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« Impact of Dynamic Pricing on the Performance of Shared Automated Vehicles in Mobility as a Service: A Systematic Review »

by

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Impact of Dynamic Pricing on the Performance of Shared Automated Vehicles in Mobility as a Service: A Systematic Review

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Abstract

Urban population growth intensifies the demand for efficient, accessible, sustainable public transportation. Traditional modes often lack the flexibility modern commuters seek, leading to integrating on-demand services like shared automated vehicles (SAVs) into mobility as a Service (MaaS) platform. Despite numerous SAV experiments globally, applying classical public transport pricing policies to SAVs within MaaS hinders profitability and delays industrial deployment. While dynamic pricing has optimised revenue and resource allocation in industries like airlines and ride-hailing services, its application in public transportation with SAVs remains underexplored. Dynamic pricing strategies must balance varied and sometimes contradictory performance objectives: profitability and affordability, reliability, and environmental friendliness. We conduct a systematic review to examine how dynamic pricing influences the performance of SAVs in MaaS. The findings suggest dynamic pricing offers immense potential for sustainable profitability and operational efficiency in public transportation services. However, it also reveals trade-offs between revenue maximisation and user affordability, as dynamic pricing may increase costs for low-income users during peak periods. Our findings emphasise the need for advanced pricing algorithms that can rapidly adapt to changes in customers' willingness to pay while balancing economic objectives with operational and social impacts.

Keywords: dynamic pricing, surge pricing, ride-hailing, ride-sharing, autonomous vehicles, MaaS

1. Introduction

Urban population growth intensifies the need for efficient, accessible, sustainable public transportation. Traditional transit modes often lack the flexibility modern commuters demand, prompting cities to integrate on-demand services such as shared autonomous vehicles (SAVs) into the Mobility as a Service (MaaS)[1] platform. On-demand SAVs can potentially improve public transportation services. They offer flexibility and responsiveness that traditional transit systems cannot match, allowing cities to reduce congestion, cut operating costs, and significantly enhance user experience (Fagnant & Kockelman, 2013). SAVs can quickly adjust their deployment based on live data and adapt to fluctuating demand patterns, enabling transport operators to manage their fleets more efficiently, optimise resource use, and ensure reliable service for users.

ULTIMO is a European project dedicated to launching the first economically viable, large-scale, on-demand autonomous public transport service. However, it faces two significant challenges. First,

[1] MaaS is a mobility service that consolidates multiple transportation modes into a user-centric platform, streamlining urban travel and improving overall service quality

most public transport systems operate at a loss and depend on subsidies that often exceed 50% of their total income (EGUM subgroup, 2022). The current situation limits the financial opportunities to further extend investment in this technology without putting intense pressure on public budgets. Second, political mandates to maintain affordable public transport fares significantly strain financing. Rising input costs, such as energy prices and capital expenses, exceed the revenue generated by the current fare pricing mechanism, which is a predominantly static pricing strategy. Moreover, socially beneficial investments in city centre services and during peak periods further increase operating costs. These challenges underscore the need for an innovative pricing strategy that balances sustainable profitability with affordability.

Classical pricing models, such as fixed fares or zone-based tariffs, have proven inadequate in addressing the dynamic nature of urban transportation (Zhou et al., 2019). These static pricing strategies often result in inefficiencies, as they fail to account for the social costs associated with peak demand, congestion, and environmental externalities (Eliasson, 2021). In contrast, dynamic pricing offers a more nuanced approach by adjusting fares in real-time based on various factors, including time of day, route congestion, and user demand. This responsive pricing mechanism aligns costs with actual market conditions and helps internalise transportation's social costs, such as traffic congestion and emissions, thereby contributing to economic and environmental sustainability (Qiu et al., 2018; Turan et al., 2020).

Moreover, as cities worldwide contend with the twin challenges of rapid urbanisation and climate change, adopting a dynamic pricing strategy for public transport services could be a helpful strategy for promoting sustainable urban mobility. Dynamic pricing can help mitigate congestion and lower greenhouse gas emissions by incentivising off-peak travel, reducing unnecessary vehicle circulation, and enhancing the overall efficiency of transit networks, thereby contributing to a cleaner, more resilient urban environment.

Despite its successful application in industries like airlines and private ride-hailing services, dynamic pricing remains underexplored in public transportation, particularly for SAVs. This gap in real-world application and research presents a unique opportunity to investigate whether dynamic pricing can bridge the revenue and efficiency gap in classical public transport fare pricing mechanisms and foster the development of sustainable urban transit systems.

This systematic review addresses these issues by examining how dynamic pricing influences the performance of on-demand SAV services and its implications for public transportation services. Specifically, we explore the potential of dynamic pricing to ensure sustainable profitability, optimise fleet utilisation, reduce passenger wait times, and lower operating costs while considering the affordability concerns for price-sensitive users. Our review critically evaluates a wide range of studies—from empirical analyses using real-world data to simulation-based models and theoretical frameworks—to comprehensively understand the potential benefits and challenges associated with implementing dynamic pricing in public transport services such as SAVs.

The question guiding this review is: What are the benefits of adopting a dynamic pricing strategy for on-demand SAVs within urban public transportation systems? Our review reveals that dynamic pricing offers immense potential for increasing revenue and operational efficiency in public transportation services. Specifically, our review shows that dynamic pricing can improve the performance of SAVs by:

- Enhancing Economic Viability: Dynamic pricing maximises revenue generation and supports cost-effective operations by adjusting fares to reflect actual demand in real-time.
- Optimising Fleet Operations: Real-time fare adjustments enable more efficient vehicle deployment, reduce idle times, and streamline resource allocation, improving overall service reliability.
- Promoting Environmental Sustainability: Dynamic pricing contributes to lower emissions and better energy efficiency by smoothing demand and reducing congestion.
- User accessibility: However, dynamic pricing could also pose affordability challenges as fluctuating fares may disproportionately burden low-income users with rigid travel schedules during peak periods.

The remainder of this review is organised as follows: Section 2 outlines the systematic review methodology, detailing the search strategies, inclusion criteria, and data extraction processes that underpin our analysis. Section 3 presents a synthesis of the findings, organised around four thematic areas: operational efficiency, economic viability, user accessibility, and environmental impact. Section 4 discusses the modelling techniques researchers employ to navigate the complexities of dynamic pricing and demand prediction. Finally, Section 5 concludes the review by discussing the implications of our findings for policy and practice.

2. Methodology

Our systematic review adheres to the PRISMA 2020 guidelines (Page et al., 2021) and incorporates elements from other established frameworks to ensure a comprehensive and rigorous process. Below, we detail our search strategies, inclusion criteria, data extraction, and synthesis methods.

2.1 Search Strategies

We developed a robust search strategy to capture various studies on dynamic pricing in urban public transportation. We searched key academic databases, including Web of Science, SpringerLink, Scopus, ScienceDirect, Mendeley, JSTOR, and EBSCO, selected for their relevance and access to high-quality, peer-reviewed articles. Our search combined keywords and phrases such as “dynamic pricing,” “surge pricing,” “on-demand shared autonomous vehicles, “ride-hailing”” and “public transportation” to identify relevant literature.

We also included grey literature such as conference papers, government and industry reports, and working papers to broaden our scope. This approach ensured that diverse perspectives and emerging research were incorporated. Additionally, we employed citation mapping tools like LitMap and VOSviewer (van Eck & Waltman, 2010) to visualise co-citation relationships and keyword co-occurrence. These tools helped us uncover influential works that standard keyword searches might miss. In total, our search strategy yielded 183 documents.

2.2 Inclusion Criteria

We established strict inclusion criteria to focus on high-quality studies directly addressing the impacts of dynamic pricing on the economic viability, operational efficiency, user accessibility, and environmental impact of SAV platforms in urban public transportation. We selected studies that provided empirical, simulation-based, and theoretical insights into dynamic pricing mechanisms and their outcomes.

Our dataset encompasses a diverse range of sources. For example, we included 19 papers from the IEEE International Conference on Intelligent Transportation Systems (ITSC). Transportation Research Part C constituted 15 papers, reflecting their leadership in intelligent and autonomous transportation systems research. Transportation Research Parts A and B include 9 and 11 papers, respectively, highlighting their importance in transportation systems and infrastructure planning. Additionally, six working papers from leading institutions such as MIT, UCLA, and Carnegie Mellon University offered valuable insights, while journals categorised as "Other" contributed 14 papers. These include interdisciplinary contributions from journals like Management Science and Manufacturing & Service Operations Management, further enriching our dataset. Here, we observe that the most important publications are characterised by interdisciplinarity and by the journal dedicated to transportation, so we think the performance of dynamic pricing in public transportation will be useful to all stakeholders.

The review focused on studies published within the last 15 years (i.e., 2009 - 2024) to ensure that the findings reflect the most recent developments in dynamic pricing and urban transportation systems. Only studies published in English were included in the review to maintain consistency in the analysis.

Temporal data analysis reveals a steady growth in research interest over time. The number of publications increased consistently from 2012 to 2024, peaking in 2020 with 21 publications—a particularly active year for research on transportation and dynamic pricing. Since 2016, the number of publications has risen, indicating that dynamic pricing and on-demand transportation have become central topics in academic and technical discussions. The field remains vibrant with strong activity in subsequent years: 15 publications in 2021, 18 in 2022, and 9 in 2024.

From Figure 1, we can already confirm the interest in questioning the interest of a dynamic pricing strategy for shared mobility services. Indeed, shared mobility services are often used for short and occasional trips. Users are, therefore, sensitive to price variations. On the supply side, dynamic pricing allows fares to be adjusted in real-time, allowing operators to maximise their revenue and optimise fleet use. Finally, in the share-mobility market, companies must adapt quickly to fluctuations in demand and the strategies of their competitors. Dynamic pricing offers them that flexibility. For public transport operators, such flexibility could be particularly helpful in bridging the revenue gap.

Figure 1. Keyword co-occurrence

Figure 1 shows the keyword co-occurrence. Here, keywords are represented as nodes, and their proximity represents their co-occurrence strength. This figure shows dynamic pricing has enormous potential for on-demand shared mobility services with autonomous vehicles.

2.3 Data Extraction and Synthesis of Findings

We adopted the European Commission Expert Group on Urban Mobility's (EGUM) definition, which describes efficient public transport as delivering reliable, affordable, environmentally sustainable, and inclusive services. Guided by this definition, we conceptualised public transport performance through four dimensions: economic viability, operational efficiency, user accessibility, and environmental sustainability. Our data extraction and synthesis processes aligned with these key performance areas. To capture diverse analytical perspectives and assess the robustness of findings on dynamic pricing, we classified the literature into three methodological categories: empirical studies, simulation-based studies, and theoretical models. Specifically, we reviewed 52 empirical studies that use real-world pricing data to provide direct evidence of financial outcomes such as revenue generation, profitability, and cost-effectiveness, 30 simulation-based studies that model hypothetical scenarios, and 31 theoretical studies that apply mathematical and economic theories to explore dynamic pricing mechanisms. This balanced representation offers deeper insights into the consistency and reliability of the findings across different analytical approaches.

We organised the literature synthesis and findings across our four thematic areas as follows:

1. Economic Viability: Examining the financial outcomes of dynamic pricing, specifically its effects on revenue generation, profitability, and cost-effectiveness. Metrics analysed include revenue levels, profitability ratios, ROI, and long-term financial stability.
2. Operational Efficiency: Evaluating the impacts of dynamic pricing on fleet performance, resource allocation efficiency, passenger wait times, and service reliability. This includes assessing how effectively dynamic pricing reduces vehicle downtime and optimises routing.
3. User Accessibility: Assessing how dynamic pricing affects affordability and equity, particularly for price-sensitive and disadvantaged user groups. We explored whether dynamic pricing enhances or restricts equitable service access.
4. Environmental Sustainability: Analysing the influence of dynamic pricing on urban environmental outcomes, specifically emission reductions, improved energy efficiency, and decreased traffic congestion.

Structuring our literature synthesis around these themes enables us to comprehensively assess dynamic pricing's potential benefits and challenges for public transportation systems.

Figure 2 illustrates the distribution and interconnections of high-impact studies on dynamic pricing. Each node represents a study, with its size corresponding to the number of citations and its position indicating publication recency (horizontal axis) and citation frequency (vertical axis). Nodes with multiple colours show studies evaluating several performance dimensions simultaneously. The figure demonstrates that recent studies increasingly integrate multiple performance dimensions compared to earlier research. This observation supports our argument that assessing dynamic pricing's impact on SAVs within public transportation should adopt a comprehensive approach.

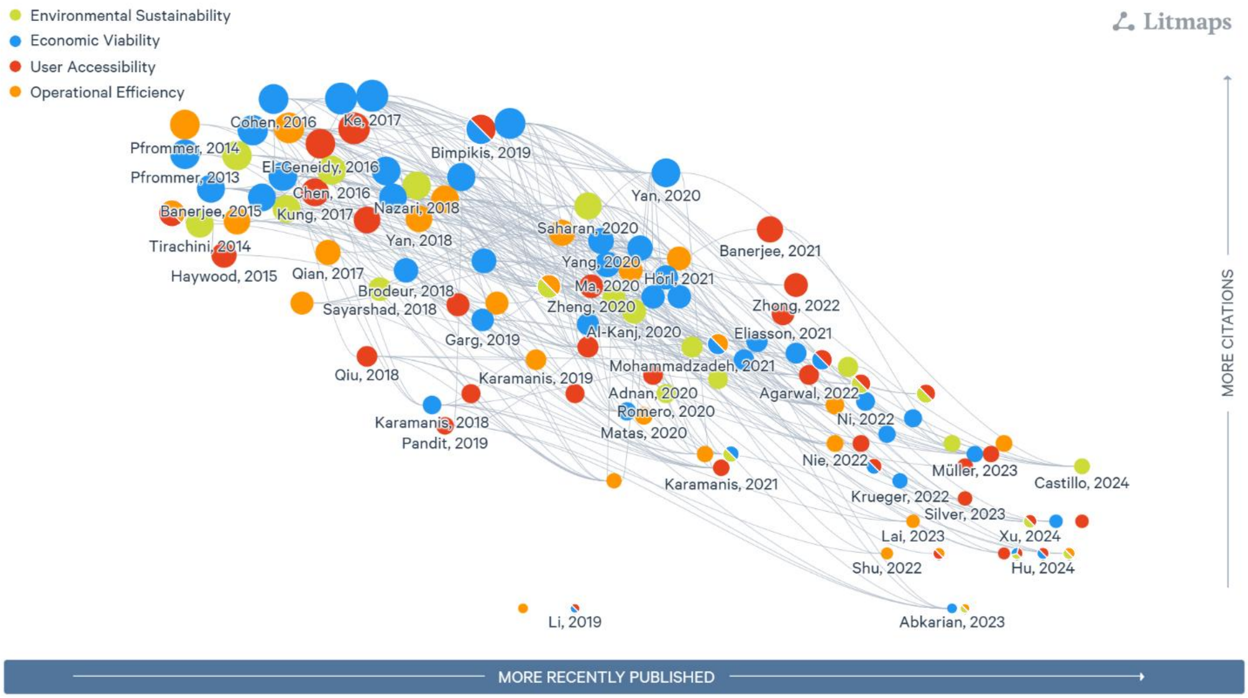

Figure 2: A map of high-impact articles illustrating how key studies interconnect through shared references.

3. Analysis and Discussion

An efficient public transport system must be reliable, affordable, sustainable, and accessible to meet urban populations' diverse needs over the long term (EGUM Subgroup, 2022). In this section, we examine how dynamic pricing shapes these key attributes and either enhances or hinders the performance of shared autonomous vehicles (SAVs) within Mobility-as-a-Service (MaaS) frameworks with autonomous vehicles.

3.1 Economic Viability

Economic viability is essential for the sustainability of public transport systems. It means generating enough revenue to cover operational costs while keeping services affordable and high quality. The literature shows that dynamic pricing improves revenue generation and reduces costs for urban transportation systems.

Dynamic pricing has shown significant potential for increasing profitability in shared vehicle systems by optimising vehicle allocation and aligning supply with fluctuating demand. Müller et al. (2023) propose a customer-centric dynamic pricing approach that adjusts fares based on the customer's location, walking distance to available vehicles, and anticipated demand. This method led to an 8% increase in profits compared to conventional pricing strategies. In another study, Müller et al. (2023b) developed a dynamic pricing approach using idle time data to optimise vehicle usage. By integrating historical idle time data and applying online optimisation, this technique resulted in an 11% improvement in operational performance and profit over existing methods.

Researchers like Bai et al. (2018), Chen et al. (2017), Qiu et al. (2018), Xu et al. (2022), and Yan et al. (2020) also show that adjusting fares in real-time to match demand fluctuations improves profitability. Operators capture higher willingness to pay during peak times and lower fares during off-peak hours, ensuring consistent revenue and balancing supply with demand. Turan et al. (2020) noted that static pricing models often untapped potential revenue during peak periods when transport operators could take advantage of commuters' increased willingness to pay to charge higher prices without significantly reducing the demand for the service. By contrast, dynamic pricing enables operators to respond swiftly to market conditions, optimising fare levels to enhance profitability. For example, during major events or peak commuting hours, fare adjustments can capitalise on the surge in demand, thereby increasing overall revenue without compromising service accessibility.

Karamanis et al. (2018) introduced a utility-based model for autonomous ride-sourcing markets that improves revenue and maintains service quality. Abkarian & Mahmassani (2023) and Wang & Xie (2021) show that applying machine learning techniques to dynamic price modelling predicts demand spikes and adjusts fares in advance, thus optimising revenue and preserving service standards.

Public sector transport authorities face the challenge of balancing revenue maximisation with user affordability. Gómez-Lobo et al. (2022) warn that higher fares may drive low-income users toward public transportation. However, in the case of public transport, higher fares could drive users towards private car usage, undermining urban city authorities' goal of promoting and increasing their share of public transport usage. Therefore, dynamic pricing must include safeguards such as fare caps during peak periods and discounts during off-peak times to keep transportation accessible (Al-Kanj et al., 2020b). Understanding demand elasticity (Krueger et al., 2023) helps these authorities adjust pricing without compromising reliability or equity.

Studies also reveal that dynamic pricing can enhance social welfare. Sayarshad & Oliver Gao (2018) report a 37% improvement in social welfare compared to flat rates. Karamanis et al. (2021) show that combinatorial double auction models boost operator earnings and social welfare through efficient ride-matching. Castillo (2018) and Cohen et al. (2016) further show that dynamic pricing increases profitability and delivers significant consumer surplus. Cohen et al. (2016) analysed nearly 50 million ride requests from Uber across four major U.S. cities and found that dynamic pricing created a consumer surplus estimated at $2.9 billion in 2015. For every dollar spent, consumers received about $1.60 in additional value. These findings indicate that dynamic pricing enhances operator revenue and provides better value to consumers.

Dynamic pricing offers a dual advantage for public sector SAVs: it increases revenue and improves user value, supporting broader objectives like increased public transport usage and reduced reliance on private vehicles. However, operators must implement it thoughtfully. Overly aggressive pricing risks alienating price-sensitive users; therefore, integrating targeted discounts and personalised incentives helps maintain financial health while ensuring social equity.

While the literature extensively documents revenue increases and improved profitability from dynamic pricing, none of the studies thoroughly examine key financial metrics such as return on investment (ROI) and cost-benefit ratios. This gap is significant because understanding these metrics is essential for assessing whether dynamic pricing can provide a robust, sustainable financial model for public transport operators, especially when subsidies are minimised or eliminated. Future research should integrate these metrics to offer a more holistic evaluation of dynamic pricing's impact on economic viability.

Also, some studies concentrate solely on economic metrics, such as revenue generation, profitability, and cost-effectiveness, while others combine economic with operational outcomes. However, most research does not extend its analysis to include other performance dimensions—user accessibility or environmental sustainability. Integrating these additional dimensions is important because financial performance alone does not guarantee long-term sustainability; understanding how revenue interacts with operational constraints and societal impacts offers a more comprehensive evaluation of dynamic pricing strategies.

3.2 Operational Efficiency

Operational efficiency is a critical performance metric that ensures public transport fleets deliver reliable, timely services. Within MaaS frameworks, many studies consider dynamic pricing as a key strategy to enhance fleet utilisation, manage congestion, and boost service reliability.

The literature shows that dynamic pricing allows transport operators to align vehicle deployment with real-time demand, ensuring SAVs are available where and when needed. Saharan et al. (2020) show that real-time fare adjustments keep vehicles in constant use, reducing idle time and cutting costs. Hörl et al. (2021) found that dynamic pricing in Zurich's automated taxi system cut idle times and shortened passenger wait times. Sun et al. (2020) confirm that even distribution of vehicle deployment throughout the day minimises underutilisation and reduces the need for extra vehicles during demand spikes. Banerjee et al. (2015) further demonstrate that dynamic pricing balances supply and demand by incentivising efficient passenger behaviour and ensuring optimal vehicle allocation.

Further research indicates that dynamic pricing reduces wait times during peak periods and enhances service reliability. Studies by Bischoff & Maciejewski (2016), Simoni et al. (2019), Neijmeijer et al. (2020), Karamanis et al. (2022), and others show that aligning vehicle deployment with demand hotspots cuts wait times by over 50% and reduces the need for manual repositioning. Bimpikis et al. (2019) highlight how spatial pricing, a form of dynamic pricing, prevents vehicle clustering in high-demand areas, ensuring coverage in underserved zones. Li & Huo (2019) illustrate that balanced fare levels and efficient routing lower fuel and maintenance costs, further enhancing profitability.
Unlike private ride-sourcing services that use surge pricing to attract more drivers (Castillo, 2018; K. Chen & Sheldon, 2016; Garg & Nazerzadeh, 2021a), public operators can use dynamic pricing to manage passenger demand directly. Operators can leverage dynamic pricing to balance supply and demand without creating additional incentives for drivers by incentivising off-peak travel or alternative routes.

Dynamic pricing also helps manage congestion in densely populated areas. Hadas et al. (2023) developed models based on vehicle crowdedness that reduce dwell times and enhance reliability. Tirachini et al. (2014) and Fournier et al. (2023) find that fare adjustments distribute passenger loads evenly, preventing vehicle clustering and reducing operational costs. Wei et al. (2020), Xu et al. (2022b), and Xu et al. (2024) show that dynamic pricing across multimodal networks and mixed markets improves traffic flow and matching efficiency.

Machine learning and artificial intelligence further boost dynamic pricing's effectiveness by processing real-time data to predict demand and optimise fleet deployment. Battifarano & Qian (2019), Müller et al. (2023), and Zhang et al. (2024) illustrate how these technologies adapt pricing models to fluctuating market conditions and evolving user behaviours. However, overreliance on dynamic pricing without integrated operational strategies may lead to inefficiencies. Pfrommer et al. (2014) found that while dynamic pricing reduced manual redistribution in London's Cycle Hire scheme, it sometimes led to vehicle clustering in a single zone. Hu et al. (2024) argue that algorithmic models may misallocate resources if existing models inaccurately predict the demand. Transport authorities must integrate dynamic pricing with robust demand forecasting, proactive vehicle repositioning, and comprehensive fleet management. This integration ensures balanced vehicle distribution, prevents misallocation, and enhances system efficiency.

These studies demonstrate that dynamic pricing improves fleet utilisation, reduces idle times, and shortens passenger wait times. Nevertheless, many researchers address these metrics in isolation or only in combination with economic factors. A gap exists in assessing how improvements in operational efficiency affect, and are affected by, user accessibility and environmental outcomes. A multidimensional approach would provide a holistic view of service performance, ensuring that gains in efficiency do not compromise other critical aspects of public transportation.

3.3 User Accessibility

User accessibility refers to the degree to which public transportation services remain affordable and reachable for all user groups. In this context, if dynamic pricing drives fares too high during peak periods, it undermines accessibility by limiting the ability of low-income or vulnerable users to afford and use the service. Research by Hu et al. (2021) and El-Geneidy et al. (2016) shows that peak-hour fare surges can restrict access for financially vulnerable individuals, deepening social inequalities in public transportation.

Low-income commuters with rigid work schedules often lack the flexibility to shift travel times. In Singapore, off-peak discounts attract more users, but without similar incentives during peak hours, those with rigid schedules face higher costs Adnan et al. (2020). Hadas et al. (2023) found that price surges in Israel similarly price out low-income users, worsening existing socioeconomic disparities. Lee et al. (2023) further emphasise that rigid work schedules leave economically disadvantaged groups dependent on costly peak-time services, adding to their financial strain and limiting affordable mobility.

Studies on consumer social learning reveal that as users grow more sensitive to pricing, their travel habits change, potentially leading to inequitable access Zhang et al. (2024b). Haywood & Koning (2015), Sun et al. (2020b), and Giorgione et al. (2020) note that while dynamic pricing can effectively manage demand, it may also raise affordability issues for price-sensitive groups. Pandit et al. (2019) advise cautious use of dynamic pricing in markets with highly price-sensitive customers to address this concern. Fournier et al. (2023b) propose a dynamic travel futures market, allowing travellers to lock in fares in advance, thus reducing cost uncertainty. Though this approach is constructive in the airline industry, its application in shared mobility services, which are often used for short and occasional trips, could be pretty challenging. Perhaps offering lower-cost routes and off-peak travel incentives can also help mitigate adverse impacts on vulnerable populations.

Recent advancements aim to enhance inclusivity by integrating policies that prioritise low-income users. Samundiswary et al. (2024) introduced models like Local Serve, which tailors prices based on users' financial capabilities and local economic conditions, reducing disparities and improving access. Similarly, Lei & Ukkusuri (2023) and Zheng & Geroliminis (2020) explored machine learning algorithms that personalise pricing based on income, travel frequency, and time of day. These strategies balance equity with profitability, making shared mobility services more inclusive.

Implementing moderate pricing and income-based adjustments, as suggested by Zhong et al. (2023) and Karamanis et al. (2022), can prevent the exclusion of low-income users while maintaining service levels. By combining these approaches, public transport operators can reap the benefits of dynamic pricing, such as reduced congestion and optimised fleet utilisation, without compromising accessibility and equity.

Here, too, we observe that the literature discussed under user accessibility typically focuses on fare affordability and the impact of dynamic pricing on vulnerable populations. However, few studies consider how these affordability issues interact with broader performance metrics, such as economic viability or operational efficiency. Evaluating user accessibility alongside other dimensions is essential to ensure that efforts to boost revenue and efficiency do not inadvertently marginalise low-income or price-sensitive users, thereby preserving equitable access to public transport.

3.4 Environmental Sustainability

Dynamic pricing offers significant environmental benefits for publicly owned SAVs within MaaS platforms. Shafiei et al. (2024) and Shatanawi et al. (2022) show that dynamic road pricing can reduce urban congestion by adjusting fares in real-time according to traffic conditions. In Melbourne, such pricing strategies decreased congestion and emissions, while simulations in Budapest revealed reduced vehicle miles travelled (VMT) during peak hours, improving air quality. These studies suggest that dynamic pricing can help public transport operators manage traffic flow more efficiently and minimise the environmental footprint of urban transportation networks.

Dynamic pricing lowers emissions and optimises road infrastructure usage. Cashore et al. (2022) developed a stochastic pricing model for ride-sharing that maintains market equilibrium and reduces unnecessary vehicle circulation during off-peak hours. Sun et al. (2020) further argue that balancing supply and demand through dynamic pricing minimises idle times and empty runs, thereby reducing fuel consumption and emissions. Additionally, Zheng & Geroliminis (2016) emphasise that real-time price adjustments in multimodal transport systems encourage users to opt for sustainable modes such as public transit or cycling, further lowering individual carbon footprints and enhancing overall network efficiency.

However, dynamic pricing also presents challenges. Zuniga-Garcia et al. (2020) warn that lower off-peak fares might trigger increased trip frequency, potentially offsetting the environmental gains. To counteract this, PTOs should implement demand management measures such as minimum fare thresholds and complementary sustainability strategies to ensure that dynamic pricing contributes to environmental goals.

Several studies infer that dynamic pricing can reduce emissions and congestion through economic and operational benefits. Nonetheless, most research does not directly measure environmental outcomes or examine how they correlate with economic and service performance. This siloed approach limits our understanding of how dynamic pricing affects public transportation across multiple dimensions. A multidimensional analysis that combines environmental metrics with financial and operational data is crucial for understanding the full impact of dynamic pricing on sustainable urban mobility.

3.5 SWOT Analysis

To synthesise the key insights from the literature, we present a SWOT analysis that evaluates the strengths, weaknesses, opportunities, and threats of implementing dynamic pricing in publicly owned SAVs within MaaS platforms. This framework examines internal capabilities and external factors that affect the performance of dynamic pricing strategies. By understanding these elements, public transport operators can develop strategies that leverage the benefits of dynamic pricing while mitigating its challenges.

Table 1 details the SWOT analysis, summarising current research and offering actionable insights for public transport operators.

Table 1. SWOT analysis of dynamic pricing in transportation

Strengths:	Weaknesses:
Revenue Optimisation: Dynamic pricing adjusts fares in real-time based on demand, capturing peak-period revenue while ensuring steady income during off-peak hours. This flexibility allows operators to respond quickly to market conditions and maximise profitability. Improved Fleet Utilisation: Dynamic pricing ensures that SAVs are available where and when needed most, reducing idle times and enhancing overall fleet efficiency. Efficient vehicle deployment minimises operational costs and improves service coverage. Enhanced Service Reliability: Dynamic pricing reduces passenger wait times and improves overall service by incentivising drivers to operate during high-demand periods. Reliable service boosts customer satisfaction and fosters higher ridership and trust in the system.	User Affordability Concerns: Higher fares during peak periods can make SAV services less accessible to low-income users, undermining social equity. This risk necessitates the development of inclusive pricing models that balance profitability with affordability. Price Volatility: Rapid fluctuations in pricing may create uncertainty for both users and operators. This volatility can lead to dissatisfaction, reduced trust in the platform, and potential market instability. Dependency on Accurate Data: The success of dynamic pricing relies on the continuous collection and analysis of real-time data. Inaccurate forecasting or data discrepancies can lead to mispricing, inefficient fleet management, and diminished service quality.
Opportunities:	Threats:
Integration with Sustainable Mobility:	Regulatory Challenges:

Dynamic pricing can promote the use of shared and electric vehicles, contributing to environmental sustainability goals. By encouraging shifts toward greener modes of transport, operators can reduce emissions and support broader climate initiatives. Expansion into New Markets: The flexibility of dynamic pricing allows transport operators to adapt their models to diverse urban environments with varying demand patterns. This adaptability creates opportunities for expansion into new markets and enhances the scalability of MaaS platforms. Use of Advanced Algorithms: Advances in AI and machine learning offer the potential to refine dynamic pricing models. Personalised pricing based on user profiles, real-time demand, and predictive analytics can improve efficiency and customer satisfaction. These technologies can help overcome data challenges and further balance equity with profitability.	Some regions impose surge pricing restrictions, limiting dynamic pricing models' flexibility. Such regulations may reduce the ability to respond dynamically to market conditions and affect overall revenue. Competition with Private car usage: Excessively high dynamic fares may drive users toward alternatives such as private car usage. This shift could reduce the market share for ride-hailing services and impact the overall effectiveness of SAV networks. Potential Environmental Backlash: While dynamic pricing aims to reduce congestion and emissions, lower off-peak fares might inadvertently increase trip frequency. This surge in travel demand, especially in high-emission areas, could negate environmental benefits and increase overall energy consumption.

This SWOT analysis provides a structured overview of the internal strengths and weaknesses and external opportunities and threats associated with implementing dynamic pricing for publicly owned SAVs within MaaS platforms. Dynamic pricing offers immense potential for PTAs and PTOs to create more efficient and responsive transportation networks. Operators can leverage it to increase revenue, improve fleet utilisation, enhance service reliability, and ensure long-term sustainable profitability. However, it is critical to integrate advanced technologies and proactive demand management strategies to address affordability concerns, price volatility, and regulatory constraints. A balanced approach that aligns economic objectives with social and environmental goals will ultimately enable sustainable and inclusive urban mobility.

4.0 Modelling Techniques for Dynamic Pricing

Implementing dynamic pricing in publicly owned SAVs within MaaS platforms depends on modelling techniques that accurately forecast demand and optimise fare prices. Researchers employ various methods to navigate the complexities of dynamic pricing and demand prediction. This review categorises these approaches into three primary groups: Optimisation Algorithms, Machine Learning and Artificial Intelligence, and Statistical Analysis and Forecasting, as illustrated in the accompanying figure.

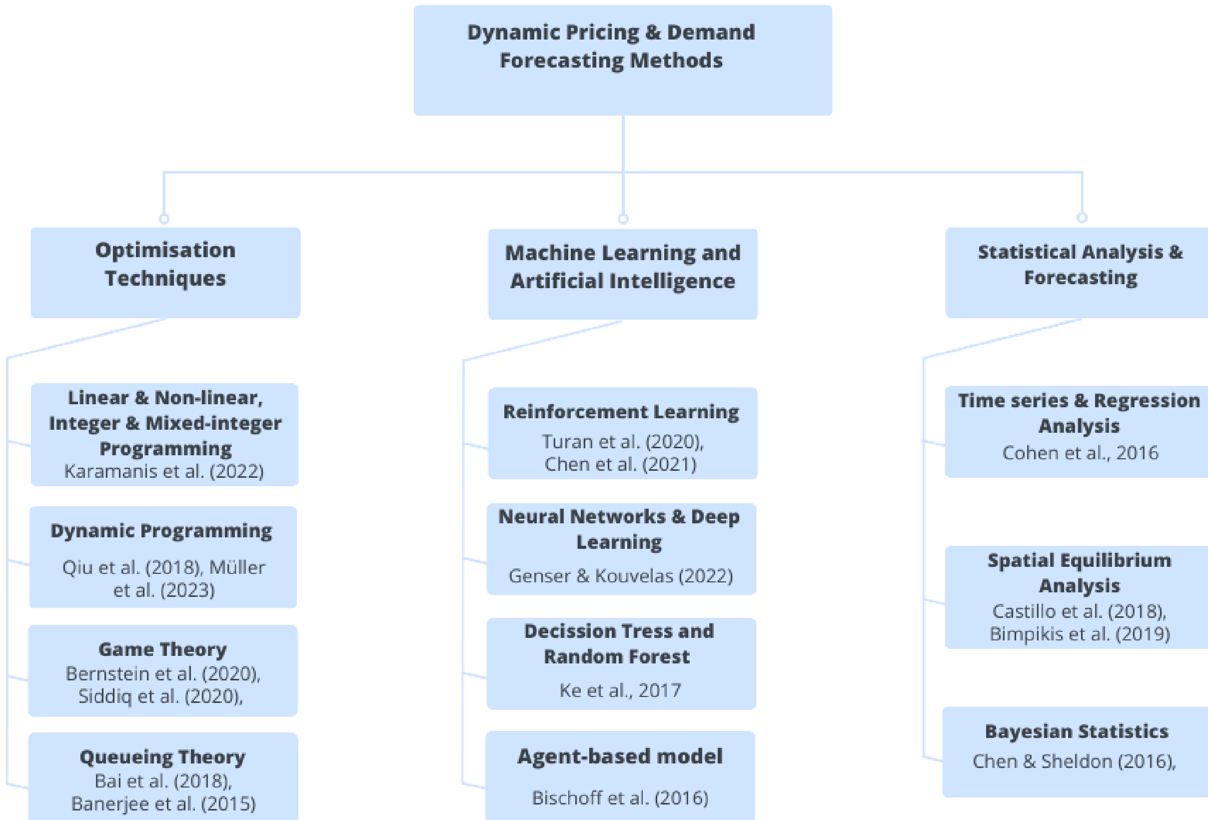

Figure 1: Categories of dynamic pricing methods

4.1 Optimisation Algorithms

Optimisation algorithms calculate optimal pricing outcomes within defined constraints, such as maximising revenue or reducing congestion. These models integrate multiple factors—including customer demand, competitor pricing, and cost structures—to adjust fares dynamically. For example, linear rolling horizon optimisation (LRHO) and dynamic system optimum (DSO) models, which use macroscopic fundamental diagrams (MFDs), compute pricing strategies that effectively manage congestion (Chen et al., 2016b). These algorithms can allow public transport operators to implement strategies that improve traffic flow and reduce bottlenecks. However, real-world variables such as sudden weather changes, traffic incidents, or unplanned events can challenge these models. Enhancing their responsiveness through adaptive elements is essential for addressing such unforeseen disruptions.

4.2 Machine Learning and Artificial Intelligence

Machine learning (ML) and artificial intelligence (AI) techniques continuously learn from new data to refine pricing strategies based on market conditions, customer behaviour, and external factors. Reinforcement learning (RL) and multi-agent deep reinforcement learning (MADRL) models, developed by Abkarian and Mahmassani (2023) and Turan et al. (2020), optimise both pricing and vehicle dispatching in competitive MaaS markets. These models improve demand forecasting accuracy, identify real-time optimal pricing, and tailor fares to specific customer segments, thereby enhancing inclusivity and efficiency. Ke et al. (2017) demonstrated that deep learning effectively addresses complex spatiotemporal forecasting challenges for short-term passenger demand, while Genser & Kouvelas (2022) employed multi-layer neural networks (MLNs) to predict pricing functions across multi-region urban networks. Although these AI-driven models offer great potential, they require meticulous data management, clear model interpretability, and careful ethical considerations.

4.3 Statistical Analysis and Forecasting

Statistical analysis and forecasting methods rely on historical data to project future trends in demand, price sensitivity, and market dynamics. Techniques such as time series forecasts and multinomial logit mode choice models (Chen et al., 2016) help researchers assess the market potential of SAV fleets. These models simulate various dynamic pricing strategies within agent-based frameworks, evaluating their impact on mode share, service quality, and operational performance. While statistical methods offer valuable insights, they often struggle in rapidly shifting environments, as historical trends may not predict sudden demand spikes. Combining these traditional approaches with real-time data and adaptive algorithms can enhance predictive capabilities and responsiveness.

Developing a dynamic pricing model for SAVs requires an approach or a model that can adapt to changing conditions in real-time, handle complex interactions between variables, and predict prices that balance demand and supply efficiently. Pricing algorithms should be able to set fares based on intricate demand functions that vary in sensitivity (Abkarian & Mahmassani, 2023). Furthermore, these algorithms should have the ability to identify non-stationary patterns—meaning, when the true value of actions changes over time, such as due to changes in customers' willingness to pay, and adjust their pricing strategies based on what they have learned from past decisions (Sutton & Barto, 2017). No single "best" technique exists, as the optimal choice depends on the specific characteristics of the service, the data available, and the goals of the pricing strategy. However, reinforcement learning stands out for its ability to adjust pricing dynamically by learning from past outcomes, making it well-suited for uncertain and complex market conditions.

Table 2 outlines the various methods used in the literature to compute dynamic prices. This table aligns with the modelling techniques discussed earlier and summarises each method's core features, key studies, strengths, and challenges.

Table 2: Price and demand modelling methods

Category	Dynamic Pricing Method Used	Key Studies	Core Features	Strengths	Challenges
Machine Learning and AI	Reinforcement Learning (Deep Q-Networks & Soft Actor-Critic)	Kastius & Schlosser (2022); Gao et al. (2024); Sun et al. (2024); Abkarian & Mahmassani (2023); Turan et al. (2020)	Uses reinforcement learning algorithms to adjust prices dynamically by learning from real-time interactions and outcomes.	High adaptability; enables personalised pricing; supports real-time decision-making.	Requires extensive training data, is computationally intensive, and has challenges with model interpretability.

Category	Dynamic Pricing Method Used	Key Studies	Core Features	Strengths	Challenges
	Multi-Layer Neural (MLN) Network Model	Genser & Kouvelas (2022)	Utilises deep neural networks with multiple layers to capture complex spatial and temporal patterns in demand and pricing functions.	Effectively models non-linear relationships; high prediction accuracy.	Demands high-quality data; risk of overfitting; increased computational complexity.
	Agent-Based Simulation (MATSim, PTV Visum)	Hörl et al. (2021); Shafiei et al. (2024); Simoni et al. (2019); Bischoff et al. (2016); Ji et al. (2024); Antonio & Maria-Dolores (2022)	Simulates the interactions of individual agents (e.g., passengers, vehicles) within a transportation network using simulation software to inform pricing strategies.	Captures emergent behaviours and system interactions; useful for scenario analysis and policy evaluation.	Computationally intensive; requires careful calibration and validation; complex implementation.
Optimisation Algorithm	Queueing-Based Analytical Model	Bai et al. (2018); Riquelme et al. (2015); Pandit et al. (2019)	Employs queueing theory to analyse system dynamics such as waiting times and service levels, optimising pricing to manage demand flow.	Based on solid analytical foundations, effective for service-level optimisation.	Simplified assumptions may not capture all real-world complexities and limited flexibility for sudden disruptions.
	Dynamic Programming – Approximate (ADP), Stochastic (SDC), & Optimal Control Theory	Chen et al. (2020); Qiu et al. (2018); Wang & Xie (2021); Muller et al. (2023); Al-Kanj et al. (2020); Garg et al. (2021); Qian & Ukkusuri (2017)	Uses dynamic programming and control theory techniques to determine optimal pricing trajectories over time, incorporating stochastic elements and constraints.	Captures temporal dynamics and uncertainty; robust for long-term optimisation.	High computational complexity; sensitive to parameter estimation; requires extensive and accurate data.

Category	Dynamic Pricing Method Used	Key Studies	Core Features	Strengths	Challenges
	Mixed-Logit Choice Model with Latent Class Analysis / Multinomial Logit Mode Choice Model	Nazari et al. (2018); Chen et al. (2016)	Statistical models that estimate consumer choice and price sensitivity by segmenting the market into latent classes.	Provides deep insights into consumer behaviour and market segmentation; supports tailored pricing strategies.	Dependent on the quality of survey/historical data; may oversimplify complex consumer behaviours.
	Combinatorial Auction-Based Simulation	Karamanis et al. (2021)	Implements auction-based mechanisms to allocate rides and determine prices through competitive bidding processes among service providers.	Facilitates efficient matching of supply and demand; promotes competitive and fair pricing.	Implementation complexity; high computational demands; may require sophisticated software solutions.
	Non-Linear Minimum Cost Flow Problem (Convex Optimization)	Karamanis et al. (2022)	Models the dynamic pricing problem as a network flow optimisation task, aiming to minimise overall costs while satisfying demand across a network.	Efficient cost minimisation; scalable for large networks; mathematically robust.	Complexity in non-linear optimisation; sensitive to initial conditions and parameter settings.
	Markov Decision Process (MDP) Framework	Ni et al. (2022)	Uses MDP to model sequential decision-making in pricing under uncertainty, capturing state transitions and reward structures over time.	Provides a structured approach for sequential decision-making; effectively captures uncertainty in dynamic environments.	Computationally intensive; may require simplifications and approximations to remain tractable.
	Game-Theoretical Analysis	Bernstein et al. (2020); Siddiq et al. (2020); Zhong et al. (2022)	Analyses strategic interactions among market participants to determine	Captures competitive behaviours; useful for policy and market	Relies on assumptions about rational behaviour; may not fully capture complex, real-world market dynamics.

Category	Dynamic Pricing Method Used	Key Studies	Core Features	Strengths	Challenges
			equilibrium pricing strategies and competitive dynamics.	structure analysis.	
	Stochastic Spatiotemporal Pricing (SSP) Mechanism	Cashore et al. (2022)	Employs stochastic models that adjust pricing based on spatial and temporal demand variations, addressing fluctuations across regions and times.	Robust to fluctuations in demand across time and space; enhances pricing resilience.	Requires high-resolution data, complex calibration, and sensitivity to spatial heterogeneity.
Statistical Analysis and Forecasting	Multivariate Extreme Value-Based Discrete Choice Model with Sampling and Endogeneity Corrections	Krueger et al. (2023); Hadas et al. (2023)	Utilises advanced discrete choice models that account for extreme values and correct for potential endogeneity in consumer decision data.	Provides detailed insights into consumer decision-making; robust to certain data issues and biases.	Computationally intensive; sensitive to model specification and estimation challenges.
	Macroscopic Fundamental Diagram (MFD)	Zheng & Geroliminis (2016); Zheng & Geroliminis (2020); Genser & Kouvelas (2022)	Uses aggregated traffic flow data to derive relationships between traffic density and flow, informing dynamic pricing and congestion management strategies.	Offers a high-level view of traffic dynamics; effective for managing congestion on a macro scale.	May oversimplify local and heterogeneous network dynamics; limited granularity.
	Contingent Valuation Method (CVM)	Haywood & Koning (2015)	It uses survey-based techniques to estimate users' willingness to pay for dynamic pricing services, capturing consumer	Direct measurement of consumer preferences; valuable for policy evaluation and pricing decisions.	Subject to response biases; limited by survey design and sample representativeness.

Category	Dynamic Pricing Method Used	Key Studies	Core Features	Strengths	Challenges
			preferences and price sensitivity.		

5. Conclusion

This paper examined the impact of dynamic pricing on the performance of SAVs integrated within MaaS platforms. We aimed to identify and understand the benefits of adopting a dynamic pricing strategy for on-demand SAVs within urban public transportation systems.

Using a systematic review methodology guided by PRISMA 2020, we searched multiple academic and grey literature sources, applied strict inclusion criteria, and extracted key data points from 183 documents. We organised our insights around four thematic areas: economic viability, operational efficiency, user accessibility, and environmental impact.

The literature shows that dynamic pricing drives revenue growth, optimises fleet utilisation, reduces passenger wait times, and cuts operational costs through more efficient resource allocation. It also smooths demand and reduces congestion, contributing to lower emissions and a cleaner urban environment. However, these benefits come with important trade-offs. For instance, some researchers highlight that dynamic pricing exacerbates social inequalities by disproportionately affecting low-income users during peak periods when fares are relatively high. Public transport operators should consider including safeguards such as fare caps during peak periods and discounts during off-peak times to keep transportation affordable.

Our review also highlights the potential of advanced pricing algorithms and robust data analytics to forecast demand spikes, adjust fares in real-time, and adapt to changing market conditions—all while maintaining service quality and reliability. Although no single "best" technique exists, many researchers consider reinforcement learning a promising tool due to its ability to learn from past outcomes and dynamically adjust pricing strategies.

We identified several research gaps. Much of the current literature centres on privately operated ride-hailing services, leaving a notable gap regarding dynamic pricing applications in publicly managed transport services such as SAV fleets. This gap reveals a need for future research to tailor dynamic pricing models to public transportation contexts. Also, understanding user perceptions and acceptance in a public sector context, where expectations for fare stability differ from those in the private market, remains an essential avenue for investigation. Furthermore, many studies assess performance dimensions in isolation rather than using a multidimensional framework that integrates economic, operational, social, and environmental impacts. Addressing these gaps through comprehensive, integrated research will provide a more holistic evaluation of dynamic pricing's potential benefits and trade-offs.

From a policy standpoint, implementing dynamic pricing in public transportation demands a careful balance between profitability goals and affordability considerations. Policymakers must invest in robust technological infrastructures that support real-time pricing while simultaneously adopting measures to protect vulnerable users. Transparent communication and public education about the benefits and mechanics of dynamic pricing will be crucial in building trust and securing public buy-in.

Dynamic pricing offers immense potential for improving the performance of SAVs within MaaS. By designing and implementing a dynamic pricing strategy harmonising economic objectives with social and environmental goals, PTAs and PTOs can create more efficient, accessible, and sustainable shared mobility services within the MaaS framework. However, methods for developing the dynamic pricing strategy must be carefully chosen and developed specifically with the ability to rapidly adapt to changes in customers' willingness to pay while balancing economic objectives with operational and social impacts.

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