cancellation policy & penalties, cancellation times, extra cost]
Bushell et al. (2022)	Australian metropolitan areas	950 PT users	RP	Random parameters logit	×	×	✓	✓	✓	×	×	alts=[private vehicle, integrated travel system/app]; attrs=[journey planning & payment, data use, timing of total price info, operator time savings, fare discounts, vehicle types, travel time, extra waiting/changes, total travel cost]

Notes: Sample size/population: number of observations. SP = stated preference, RP = revealed preference, Sim = simulation data. Model: MNL = multinomial logit, Mixed logit / RPL = random-parameters logit, ICLV = integrated choice and latent variable model, LVLC = latent variable–latent class model, EC-MNL = error-component multinomial logit, ZIP = zero-inflated Poisson (regression component), Kernel-logit = kernel-based logit extension. Sub./bundle: indicates whether the choice set includes MaaS subscription plans or bundled service offers. Latent vars: indicates whether the model includes explicit latent constructs. Hetero.: indicates whether preference heterogeneity is captured. Block: indicates whether the SP design is blocked. Adoption: indicates whether MaaS adoption is an explicit research objective. Pricing/WTP: indicates whether pricing and WTP are a key research focus. Abbreviations: PT = public transport, CS = car-sharing, BS = bike-sharing, ES = e-scooter sharing, UAT = urban air taxi, hh = households, ind. = individuals. Country codes: DE = Germany, UK = United Kingdom, PL = Poland, CZ = Czech Republic.

In Seoul, Kim et al. (2021b) employed an ICLV model to examine intermodal MaaS choices and reported that pro-technology attitudes significantly increase the likelihood of MaaS uptake. Extending this approach, Kim and Rasouli (2022) incorporated a hierarchical latent-variable and latent-class structure in which broader lifestyle-based classes mediate the MaaS subscription decision. Recent work continues to demonstrate the value of latent constructs. Kriswardhana and Esztergár-Kiss (2025) augmented a choice model with multiple psychological latent variables (e.g., environmental concern, technology readiness) and demonstrated how these attitudes influence MaaS adoption. Liu et al. (2024a) embedded a latent risk-perception factor into a mixed logit model of MaaS plan choice, showing that accounting for heterogeneity in risk attitudes can substantially affect the estimated WTP for MaaS plans.

3.3.6. Ordered logit models

Ordered response models are used when MaaS-related outcomes are measured on an ordinal scale, such as levels of agreement or intention, although they appear less frequently than nominal choice models. For example, Soria et al. (2023) applied an ordered logit to survey data from Chicago transit riders to analyze their intention to return to transit and their willingness to ride more if MaaS-style integrated fares (covering ride-hailing and micromobility) were in place. By preserving the ranking information of the responses, the ordered model captured gradations in willingness that a binary or multinomial formulation might overlook.

3.4. Other statistical models

Beyond traditional random-utility models, a broad range of statistical techniques have been applied to study MaaS adoption and impacts. For example, the confirmatory factor analysis (CFA) and structural equation modeling (SEM) to capture latent psychological constructs, latent class and mixture models are used to uncover hidden user segments, various regression models, including regularized, ordinal, and mixed-effects models to link attitudes with intentions, and integrated simulation or panel frameworks. Combined with survey and behavioral datasets, these methods help measure latent readiness, profile early adopters, evaluate user experiences, and assess distributional impacts of MaaS.

3.4.1. Factor analysis and structural equation models

Several studies use exploratory or confirmatory factor analysis (EFA/CFA) combined with structural equation modeling to examine how latent psychological factors influence MaaS adoption. For example, Lopez-Carreiro et al. (2024) reduced a broad set of attitudinal and personality variables into a few underlying factors via EFA, then built an SEM linking those latent factors to the intention to adopt MaaS. The model explained more than half of the variance in MaaS adoption intention and identified three key barriers: low willingness to use multiple transport modes, low affinity for technology, and perceived unreliability of new mobility services. Similarly, Dzisi et al. (2023) applied an SEM based on the UTAUT framework to paratransit operators in Ghana, finding that performance expectancy, effort expectancy, familiarity with ride-hailing, and social influence significantly affect these operators' intentions to participate in MaaS. Focusing on college students, Kriswardhana and Esztergár-Kiss (2023) employed a two-step SEM: first identifying latent constructs such as technology readiness, performance expectancy, and uncertainty avoidance, and then relating them to preferences for MaaS app features (e.g., integrated route planning, one-stop booking, cashless payment, e-ticketing) and overall interest in MaaS. In addition, Zijlstra et al. (2020) used CFA to construct a composite "Latent Demand for MaaS" index from indicators like tech-savviness, desire for travel information, a multimodal mindset, preference for transport flexibility, and general innovativeness.

Other research has aimed to uncover unobserved heterogeneity in MaaS readiness through latent class analysis and clustering. For instance, Alonso-González et al. (2020) performed a latent class cluster analysis (using attitudinal factors as inputs) and identified five distinct traveler segments, ranging from a highly "MaaS-ready" group (flexible and multimodal) to a car-centric group with minimal interest in MaaS. In Lopez-Carreiro et al. (2024), a post-SEM cluster analysis similarly yielded four profiles of travelers from "Traditional car-supporters" to "MaaS admirers" differentiated by their levels of multimodality, technology affinity, and environmental concern. These studies advocate for model-based segmentation approaches, such as latent class cluster analysis (LCCA), to define user groups. Such approaches reduce arbitrariness in segment definition and help mitigate misclassification issues relative to simple heuristic clustering (Kriswardhana and Esztergár-Kiss, 2023).

Table 8
Overview of other statistical models in MaaS studies.

Study	Data	Methodology Used						Variables Included				Fit Ind.	Key Outcome/Focus
		EFA/CFA	SEM	Regression	Cluster	Simu.	Exp.	Att.	Demog.	Travel	Tech		
Zijlstra et al. (2020)	Netherlands MPN panel, wave 5; survey Jun 2018; $n=1547$; features from 2017 wave.	✓	×	✓ (Lasso)	×	×	×	×	✓	✓	×	✓	Identified likely early MaaS adopters (young, high-SES frequent travelers); suggested potential externality reductions.
Qiao and Yeh (2023)	Chengdu: mobile traces (Dec 3, 2018), POIs, stops, OSM network; house prices (Lianjia, Aug 2021).	×	×	✓ (OLS)	×	✓	×	×	✓	×	×	×	MaaS reduced travel distance/time; shared mobility increased occupancy, reduced walking, MaaS improved equity.
Lopez-Carreiro et al. (2024)	Randstad (NL) web survey; Apr-Jun 2019; $n=418$; quota sampling; pilot $n=300$.	✓ (EFA)	✓	×	✓	×	×	✓	✓	✓	✓	✓	The variance in intention to adopt MaaS; four user clusters identified. Barriers: low multi-modality, low tech affinity, reliability, etc.
Dzisi et al. (2023)	Kumasi (Ghana) paratransit operators; field survey Oct 2020; $n=181$ across 4 stations.	×	✓	×	×	×	×	✓	✓	×	✓	✓	Performance expectancy, effort expectancy, social influence, and ride-hailing familiarity significantly increased intentions to adopt MaaS.
Kriswardhana and Esztergár-Kiss (2023)	Survey-based empirical data on university students (country/year as reported in paper).	×	×	×	✓ (LCCA)	×	×	✓	✓	×	×	×	Identified five distinct student segments (MaaS neutral, enthusiast, opponent, avoider, lover), indicating privacy, ease-of-use, safety concerns.
Alyavina et al. (2024)	UK online survey; Feb–Jul 2020; $n=427$; 40 Likert items & 2 intention items.	✓ (PCA)	×	✓ (OLR)	×	×	×	✓	✓	✓	×	×	Attitudinal factors and predicted intentions to reduce car ownership and increase public transport use under MaaS.
Alonso-González et al. (2020)	Netherlands urban MPN survey; May 2018; $n=1006$ valid (18&, smartphone users).	✓ (EFA)	×	×	✓ (LCCA)	×	×	✓	✓	✓	✓	×	Revealed five attitudinal segments; a “MaaS-FLEXI-ready” group had the highest adoption likelihood, while car owners were least likely.
Hoerler et al. (2020)	Swiss Household Energy Demand Survey, $n = 995$; includes information policy and open-ended responses	×	×	✓ (Binary logistic)	×	×	✓	✓	✓	✓	×	✓	Explained openness to use MaaS, testing demographic, mobility-use, and psychological drivers, plus policy treatments.
Chen et al. (2025)	Online survey of operating MaaS scheme users, Taiwan $n = 459$	✓	✓	×	✓	×	×	✓	✓	✓	✓	✓	uncovers the effects of service-experience dimensions on satisfaction and 4 latent segments.
Yu et al. (2025)	Shanghai Suishenxing MaaS platform; 10,000 new registrants via Alipay; four weekly discount tiers.	×	✓	✓ (Logit)	×	×	✓	×	✓	✓	×	×	Quasi-experimental evaluation of incentives for new MaaS users: higher initial discounts boosted short-term adoption but did not guarantee long-term retention compared to organic sign-ups.
Bruzzone et al. (2025)	Long-distance trips between municipalities in Trento/Bolzano and Verona, PT fares/timetables, motorway tolls, GIS-based data	×	×	×	×	✓	×	×	×	✓	×	×	An adapted travel-cost accessibility framework to compare long-distance MaaS vs driving under policy scenarios.

Notes: EFA/CFA = exploratory/confirmatory factor analysis; SEM = structural equation modeling; Simu. = simulation; Exp. = experimental design. Att. = attitudinal; Demog. = demographic; Travel = travel behaviour; Tech = technology-related variables. Fit Ind. = reported model fit or validation indicators.

3.4.2. Regression and mixed-effects models

Regression-based analyses have been used to identify key predictors of MaaS-related intentions and behaviors. Alyavina et al. (2024), for example, conducted a UK survey and applied principal component analysis to distill respondents' attitudes into a few factors, which were then included in ordinal logistic regressions. Their models examined the likelihood that individuals would reduce car ownership or replace public transit trips with MaaS alternatives, based on attitudinal factors, past travel behavior, and demographic characteristics. In another study, Zijlstra et al. (2020) applied Lasso-regularized regression to a rich set of over 80 variables from travel diaries and socio-demographic data to predict likely early adopters of MaaS. The selected regularization technique identified a subset of influential predictors, yielding a profile of prospective MaaS subscribers: they tend to be younger, well educated, and higher-income individuals who already frequently use modes such as rail and air travel. In addition to survey analyses, some studies combine regression with simulations to evaluate MaaS scenarios. For example, Qiao and Yeh (2023) embedded regression within a distributive justice framework and simulated various Mobility-on-Demand scenarios in Chengdu, distinguishing MaaS-type integrated services from simpler shared mobility, comparing floating versus stop-based vehicle operations, and assessing how accessibility outcomes differ across socioeconomic groups. In addition to survey analyses, some studies combine regression with simulations to evaluate MaaS scenarios. For instance, Qiao and Yeh (2023) embedded regression analysis within a distributive justice framework to simulate various Mobility-on-Demand scenarios in Chengdu. This study compared a fully integrated MaaS-like service against simpler shared mobility setups, as well as different operational models. The outcomes were used to assess how each scenario would affect accessibility across different socioeconomic groups, thereby highlighting the equity implications of MaaS and related new mobility services.

3.4.3. Integrated simulation and panel-based models

A final strand combines simulation and panel-based choice modeling to evaluate system performance and behavioural dynamics under alternative MOD/MaaS configurations. In Qiao and Yeh (2023), a multi-agent simulation assesses eight MOD public transport scenarios in Chengdu, distinguishing Shared Mobility (SM) from MaaS and contrasting floating versus stop-based fleet operations with different vehicle capacities. Using mobile phone trajectories, points of interest, public transport stop data, an OpenStreetMap-derived network, and spatial house-price information, the model generates system indicators (travel distance/time, waiting time, walking distance, dispatched vehicles, occupancy, and empty vehicle-kilometres). These outputs support an equity-oriented comparison, suggesting, for example, that MaaS tends to outperform SM in distance/time, that SM can reduce walking and increase occupancy, and that stop-based MaaS may narrow equity gaps, whereas floating services are relatively exclusionary (Qiao and Yeh (2023)). Panel-data choice modeling is integrated with latent segmentation in Matowicki et al. (2024), where kernel-logit specifications are estimated separately within the FMM-derived classes. By handling repeated individual responses and incorporating LCM-based attitudinal constructs, this framework captures both within-person dependence and between-class heterogeneity in preferences across public transport and MaaS alternatives, without imposing restrictive distributional assumptions on taste parameters. These simulation- and panel-based approaches complement SEM and regression studies by linking behavioural drivers to system-level performance and distributional outcomes under alternative MaaS designs.

3.5. Data-driven and predictive machine learning models

Machine learning (ML) models including reinforcement learning (RL) and deep learning (DL) have gained traction as high-frequency mobility data have become increasingly available (e.g., app logs, smart-card transactions, real-time traffic feeds, weather observations, and socio-demographic data). These ML models are particularly useful for decisions that must be made rapidly, at fine spatial-temporal resolution, or in settings where classical discrete-choice and optimization models become difficult to calibrate or scale. Across both emerging MaaS platforms and more mature deployments, these learning methods are now used to DL for travel behavior prediction and RL for dynamic decision-making.

3.5.1. Deep learning for travel behavior prediction

Deep learning methods have been increasingly adopted to predict travel demand, usage patterns, and MaaS adoption, often achieving higher predictive accuracy than traditional approaches. Many studies formulated MaaS uptake as a supervised learning problem. For example, Duan et al. (2022) developed a two-stage artificial neural network trained on survey data containing 33 behavioural, institutional, environmental, and socio-economic features to estimate individuals' likelihood of using MaaS for different trip purposes (work, social, and general). More recent studies leverage rich operational datasets and advanced architectures to forecast multimodal behaviour at scale. Xi et al. (2025c) proposed a multi-task Transformer-based model (PTBformer-MMoE) to predict individual travel behaviour, such as the monthly usage frequency of bus, rail, ferry, tram, and the expected monthly travel fare, using more than a billion smart-card trip records from multimodal public transport system covering over 150 million users in Australia. The proposed PTBformer-MMoE model reports state-of-the-art accuracy relative to nine baseline methods, enabling downstream applications such as proactive capacity planning and personalized MaaS bundle recommendations. Liu et al. (2024b) compared econometric approaches and ML models for predicting weekly MaaS usage across modes and found that a neural network with shared representation layers and mode-specific outputs achieved the strongest out-of-sample fit, outperforming linear regression, discrete-continuous choice models, and gradient-boosted trees. To preserve actionability, they combined SHAP-based attribution with post-prediction clustering via a k-prototypes algorithm to derive traveller segments using both observed attributes and predicted behaviour. Bayliss et al. (2025) used feed-forward neural networks to approximate shortest-path travel time (and distance) between any two locations within an origin and destination transfer zone, enabling fast real-time guidance for transfer-point/path optimization in ML-TZSA.

3.5.2. Reinforcement learning for dynamic decision-making

MaaS platforms frequently face sequential and real-time decisions under uncertainty, such as selecting which journey offer to recommend next, adjusting prices dynamically, or dispatching and rebalancing vehicles to match evolving demand. Reinforcement learning is well-suited to these settings because it learns policies that optimise long-run objectives through interaction with the environment. Chu and Guo (2023a) casted multi-objective journey recommendation as a Markov decision process in which the platform agent learns to propose multimodal trips that balance passenger satisfaction with operator profit. Using a deep RL approach with a proportional-fairness reward, their learned policy reportedly increases operator profit by a factor of 2.3 relative to static recommendation rules while maintaining high user retention, demonstrating the potential of learned policies to outperform heuristic strategies in complex MaaS ecosystems. Chu and Guo (2023b) reformulated the centralized RL approach as a privacy-preserving federated deep RL framework suitable for city-scale learning with sensitive user data. In their federated DDPG setup, passengers train local models on personal trip histories and share only encrypted updates for server-side aggregation, enabling a system-wide policy without direct exposure of raw individual data.Chu and Guo (2024) further examined security risks by modeling malicious behaviour in RL-based MaaS coordination. They introduce a multi-agent RL formulation with a spatial discount factor to encourage cooperation and then simulate "passenger spoofing" attacks in which adversarial agents inject false information to degrade platform performance. Their results indicate that adversarial manipulation can substantially reduce profits and user satisfaction, motivating robust (or adversary-aware) training and defensive mechanisms before deployment. Yan et al. (2025) developed an enhanced double Q-learning algorithm (Q-EDQ) for on-demand multimodal route planning in an extensive urban network, integrating metro, bus, car-sharing, and walking in Xi'an. Their agent learns door-to-door paths that minimize generalized travel cost (e.g., time, cost, transfers) and uses an annealing exploration strategy to improve convergence. Compared with heuristic search and a genetic-algorithm baseline, the learned policy reportedly identifies lower-cost routes while scaling from dense central areas to broader metropolitan regions.

3.6. Game theory and mechanism design

Game theory and mechanism design have been applied in MaaS to model strategic interactions among multiple self-interested actors, and to design allocation and pricing rules that remain stable and incentive-compatible after implementation. Unlike single-operator optimization, these models account for platform competition, multi-sided market structures, heterogeneous user groups, and bounded rationality when relevant. The literature can be organized into: (i) Market-structure, matching, and assignment games; (ii) Incentive-compatible auction-based mechanisms; (iii) Evolutionary games for public-private coordination.

Table 9
Overview of data-driven and predictive Machine Learning models in MaaS studies.

Title	Application	Method type	Data / Inputs	Learning Setup	Output	Multi-modal	Real-time
Bayliss et al. (2025)	MaaS multi-objective journey planning, pricing & dispatch	Supervised DL travel-time model & zone search	Graph (non-PT); GTFS (routes, timetables, calendar, fares, shapes); real-time arc travel times; features: O/D lon–lat, rel. to TZ centroids, crow-flight; Solent: ped/bike/road & bus/ferry/train	Supervised regression on sampled OD travel times; back-prop to minimise prediction error	Pareto multimodal journeys (time, cost, CO$_2$, etc.)	✓	✓
Xi et al. (2025c)	Personalized monthly PT usage & fare prediction for MaaS	Multi-task Transformer (PTBformer-MMoE; MFS-ATT, MOD-ATT; DWA)	Queensland go card 01/2021–01/2023; 0.9611B trips; 1.5822M users; 36 monthly time-series features & 28 OD-pair features across 4 modes; passenger-type	12-month sliding-window, multi-task training, Min–Max scaling; 6 experts, 5 softmax gates	individual multi-mode frequency class & expected monthly fare	✓	✗
Duan et al. (2022)	Predicting MaaS use intention by trip purpose	Supervised ML (ANN / MLP classifier)	Online survey of 331 Australians; 33 predictors (socio-economic, travel patterns/options, Covid-19 mode-change, transaction cost, network externalities, institutional factors, environmental concerns)	Two-stage ANN: Stage-1 uses all predictors to rank importance; Stage-2 retrains with top-10 predictors	Adoption probabilities for different trip types; key socio-demographic and travel drivers	✗	✗
Chu and Guo (2023b)	Personalized MaaS journey planning with long-run passenger retention and operator profit fairness.	DRL coupled with an ILP journey planner	Passenger state: dynamic satisfaction & static characteristics, multimodal network attributes and costs with capacity	agent outputs utility weights; passengers accept based on retention dynamics, reward balances operator profits.	Passenger-specific utility weights and optimal journey plan; improved retention and profit	✗	✓
Chu and Guo (2024)	Behaviour-aware MaaS planning/dispatch with PSA attacks	Multi-agent DDPG with spatial discount (MARL)	Simulated MaaS flows on NYC taxi-zone network (63/963) and synthetic 6×6 grid (36/360)	Cooperative model-free MARL with discrete time steps; spatial discount to enhance cooperativeness	System profit and passenger satisfaction under spoofing vs normal users	✗	✓
Yan et al. (2025)	Real-time multi-modal path planning (metro/bus/car-share/walk)	RL: Q_EDQ double Q-learning with annealed exploration	Xi'an MaaS PT network; Amap car-sharing stops; edge inputs: routes, monetary expense, travel time	Q-learning on a multi-modal super-network with random O–D; double-Q with annealed exploration	Low-cost multimodal paths (time, cost, transfers)	✓	✓

Notes: "Multi-agent" covers multi-agent or federated RL settings in which multiple decision-makers or local learners interact. "Multi-modal" means that two or more transport modes are modelled jointly (e.g., bus, rail, car-share, walk), and "Real-time" indicates that the method is designed for online or near-real-time path planning or control. RL: reinforcement learning; DDPG: Deep Deterministic Policy Gradient; GA: genetic algorithm; TF: Transformer; O-D: origin-destination; TZ: traffic zone.

3.6.1. Market-structure, matching, and assignment games

Existing studies have modeled MaaS as a market with multiple competing suppliers and a demand side that responds to prices and bundle attributes. van den Berg et al. (2022) compared alternative MaaS organizational forms (Integrator, Platform, Intermediary) against a free-competition baseline, showing how different power structures and pricing assumptions lead to changes in prices, profits, consumer surplus, and overall welfare. Extending the two-operator setting, McHardy (2024) formulated a market-structure pricing game on a differentiated transport network. They compared free-market operator pricing to various platform regimes (integrator, passive, intermediary, and multi-operator ticket-card models) and showed that as the number of operators or substitutability increases, the welfare ranking can flip: an integrator may curb pro-competitive forces even though platform profit incentives often favor welfare-inferior intermediary structures. For internal allocation challenges (rather than external competition), cooperative game and matching-theoretic approaches are natural. For example, (Pantelidis et al., 2020) formulated MaaS fare splitting and cost sharing as a stable matching (assignment) game, ensuring that no coalition of users and operators can deviate to improve their payoffs. Similarly, Liu and Chow (2024) studied many-to-many assignments in MaaS-like shared ride markets with capacity and subsidy components. Their solution is obtained via an optimization model, but the design criterion is game-theoretic: no user–provider pair would prefer to match outside the platform.

3.6.2. Incentive-compatible auction-based mechanisms

Xi et al. (2023a) proposed an auction-based MaaS mechanism where trip requests are treated as mode-agnostic mobility resources. Users bid according to their WTP and experience-related preferences, and a MaaS regulator allocates these resources to maximize social welfare. The mechanism is incentive-compatible (IC), individually rational (IR), and budget-balanced (BB). The allocation problem is formulated as a MILP and solved via a primal–dual online algorithm. Likewise, Ding et al. (2023) developed an auction mechanism in which travelers reveal their truthful valuations and multidimensional requirements (e.g., time windows and sharing tolerance) for multimodal trips. A VCG-style payment scheme in an offline benchmark guarantees IC and IR, and the authors design online versions of the mechanism with provable competitive ratios for real-time arrivals.

3.6.3. Evolutionary games for public-private coordination

Ye and Zheng (2024) employed a tripartite evolutionary game involving the government, transport service providers (TSPs), and travelers. Each stakeholder population adapts its strategy with bounded rationality, allowing the study to identify how incentives, regulatory intensity, and user responsiveness co-evolve and under what conditions the system converges to a stable MaaS implementation pathway. This evolutionary perspective complements the static Nash and Stackelberg formulations above, and it is especially useful for policy design, phased MaaS roll-outs, and scenarios where regulators aim to steer the ecosystem toward cooperation rather than pure price competition. MaaS is intrinsically multi-actor. Market-structure models focus on strategic pricing and bundle design under competition (van den Berg et al., 2022; McHardy, 2024; Xi et al., 2024a, 2023b). Cooperative and matching-based formulations target self-enforcing allocations within the platform (Pantelidis et al., 2020; Liu and Chow, 2024). Mechanism-design studies develop real-time rules that incentivize truthful reporting while promoting efficiency (Xi et al., 2023a; Ding et al., 2023). Evolutionary games explain how governments, TSPs, and users may gradually align on MaaS adoption (Ye and Zheng, 2024).

4. Methodological Analysis across Key Themes

This section cross-maps the four MaaS research themes (demand, supply, ecosystem, platform/bundle design; Section 2) with six methodological families (Section 3). Beyond identifying prevalent approaches, this mapping (i) explains why specific methods concentrate in particular themes, (ii) clarifies which decision variables and outcomes each family can credibly represent (e.g., welfare-consistent WTP, operational feasibility, strategic equilibria), and (iii) pinpoints recurring methodological mismatches that arise when modeling MaaS as a coupled socio-technical system rather than as separate demand, operations, and governance modules. Tables 11–14 index representative studies by theme and modeling family, and Figure 6 visualizes how detailed techniques flow across themes.

Figure 6 shows a three-level mapping of the methodological landscape: (i) four substantive themes such as demand, supply, ecosystem, platform bundle design, (ii) six modeling families, i.e., discrete choice models (34), optimization models (17), other statistical models (14), simulation models (12), data-driven predictive and machine learning models (7), game theory and mechanism design (8), and detailed techniques within each family, e.g., (i) simulation of MaaS demand, emissions, and accessibility, simulation of MaaS operational performance, multi-scale MaaS simulation platforms, simulation of two-sided market and subscription within optimization models; (ii) strategic and tactical operational decisions; assignment, matching and allocation in MaaS systems; bilevel optimization models in MaaS systems within optimization models; (iii) binary choice models, multinomial choice models, nested logit, mixed Logit, hybrid choice and latent class models , ordered logit models within DCM; (iv) factor analysis and structural equation models, regression and mixed-effects models, integrated simulation and panel-based models within other statistical models; v) deep learning for travel behavior prediction, reinforcement learning for dynamic decision-making within data-driven predictive and machine learning models; vi) market-structure, matching, and assignment games, incentive-compatible auction-based mechanisms, Evolutionary games for public-private coordination within game theory and mechanism design. This mapping reveals a division of modeling aligned with decision horizons: behavioral valuation and heterogeneity are addressed through econometric and attitudinal methods; operational feasibility and network feedback are addressed through simulation and optimization; and

Table 10
Overview of game theory and mechanism design in MaaS studies.

Title	Players	Strategy space	Mechanism / Equilibrium	Payoffs	Stackelberg	Auction	Evolutionary
Xi et al. (2023b)	MaaS regulator; mobility users; delivery users.	Regulator as leader sets surcharge and reward ratio; users as followers choose MaaS bundles.	Bilevel Stackelberg game with two-class bundle-choice user equilibrium under a bilateral surcharge–reward scheme.	Regulator minimizes total equilibrium system cost of mobility and delivery; each user minimizes own travel cost.	✓	×	×
Xi et al. (2023a)	MaaS regulator; MaaS users (travellers).	Regulator decides which MaaS bundles to offer and allocates mobility resources; users accept or reject bundles based on reserve utility.	Auction-based online resource allocation mechanism satisfying IC, IR, BB.	Regulator maximizes social welfare; each user maximizes own utility relative to an outside option.	×	✓	×
Ye and Zheng (2024)	Government; TSPs; travellers.	Government chooses whether to provide policy support; TSPs choose to join MaaS or not; travellers choose to use MaaS or not; strategies evolve in stakeholder populations.	Tripartite evolutionary game with replicator dynamics leading to evolutionary stable strategies (ESS).	Government benefits from improved operational efficiency and reduced emissions; TSPs gain business opportunities and attractiveness; travellers gain more convenient travel.	×	×	✓
van den Berg et al. (2022)	Transport firms; MaaS provider (integrator platform); travellers.	Transport firms and MaaS provider set wholesale and retail prices; travellers choose services across networks under different business models.	Non-cooperative price competition: Bertrand–Nash pricing for integrator and platform models; Stackelberg price game (wholesale–retail) for the intermediary model.	Transport firms and MaaS provider maximize profits; traveller surplus and overall welfare are evaluated and compared across business models.	✓	×	×
McHardy (2024)	Operators (transport providers); MaaS business platform.	Operators choose service prices (and frequencies); platform designs ticketing and multi-operator products across different platform configurations.	Market equilibria under multiple MaaS platform models: free-market, integrator, passive platform, intermediary platform, and multi-operator ticket card (MTC).	Operators maximize profits; platform structure affects consumer surplus and social welfare across platform models.	×	×	×
Ding et al. (2023)	Travellers; transport service providers (TSPs); MaaS operator.	Travellers submit multidimensional trip demands; MaaS operator allocates mobility resources and sets prices; TSPs provide resources to platform.	VCG-based auction for mobility resource allocation and pricing, designed to satisfy IR, IC, and non-negative prices.	TSPs obtain non-negative profits from participating; MaaS operator maximizes its platform utility and system efficiency; travellers obtain non-negative utility.	×	✓	×

ecosystem performance is addressed through strategic interaction and incentive-compatible design.

Demand-side studies predominantly employed discrete choice models (DCMs) and attitudinal/segmentation techniques to identify preferences, WTP, and heterogeneity in MaaS adoption and bundle valuation (e.g., Matyas and Kamargianni, 2019; Ho et al., 2021a; Hensher et al., 2021; Polydoropoulou et al., 2020). By contrast, supply-side studies were prescriptive: simulation and optimization dominated due to operational questions (fleet sizing, routing, dispatch, service design) that required feasibility constraints and network feedback (Becker et al., 2020; Labee et al., 2022; Cheng et al., 2022; Frank et al., 2024). Ecosystem studies further emphasized strategic interaction: game theory and mechanism design became central since MaaS performance and welfare hinged on incentives, market structure, and data-sharing rules rather than a single actor's decisions (van den Berg et al., 2022; McHardy, 2024; Xi et al., 2024b; Ding et al., 2023). MaaS platform and bundle design lie at the intersection of these layers.

A persistent cross-layer gap stemmed from data and calibration frictions. The reliance on SP-based DCMs reflected limited revealed-preference (RP) and operational data; conversely, many operations and ecosystem models used stylized users or synthetic demand functions because empirically grounded preference structures were difficult to embed in network- and rule-constrained decision models. This mismatch between behaviorally rich valuation models and operationally detailed control has motivated calls for coupling architectures (e.g., embedding estimated utilities into simulation and optimization, or using decision-centric learning to calibrate demand response), which remain relatively uncommon.

Data-driven prediction and reinforcement learning (RL) appeared across themes but were less prevalent than established methods in Econometrics or Operations Research. Where applied, these approaches typically focused on prediction (e.g., adoption or usage forecasting) or sequential control (e.g., dispatch, routing, recommendations) rather than end-to-end MaaS decision support that concurrently learns preferences, optimizes operations, and respects governance constraints (Liu et al., 2024b; Chu and Guo, 2023a; Yan et al.,

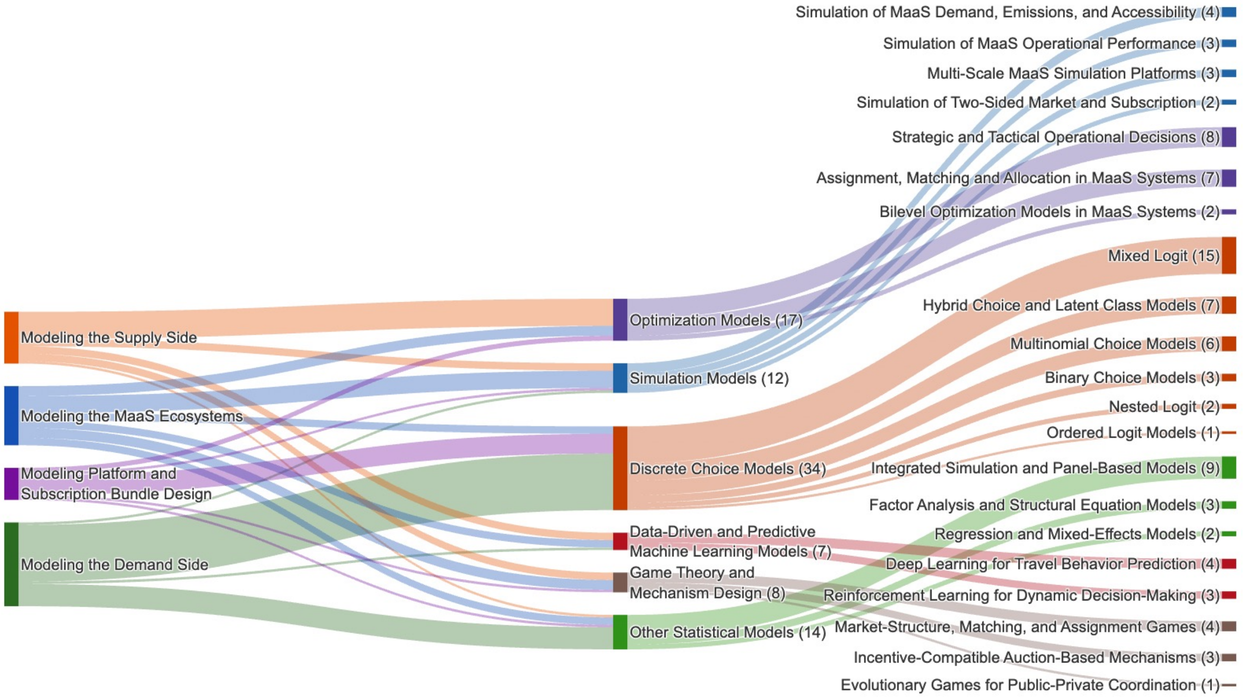

Figure 6: Classification of key research themes and modeling methods in MaaS literature.

2025; Xi et al., 2025c).

4.1. Methodological modeling for the demand side of MaaS studies

Demand-side modeling was primarily behavioral and valuation-oriented; hence, it relied heavily on discrete choice and related econometric methods (Table 11). The main goal was to quantify how travelers trade off bundle attributes (price, included modes, usage caps, reliability, convenience) and how these valuations vary across individuals and contexts. Mixed logit and other random-utility models formed the empirical backbone, enabling WTP inference and credible substitution patterns under counterfactual MaaS designs (e.g., Matyas and Kamargianni, 2019; Ho et al., 2021a; Hensher et al., 2021; Polydoropoulou et al., 2020; Wang et al., 2024). Many MaaS adoption questions were heterogeneity-dominated: average WTP was less informative than identifying segments with fundamentally different propensities to subscribe, share, or abandon private car use, reinforcing the use of random-parameter and segment-specific models.

A second demand-side pillar introduced latent constructs such as attitudes, norms, perceived risk, technology affinity, and environmental concern that mediate MaaS uptake. Hybrid choice (ICLV) models extend utility functions to include psychological and lifestyle factors, improving interpretability and enabling policy-relevant segmentation (e.g., Vij et al., 2020; Kim et al., 2021b; Kim and Rasouli, 2022; Liu et al., 2024a). Complementary statistical approaches, such as factor analysis/SEM, latent class/mixture models, clustering, and composite indicator profiles, have profiled readiness and early-adopter archetypes, especially when detailed behavioral data were limited (Zijlstra et al., 2020; Alonso-González et al., 2020; Lopez-Carreiro et al., 2024; Alyavina et al., 2024). Conceptually, these methods operate upstream of DCMs: they clarify who might adopt and why, whereas DCMs quantify which design levers (prices, caps, included modes) shift adoption probabilities.

Simulation and machine learning became relevant when demand was viewed as dynamic, context-dependent, or network-embedded. Agent- and activity-based simulations captured feedback effects from congestion and service design, allowing demand responses to emerge through interaction and adaptation (Djavadian and Chow, 2017; Zhou et al., 2023). Supervised learning and explainable ML were applied to predict adoption/usage and to capture nonlinear interactions among sociodemographics, attitudes, and bun-

Table 11
Methodological modeling for the demand side in MaaS literature.

Modeling approach	References
Simulation models	Zhou et al. (2023)
Optimization models	−−
Discrete choice models	Ho et al. (2018, 2021a, 2020); Ho (2022); Hensher et al. (2021); Matyas and Kamargianni (2019); Guidon et al. (2020); Polydoropoulou et al. (2020); Vij et al. (2020); Wang et al. (2024); Zhao et al. (2025); Militão et al. (2025); Bushell et al. (2022); Li et al. (2023); Krauss et al. (2022a); Yao et al. (2025); Kim et al. (2021b); Kim and Rasouli (2022); Kriswardhana and Esztergár-Kiss (2025); Chen et al. (2023); Bahamonde-Birke et al. (2023); Liu et al. (2023, 2024a); Coppola et al. (2025); Soria et al. (2023); Tsouros et al. (2021); Matowicki et al. (2024); Kim et al. (2021a)
Other statistical models	Ho (2022); Alonso-González et al. (2020); Zijlstra et al. (2020); van't Veer et al. (2023); Lopez-Carreiro et al. (2021, 2024); Chen and He (2023); Alyavina et al. (2024); Hoerler et al. (2020)
Data-driven and predictive machine learning models	Duan et al. (2022)
Game theory and mechanism design	Xi et al. (2023a)

dle features (Duan et al., 2022; Liu et al., 2024b; Xi et al., 2025c). A key opportunity lies in combining these approaches: ML can improve predictive accuracy and leverage high-dimensional signals, while choice models preserve behavioral structure and welfare consistency. However, most studies deployed these toolkits in parallel rather than as integrated, decision-centric pipelines.

4.2. Methodological modeling for the supply side of MaaS studies

Supply-side MaaS studies are inherently prescriptive: they ask how integrated services should be configured and controlled under capacity, cost, and operational constraints, and how these choices propagate to network performance, emissions, and distributional outcomes. Accordingly, simulation and optimization dominate this theme (Table 12; Figure 6).

Simulation serves as a virtual laboratory for evaluating MaaS operations under realistic multimodal interactions. Agent-based city-scale experiments quantify system-wide impacts (congestion, mode shift, welfare) under alternative integration scenarios (Becker et al., 2020; Labee et al., 2022), while multi-agent simulations reveal equity and spatial justice implications of various fleet and service configurations (Qiao and Yeh, 2023; El-Agroudy et al., 2022; Bürstlein et al., 2021; Camargo et al., 2021). The key advantage is endogenous feedback: simulation captures congestion and interaction effects that can invalidate static evaluations of MaaS pricing or service quality. Optimization models formalize strategic and tactical supply decisions such as fleet sizing, service zoning, tariff setting, capacity allocation, and network-aware service design, often balancing cost, revenue, and performance metrics (Cheng et al., 2022; Frank et al., 2024; Klopfer et al., 2023; Yao and Zhang, 2024; Liu and Ouyang, 2021; Lee et al., 2022; Rasulkhani and Chow, 2019; Pandey et al., 2019). For decision support, optimization is the primary vehicle for translating MaaS goals into implementable policies. A main limitation is demand representation: many optimization models use elasticities, WTP, or participation functions that are simplified relative to the behavioral richness found in demand-side studies.

A smaller but growing strand introduces learning-based control for real-time routing, dispatch, and recommendation. RL formulations treat MaaS operations as sequential decision problems on integrated networks (Yan et al., 2025; Chu and Guo, 2023a), whereas dynamic discrete-choice and hyperpath frameworks offer interpretable alternatives for whole-day journey planning (Song et al., 2021). These approaches are most compelling when MaaS is modeled as a closed-loop system: platform actions (pricing, dispatch, recommendations) alter perceived service quality (e.g., wait times, reliability), which in turn reshape demand and downstream outcomes. Auction and allocation mechanisms demonstrate how operational control can incorporate market-design constraints such as incentive compatibility and individual rationality (Xi et al., 2023a). This is particularly relevant when multiple operators contribute capacity and data, and operational decisions cannot be centrally enforced without aligned incentives.

Overall, the supply-side methodological frontier has shifted from stand-alone simulation or deterministic optimization toward integrated pipelines that combine prediction, feasibility-aware optimization, and adaptive control under uncertainty (Liu et al., 2024b; Xi et al., 2025c; Bayliss et al., 2025).

Table 12
Methodological modeling for the supply side in MaaS literature.

Modeling approach	References
Simulation models	Becker et al. (2020); El-Agroudy et al. (2022); Bürstlein et al. (2021); Camargo et al. (2021)
Optimization models	Yao and Zhang (2024); Xi et al. (2023a); Cheng et al. (2022); Klopfer et al. (2023); Song et al. (2021); Nguyen-Phuoc et al. (2023); Liu and Ouyang (2021); Lee et al. (2022); Rasulkhani and Chow (2019); Pandey et al. (2019); Camargo et al. (2021); Bayliss et al. (2025)
Discrete choice models	−−
Other statistical models	Dzisi et al. (2023)
Data-driven and predictive machine learning models	Liu et al. (2024b); Yan et al. (2025); Xi et al. (2025c); Bayliss et al. (2025)
Game theory and mechanism design	Yao and Zhang (2024); Rasulkhani and Chow (2019); Ye and Zheng (2024); Xi et al. (2024a)

Table 13
Methodological modeling for the MaaS ecosystems.

Modeling approach	References
Simulation models	Franco et al. (2020); Qiao and Yeh (2023); Labee et al. (2022); Djavadian and Chow (2017); Kraus et al. (2023); Nayeem et al. (2024); Oh et al. (2020)
Optimization models	Xi et al. (2024b); Frank et al. (2024); Klopfer et al. (2023); Liu and Chow (2024); Xi et al. (2023b)
Discrete choice models	Kraus et al. (2023); Wong and Hensher (2021); Ren et al. (2024); Xie et al. (2019)
Other statistical models	Bruzzone et al. (2025); Basu and Ferreira (2021)
Data-driven and predictive machine learning models	Chu and Guo (2023a,b, 2024)
Game theory and mechanism design	Xi et al. (2024b); van den Berg et al. (2022); Pantelidis et al. (2020); McHardy (2024); Pan and Sun (2024)

4.3. Methodological modeling for MaaS ecosystems

Ecosystem-level modeling treats MaaS as a multi-actor market with explicit governance structures. Key elements are not only trips and fleets, but also contracts, data sharing, interoperability, platform roles, and regulatory interventions. As a result, the methodological center of gravity shifts toward game theory and mechanism design (Table 13), supplemented by simulation and optimization when ecosystem rules must be stress-tested under network constraints and heterogeneous agents.

Non-cooperative models examine platform competition, pricing, and welfare under different organizational structures (e.g., integrator vs. intermediary) and strategic behaviors by platforms and transport providers (van den Berg et al., 2022; McHardy, 2024; Xi et al., 2024b). These models are essential because key outcomes (prices, service quality, investment incentives) depend on market structure and cannot be credibly evaluated under the assumption of a benevolent planner. Cooperative game and matching formulations address how users and operators can be allocated, subsidized, or compensated in stable, self-enforcing ways when participation is voluntary and surplus distribution matters (Pantelidis et al., 2020; Liu and Chow, 2024). These approaches are particularly relevant for governance questions, e.g., who joins MaaS and on what terms, and for diagnosing integration failure modes, such as when no individually rational, stable agreements exist.

Mechanism design for incentive-compatible platform rules. Mechanism-design studies translate ecosystem goals into auction and market rules that ensure incentive compatibility, individual rationality, and desirable budget properties for allocation and pricing (Xi et al., 2023a; Ding et al., 2023). This work converts normative objectives (efficiency, fairness, participation) into implementable platform rules, mainly when MaaS depends on decentralized contributions from multiple providers.

Simulation and optimization to connect governance with operational feasibility. Ecosystem modeling employs simulation to capture emergent dynamics, adoption feedback, and day-to-day adjustments in two-sided markets (Djavadian and Chow, 2017; Oh et al., 2020; Nayeem et al., 2024). Optimization methods appear when governance choices interact with operations and sustainability constraints (e.g., system design, emissions, resource allocation across partners) (Klopfer et al., 2023; Frank et al., 2024; Xi et al., 2023b). One limitation is empirical grounding: ecosystem models rely on simplified demand and cost assumptions, which limit their policy relevance when distributional impacts depend on heterogeneity.

Table 14
Methodological modeling for MaaS platform and subscription bundle design.

Modeling approach	References
Simulation models	Reck and Axhausen (2020)
Optimization models	Zhou et al. (2024); Hörcher and Graham (2020); Xi et al. (2024c,a)
Discrete choice models	Ho et al. (2021a); Ho (2022); Hensher et al. (2021); Guidon et al. (2020); Polydoropoulou et al. (2020); Grau et al. (2025); Wang et al. (2024); Zhao et al. (2025); Militão et al. (2025); Caiati et al. (2020); Bahamonde-Birke et al. (2023); Coppola et al. (2025); Hörcher and Graham (2020)
Other statistical models	Ho (2022); Kriswardhana and Esztergár-Kiss (2023)
Data-driven and predictive machine learning models	Liu et al. (2024b); Xi et al. (2025c)
Game theory and mechanism design	Ding et al. (2023)

4.4. Methodological modeling for MaaS platform and subscription bundle design

Platform and subscription bundle design sat at the interface of demand, supply, and ecosystem perspectives and therefore exhibited the most hybrid methodological profile (Table 14). A MaaS platform designs a menu of bundles (attributes, caps, included modes), prices, and rules that are attractive to heterogeneous users, feasible under supply constraints, and sustainable under multi-actor governance and competition.

Behavioral valuation for plan design. Platform and subscription bundle design sits at the interface of demand, supply, and ecosystem perspectives and thus exhibits the most hybrid methodological profile (Table 14). The core design problem is inherently decision-centric: a platform must choose a menu of plans (attributes, caps, included modes), prices, and rules that appeal to heterogeneous users, are feasible under supply constraints, and are sustainable under multi-actor governance and competition.

Plan valuation typically relies on stated-choice experiments combined with mixed logit or hybrid choice models to quantify WTP for bundle attributes and segment-specific adoption responses (Guidon et al., 2020; Polydoropoulou et al., 2020; Caiati et al., 2020; Wang et al., 2024; Ho et al., 2021a). These models provide fundamental design inputs: segment-level adoption probabilities, substitution between plans and pay-as-you-go, and welfare-consistent valuations of reliability and convenience.

Behavioral primitives feed into prescriptive layers such as reliability-oriented fare design (Zhou et al., 2024), pricing and ownership/subscription models with long-run congestion feedback (Hörcher and Graham, 2020), or corporate MaaS and fleet/bundle optimization (Frank et al., 2024). This literature shows that bundle design is not mere price discrimination: service quality and reliability constraints shape the feasible set of offers, and long-run effects (e.g., changes in car ownership) can dominate welfare outcomes.

Emerging work couples prediction with decision-making via "predict–then–optimize" pipelines, where ML-based WTP or usage forecasts drive assortment, resource allocation, or pricing decisions under constraints (Xi et al., 2024c; Liu et al., 2024b). This represents a shift from evaluating pre-defined bundles to algorithmically designing bundles. A key challenge is maintaining behavioral realism and interpretability when high-capacity predictors are embedded in optimization loops.

When bundle design is influenced by platform competition or public regulation, game-theoretic and mechanism-design considerations become part of the design process rather than an external context (Xi et al., 2024b; van den Berg et al., 2022; Ding et al., 2023). In such cases, the optimal bundle is not simply profit- or adoption-maximizing under fixed demand, but one that remains viable under strategic responses by operators, competitors, and regulators.

The MaaS platform and bundle literature suggest a key frontier in end-to-end integration: linking preference learning, operational feasibility, and governance constraints within unified decision frameworks.

Across themes, no single methodological family can credibly span the entire MaaS stack in isolation. A pragmatic interpretation of the literature is to view MaaS modeling as a modular architecture in which: (i) DCM/ICLV and segmentation techniques recover behavioral primitives (WTP, adoption, substitution) (Polydoropoulou et al., 2020; Vij et al., 2020); (ii) simulation and optimization translate these primitives into feasible operational policies with network feedback (Becker et al., 2020; Cheng et al., 2022); and (iii) game theory and mechanism design impose governance, competition, and incentive constraints to determine whether integration is implementable and welfare-improving (van den Berg et al., 2022; Xi et al., 2023a, 2024b; Ding et al., 2023). Learning-based methods (prediction and RL) are most valuable when embedded within such decision-centric loops rather than used as stand-alone predictors (Liu et al., 2024b; Chu and Guo, 2023a; Yan et al., 2025). Despite increasing sophistication, cross-layer coupling remains uneven: behavioral richness often fails to propagate into operational control, and ecosystem models frequently rely on stylized demand, thereby motivating the cross-cutting research gaps discussed in Section 5 and informing the future agenda in Section 6.

5. Research Gaps in MaaS Modeling

After a decade of rapid growth, MaaS modeling now spans demand, operations, and ecosystem governance. However, the literature remains methodologically fragmented and increasingly misaligned with emerging real-world MaaS developments. Beyond the original platform-centric vision, MaaS is evolving to encompass multi-platform competition, cross-operator collaboration (Collaboration-as-a-Service, CaaS), cross-sector integration (Mobility-as-a-Feature, MaaF), electrified service portfolios (eMaaS/ECSaaS), and private/community asset integration (PAaaS/PCaaS and community car clubs, CCC). These developments are often accompanied by policy- and KPI-driven governance frameworks.

These shifts expose a persistent fault line: the coupling between behaviorally rich demand models and operationally detailed platform models remains weak, and market structure and governance are rarely endogenized. As a result, many studies have either (i) explained adoption and WTP with limited operational realism and few institutional constraints, or (ii) optimized fleets, pricing, and allocations using simplified representations of heterogeneous user behavior, trust, and life-cycle dynamics. The six gap areas outlined below summarize these limitations and motivate the 20 research directions proposed in Section 6.

Gap 1: Limited RP grounding and operational evidence for MaaS/MaaF ecosystems. Despite significant research, reliance on stated-preference (SP) surveys and synthetic networks remains pervasive, with limited revealed-preference (RP) and operational data available to calibrate and validate MaaS models. Most adoption and bundle-choice studies use hypothetical menus and pricing in conjoint/SP experiments (Ho et al., 2018; Matyas and Kamargianni, 2019; Guidon et al., 2020; Polydoropoulou et al., 2020; Vij et al., 2020; Kraus et al., 2023). SP data have been indispensable in early markets, but can overstate responsiveness when real-world frictions dominate (payment salience, reliability, app usability, customer support, crowding, habitual routines). RP evidence from MaaS pilots remains scarce and geographically concentrated (Hensher et al., 2021; Ho, 2022). Even when available, data access constraints hinder reproducibility, benchmarking, and cross-city validation. A similar empirical deficit exists on the supply and ecosystem side: many optimization, simulation, and game-theoretic models rely on stylized demand or synthetic travel patterns (Pantelidis et al., 2020; Liu and Chow, 2024), limiting confidence that predicted equilibria, auction outcomes, or pricing policies will hold under real transaction logs, service disruptions, and institutional constraints. These data constraints are reinforced by governance frictions, privacy regulations, commercial sensitivities, and weak incentives to share data across TSPs, platforms, and public agencies, challenges amplified under MaaF, where non-mobility service providers (NMSPs) also hold relevant data and shape incentives. Although privacy-preserving learning and federated approaches have been proposed (Chu and Guo, 2023b), no widely adopted data-sharing standard meets legal compliance, auditability, and cross-context comparability. Moreover, selection biases (e.g., income, digital skills, accessibility) remain largely uncorrected despite evidence of their importance for MaaS readiness (Lopez-Carreiro et al., 2024; Alyavina et al., 2024; Zijlstra et al., 2020). This gap motivates RD 1 (RP–SP integration and external validity) and RD 5 (data sharing, privacy, and federated learning); addressing it is critical for the credibility of governance- and KPI-driven frameworks (RD 11).

Gap 2: Static and incomplete user modeling under platform evolution, cross-sector incentives, and life-cycle dynamics. Even behaviorally rich demand models have often been treated as static snapshots. Discrete choice, hybrid (ICLV), and segmentation models capture heterogeneity in WTP, latent attitudes, and risk perceptions for MaaS bundles (Ho et al., 2018; Polydoropoulou et al., 2020; Kim and Rasouli, 2022; Wang et al., 2024; Liu et al., 2024a; Vij et al., 2020). However, segments are typically fixed (e.g., “early adopters” vs. “skeptics” (Alonso-González et al., 2020; Zijlstra et al., 2020; Yao et al., 2025)) with limited representation of how users transition as they gain experience, as competing offers evolve, or as reliability and perceived fairness change. Similarly, MaaS products are often modeled as stand-alone decisions rather than as parts of a household’s broader mobility portfolio. Few models jointly represent

MaaS subscriptions with car ownership, leasing, or other mobility contracts, or allow multi-homing across competing MaaS providers (Hörcher and Graham, 2020; Caiati et al., 2020; Bahamonde-Birke et al., 2023). These omissions limit analysis of retention, churn, and switching, factors that can drive long-run impacts and business viability. This limitation is even more consequential under MaaF and corporate/community variants (e.g., employer-led incentives, C-MaaS, or community car clubs (CCC)), where adoption and usage are shaped by cross-sector rewards, trust, and institutional affiliation rather than mobility attributes alone.

Personalization and dynamic bundling remain underdeveloped relative to actual platform capabilities. Most bundle-design studies evaluate only a few predefined menus via SP experiments (Guidon et al., 2020; Caiati et al., 2020), rather than learning individual preferences and adapting offerings over time based on usage and contextual factors, e.g., seasonality, disruptions, special events. Advanced ML appears in isolated work on adoption/usage prediction (Duan et al., 2022; Liu et al., 2024b; Xi et al., 2025c) and explainability (Liu et al., 2024b), but ML is rarely integrated into behaviorally consistent choice frameworks or decision-centric design pipelines. Empirical trials also indicate strong habit persistence and "menu rejection": many users will not pay for bundles containing options they do not anticipate using. This suggests a need to model choice overload and to shift from generic bundles toward individualized, usage-adaptive plans aligned with stable routines and constraints (Ho et al., 2021b). This gap motivates RD 2–RD 4 (hybrid choice–ML integration, dynamic learning, adaptive bundling), RD 16 (loyalty/churn and life-cycle modeling), and RD 17 (context-sensitive transferability and inclusion).

Gap 3: Weak coupling between demand, operations, and experienced service quality. A central limitation is the weak coupling between behavioral demand models and operational (simulation/optimization) models of MaaS supply, pricing, and reliability. On the demand side, discrete choice and hybrid choice models provide interpretable trade-offs and heterogeneous WTP estimates (Ho et al., 2018; Polydoropoulou et al., 2020; Kim and Rasouli, 2022; Vij et al., 2020). On the supply side, MaaS operations are modeled via optimization, queueing, and agent-based simulation to design fleets, match requests, and schedule services subject to capacity and cost constraints (Becker et al., 2020; Frank et al., 2024; Cheng et al., 2022; Camargo et al., 2021; Labee et al., 2022). Yet behavioral richness rarely propagates into the operational layer: many operational assessments rely on generalized costs, representative users, or static elasticities instead of empirically calibrated discrete-choice or ICLV utilities. Consequently, feedback among dynamic pricing, experienced service quality (wait times, crowding, missed connections), and heterogeneous preferences is only weakly represented. The same disconnect appears in ecosystem-level models. Game-theoretic and mechanism-design formulations (including multi-leader multi-follower competition and auction-based allocation) (van den Berg et al., 2022; Xi et al., 2023a, 2024b; Pantelidis et al., 2020; Liu and Chow, 2024) often employ stylized demand functions, which limit inference about welfare and equity when preferences are heterogeneous and context-dependent. Only a few studies explicitly couple demand and supply, e.g., by linking subscription adoption, car ownership, and mode choice decisions (Hörcher and Graham, 2020; Hensher et al., 2021), embedding discrete choice in whole-day dynamic decision-making (Song et al., 2021), or representing day-to-day learning in a two-sided market (Djavadian and Chow, 2017). Emerging approaches such as RL controllers that update passenger utilities (Chu and Guo, 2023a) and bilevel predict–then–optimize" subscription design (Xi et al., 2024c) are promising but remain rare. Evidence from deployments indicates that price discounts alone rarely compensate for weak door-to-door convenience; thus, models should treat experienced reliability, platform effort" frictions (setup, refunds, customer support), and perceived hassle as co-determinants of sustained behavior change alongside price. In-app feedback and outcome-based rewards (e.g., verified emissions savings, tradable "green credits") are also rarely included in closed-loop models, despite their potential to reinforce repeated use. This gap motivates RD 6 (closed-loop demand–supply coupling), RD 7 (behavioral realism for ecosystem actors), and RD 8 (joint pricing-operations-reliability optimization). It becomes even more critical as new asset types (ECSaaS, PAaaS/PCaaS, CCC) introduce additional operational constraints and behavioral frictions.

Gap 4: Underdeveloped uncertainty, adaptation, safety, and reliability modeling in next-generation MaaS. MaaS systems face volatility (demand surges, congestion, incidents, strikes, extreme weather) and behavioral adaptation (learning, inertia, trust dynamics, gaming, strategic responses). Yet many demand and operational models are static or scenario-based. Demand models typically represent preferences at a single point in time; only a few incorporate longitudinal evidence to capture habit formation, churn, or attitudinal change (Hensher et al., 2021; Ho, 2022). Some demand models include risk attitudes in utility functions (Liu et al., 2024a), but the evolution of perceived uncertainty under changing conditions (e.g., reliability guarantees, price volatility, regulatory interventions) is rarely modeled endogenously. Latent constructs like trust and perceived fairness appear in hybrid models (Kim et al., 2021b; Kim and Rasouli, 2022), but they typically do not update through experience in a closed-loop fashion. On the supply side, deterministic or myopic approaches dominate dispatch, matching, and rebalancing; robust/stochastic optimization and disruption stress-testing are rare, and RL controllers are often trained in simplified settings with limited attention to resilience, equity, or safety constraints (Chu and Guo, 2023a; Yan et al., 2025). This gap will widen as MaaS integrates automation, electrification, and new service layers: automated fleets require explicit safety envelopes and fail-safes (Pinto et al., 2020), electrified operations require reliable charging and energy management, and novel services (e.g., drone logistics, urban air mobility) introduce weather, noise, and regulatory uncertainties. Overall, reliability is integral to MaaS quality: users judge platforms not only by expected time/cost, but also by variability, missed connections, cancellation risk, and the credibility of guarantees. This gap motivates RD 3 (dynamic learning-based user modeling) and RD 9 (robust/adaptive operational control), and underscores the need for uncertainty-aware extensions in RD 18–RD 20 (automation, air mobility/logistics, grid-interactive electrification).

Gap 5: Disconnection between market structure, governance, and operational feasibility under multi-stakeholder trade-offs. Many MaaS studies treat governance and market structure as exogenous, rather than modeling them endogenously. In reality, MaaS may be delivered by competing platforms, public–private partnerships, regulated integrators, or consortium-based alliances (as in CaaS), with strategic interactions shaped by data-sharing rules, interoperability, subsidies, consumer protections, and competition policy. Yet much of the modeling literature assumes a single platform, simplifying competition, multi-homing, and network effects. Even when competition is modeled (Xi et al., 2024b) or allocation mechanisms are proposed (Xi et al., 2023a), behavioral realism and operational detail are often lacking, limiting policy relevance. Another governance gap is the rarity of explicit multi-objective formulations to quantify stakeholder trade-offs (profit, welfare, equity, emissions, coverage). Equity and accessibility are usually assessed ex post (e.g., spatial justice indicators (Qiao and Yeh, 2023) or income-stratified adoption (Lopez-Carreiro et al., 2024; Alyavina et al., 2024)) rather than embedded as constraints or objectives in optimization, market design, or platform control. Sustainability is likewise addressed via scenario comparisons (Labee et al., 2022) or isolated corporate MaaS models (Klopfer et al., 2023), instead of being consistently linked to behavioral responses, platform incentives, and regulatory rules. These limitations become more pronounced under MaaF and KPI-driven contracting, where non-mobility service providers (NMSPs) participate and authorities tie rewards to societal KPIs. Another blind spot is the conflation of funding for platform development with funding for user-facing incentives: behavioral change depends primarily on the latter (discounts, credits, reward schemes), with direct implications for commercial viability and the public sector's role. Similarly, real-world deployments face "ego-system" frictions (branding concerns, fear of diluting incumbent markets, reluctance to offer attractive cross-operator deals) that are seldom modeled in governance and market-structure frameworks. This gap motivates RD 10–RD 13 (competition/cooperation, governance and incentive design, multi-objective optimization, multi-actor simulation) and connects directly to RD 14 (equity-by-design, sustainability-constrained optimization).

Gap 6: Limited system-of-systems modeling for long-run impacts, transferability, and cross-sector constraints. MaaS modeling still lacks a system-of-systems perspective connecting short-run platform operations to long-run urban outcomes and cross-sector constraints. Most models focus on near-term adoption, mode shift, or operational performance, with limited representation of longer-term feedback on car ownership, transit funding, land use, or housing. Some studies link MaaS subscriptions to car ownership and travel outcomes (Hörcher and Graham, 2020; Hensher et al., 2021), and others quantify life-cycle impacts (Klopfer et al., 2023), but comprehensive multi-period frameworks spanning decades are rare. This is problematic because MaaS can create path dependencies: for example, diverting riders from transit can reduce transit fare revenue and service frequency, thereby reshaping MaaS competitiveness and equity outcomes. Scalability and generalizability issues compound the problem. Large-scale simulations (Becker et al., 2020;

Labee et al., 2022; Nguyen-Phuoc et al., 2023; Oh et al., 2020) often require bespoke implementations, and parameter transferability across cities and populations remains under-tested (Ho et al., 2018; Zijlstra et al., 2020; Kraus et al., 2023; Coppola et al., 2025). Moreover, many models treat infrastructure and regulatory constraints (curb space, transit capacity, parking, fare rules) as exogenous (Zhou et al., 2024), risking overly optimistic scaling scenarios. MaaS is increasingly intertwined with adjacent systems that are often omitted or simplified: EV charging and grid capacity, ICT reliability and cybersecurity, corporate mobility management, automated fleets, and integrated passenger–delivery ecosystems (Frank et al., 2024; Klopfer et al., 2023; Basu and Ferreira, 2021; Xi et al., 2023b). Without explicit coupling, models can miss binding constraints and unintended spillovers. This gap motivates RD 15–RD 17 (long-run feedbacks, life-cycle dynamics, contextual transferability) and sets the stage for RD 18–RD 20 (coupling with automation, air mobility/logistics, and grid-interactive electrification, including eMaaS and ECSaaS).

6. Future Research Agenda for MaaS Modeling

Building on the six research gaps identified in Section 5, we propose 20 research directions (RDs), grouped into five thematic clusters to provide an actionable roadmap: (i) data-driven behavioral modeling (RD 1–RD 5, Section 6.1); (ii) demand–supply integration and operations (RD 6–RD 9, Section 6.2); (iii) multi-sector partnerships and Mobility as a Feature (RD 10–RD 13, Section 6.3); (iv) planning, equity, and long-term impacts (RD 14–RD 17, Section 6.4); and (v) emerging technologies for next-generation MaaS (RD 18–RD 20, Section 6.5).

6.1. Data-driven behavioral modeling

RD 1: From SP to RP-grounded MaaS behavior models. Most MaaS demand studies relied on stated-preference (SP) surveys due to limited access to operational data, raising concerns about external validity. A key priority is to anchor MaaS adoption, plan choice, and willingness-to-pay (WTP) in revealed preference (RP) evidence from pilots and deployments. This includes joint RP–SP estimation and experimental designs explicitly targeting known biases (e.g., uncertainty, habit, disruption exposure) (Ho et al., 2021a; Ho, 2022; Hensher et al., 2021; Kriswardhana and Esztergár-Kiss, 2025). From a modeling standpoint, this implies (i) fusing RP and SP data with appropriate scale parameters and measurement-error corrections; (ii) incorporating state dependence or inertia (e.g., dynamic discrete choice or hidden-state models) to capture habitual behavior; and (iii) using reliability-aware utility specifications that treat on-time performance and disruption risk as core attributes. MaaS uptake may also hinge on perceived "effort" and seamlessness in assembling and executing multimodal trips. Therefore, future RP/SP instruments and behavioral models should estimate effort-related attributes (and heterogeneity in effort tolerance) rather than assuming platforms are frictionless (Hensher and Xi, 2022).

RD 2: Choice-based optimization models for user-centric MaaS. MaaS decisions span multiple horizons (plan adoption and subscription, then trip-level mode and route choice), yet many studies model these layers in isolation. Discrete choice models (DCMs) provide behavioral structure and welfare-consistent trade-offs, whereas machine learning (ML) captures nonlinearities and high-dimensional interactions at scale Duan et al. (2022); Liu et al. (2024b); Xi et al. (2025c). A key direction is to combine these strengths via (i) structure-guided ML (neural architectures that preserve utility maximization, substitution patterns, and feasibility constraints) and (ii) hybrid choice–ML pipelines where ML learns latent tastes or contexts feeding into logit/nested-logit components. Beyond prediction, MaaS design is decision-centric: models should connect estimated demand to pricing, bundling, and operational decisions using predict-then-optimize or equilibrium-based formulations that couple demand modules with platform optimization (Xi et al., 2024c; Yao and Zhang, 2024). The core challenge is to preserve behavioral consistency while maintaining computational tractability as demand and platform decisions co-evolve.

RD 3: Real-time, context-aware, and adaptive user modeling. MaaS platforms generate continuous data streams that enable updating of preferences within-day and across days. Future work should shift from static, one-shot choice models to dynamic user models that capture learning from experience, context dependence under disruptions, and evolving preferences in response to realized wait times, reliability, and crowding. Foundations exist in agent-based day-to-day learning models (Djavadian and Chow, 2017) and reinforcement learning approaches to adaptive decision-making. For MaaS-specific modeling, priorities include (i) capturing habit formation, loyalty, and preference drift; (ii) incorporating latent-variable dynamics in hybrid choice models to represent attitudes that evolve with experience; and (iii) relaxing static equilibrium assumptions via evolutionary or learning-based formulations in which users, operators, and regulators co-adapt (e.g., tripartite evolutionary games) (Kim and Rasouli, 2022; Kriswardhana and Esztergár-Kiss, 2025; Ye and Zheng, 2024). Such dynamic models are essential for forecasting retention, demand volatility, and stable personalization under feedback effects.

RD 4: Personalized and adaptive MaaS bundle recommendation. Bundling is central to MaaS, yet bundle design remains poorly understood because evidence largely comes from predefined menus tested in SP surveys (Caiati et al., 2020; Matyas and Kamargianni, 2019) or limited pilots (Ho, 2022). A key barrier is that travelers may reject bundles that include modes they rarely use; thus, personalization is essential only when longitudinal usage data allow the learning of stable routines, constraints, and substitution patterns. A priority is personalized, adaptive bundling that learns heterogeneous mobility portfolios from usage data and updates bundle menus and prices over time (reflecting seasonality, events, and persistent shifts in behavior). This requires models that couple (i) plan-choice or adoption modules (capturing substitution between subscription plans and pay-as-you-go options) with (ii) optimization routines that select bundle attributes and prices under capacity, equity, and incentive-compatibility constraints, while accounting for strategic user responses. From a MaaF perspective (Hensher and Hietanen, 2023), bundles may extend beyond mobility-only packages toward cross-sector, multi-service offerings where non-mobility service providers (NMSPs) shape travel behavior via rewards. Recommendation models should therefore represent multi-category preferences and quantify both the behavioral impacts and the business case for incentive provision by NMSPs (Hensher et al., 2024).

RD 5: Data sharing, privacy, and federated learning. MaaS modeling relies on sensitive, proprietary data (user trajectories, preferences, fleet states, network performance), and fragmented ownership of these data has hindered calibration and validation. Privacy-preserving approaches, including federated learning, can enable joint model training without centralizing raw data (Chu and Guo, 2023b). For MaaS, this motivates modeling architectures that explicitly account for (i) heterogeneous data distributions across partners and their implications for convergence; (ii) interoperable data schemas and APIs for near-real-time exchange; and (iii) governance structures defining data access rights, auditing, and accountability. Data sharing itself should be modeled as endogenous: game theory van den Berg et al. (2022); McHardy (2024); Xi et al. (2024a) and mechanism design Xi et al. (2023a); Ding et al. (2023) can inform incentive-compatible sharing protocols and "human-in-the-loop" governance that aligns commercial and public objectives.

6.2. Demand–Supply Integration and Operations

RD 6: Demand–supply coupling for MaaS control. A persistent limitation in current models is the weak coupling between behaviorally rich demand representations (e.g., DCM or ICLV models) Polydoropoulou et al. (2020); Kim and Rasouli (2022); Vij et al. (2020) and operationally detailed supply models (simulation or optimization) Becker et al. (2020); Frank et al. (2024); Yan et al. (2025). A priority is to develop integrated frameworks that embed utility-based and attitudinal components directly in supply-side agents and decision rules, enabling feedback between platform levers (pricing, bundling, fleet sizing) and system outcomes (congestion, reliability, revenue, welfare) (Hörcher and Graham, 2020). The prevailing predict-then-optimize approach (Bayliss et al., 2025; Xi et al., 2024c) should evolve into an online closed-loop control paradigm where prediction and optimization update each other in real time (for dispatch, dynamic pricing, capacity allocation) under uncertainty.

RD 7: Behavioral realism for providers and multi-actor MaaS ecosystems. While traveler behavior models have become increasingly sophisticated Polydoropoulou et al. (2020); Kim and Rasouli (2022); Liu et al. (2024a), supply-side actors are often simplified as fully rational profit maximizers in optimization models Frank et al. (2024) or game-theoretic models Xi et al. (2024b). Future modeling should account for bounded rationality, learning processes, heterogeneous constraints, and institutional frictions faced by operators, drivers, and platform managers. Promising foundations include multi-agent or two-sided market models with day-to-day learning dynamics (Djavadian and Chow, 2017) and evolutionary games capturing adaptive strategies among governments, operators, and users (Ye and Zheng, 2024). Methodologically, bilevel and multi-agent formulations (Yao and Zhang, 2024; Xi et al., 2024b) can jointly represent demand estimation and platform-side objectives, yielding equilibrium-consistent MaaS design tools rather than a "predict-then-optimize" framework.

RD 8: Joint optimization of pricing, operations, and reliability under uncertainty. MaaS requires co-optimizing pricing and operations: tariffs and bundles should not be set based solely on static preferences, nor should operations be optimized under simplistic demand assumptions. Models must jointly optimize prices, service configurations, and operational controls, including products that monetize service quality via reliability guarantees (e.g., premium fares with explicit reliability thresholds) (Zhou et al., 2024). High-fidelity demand and WTP predictions from ML, using techniques such as deep learning (Liu et al., 2024b) or Transformers (Xi et al., 2025c), should feed decision layers that dynamically adjust menus, prices, and resource allocation (Xi et al., 2024c; Bayliss et al., 2025). Key challenges include ensuring behavioral consistency, maintaining tractability at scale, and achieving stability as pricing and operations co-evolve.

RD 9: Robust and adaptive MaaS operations with safety and service guarantees. MaaS operations face volatility, disruptions, and strategic user responses, and deterministic optimization often yields fragile solutions. Future work should incorporate stochastic, robust, and distributionally robust optimization to hedge against demand and network variability. It should also couple adaptive controllers (including reinforcement learning) with explicit safety and service constraints, and perform stress tests under rare events and adversarial conditions. One promising concept is real-time co-adjustment of fares and reliability/capacity guarantees during demand surges, supported by self-tuning controllers that reallocate capacity during emergencies (Zhou et al., 2024). The modeling emphasis should be on measurable robustness: ensuring service-level feasibility across scenarios, bounding welfare losses, and enhancing operational resilience.

6.3. Multi-sector Partnerships and Mobility as a Feature

RD 10: Competition–cooperation and coalition formation in MaaF-enabled ecosystems. MaaS is evolving into Mobility-as-a-Feature (MaaF), where mobility is embedded in broader service ecosystems led by non-mobility service providers (NMSPs) rather than a single mobility broker (Hensher and Hietanen, 2023; Hensher et al., 2024). This implies a market environment with multi-platform competition, user multi-homing and switching, and selective cooperation (through interoperability, revenue clearinghouses, or operator alliances) (Merkert et al., 2020). In one institutional model, a competitively tendered common-access framework could allow multiple MaaS consortia to operate under common standards and compete based on societal KPIs, reframing competition as procurement-mediated rivalry (Hensher et al., 2023). Key modeling directions include: (a) oligopoly and two-sided platform models with endogenous pricing, bundling, and coverage; (b) cooperative game and coalition-formation models capturing CaaS-style alliances and coopetition (Merkert et al., 2020); and (c) equilibrium models with multi-homing, network effects, and switching costs under MaaF, where mobility is bundled with non-transport services (Hensher and Hietanen, 2023). Additionally, assignment games and stable matching formulations (Pantelidis et al., 2020) can be extended to represent consortium formation and user–bundle matching when offerings span mobility and other services. Multi-leader multi-follower games (Xi et al., 2024b) offer a basis for strategic interactions but require extensions for cross-sector stakeholders and new asset paradigms (e.g., electric car sharing as a service, ECSaaS, and personal/community car-as-a-service, PCaaS/CCC) that reshape competitive advantage through access to electric fleets or private asset pools (Hensher et al., 2022; Hensher, 2022b).

RD 11: Governance and KPI-linked incentives. MaaF and "utopian" governance perspectives suggest treating regulation and platform governance as endogenous design variables. For example, tendering authorities can mandate standards, define societal KPIs, and tie operator rewards to verified outcomes (Hensher et al., 2023). MaaF also foregrounds incentive mechanisms funded via multi-service portfolios, implying that governance models should capture how NMSPs structure incentives, data collection, and accountability to deliver scalable behavior change (Hensher and Hietanen, 2023; Hensher et al., 2024). Modeling directions include bilevel or tri-level formulations in which authorities choose policy instruments (data mandates, interoperability requirements, KPI-linked rewards, subsidies), platforms respond via bundle design and pricing, and users respond via adoption and travel choices. These interactions can be implemented through bilevel optimization, equilibrium-with-constraints, or MPEC formulations (Merkert et al., 2020). In addition to monetary discounts, governance models should consider non-financial instruments (e.g., certification, public recognition, digital badges tied to verified outcomes) to motivate participation when direct subsidies are limited. Models should also distinguish subsidies for building MaaS platforms from subsidies (or cross-sector funding) that reshape the user-facing offer, since these act through different mechanisms. Incentive design can leverage mechanism design and contract theory, especially when rewards depend on verified reductions in car-kilometers or participation in employer/insurer programs (Xi et al., 2023a; Ding et al., 2023; Hensher et al., 2023). Asset-inclusive paradigms (ECSaaS, PAaaS/PCaaS, CCC) introduce additional governance requirements for trust, safety, and verification; models should incorporate compliance and verification costs, risk allocation, and privacy-preserving architectures as constraints shaping feasible governance (Hensher et al., 2022; Hensher, 2022b).

RD 12: Multi-objective decision making for multi-stakeholder MaaS portfolios. In a MaaF ecosystem, "optimal" design is inherently multi-objective and multi-stakeholder: agencies, MaaS consortia, NMSPs, and communities may value different outcomes (profitability, risk reduction, customer retention, social license, emissions reduction, accessibility) (Hensher and Hietanen, 2023; Hensher et al., 2024). This complexity grows with ECSaaS and private/community asset models (PAaaS/PCaaS and CCC), which seek to expand accessibility while aligning car use with sustainability goals (Hensher et al., 2022; Hensher, 2022b). The "ideal" tendered framework explicitly links rewards to societal KPIs (Hensher et al., 2023). RD 12 therefore emphasizes multi-objective optimization (e.g., exploring Pareto frontiers, ϵ-constraint methods, goal programming) and multi-criteria decision analysis, coupled with behavioral adoption models so that portfolio designs are evaluated under realistic user responses and MaaF-style incentives (Hensher and Hietanen, 2023). For ECSaaS, optimization should jointly account for fleet sizing, charging constraints, and spatiotemporal availability, using stochastic or robust formulations as appropriate (Hensher et al., 2022). For PAaaS/PCaaS and CCC, portfolio design must account for participation uncertainty, trust and safety screening, and matching reliability, motivating hybrid models that integrate matching/assignment with service design optimization under sparse-demand conditions (Hensher, 2022b).

RD 13: Multi-actor simulation and digital twins for MaaS ecosystems. Modeling MaaF ecosystems and asset-inclusive MaaS requires simulation environments where users, multiple platforms, operators, NMSPs, and public authorities are represented as interacting agents whose strategies co-evolve (Hensher and Hietanen, 2023; Hensher et al., 2024). Future agent-based models (ABMs) should incorporate platform and institutional adaptations: dynamic bundling and pricing, employer/insurer incentives, corporate MaaS (C-MaaS) deployments, formation and dissolution of CaaS-style alliances, and KPI-linked rewards and compliance updates by tendering authorities (Merkert et al., 2020; Hensher et al., 2023). RD 13 advocates hybrid digital-twin architectures that combine ABM with (i) assignment and congestion feedback; (ii) discrete choice and learning components for adoption, multi-homing, and behavior change; and (iii) integrated simulation–optimization for policy and portfolio refinement.

Incorporating ECSaaS requires operational electric vehicle fleet modules (battery state of charge, charging queues, repositioning) to evaluate whether shared electric cars increase MaaS attractiveness without increasing total vehicle-kilometers traveled (Hensher et al., 2022). Incorporating PAaaS/PCaaS and CCC requires modeling community agents with stochastic availability, trust, and safety screening processes, and embedded matching mechanisms (e.g., dynamic matching, stable matching, or market-clearing) to assess reliability and equity outcomes (Hensher, 2022b; Pantelidis et al., 2020). Recent calls for multi-actor MaaS simulations provide a starting point (Ye and Zheng, 2024), but next-generation models should explicitly embed MaaF and asset-inclusive paradigms to support governance testing and deployment planning.

6.4. Planning, Equity, and Long-Term Impacts

RD 14: Equity-aware and sustainability-constrained optimization by design. Equity, accessibility, and environmental impacts have seldom been embedded directly in MaaS decision models and are often assessed only ex post. For example, some ABM studies quantified emissions outcomes Labee et al. (2022) or related accessibility gains to socioeconomic status Qiao and Yeh (2023). A key priority is to adopt an equity-by-design approach: incorporate equity and sustainability directly as objectives or constraints in MaaS design (e.g., ensuring minimum accessibility for vulnerable groups, meeting emissions budgets, or guaranteeing service reliability in disadvantaged neighborhoods) Klopfer et al. (2023); Liu et al. (2024b). Possible approaches include using distributional weights, imposing district-level service minimums, and implementing pricing policies that incentivize low-carbon trip chaining, all coupled with heterogeneous demand inputs from attitudinal and socioeconomic data (Franco et al., 2020; Becker et al., 2020; Qiao and Yeh, 2023).

RD 15: Life-cycle impacts and long-run system feedback loops. MaaS adoption can trigger long-run shifts that feed back into MaaS viability and overall system performance. For instance, reduced private car ownership can increase reliance on shared services and transit (Hörcher and Graham, 2020), whereas poorly governed MaaS might divert riders from transit, leading to service cuts and amplified inequities. Capturing these dynamics requires linking MaaS models to long-term travel-demand and land-use or system-dynamics frameworks. Multi-period decision structures that connect long-run decisions (car ownership), medium-run decisions (MaaS subscription), and short-run choices (mode and route) provide a foundation (Ho et al., 2021a; Hörcher and Graham, 2020). Integrating MaaS into land-use transport interaction (LUTI) models can reveal whether MaaS supports urban densification or enables sprawl, and should explicitly represent induced demand, endogenous transit supply responses, and congestion feedback.

RD 16: Modeling retention and loyalty for MaaS subscriptions. Beyond initial adoption, MaaS subscriptions depend on customer life-cycle dynamics (retention, churn, and re-engagement), yet most models capture only a single adoption decision or short pilot period. Future research should model user trajectories from awareness to adoption, sustained use, churn, and reactivation, employing methods like survival analysis, latent class trajectory models, hidden Markov or state-space models, and marketing analytics approaches. Evidence indicates that one-time incentives can spur trials but not long-term persistence (Matyas and Kamargianni, 2019; Yu et al., 2025), whereas panel data link continued use with personalization and reliability (Ho, 2022). Embedding loyalty dynamics into longitudinal planning models (e.g., LUTI frameworks) enables simulation of feedback loops among MaaS uptake, car ownership, urban form, and sustainability outcomes (Hörcher and Graham, 2020; Bahamonde-Birke et al., 2023; Hensher et al., 2021; Basu and Ferreira, 2021).

RD 17: Generalizable MaaS modeling across regions and populations. MaaS research and modeling to date have been concentrated in a narrow set of contexts (typically European, transit-rich cities), raising concerns about transferability. A priority is to extend MaaS modeling to the Global South, smaller cities, and more diverse demographic segments, explicitly accounting for informal transport, cash-based payment norms, different WTP profiles and constraints, and infrastructure limitations (Hasselwander et al., 2022). Inclusive modeling should also represent the needs of older adults, low-income travelers, and persons with disabilities by incorporating factors such as digital literacy, accessibility requirements, safety perceptions, and differing mode preferences or valuations. For low-density and rural areas, potential service extensions include private or community asset-sharing models (PAaaS/PCaaS), community-based mobility memberships, and corporate MaaS (C-MaaS) or community car club (CCC) schemes aligned with employer-led or community-led mobility management initiatives (Hensher, 2022b; Xi et al., 2025a).

6.5. Emerging Technologies for Next-Generation MaaS

RD 18: Connected, automated, and modular road fleets in MaaS models. Next-generation MaaS will likely integrate connected and automated vehicles (CAVs) and modular fleets (vehicles with reconfigurable capacity). Early simulation evidence suggests automation can alter optimal fleet sizing and routing, and may increase total vehicle-kilometers traveled unless managed carefully (Pinto et al., 2020). MaaS models should therefore endogenize (i) connectivity (e.g., V2X communications latency and coverage as reliability factors); (ii) automation (e.g., safety envelopes, minimum headways, fallback control rates); and

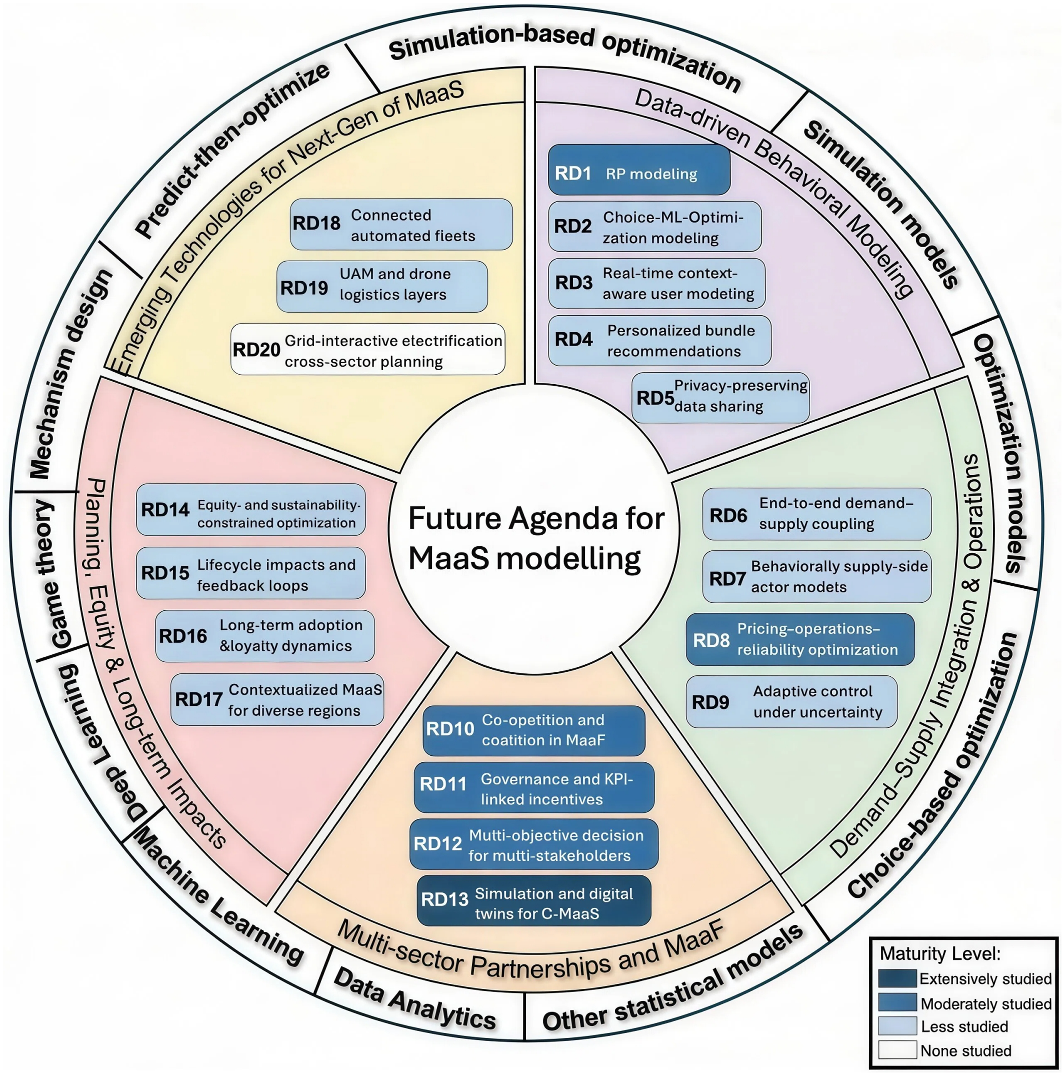

Figure 7: The research agenda of MaaS modeling research

(iii) modularity (e.g., vehicle split/merge rules at hubs, convoy formations, and dwell-time penalties). Automation sub-models should represent empty vehicle repositioning and unoccupied running under different ownership or sharing regimes, since these behaviors can erode sustainability gains even if passenger comfort improves. Methodologically, this calls for mixed-autonomy simulations coupled with network assignment and dynamic control, and safety-aware fleet management with explicit constraints (or calibrated surrogates). On the demand side, behavioral models should also treat trust in automation as an evolving attribute affecting mode choice.

RD 19: Urban air mobility and drone logistics as MaaS layers. Urban air mobility (UAM) and unmanned aerial vehicle (UAV) logistics introduce modeling requirements distinct from ground-based MaaS. These include vertiport and micro-hub siting, airspace capacity management, weather variability, noise exposure, and seamless intermodal transfers (He et al., 2022). Future models should incorporate aerial services as additional MaaS or Delivery-as-a-Service (DaaS) layers, jointly representing facility siting and sizing, air/ground slot allocation and scheduling, and end-to-end itinerary planning under constraints such as urban air traffic management (UTM) protocols, beyond-visual-line-of-sight (BVLOS) rules, vehicle battery and payload limits, and transfer penalties. Time-expanded network formulations with chance-constrained or robust optimization can ensure feasibility under uncertainty, while reporting outcomes like reliability, utilization rates, community noise exposure, and equity impacts.

RD 20: Grid-interactive electrification and cross-sector co-planning toward eMaaS. As MaaS becomes increasingly electrified and digitally orchestrated, its design becomes a coupled transport–energy–ICT problem. This motivates the notion of eMaaS, where electric modes dominate, and mobility operations are coordinated with power grids, charging/refueling infrastructure, and communications networks. A core modeling direction is to co-optimize electric vehicle charging and hydrogen refueling (for buses, trucks, and other range-critical services) alongside eVTOL battery operations, accounting for feeder capacity limits, dynamic electricity tariffs, renewable supply variability, battery degradation, and energy storage logistics. One practical approach is to combine long-horizon siting and sizing optimization (e.g., a stochastic or robust MILP) with short-horizon model predictive control for real-time charging, refueling, battery swapping, and vehicle dispatch, augmented by carbon-aware pricing and vehicle-to-grid or hydrogen-to-power strategies for peak shaving. Moreover, since MaaS increasingly depends on reliable connectivity for real-time coordination and automation, models should explicitly represent ICT failures and cyber-attacks as disruption scenarios and operational constraints. Governance considerations include fair energy allocation among operators, data telemetry privacy, and the auditability of emissions-reduction claims. Model evaluations should report metrics such as CO_2 per passenger-kilometer or ton-kilometer, capital and operating costs versus service quality, peak-load impacts on the grid, resilience to outages, and equitable access to charging/refueling across districts. Finally, "electric car sharing as a service" (ECSaaS) has been proposed as a pathway toward eMaaS, while recognizing the continued role of cars within a public mobility ecosystem. This underscores the need for integrated modeling of electric fleet sizing, charging operations, energy-network coupling, and behavioral substitution effects when e-car sharing complements public and active modes (Hensher et al., 2022).

Figure 7 presents a comprehensive research agenda for MaaS modeling, categorizing twenty research directions (RDs) into five thematic clusters spanning data-driven behavioral models, operations, multi-sector partnerships, planning, and emerging technologies. The color-coded maturity levels illustrate a diverse research landscape: foundational areas such as revealed preference modeling (RD1) and choice-based optimization (RD2) are relatively well established, whereas significant knowledge gaps remain in interdisciplinary and emerging fields. Specifically, the “Emerging Technologies” cluster (RD18–RD20), which includes connected automated fleets, urban air mobility, and grid-interactive electrification, remains largely unexplored. Furthermore, complex institutional topics such as governance incentives (RD11) and privacy-preserving data sharing (RD5) are also underdeveloped. The roadmap, therefore, calls for a paradigm shift from traditional, transport-centric models toward dynamic, multi-sector frameworks, or "Mobility-as-a-Feature," that integrate equity considerations, long-term feedback loops, and advanced methodologies such as deep learning and game theory.

6.6. Practical Implications

For industry practitioners and MaaS platform operators, the past decade of modeling progress translates into concrete priorities for design and decision-making. The overarching message is that user behavior must anchor product design, and that MaaS value propositions should be made empirically testable by linking bundle attributes, perceived friction, and service performance to uptake, usage, and retention. Evidence on WTP and attribute trade-offs from demand modeling can inform plan tiering, pricing, and targeted incentives (Ho et al., 2018; Vij et al., 2020; Caiati et al., 2020). However, the literature emphasizes that simply bundling existing modal services adds little value unless platforms reduce decision effort, increase perceived seamlessness, or provide salient incentives. Operators should therefore model and measure friction-related attributes (e.g., transfer hassle, uncertainty, cognitive burden) as core drivers of adoption and repeat use (Hensher and Xi, 2022; Hensher, 2022a). This aligns with the MaaF paradigm, where mobility demand can be shaped through multi-service incentives funded by non-mobility partners (Hensher and Hietanen, 2023; Hensher et al., 2024).

Simulation and optimization tools provide practical platforms for testing fleet sizing, rebalancing, and pricing policies prior to deployment. City-scale ABMs (Becker et al., 2020; Labee et al., 2022) and emerging closed-loop simulation–optimization approaches (Xi et al., 2024c; Chu and Guo, 2023a) support a decision pipeline: calibrate demand modules, stress-test operations under uncertainty and disruptions, and iteratively adjust bundle, pricing, and dispatch policies until KPI performance is robust across scenarios. Pilot studies have highlighted both the behavioral potential of MaaS and persistent challenges in user retention and stakeholder alignment (Hensher et al., 2021; Ho, 2022; Yu et al., 2025). This suggests that operators should treat churn and loyalty dynamics, as well as contracting risks, as first-class modeling considerations rather than assuming one-off adoption. Structuring partnerships and financial settlements among service providers is equally central. Ecosystem models of platform arrangements can inform viable partnership configurations (van den Berg et al., 2022; McHardy, 2024; Xi et al., 2024b). The concept of MaaS 2.0 via Cooperative MaaS (CaaS) highlights that success will depend on operator-facing collaboration mechanisms (standardized contracts, settlement and clearing systems, interoperability rules) that lower transaction costs and enable the delivery of integrated offers at scale (Merkert et al., 2020). Finally, expanding the MaaS portfolio has immediate modeling implications for practice. For instance, the introduction of ECSaaS requires integrated modeling of electric fleet sizing, charging operations, energy grid interaction, and behavioral substitution when e-car sharing complements public and active modes (Hensher et al., 2022). Similarly, incorporating PAaaS/PCaaS or corporate MaaS (C-MaaS) offerings for employers and low-density areas necessitates models that capture participation uncertainty, trust, and safety constraints, and organizational incentives (Hensher, 2022b).

For policymakers and public agencies, this review underscores that MaaS outcomes are shaped as much by governance and institutional design as by algorithms. Market-driven MaaS can diverge from public goals without active policy guidance; therefore, agencies should treat data-sharing mandates, interoperability standards, consumer protections, and competition safeguards as explicit policy levers rather than as background conditions. "Utopian" governance proposals illustrate this by framing MaaS as a competitively tendered ecosystem in which a public authority sets societal KPIs and links rewards to verified outcomes across multiple consortia (Hensher et al., 2023). The MaaF paradigm further shifts attention toward cross-sector incentive programs and accountability for measured outcomes (Hensher and Hietanen, 2023; Hensher et al., 2024), while the CaaS model suggests that policy can lower coordination barriers by facilitating operator-facing interoperability (common contracting standards, shared settlement mechanisms, unified rules) (Merkert et al., 2020). These perspectives indicate that the binding constraints on MaaS success are often institutional and related to supply-side integration, reinforcing the need to represent governance variables explicitly in evaluation models (Hensher, 2022a). Equity considerations also demand a proactive approach: policies that recognize asset-inclusive pathways (e.g., PAaaS/PCaaS, C-MaaS, and CCC models) can expand service coverage in contexts where car access remains essential, provided those innovations are aligned with accessibility and sustainability goals (Hensher, 2022b).

Over the past decade, MaaS modeling has evolved from isolated demand estimation exercises to integrated, ecosystem-level analyses. Early studies typically took a demand-centric approach, using discrete choice models and hypothetical scenarios to predict MaaS adoption and bundle preferences. In subsequent years, researchers began incorporating supply-side dynamics (fleet operations, routing, service availability) and platform decision-making into their models, moving toward simulations that couple traveler behavior with system performance. More recently, the field has advanced to capture multi-actor interactions and governance frameworks. Instead of the original single-broker vision, current models explore scenarios in which competing or collaborating MaaS providers, cross-sector integrations, and regulatory oversight mechanisms are present. This evolution from basic demand models to full ecosystem representations reflects a significant broadening of scope and complexity in MaaS research. Despite this progress, several gaps remain, including overreliance on SP data and limited integration of demand- and supply-side models. Many models fail to capture the dynamic, personalized nature of MaaS usage, which evolves as user preferences and platform offerings change. Furthermore, long-term decisions and cross-sector influences are largely overlooked. Few frameworks endogenize car ownership alongside MaaS adoption, or consider how employer-led incentives (corporate MaaS) or community-based car sharing (PAaaS/PCaaS, CCC) influence MaaS uptake.

Addressing these challenges will require both methodological innovations and supportive policy measures. On the modeling side, a top priority is developing integrated demand–supply simulation environments that tightly couple traveler behavior with operational decision-making. Hybrid agent-based models and digital twins can capture real-time feedback loops, for example, how congestion and wait times influence mode choice and how those choices, in turn, affect network conditions. Such closed-loop models would enable stress-testing of MaaS designs under realistic conditions, revealing emergent issues such as peak-period capacity shortfalls or the effects of adaptive pricing. Improving data integration is equally critical: using more revealed-preference data from MaaS pilots and deployments will enhance model realism. Where data sharing is difficult, privacy-preserving analytics and federated learning approaches can allow collaboration without centralizing sensitive data. Establishing common data standards and partnerships (with public-sector support) could also facilitate the exchange of usage, revenue, and performance data needed to validate models at scale. Additionally, incorporating stochastic elements and robust optimization into MaaS models can make findings more resilient. By modeling uncertainties, demand spikes, vehicle failures, labor strikes, extreme weather, and optimizing decisions for performance across these scenarios, models can identify strategies such as fleet sizes, pricing schemes, and incentive levels that remain effective even when conditions deviate from expectations. Such robustness is particularly valuable for policymakers and operators concerned with reliability and risk.

Equally important is embedding policy and institutional considerations into MaaS modeling frameworks. Future models should treat regulatory settings and governance arrangements as endogenous design variables rather than fixed inputs. Bilevel or tri-level formulations can represent interactions among authorities, platforms, and users: for example, a public agency sets policies such as standards, subsidies, and integration requirements; MaaS operators optimize services in response; and travelers make adoption and usage decisions accordingly. This approach enables quantitative evaluation of policy levers, such as comparing how a subsidy, a congestion charge, or a data-sharing mandate would cascade through the system to impact ridership and welfare. Incorporating incentive mechanisms and contract designs is also vital: concepts from mechanism design, such as auctions for mobility contracts and performance-based payments, can be integrated to examine how best to align MaaS operations with societal goals. Moreover, models must adapt to emerging MaaS paradigms. As mobility becomes offered "as a feature" (MaaF) and as new sharing models involve private or community assets, assumptions about market structure and actor behavior must evolve. This means accounting for scenarios with multiple competing or cooperating platforms, representing trust and safety processes for peer-to-peer asset sharing (screening, insurance, reliability in PAaaS/PCaaS contexts), and including the role of non-mobility stakeholders (employers, insurers, housing providers) that incorporate MaaS into their services. Simulating such ecosystems will help anticipate how MaaS might scale and what policy guardrails are needed, e.g., ensuring competition and interoperability, protecting privacy, and maintaining inclusive access as MaaS diversifies.

7. Conclusion

This study systematically reviews a decade of MaaS modeling research (2015–2025), revealing a transition from early feasibility and user-adoption studies toward a complex socio-technical, multi-actor ecosystem aimed at informing policy and planning. Using a PRISMA-guided selection of 92 journal articles, we develop a method-first analytical framework that organizes MaaS modeling methods into six families aligned with four core research themes. Mapping these methods onto the key themes, such as traveler demand, supply and operations, MaaS ecosystem governance, and platform and bundle design, clarifies where modeling evidence is relatively mature and where cross-layer coupling or empirical validation remains limited. This structured mapping makes the field's progress legible as a series of methodological milestones, while exposing the constraints that limit current model-based guidance for MaaS policy and practice.

A first milestone is the consolidation of behavioral valuation as the empirical backbone of MaaS demand modeling. Demand-side studies predominantly estimated discrete choice models to quantify travelers' WTP, preference heterogeneity, and subscription uptake under alternative bundle offerings. Advanced models, such as hybrid choice models and market segmentations, improved interpretability by incorporating attitudes, lifestyle factors, and risk perceptions, thereby moving beyond purely demographic explanations of MaaS adoption. However, the empirical base of these studies remained largely reliant on stated-preference data; revealed-preference evidence from real-world deployments was comparatively scarce, limiting the transferability of findings across different cities and market contexts. A second milestone is the shift from adoption-centric analyses to operationally grounded decision support. As MaaS pilots and integrated service concepts expanded, simulation and optimization models increasingly incorporated practical considerations, including capacity constraints, congestion feedback, fleet dispatch rules, and network performance metrics. These modeling approaches improved awareness of operational feasibility and allowed researchers to stress-test integrated MaaS operations, yielding insights that simpler analytical models could not provide. A persistent limitation, however, is that greater operational realism was not always matched by behavioral realism. Many prescriptive models still rely on simplified demand functions, representative "average" users, or static elasticity assumptions. These simplifications limit the models' ability to capture how platform levers (pricing, bundling, recommendations) interact with experienced service quality (e.g., waiting times, reliability, crowding, missed connections) to shape heterogeneous traveler responses over time. A third milestone is the emergence of ecosystem-scale modeling, which treats MaaS as a multi-actor market shaped by governance structures, incentives, and strategic interactions. Game-theoretic formulations, stable matching/assignment games, and mechanism design approaches moved beyond the assumption of a single integrated operator to examine competitive and cooperative scenarios among multiple stakeholders, as well as implementable allocation rules under voluntary participation. These models improved the field's ability to reason about contracts, revenue/cost sharing, incentive compatibility, and welfare distribution across platforms, service operators, and users. Yet, MaaS ecosystem models often rely on stylized behavioral primitives and are empirically calibrated only sparsely, which constrains their claims about distributional impacts and policy performance, especially in contexts where heterogeneity, user trust, switching behavior, and multi-homing using multiple platforms are decisive factors.

To address current gaps, we propose a comprehensive agenda of 20 research directions. These priorities include developing richer data-driven behavioral models that incorporate real-world usage data; achieving tighter coupling of demand and supply models by integrating experienced service quality into operational decision-making; fostering multi-sector partnerships and exploring the Mobility-as-a-Feature paradigm to embed MaaS within broader service ecosystems; incorporating equity-aware planning and assessing long-run societal impacts of MaaS; and ensuring the responsible use of emerging technologies (such as autonomous vehicles and AI-driven analytics) in next-generation MaaS platforms. Overall, this review offers a coherent framework for researchers to compare, position, and cumulatively advance MaaS modeling efforts. We also provide evidence-oriented guidance for practitioners and public agencies to assess model-based claims, identify which decisions are most amenable to analytical support, and design the data standards and regulatory settings needed for credible MaaS evaluation and scale-up. Advancing along this research agenda will improve the robustness and policy alignment of MaaS decision support, ultimately contributing to more sustainable, efficient, and inclusive multimodal urban mobility systems.

Key Takeaways

- MaaS modeling matured significantly between 2015 and 2025, shifting focus from user adoption and bundle valuation toward operational control and ecosystem governance. The latest wave of studies emphasizes governance and incentive mechanisms, as well as "next-generation" ecosystem designs incorporating private cars and even non-mobility services to achieve real-world impact.

- MaaS modeling methods are now diverse and powerful enough to inform platform design and policy decisions. However, using each method effectively requires aligning its assumptions and outputs with the appropriate decision-making layer. The unified framework and cross-layer mapping introduced in this review provide a structured basis for matching each modeling approach to its suitable context and decision level.

- Different modeling methods play complementary roles in MaaS analysis. Simulation and optimization models provide feasibility-aware decision support but often rely on simplified demand representations, thereby limiting the behavioral realism of their operational recommendations. Ecosystem-scale methods (e.g., game theory, stable matching, mechanism design) clarify how incentives, contracts, and market structure influence MaaS outcomes, but their findings remain fragile without stronger empirical calibration and distributional analysis. Machine learning techniques have emerged rapidly, yet they are rarely integrated into closed-loop, policy-constrained MaaS decision pipelines.

- The next generation of MaaS decision support should shift toward end-to-end modeling frameworks, such as predict-then-optimize, choice-based optimization, and simulation-based optimization, that explicitly link what users value (e.g., their preferences and WTP) with what mobility systems can reliably deliver. Such frameworks would also better equip transport regulators with tools to steer MaaS outcomes under uncertainty, especially as new vehicle technologies and data streams emerge.
- Equity, sustainability, and governance considerations should be embedded directly into MaaS models through explicit objectives, constraints, and performance metrics, rather than evaluated only after implementation. This proactive integration ensures that MaaS platforms are designed and assessed with social welfare and public interest in mind from the outset.

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