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Review

Leveraging Big Data and AI for Sustainable Urban Mobility Solutions

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Abstract

Urban population growth is intensifying pressure on mobility systems, with road transportation contributing to environmental and sustainability challenges. Policymakers must navigate complex uncertainties in addressing rising mobility demand while pursuing sustainability goals. Advanced technologies offer promise, but their real-world effectiveness in urban contexts remains underexplored. This meta-review comprised three complementary studies: a broad analysis of sustainable mobility with Norwegian case studies, and systematic literature reviews on digital twins and Big Data/AI applications in urban mobility, covering the period of 2019–2024. Using structured criteria, we synthesised findings from 72 relevant articles to identify major trends, limitations, and opportunities. The findings show that mobility policies often prioritise technocentric solutions that unintentionally hinder sustainability goals. Digital twins show potential for traffic simulation, urban planning, and public engagement, while machine learning techniques support traffic forecasting and multimodal integration. However, persistent challenges include data interoperability, model validation, and insufficient stakeholder engagement. We identify a hierarchy of mobility modes where public transit and active mobility outperform private vehicles in sustainability and user satisfaction. Integrating electrification and automation and sharing models with data-informed governance can enhance urban liveability. We propose actionable pathways leveraging Big Data and AI, outlining the roles of various stakeholders in advancing sustainable urban mobility futures.

Keywords: urban mobility; sustainable mobility; big data; digital twins; machine learning; deep learning

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1. Introduction

Human mobility, defined as the movement of people across space and time, shows patterns at the individual level that are constrained by consistent time and money budgets [1,2]. The average person makes three–four trips daily totalling 1 h, with 80% of mileage occurring within 50 km of their homes. Transportation accounts for 11–15% of personal disposable income and 15–25% of household expenditure in Europe and the US.

These mobility patterns drive transportation systems that are highly interconnected with environmental, social, and economic domains [1,3]. In 2020, transportation accounted for 21.5% of global CO_2 emissions, with 74.5% coming from road vehicles (45.1% passenger, 29.4% freight), as shown in Figure 1. Road transportation thus contributes 16.0% of global CO_2 emissions.

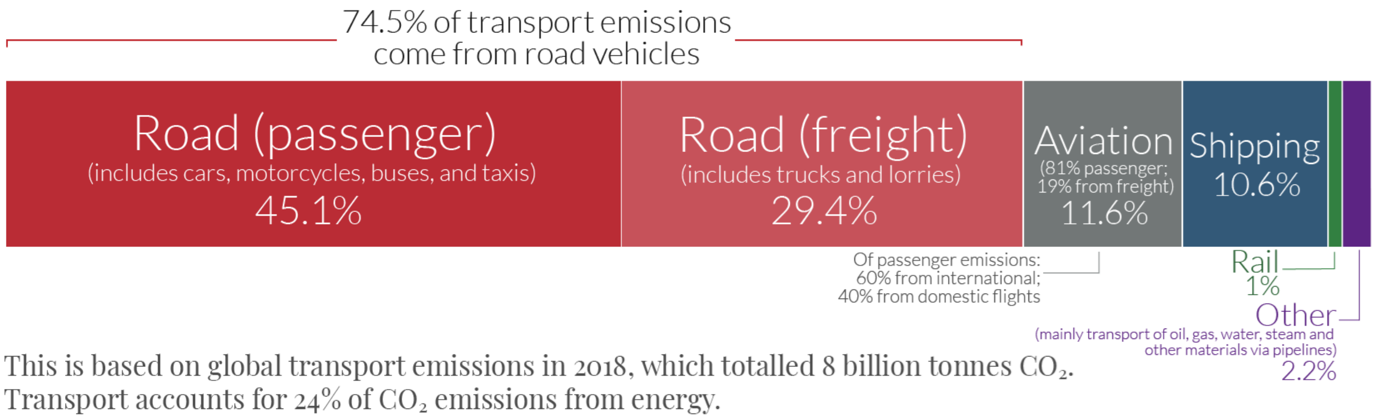

Figure 1. Breakdown of global transportation emissions. Adapted from Ritchie and Roser [4].

In addition, the size and population of urban centres continues to grow at an accelerating pace, placing strain on existing transportation infrastructure. An estimated 56% of the world's population currently lives in cities, with the urban population expected to more than double by 2050 [5]. The absolute and relative contributions of urban mobility to global emissions are expected to rise as transportation demand grows with urban expansion and rising incomes [4].

While technological innovations like electrification and hydrogen fuels can offset some projected increases, their effectiveness is limited for long-distance freight due to the impracticality of large batteries or fuel tanks. Furthermore, there is growing discourse around liveable cities aimed at enhancing quality of urban life while dealing with traffic congestion and noise pollution.

Therefore, city planners face the challenge of crafting urban mobility policies that satisfy increasing service demand while reducing environmental impact and improving liveability. Although advances in big data (BD), artificial intelligence (AI), and digital twins (DTs) offer new paradigms for data-driven decision-making in mobility policy formulation, these technologies remain underexplored in urban mobility applications.

Formulating effective mobility policies requires understanding how cultural, geographical, and economic factors shape mobility patterns and influence policy success. Norway's unique context—emphasising sustainability and strong public services while facing geographic challenges from fjords, mountains, and the harsh climate—provides a distinctive setting for exploring urban mobility within European contexts. Norwegian wealth from natural resources supports investment in green technologies, yet geographic constraints present unique infrastructure challenges that require resilient solutions.

This paper assesses the current status of sustainable urban mobility through a systematic literature review, using Norway as a case study to examine policy strengths and limitations. It explores how big data, AI, and digital twins can support sustainable mobility by enabling data-driven policymaking and collaborative public engagement. Two complementary systematic literature reviews examine: (1) digital twins for future mobility solutions through data-driven policymaking and public engagement, and (2) Big Data and AI for analysis and predictive modelling of spatiotemporal urban mobility patterns.

The contributions of this paper can be summarised as follows:

1. It provides an updated overview of the state of sustainable urban mobility, with a critical examination of the challenges associated with existing policies and initiatives in Norway, revealing how seemingly progressive mobility policies can exacerbate social inequalities.
2. It presents a systematic literature review of the state of the art, as well as challenges and knowledge gaps, in the application of digital twins for sustainable urban mobil-

ity, demonstrating how these technologies can bridge urban planning theory with technological innovation.
3. It presents another systematic literature review identifying current methods and best practices in the use of AI techniques for analysing and modelling big data from urban mobility, with particular focus on predictive modelling and multimodal integration frameworks.
4. It discusses the potential impacts of future mobility developments on sustainability goals, including the emergence of a seventh transportation revolution driven by decarbonisation, connected autonomous vehicles, and transformed mobility services.
5. It proposes concrete stakeholder-specific recommendations for leveraging contemporary Big Data and AI paradigms as decision support tools while addressing critical limitations including data privacy, model interpretability, and institutional barriers.

The rest of this paper is organised as follows: Section 2 outlines the systematic methodology for literature selection and quality assessment in the three complementary reviews. Section 3 examines the current state of sustainable urban mobility policies and implementation challenges through Norwegian case studies. Section 4 presents systematic reviews of digital twins, big data, and AI technologies for urban mobility applications. Section 5 synthesises findings and proposes data-driven solutions for sustainable mobility planning and implementation. Section 6 summarises our key findings and provides stakeholder recommendations for sustainable urban mobility transitions.

2. Methodology

This paper employs a meta-review approach comprising three complementary studies (see in Supplementary Materials): (1) a broad review of sustainable mobility literature with Norwegian case studies, (2) a systematic literature review (SLR) of digital twins (DTs) for sustainable urban mobility, and (3) another SLR examining artificial intelligence (AI) techniques—specifically machine learning (ML) and deep learning (DL)—for analysing and modelling big data from mobility systems. This section outlines the systematic methodology for literature selection from digital libraries, including the structured selection process, quality assessment criteria, and methodological limitations.

Due to their technical content, the two SLRs were conducted according to the process outlined by Carrera-Rivera et al. [6] for computer science research. The process begins by formulating research questions using the PICOC (Population, Intervention, Comparison, Outcome, and Context) framework to clearly define the focus of the review. Next, relevant digital libraries are selected, and inclusion/exclusion criteria are established to filter the articles. Search strings are then constructed based on the PICOC criteria, and articles are gathered from the chosen databases. The gathered articles are screened for duplicates, and a quality assessment is conducted based on predefined criteria. Finally, relevant data is extracted, followed by quantitative and qualitative analysis, leading to the synthesis and reporting of findings.

2.1. PICOC Criteria

The PICOC criteria provide a structured approach to an SLR, helping to define its scope and formulate precise research questions. PICOC ensures that the review is both comprehensive and targeted by facilitating the formulation of search queries and the selection of relevant articles. Table 1 explains each PICOC element and outlines the specific keywords used to enhance the rigour and clarity of both SLRs conducted in this review. These criteria subsequently informed the development of search strategies and quality assessment frameworks for each sub-review.

Table 1. The PICOC criteria defining the scope for the SLRs.

Elements	Description	Digital Twins	Big Data and AI
Population	This can be a specific role, an application area, or an industry domain.	Digital Twins	Urban Mobility
Intervention	The methodology, tool, or technology that addresses a specific issue.	Deep Learning, Big Data	Big Data
Comparison	The methodology, tool, or technology in which the intervention is compared.	Not Applicable	Not Applicable
Outcome	The key factors of interest to practitioners or the expected results of the intervention.	Communicate Insights, Physical Realism	Analysis, Forecasting, Modelling, Validation
Context	The setting in which the comparison occurs.	Urban Mobility, Sustainable Mobility	Transport Planning, Public Transit

2.2. Research Questions

To orient the overall review process, two broad themes were established to guide the subsequent reviews and ensure they remained complementary. The first theme focused on exploring the global state of sustainable mobility, with emphasis on how Norway fits within this broader context while identifying challenges faced by urban mobility initiatives through key case studies. The second theme centred on how big data, AI, and digital twins are being used to advance sustainable mobility policies and goals while considering the limitations of these technological approaches and exploring potential areas for improvement. Using these themes and the PICOC criteria in Table 1, the research questions for each sub-review were formulated as follows:

1. Review on "Sustainable Mobility":
   - Q1. What is the current state of sustainable urban mobility, considering historical developments and current statistical data?
   - Q2. What are the key challenges associated with existing urban mobility policies and initiatives?
   - Q3. How might future technologies impact sustainability goals, and what uncertainties do these developments present for policymakers?
   - Q4. What role does scientific research play in shaping policymaking and guiding the discourse on sustainable mobility?
2. SLR on "Digital Twins":
   - Q1. How can digital twins, supported by Big Data and AI, be used to inform data-driven policymaking for urban mobility systems?
   - Q2. How do digital twins improve the transparency, and effectiveness of mobility policy interventions?
   - Q3. What are the key challenges and limitations in applying digital twins for urban mobility systems, and how can these be addressed?
   - Q4. What role can digital twins play in enabling collaborative public engagement in the design and operation of urban mobility systems?
3. SLR on "Big Data and AI":
   - Q1. What are the primary sources of the big data used for mobility analysis and modelling?
   - Q2. What ML and DL algorithms are commonly applied for analysing and modelling mobility data?

Q3. What are the advantages and disadvantages of different data sources and algorithms used for mobility analysis?
Q4. What key insights have been extracted from urban mobility data, and how have said insights informed policymaking?

2.3. Inclusion and Exclusion Criteria

The inclusion and exclusion criteria for the articles selected for the sub-reviews were defined based on the PICOC criteria and the research questions. The criteria were applied to each sub-review, ensuring that the selected articles were relevant, of high quality, and aligned with the themes of the overall meta-review process. For all three sub-reviews, only articles published from 2019 to November 2024 were considered. This temporal restriction ensured that the articles were recent and relevant, especially given the rapid advancements in the fields of big data, AI, and digital twins. The details of the inclusion and exclusion criteria, along with the rationale for their selection, are summarised in Table 2. These criteria ensured methodological rigour while maintaining consistency with the overarching themes of the meta-review.

Table 2. Inclusion and exclusion criteria for the articles selected for the reviews.

Criteria	Inclusion	Exclusion and Justification
Type of Study	Peer-reviewed journal articles or conference proceedings	Non-peer-reviewed articles, grey literature, and book chapters were eliminated to ensure the quality and reliability of the articles.
Language	English	Non-English articles were excluded to avoid translation issues and ensure consistency in the review process.
Accessibility	Available in the Scopus and Web of Science (Core Collection) digital libraries	Articles not accessible through these databases were excluded to ensure that the articles featured in the review can be easily accessed by readers and researchers.
Content Focus	Relevant to the research questions outlined in Section 2.2	Articles that do not address at least two of the research questions for their sub-review or are not relevant to the themes of the review were excluded. This ensured that the selected articles contribute meaningfully to the overall review process.

2.4. Quality Assessment Checklist

To ensure the quality and relevance of the articles included in the reviews, a structured quality assessment checklist was developed. This checklist was directly informed by the research questions and the PICOC criteria outlined in Table 1. For each sub-review, specific assessment criteria were defined to evaluate how well each article addressed the corresponding research questions.

Articles were independently scored against these criteria, with higher scores reflecting stronger alignment with the review's objectives. Only articles achieving a minimum score of 3 were retained for the final synthesis, ensuring that the selected literature made a meaningful contribution to the overarching themes of the meta-review. The details of the assessment criteria for each sub-review are summarised in Table 3. The following scoring rubric was used for all criteria established in the quality assessment: 1—No (Score: 0); 2—Partially (Score: 0.5); 3—Yes (Score: 1).

Table 3. Quality assessment checklist for the articles selected for the reviews.

Assessment Criteria
Review on "Sustainable Mobility":
1. Does the study focus on mobility systems within the context of sustainability or energy transition goals, with a defined geographic or modal scope?
2. Are empirical methods used to assess the impact, performance, or adoption of sustainable mobility interventions, with appropriate policy or governance context?
3. Is there discussion on the current state of sustainable urban mobility, including key challenges and the role of scientific research in policymaking?
4. Does the discussion include the potential impact of future technologies on sustainability goals and the uncertainties they present for policymakers?
SLR on "Digital Twins":
1. Is the development, implementation, or evaluation of a digital twin system central to the study, with clear application to urban mobility?
2. Does the digital twin incorporate real-time or simulated urban data with appropriate technical implementation?
3. Is the system used for urban planning, visualisation, or participatory feedback, rather than solely technical modelling?
4. Are the key challenges and limitations in applying digital twins for urban mobility systems identified?
SLR on "Big Data and AI":
1. Does the study combine the application of big data techniques with artificial intelligence models within a transportation or mobility context?
2. Are performance metrics reported and compared against baseline methods or benchmarks, with an adequate description of the modelling approach?
3. Are the primary sources of big data, commonly applied ML/DL algorithms, and their advantages and disadvantages for mobility analysis identified and discussed?
4. How are key insights extracted from urban mobility data summarised, including their impact on policymaking and the limitations of current approaches?

2.5. Database Search Queries

To ensure comprehensive coverage, the Scopus and Web of Science (Core Collection) digital libraries were selected as sources based on their disciplinary strengths. Scopus is known for its extensive coverage of engineering and computer science literature, while Web of Science is recognised for its broad coverage across various disciplines, including social sciences and humanities [7,8].

Thus, the articles for the "Sustainable Mobility" sub-review were sourced exclusively from Web of Science, and those for "Digital Twins" were sourced from both Scopus and Web of Science due to the interdisciplinary nature of the domain, while those for "Big Data and AI" were sourced exclusively from Scopus owing to its broader coverage of technical disciplines. The "Sustainable Mobility" search results were also manually augmented with additional articles to ensure the inclusion of key statistical sources relevant to the review.

Given the technical focus of this meta-review on leveraging big data, AI, and digital twins for sustainable urban mobility solutions, the search queries for the "Big Data and AI" SLR were confined to the Engineering and Computer Science subject areas. This restriction ensured that only technically oriented articles were included, excluding those that, although relevant to urban mobility, do not contribute directly to understanding how BD/AI technologies can shape future mobility solutions. This approach aligns with the overarching goal of examining technological innovations that support data-driven decision-making in mobility systems, rather than broader policy or social studies of mobility.

Taking into account the inclusion and exclusion criteria, the search queries for each sub-review were constructed based on the PICOC criteria and the research questions. The search queries were designed to be broad enough to capture relevant articles while also being specific enough to filter out irrelevant ones.

1. Review on "Sustainable Mobility": Web of Science

```
TS=("urban mobility" AND (history OR sustainable OR norway))
AND DT=(Article OR Proceedings Paper)
AND LA=(English) AND DOP=(2019/2024)
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2. SLR on "Digital Twins": Web of Science and Scopus

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TS=("digital twins" AND ("mobility" OR "transportation" OR "big data"
OR "realism" OR "deep learning" OR "DL"))
AND DT=(Article OR Proceedings Paper)
AND LA=(English) AND DOP=(2019/2024)
-- -- --
TITLE-ABS-KEY("digital twins" AND ("mobility" OR "transportation"
OR "big data" OR "realism" OR "deep learning" OR "DL"))
AND DOCTYPE(ar OR cp)
AND LANGUAGE (english) AND PUBYEAR > 2018
```

3. SLR on "Big Data and AI": Scopus

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TITLE-ABS-KEY(("mobility" OR "transit" OR "transport*")
AND ("big data" OR "crowdsourced data")
AND ("analysis" OR "pattern" OR "spatio-temporal" OR "trend"
OR "forecasting" OR "congestion" OR "flow" OR "management"
OR "model*" OR "algorithm" OR "deep learning" OR "machine learning"
OR "neural network" OR "predicti*" OR "time series"))
AND SUBJAREA(COMP OR ENGI) AND DOCTYPE(ar OR cp)
AND LANGUAGE(english) AND PUBYEAR > 2018
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2.6. Article Selection Process and Results

Through a systematic four-stage selection process, relevant articles were identified for each sub-review, with the methodology summarised in Table 4 following the "Preferred Reporting Items for Systematic Reviews and Meta-Analyses" (PRISMA) guidelines. Given the distinct nature of each sub-review, the appropriate selection process was adapted while maintaining rigorous quality standards.

For the "Sustainable Mobility" review, the identification stage retrieved 1058 articles from Web of Science after applying initial filters for language (English) and document type (articles/proceedings). During the screening phase, no duplicates or retractions were found, while 911 irrelevant articles were excluded following title/abstract screening, reducing the total to 147. The eligibility assessment applied full-text quality evaluation, excluding 136 articles and retaining 11. The inclusion stage added 21 articles: 9 from reference lists and 12 manually identified key statistical sources, resulting in a final selection of 32 articles.

For the "Digital Twins" SLR, the identification stage retrieved 4156 articles from both Web of Science (795) and Scopus (3361) after initial filtering. Screening removed 520 duplicates and retractions, followed by the exclusion of 3468 irrelevant articles after title/abstract screening, reducing the total to 168. Full-text quality assessment excluded 154 articles, retaining 14. The inclusion stage added 3 articles from reference lists and manuscript updates, yielding a final selection of 17 articles.

Table 4. PRISMA-style summary of the selection process for the articles included in the meta-review.

Stage	Description	*n* Articles
	Review on "Sustainable Mobility":	
Identification	+ Articles retrieved from digital libraries after initial filtering − Filters applied: language (English) and document type (articles/proceedings) Web of Science: (*n* = 1058)	1058
Screening	− Duplicates and retractions removed: (*n* = 0) − Irrelevant articles excluded after title/abstract screening: (*n* = 911)	1058 147
Eligibility	− Articles excluded after full-text quality assessment: (*n* = 136)	11
Inclusion	+ Additional articles from reference lists: (*n* = 9) + Key statistical sources manually added: (*n* = 12)	20 = 32
	SLR on "Digital Twins":	
Identification	+ Articles retrieved from digital libraries after initial filtering − Filters applied: language (English) and document type (articles/proceedings) Web of Science: (*n* = 795); Scopus: (*n* = 3361)	4156
Screening	− Duplicates and retractions removed: (*n* = 520) − Irrelevant articles excluded after title/abstract screening: (*n* = 3468)	3636 168
Eligibility	− Articles excluded after full-text quality assessment: (*n* = 154)	14
Inclusion	+ Additional articles from reference lists and manuscript updates: (*n* = 3)	= 17
	SLR on "Big Data and AI":	
Identification	+ Articles retrieved from digital libraries after initial filtering − Filters applied: language (English) and document type (articles/proceedings) Scopus: (*n* = 5139)	5139
Screening	− Duplicates and retractions removed: (*n* = 14) − Irrelevant articles excluded after title/abstract screening: (*n* = 4314)	5125 811
Eligibility	− Articles excluded after full-text quality assessment: (*n* = 788)	23
Inclusion	+ Additional articles from reference lists and manuscript updates: (*n* = 0)	= 23

For the "Big Data and AI" SLR, the identification stage retrieved 5139 articles from Scopus after initial filtering. Screening removed 14 duplicates and retractions, followed by the exclusion of 4314 irrelevant articles after title/abstract screening, reducing the total to 811. Full-text quality assessment excluded 788 articles, retaining 23. No additional articles were added during the inclusion stage, resulting in a final selection of 23 articles.

Figure 2 provides a bibliometric overview of the articles selected for the meta-review, highlighting the number of articles included in each sub-review and their distribution by year. In total, 72 articles were included in this meta-review, based on stringent criteria that ensured alignment with the broad themes of the overall review process.

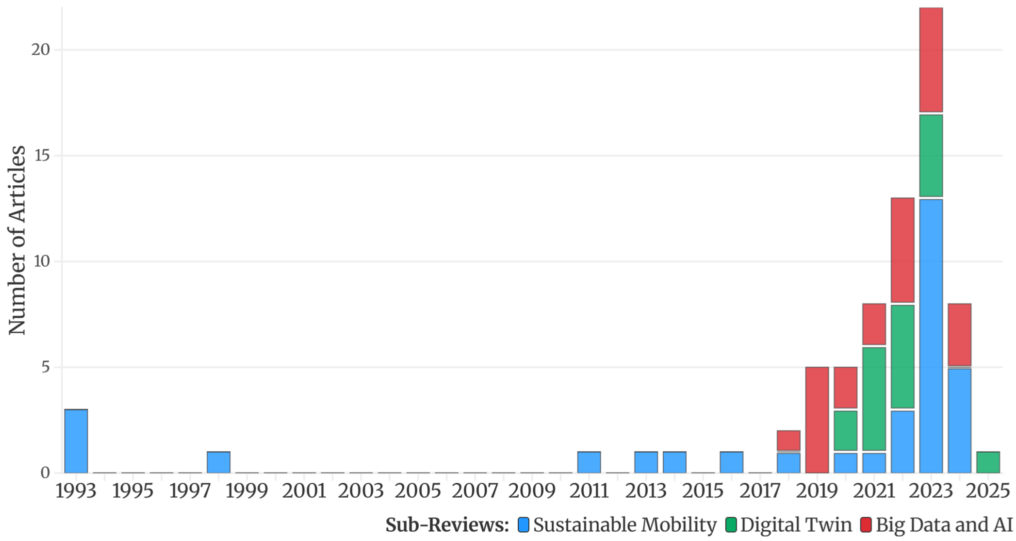

Figure 2. Final selection of articles for the meta-review, by year and sub-review. The total number of articles included in the meta-review is 72.

2.7. Methodological Limitations and Considerations

Several methodological limitations should be noted. First, the review was restricted to English-language articles, which may introduce linguistic bias by excluding relevant studies published in other languages. The temporal scope (2019–2024) was selected to ensure recency but may overlook earlier foundational work that remains influential. Similarly, the choice to focus on technically oriented studies in the "Big Data and AI" sub-review reflects the research aims but may limit contributions from interdisciplinary perspectives that inform real-world implementation.

The database selection was guided by disciplinary relevance, although some relevant literature may fall outside these platforms. Quality assessment was carried out by the lead author using structured criteria, which helps standardise evaluation but cannot fully eliminate the potential for subjectivity. These limitations are mitigated, in part, by a transparent methodology, a broad and reproducible search strategy, and a clearly defined assessment framework.

The following section synthesises the selected literature across the three sub-reviews, beginning with an examination of sustainable mobility policies, challenges, and implementation experiences that provide the foundation for understanding how emerging technologies might address current gaps in mobility planning and policy implementation.

3. Sustainable Urban Mobility: Current State and Challenges

This section examines the current state of sustainable urban mobility by reviewing the literature on policy development, implementation challenges, and emerging trends. Drawing on historical perspectives and contemporary case studies, particularly from Norway, we analyse how mobility policies have evolved and identify persistent barriers to sustainable transitions. The review reveals tensions between technological innovation and sustainability goals, highlighting the need for evidence-based approaches that can bridge policy formulation with real-world implementation.

3.1. Historical Background on Human Mobility

Transport revolutions are innovations in transportation systems that produce or allow significant societal changes, occur in a limited time span with respect to the previous evolutionary period, and give rise to subsequent evolutions over an extended period of time [3]. These revolutions share two common characteristics that go beyond the individual technological innovations, resulting in significant changes to society in unpredictable ways within short time frames [3]. The first is the "law of unintended consequences," where innovations emerge from needs unrelated to transport or lead to unforeseen forms of transport during early adoption. The second is "super additivity" where the combined impact of multiple innovations is greater than the sum of their individual effects.

Human mobility is intricately linked with innovations in transportation systems that facilitate greater movement at lower costs or increased speeds while staying within consistent time and money budgets [9]. The combination of unintended consequences and super additivity resulting from transport revolutions presents policymakers with the challenge of navigating profound uncertainties to shape desirable mobility futures. The sources of these uncertainties can be classified into three main factors [3,9]:

1. Demand: This includes socioeconomic variables related to travel demand, as well as users' trip and travel behaviour, resulting in new consumption patterns.
2. Supply: This encompasses supply performance and disruptive technological innovations, leading to major changes in transport infrastructure provision.
3. Context: This involves societal values and preferences, which influence global and local regulations.

However, this categorisation understates the impact of evolving individual preferences (e.g., remote work), new social dynamics (e.g., online shopping), and emerging technologies (e.g., virtual collaboration tools) in reshaping mobility demand. Furthermore, contextual uncertainties may overlook global externalities such as geopolitical factors and evolving environmental regulations, which can rapidly affect local policies. It is also useful to distinguish between short-term volatility and long-term uncertainties, as each requires different policy approaches.

Historically, scientific research has significantly influenced policy discourse through conceptual changes in perspectives and methodological advances in data collection, analysis, and modelling techniques [9]. Despite advances in mobility models, their utility was limited by data availability [10] until the early 21st century, when widespread adoption of mobile phones and GPS enabled fine-grained analysis of human movement [2].

Scientific research has become indispensable for policymakers in addressing mobility uncertainties and societal changes. Jones [11] discusses a three-stage model of urban transportation policy development observed in many cities, spanning 40–60 years in larger cities:

1. Traffic Growth Policies: Early urban economic growth led to increased car ownership and a focus on expanding road infrastructure and parking to manage rising vehicle traffic, often at the expense of public transit and pedestrian spaces.
2. Traffic Containment Policies: Policies shifted to prioritise efficient movement of people over vehicles, promoting public transit systems and introducing car use restrictions, leading to increased investment in rail and bus systems.
3. Liveable Cities: Emphasis shifted to enhancing urban quality of life and meeting people's activity needs, with a focus on reducing unnecessary travel, promoting walking and cycling, and improving public spaces.

This evolution, illustrated in Figure 3, shows a lag between policy emphasis and actual motorisation levels. The left vertical axis (dotted blue line) indicates the level of motorisation (e.g., car ownership per 1000 people and car modal share). The right vertical axis (solid red line) conceptually represents the extent to which transport policy prioritises motor vehicles, especially private cars. These development patterns have been documented across the USA, Europe, and Asia [9,10,12,13], with Europe occupying a middle ground between American individualistic approaches and Japan's collectivist, transit-oriented model.

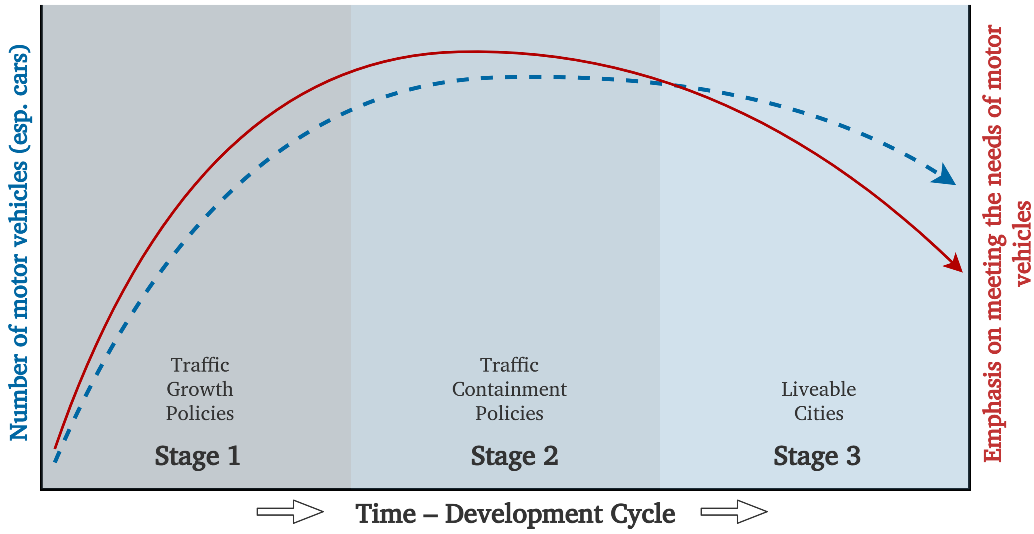

Figure 3. Three-stage model of urban transport policy development. The blue dotted line shows motorisation levels; the red solid line shows the policy emphasis on private vehicles. Adapted from [11].

The decline in motorisation emphasis shown in Figure 3 is supported by evidence from eight industrialised countries—the USA, Canada, Sweden, France, Germany, the UK, Japan, and Australia—showing that vehicle travel growth has stagnated or declined since 2003 [14]. However, many cities struggle to transition from car-based (stage 1) to sustainable (stage 2/3) mobility policies due to factors including urban structure, political interests, and public perception [11].

3.2. Smart and Sustainable Urban Mobility

The concept of Smart and Sustainable Urban Mobility (SSUM) is a key dimension of the European Green Deal Strategy, aimed at addressing urban mobility and transport challenges within the European Union [5]. The "sustainable" aspect focuses on solutions aimed at reducing pollution and protecting the environment. The "smart" aspect involves the use of information and communication technologies in urban mobility to enhance the quality, comfort, and speed of travel. Sustainable mobility is generally conceptualised around the following three core aspects [3]:

1. Social sustainability, which focuses on improving quality of life, social equity, and safety by ensuring easy access to transportation and reducing accident frequency.
2. Economic sustainability, which aims to make mobility more efficient and cost-effective, ensuring that the economic benefits outweigh the costs.
3. Environmental sustainability, which emphasises enhancing environmental quality by reducing emissions and energy consumption across various sectors.

With the recent emphasis on SSUM, transportation policies have shifted towards creating "liveable cities", viewing mobility as derived from demand for activities and access to opportunities. This activity-based approach supports the argument that transportation policy should prioritise enhanced accessibility to facilities rather than catering solely to mobility [9]. This aligns with "Stouffer's Law of Intervening Opportunities", which suggests that travel patterns are determined by the distribution of opportunities across space [2]. Consequently, dominant low-carbon planning models aim at creating polycentric urban regions through transit-oriented development and compact city strategies [15].

However, strategies focused on minimising time and cost can result in increased travel demands, which must be addressed even when some demand shifts to non-car modes. Consumer travel behaviour is influenced by car availability, service provision across different modes, and their associated times and costs [1,9]. Although evidence from European cities shows that urban car traffic growth can be decoupled from economic growth through policy actions, there remains a need to address increased demand across all mobility modes due to rising urban populations.

Future SSUM solutions require a broader perspective on "socio-technical systems", combining advanced technologies with changes in business and social practices. Policy thinking to this end also needs to consider transportation as a derived demand. The socio-technical perspective aligns with the ASI framework, commonly applied to transportation sector decarbonisation [3]:

1. Avoid: Reduce unnecessary polluting trips (fewer vehicle-kilometres travelled for passengers and freight).
2. Shift: Use less-polluting transport modes (such as mass transit or railways).
3. Improve: Reduce pollution of vehicles within each mode (low-carbon-energy technologies and/or emission-optimised operations).

3.3. Current Status of Sustainable Mobility

Sustainable urban mobility plans (SUMPs) are increasingly being used to promote sustainable transport and reduce the negative impacts of urban mobility [16,17]. Figure 4 shows that CO_2-equivalent emissions per passenger-kilometre vary significantly across mobility modes, giving rise to the sustainable mobility hierarchy: walking > cycling > public transit > electric vehicles > private vehicles > air travel.

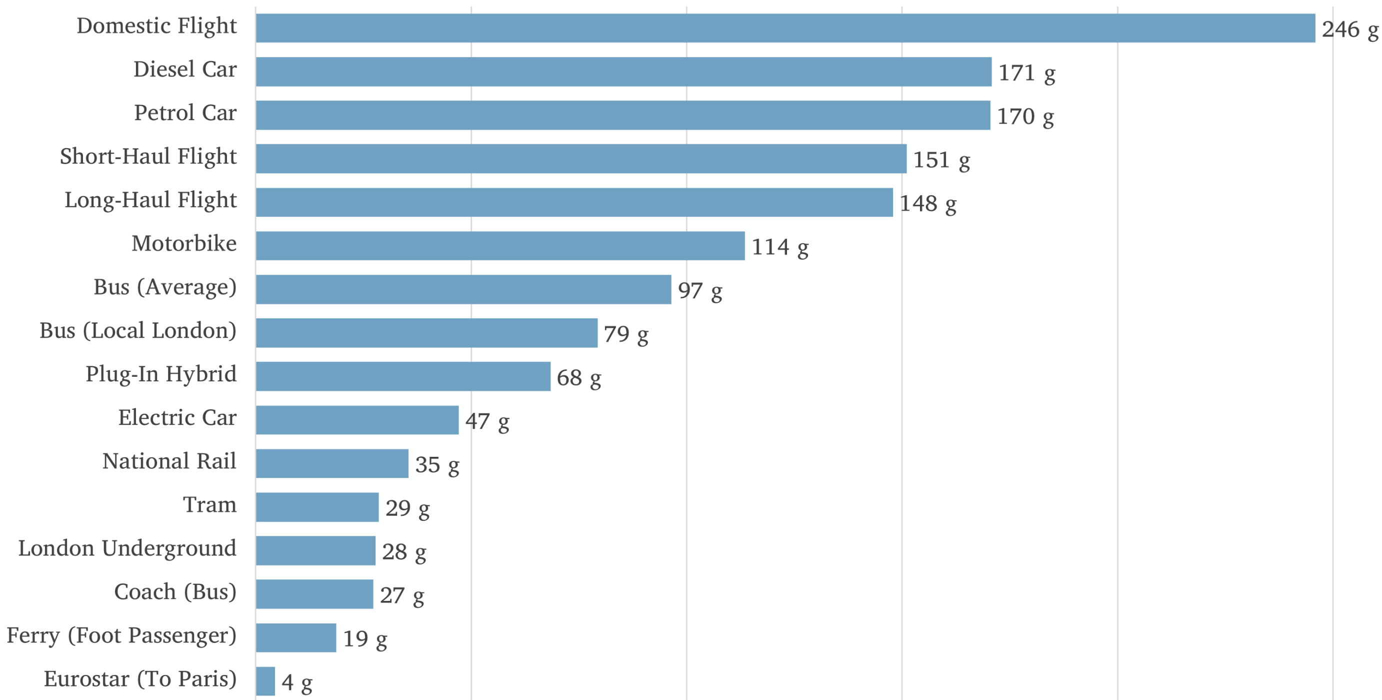

Figure 4. Breakdown of emissions by mobility mode in the UK, 2022. Adapted from [18].

Thus, public transit and active mobility (walking and cycling) are the most desirable travel modes in the pursuit of future SSUM solutions. Walking accounts for ∼20–30% of all trips globally, increasing to ∼41% in major European cities, with 85% of public transit trips involving walking components [16]. However, Figure 5 reveals that lack of convenient access to public transit remains a global challenge.

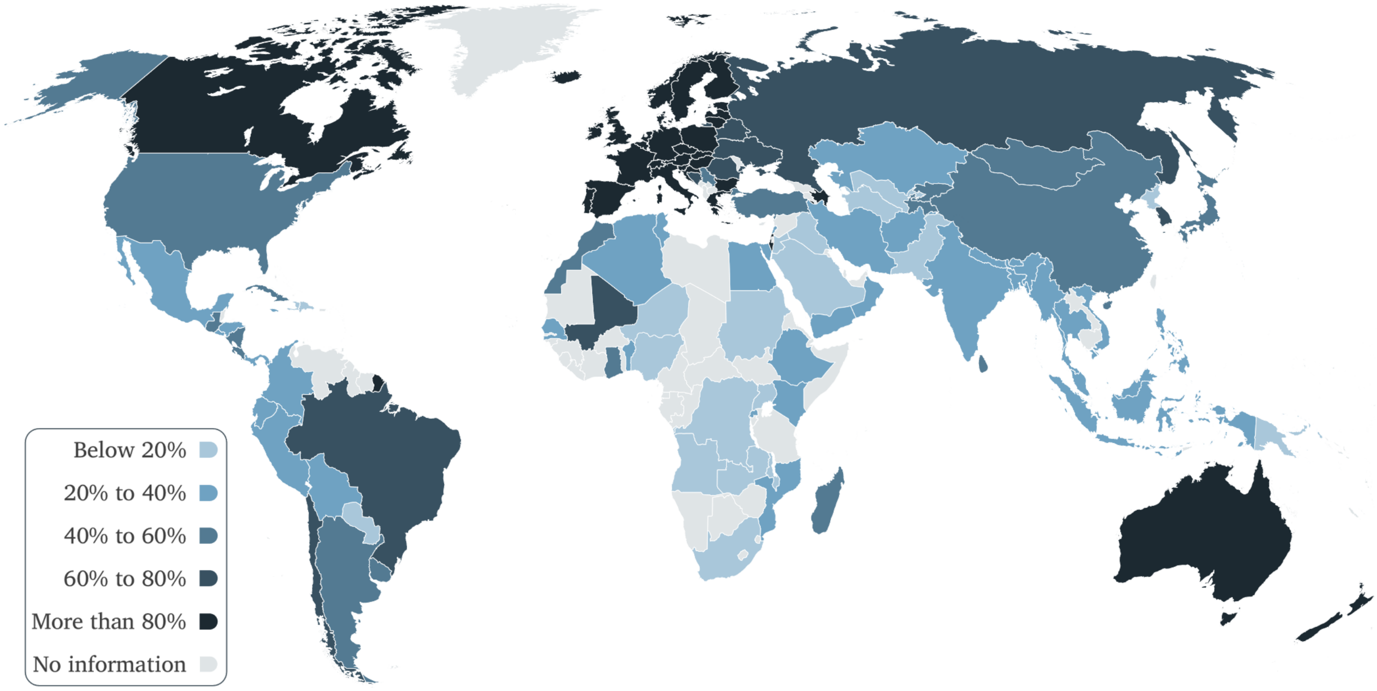

Figure 5. Share of urban populations with convenient access to public transit. Adapted from [16].

Despite its low emissions per passenger-kilometre, rail transportation's inclusive speeds are often comparable to those of cars due to access times, transfers, and indirect routes [1]. Enhancing efficiency and speed of sustainable mobility modes is crucial for competing with driving in terms of convenience [9]. Electric vehicles and car sharing serve as bridges between personal vehicles and public transit, offering reduced emissions per passenger-kilometre travelled, especially when combined with low-carbon grids.

3.3.1. Electromobility and Regional Variations

While electrification is often promoted as a key SSUM component, its effectiveness depends on low-carbon (nuclear and renewable) electricity grids. The share of national electricity from low-carbon sources indicates which regions are best positioned to leverage electrification [19], though higher EV costs favour wealthier regions and groups [3,20]. Figure 6 compares electricity sources across countries, with 39.4% of global electricity generated from low-carbon sources in 2023 [19], led by Norway at 98.5%.

Norway, with its low-carbon grid, exemplifies the potential for electrification in SSUM. EVs accounted for 80% of new car sales in 2022, supported by government subsidies and incentives. However, EV ownership remains disproportionately higher among wealthier households, with the top 10% purchasing 37% of new EVs in 2019, while EVs contributed only 7% of total car-kilometres driven [20].

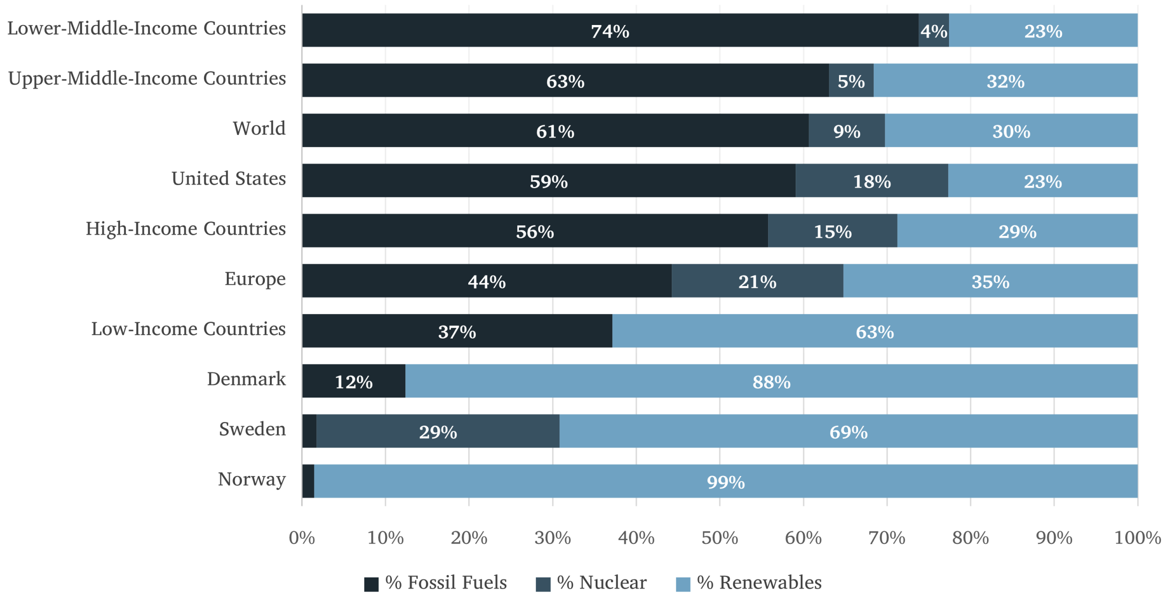

Figure 6. Electricity generation from fossil fuels, nuclear power, and renewables, 2023. Adapted from [19].

3.3.2. Transit-Oriented Development

Transit-oriented development (TOD) promotes dense, mixed-use developments around transit stations to encourage sustainable mobility modes. Norway's "public transport node development" strategy exemplifies this approach, aiming to create walkable communities while reducing car dependency [21]. Figure 7 illustrates Oslo's TOD plan, with workplaces (light blue region) within 600 m and housing (light green region) within 2000 m of transit hubs.

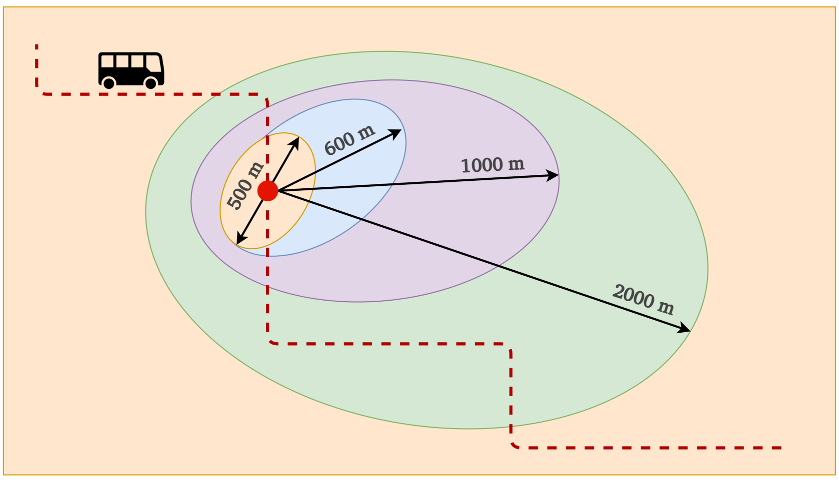

Figure 7. Transit-oriented development plan for Oslo, Norway. Adapted from [15].

An empirical analysis of 20 Norwegian cities reveals that higher city densities lead to shorter distances to activities and increased percentages of sustainable travel modes, particularly for trips to city centres. However, dense mixed-use zones outside inner cities can increase car use and commute distances. Public transit becomes most competitive when activities are concentrated in dense zones and dwellings are within walking distance of stations [21].

3.4. Implementation Challenges and Policy Gaps

Sustainable mobility transitions face significant gaps between policy formulation, implementation, and real-world outcomes. This section reviews some of the key challenges and issues identified in the literature.

3.4.1. Technocratic Planning Approaches

Sustainable urban mobility policies often overlook the social implications of transitions and their impact on residents' daily lives. Low-carbon models like TOD and compact city strategies prioritise physical determinism and assume idealised behaviour, neglecting the complex spatiotemporal dynamics of everyday life [15]. These models emphasise functional spaces and rational travel behaviour while disregarding preferences, emotions, and social practices crucial for encouraging sustainable behaviour [9].

The disconnect between mobility policies and daily mobility realities constrains efforts to shift travel habits towards sustainable modes. A pertinent example is public transit, which typically operates on fixed schedules and routes that may not accommodate the diverse spatiotemporal constraints and routines of individuals [15].

3.4.2. Technology-Centred Solutions

While smart mobility initiatives aim to prioritise sustainable modalities and reduce congestion, research shows that smart mobility often has a weak correlation with sustainability objectives [22,23]. A key challenge is that smart mobility initiatives are primarily implemented for technological reasons rather than with clear sustainability goals. They often prioritise environmental impact and efficiency while overlooking the social dimensions and safety considerations essential for creating liveable cities [23].

These technology-driven interventions are based on the belief that increased efficiency and market opportunities lead to sustainability, rather than reducing consumption. This results in less attention being paid to conventional mobility solutions that may be equally effective in meeting sustainability objectives [23].

3.4.3. Assessment and Measurement Challenges

Assessing the real-world impacts of smart mobility initiatives and evaluating their effectiveness in meeting stated objectives remains challenging. An analysis of Nordic Smart Cities Network initiatives found that most lacked measurable targets and clear benchmarks for success, despite potential indicators such as usage volumes, congestion, emissions, and travel time [23]. There is also a lack of standardised indicators to effectively evaluate initiatives and compare different mobility scenarios [22].

The European Commission's 13 Sustainable Urban Mobility Indicators (SUMIs) represent progress in evaluation frameworks, with studies showing that the most influential indicators relate to public transit availability, multimodal integration, and traffic congestion [17]. The most effective strategies include transit-oriented development, traffic pacification, enhancing public transit, and promoting active mobility, with SUMIs enabling evaluation and comparison of their real-world effects.

3.4.4. Higher-Order Effects of Electromobility

The disconnect between smart mobility and sustainability is evident in electromobility's higher-order effects. The literature indicates that electromobility might lead to increased car usage, ownership, and dependency [1,3,9]. While electromobility contributes to environmental sustainability, its impact on economic sustainability is minimal, and it can negatively affect social sustainability. The transition may make car travel more appealing, worsening issues associated with urban automobility, including traffic congestion and reduced demand for public transit services [20]. These effects also apply to other technology-focused initiatives unless deliberately coupled with shifts toward shared mobility, public transit, or active mobility [23].

3.5. Norwegian Case Studies: Policy Implementation Challenges

The implementation challenges of sustainable mobility policies are exemplified in Norway's major cities, where electric automobility and technocratic planning approaches have produced mixed outcomes.

3.5.1. Bergen: ASI Framework Implementation

Bergen, with 40% EVs and 11% PHEVs among registered private vehicles as of 2023 [24], has implemented the ASI framework with varied results [20]. The "Avoid" strategy established car-free zones but faced implementation challenges in suburban areas. The "Shift" strategy introduced light rail, which altered mode distributions and reduced car trips along the corridor. However, the "Improve" strategy's reliance on EV subsidies has paradoxically prompted proposals for new highways and a shift from zero-growth to zero-emissions targets.

The policy conflicts between "Avoid–Shift" strategies (car-free zones, light rail) and the "Improve" strategy (electromobility) have created tensions. New highways primarily benefit car users, reinforcing car-centric planning at the expense of public transit and active mobility. The strong correlation between wealth and EV ownership has generated calls to redirect subsidies towards public transit investments, illustrating how electrification may address environmental sustainability while neglecting the economic and social dimensions. However, characterising EV ownership solely as a luxury may oversimplify the issue, overlooking practical realities for households in car-dependent environments.

The contradictions between the "Avoid–Shift" and "Improve" strategies have become politically contentious. The compact city plan has contributed to rising urban rent and concerns about gentrification, raising questions about the credibility of urban planners [20]. The policy of funding public transit through congestion tolls has intensified resistance, with critics arguing that such measures represent unfair penalties on residents dependent on cars.

3.5.2. Oslo: Regional Planning Challenges

Oslo has 39% private EVs but the highest private car usage (∼31%) among major European cities [16,24]. In studying the Greater Oslo Region's transport-oriented development plan, Wikstrøm and Røe [15] revealed several implementation challenges from discussions with local stakeholders. Local planners reported conflicts between local place-making ambitions and broader regional principles, along with concerns about the plan's perceived rigidity hindering its implementation. Municipal infrastructure development has lagged behind demand, creating deficits in both physical and social infrastructure.

Local residents expressed concerns about the impacts of density on the urban environment and quality-of-life perceptions. These discussions highlighted the technocratic nature of regional planning, often prioritising technical principles over the daily needs and lived realities of residents. Stakeholders noted the importance of being able to reference regional planning principles when facing resistance from local politicians and inhabitants, reflecting the tension between technical planning approaches and democratic participation.

3.6. Summary: Towards Evidence-Based Mobility Solutions

This review identifies key challenges in sustainable mobility transitions: the disconnect between smart and sustainable mobility objectives, technocratic planning approaches that overlook social realities, assessment difficulties due to lack of standardised indicators, and higher-order effects of electromobility that may undermine broader sustainability goals. The Norwegian case studies illustrate how these challenges manifest in practice, revealing tensions between different ASI strategies and resistance to top-down planning approaches.

Social equity considerations emerge as a critical dimension in sustainable mobility policy implementation, as evidenced by the Norwegian case studies, where EV subsidies disproportionately benefit wealthier households and planning policies contribute to gentrification concerns. However, comprehensive analysis of social equity implications requires dedicated methodological expertise in social sciences that extends beyond this review's technical focus. Readers interested in equity frameworks for mobility policy are directed to Jeekel and Martens [25], Delbosc and Currie [26], and Guo et al. [27] for conceptual approaches to distributive justice, accessibility impacts, and equity trade-offs in transport systems.

The challenges identified in this review underscore the need for more sophisticated technical solutions that can bridge the gap between policy formulation and implementation. Future research combining qualitative surveys on mobility patterns with quantitative big data analysis could provide deeper insights into the Norwegian context and inform more effective policy interventions. This need for enhanced analytical capabilities and evidence-based approaches directly motivates the examination of emerging technologies—particularly digital twins, big data analytics, and artificial intelligence—that might address the identified gaps in sustainable mobility planning and implementation through data-driven decision-making and improved stakeholder engagement.

4. Big Data, AI, and Digital Twins in Urban Mobility

This section systematically reviews three complementary technological paradigms that offer significant potential for addressing the sustainable urban mobility challenges identified in the previous section: digital twins (DTs), big data (BD) analytics, and artificial intelligence (AI). These technologies are analysed through thematic categories—infrastructure planning, citizen engagement, and predictive modelling—to assess their collective capacity to support evidence-based policymaking, enhance public participation, and enable more effective mobility interventions. The review synthesises findings from 40 studies, examining critical limitations regarding data integration, model validation, and stakeholder engagement to inform future research directions.

4.1. SLR: Digital Twins

Digital twins represent virtual replicas of physical systems that enable real-time monitoring, analysis, and optimisation. For urban mobility, we adopt Rasheed et al. [28]'s definition: *"a virtual representation of a physical asset or process enabled through data and simulators for real-time prediction, optimization, monitoring, control, and informed decision-making."* This review encompasses digital twins operating at capability levels 1–4 [29]: descriptive (real-time representation), diagnostic (condition monitoring), predictive (future-state forecasting), and prescriptive (intervention recommendations).

4.1.1. Urban Infrastructure Planning and Optimisation

Digital twins demonstrate substantial potential for infrastructure planning and traffic management. Schrotter and Hürzeler [30] highlight how Zurich's comprehensive digital twin integrates 3D spatial models with real-time sensor data to support lifecycle management of urban infrastructure. Similarly, Li and Zhang [31] implement a dynamic traffic flow model for highways using radar and camera sensor fusion, enabling real-time traffic optimisation.

Transportation-focused applications show particular promise for system-wide analysis. Zhang and Zhang [32] demonstrate how Wellington's transit-oriented digital twin connects key urban nodes (airport, city centre, business districts) through integrated traffic flow and public transit data, enabling scenario testing for congestion management and transit preferences. Tu et al. [33] extend this approach with predictive capabilities for infrastructure efficiency estimation and investment planning in intelligent transportation systems.

These capabilities are further enhanced by advanced data integration frameworks. Zhang et al. [34] develop dynamic and static data fusion methods for intelligent transport systems, effectively analysing spatiotemporal patterns and visualising intersections for traffic modelling applications. Wang et al. [35] complement this through deep learning and edge computing approaches that optimise traffic perception algorithms, achieving improved recognition accuracy and enhanced training efficiency for smart city implementations.

However, these infrastructure-focused applications face significant scalability challenges. Clemen et al. [36] observe that Hamburg's bike-sharing digital twin, while effective for reducing simulation uncertainty, struggles with system complexity as data sources proliferate. The computational demands and maintenance requirements increase substantially with system scale, potentially limiting these applications' practical deployment.

4.1.2. Citizen Engagement and Participatory Planning

A distinctive strength of digital twins lies in their capacity to enhance public participation in urban planning processes [37,38]. White et al. [39] demonstrate this through Dublin's Docklands digital twin, which enables citizens to explore urban planning proposals in 3D virtual environments, providing direct feedback on skyline alterations, green-space design, and flood risk scenarios. This approach addresses the technocratic criticisms identified in Section 3.4 by making complex planning decisions more accessible and transparent.

Dembski et al. [40] extend this participatory approach through Herrenberg's VR-enabled digital twin, which integrates 3D models, street networks, and mobility simulations for public engagement. The system demonstrates how visualisation technologies can bridge the gap between technical planning tools and public understanding, potentially reducing the resistance to sustainable mobility policies observed in Norwegian cities.

However, these participatory applications face significant limitations in stakeholder engagement. Papyshev and Yarime [38] highlight the challenge of encouraging public participation in data generation for urban digital twins, noting that privacy concerns and the complexity of interfaces can limit citizen involvement. This tension between data requirements and public engagement remains a critical barrier to the implementation of these applications.

4.1.3. Human-Centric Urban Design

Digital twins are increasingly incorporating human-centric design principles to enhance urban liveability [41]. Luo et al. [42] introduce a framework that integrates objective environmental analysis with subjective visual perception, demonstrated through Singapore's urban greenway design. This approach enables evaluation of urban scenarios through semantic segmentation, parametric spatial analysis, and immersive perception capture.

Environmental-comfort applications show particular promise for pedestrian-oriented planning. Gholami et al. [43] propose a digital twin for evaluating thermal comfort in Imola's pedestrian networks through real-time shade pattern simulation. Liu et al. [44] develop a complementary geospatial AI framework that predicts sidewalk comfort by capturing spatiotemporal variations in pedestrian behaviour and environmental interactions.

These human-centric applications extend beyond individual comfort assessment to address broader mobility challenges. Bachechi [45] demonstrate how urban digital twins can simultaneously investigate traffic–air quality relationships through environmental simulation models and analyse multimodal transport interactions to identify underserved areas requiring enhanced transportation services.

These human-centric applications demonstrate the potential for digital twins to support the accessibility-focused planning approaches discussed in Section 3.1. However, they also reveal limitations in data integration, as Liu et al. [44] explicitly note the need for broader dataset integration to enhance model robustness and accuracy.

4.1.4. Comparative Analysis of Digital Twin Applications

The reviewed digital twin applications reveal distinct strengths and limitations across different urban mobility contexts. Infrastructure-focused applications [30,32,33] excel at system-wide analysis and scenario testing but struggle with scalability and computational demands. Participatory applications [39,40] demonstrate superior public engagement potential but face challenges in sustained citizen participation and data privacy.

Critical limitations emerge across all applications. Data integration challenges persist, as digital twins struggle to incorporate diverse data sources with varying spatiotemporal resolutions. Model validation remains problematic, with uncertainty about long-term simulation accuracy and real-world representativeness. Stakeholder engagement, while improved through visualisation, still requires significant resources and technical expertise that many municipalities lack.

These limitations highlight the need for more sophisticated approaches that combine digital twins' capabilities with advanced analytics and artificial intelligence. The following section examines how Big Data and AI techniques can address these challenges while creating new opportunities for mobility analysis.

4.2. SLR: Big Data and AI

Big data and artificial intelligence represent complementary technological paradigms that enable sophisticated analysis of urban mobility patterns. Following Rathore et al. [46], big data encompasses information characterised by significant volume, high-velocity generation, and heterogeneous structure, while AI refers to computational systems that emulate human cognitive abilities for complex problem-solving [47]. Machine learning methods, particularly deep learning architectures, prove especially valuable for extracting patterns from large-scale mobility datasets due to their capacity for automatic feature extraction and representation learning.

4.2.1. Traffic Flow Prediction and Network Analysis

Traffic flow prediction represents the most mature application of Big Data and AI in urban mobility. Berlotti et al. [48] demonstrate a two-level approach for traffic management in Catania, using unsupervised clustering to extract patterns followed by supervised models for forecasting—addressing the practical challenge of limited sensor coverage. Advanced architectures show increasing sophistication, with Deng et al. [49] transforming time-series data into image-like formats for simultaneous spatiotemporal analysis, and Fiorini et al. [50] combining 3D-CNN and LSTM networks to capture complex spatial and temporal correlations.

Ensemble methods and crowdsourced-data approaches extend prediction capabilities to address coverage limitations. Cottam et al. [51] propose Dynamically Weighted Ensemble models combining XGBoost, LSTM, Stacked Autoencoders, and Gated Residual Networks to estimate vehicular flow rates using crowdsourced data across Arizona highways, providing cost-effective solutions for large-scale traffic estimation. Bae et al. [52] complement this with real-time spatiotemporal queue detection algorithms using flow-density data for probabilistic traffic phase transition detection.

Network-based approaches leverage graph structures for enhanced prediction accuracy. Liu et al. [53] model road networks as weighted graphs where traffic dynamics are captured through continuously updated edge weights. Zeng and Tang [54] advance this approach with spatiotemporal multigraph networks for lane-level traffic flow prediction, while Dong et al. [55] propose dynamic network representations learned from vehicle trajectories. Yang et al. [56] extend these methods by integrating spatiotemporal dependencies for network-wide traffic speed propagation prediction using deep learning techniques.

Transit network dynamics present unique analytical challenges addressed through temporal graph modelling. Maduako et al. [57] introduce Time-Varying Graph models to analyse dynamic relationships between topological structure and mobility patterns in transit networks, using bus feeds from Moncton to capture spatiotemporal changes. This approach enables identification of busy routes, congestion points, and trip duration variability, demonstrating the potential for comprehensive transit system analysis.

Optimisation techniques further enhance prediction capabilities through algorithmic refinements. Jegadeesan et al. [58] combine Gated Recurrent Units with Grey Wolf Optimizer algorithms to improve forecasting accuracy, while Moumen et al. [59] evaluate multiple machine learning approaches (Logistic Regression, Decision Tree, Facebook Prophet, and LSTM) for intersection-level predictions and traffic signal optimisation. These comparative studies highlight the importance of algorithm selection for specific urban contexts and operational requirements.

However, validation challenges persist across traffic prediction applications. Peng and Miller [60] find that multivariate models generally outperform univariate approaches, but generalisation to other contexts remains uncertain. Cottam et al. [51] address coverage limitations through crowdsourced data fusion, yet this approach introduces data quality concerns that limit model reliability.

4.2.2. Public Transit Optimisation

Public transit applications showcase the potential for operational improvements through predictive analytics. Che et al. [61] integrate passenger flow analysis with train production and scheduling in Hangzhou, using deep learning models (CNN, LSTM, GRU) to optimise resource allocation and improve service efficiency. Shen et al. [62] complement this with spatiotemporal passenger flow prediction using automatic fare collection data, converting dynamics into two-dimensional matrices for enhanced station correlation analysis.

Event-based prediction represents an emerging capability for public transit systems. Zhao and Ma [63] develop hybrid models combining multiple algorithms for metro passenger flow prediction during planned events, demonstrating effective scenario transitions between normal and event conditions. Zoric et al. [64] propose cost-effective solutions using Bluetooth beacons and mobile applications for crowdsourced data collection, achieving promising results for tram network optimisation.

When dealing with noise and irregularities in transit data, advanced feature extraction techniques can enhance prediction robustness. Zhu et al. [65] combine Deep Belief Networks for feature extraction with Support Vector Machines for short-term passenger flow predictions, demonstrating improved handling of complex metro data patterns from Qingdao.

These applications highlight the importance of data fusion for comprehensive mobility analysis. However, they also reveal limitations in stakeholder engagement, as Zoric et al. [64] note challenges in encouraging public participation without financial incentives.

4.2.3. Urban-Scale Mobility Pattern Analysis

Large-scale mobility pattern analysis demonstrates the potential for city-wide insights through big data analytics. Liu and Dong [66] use GPS data from Phoenix to predict daily mobility patterns with 12 h horizons, employing spatial clustering and LSTM models for energy efficiency improvements. Wang and Su [67] develop spatiotemporal prediction frameworks for citywide mobility forecasting, successfully tested on taxicab and cycling datasets from Beijing and New York.

Alternative data sources offer new opportunities for mobility analysis. Aljeri [68] propose using social network data as a proxy for human mobility patterns, revealing predictable patterns despite individual differences. This approach addresses data accessibility challenges but raises questions about representativeness and privacy.

Critical limitations emerge in the interpretability and practical application of these models. The "black-box" nature of deep learning models conflicts with the transparency required for policy decision-making. Deng et al. [49] propose enhancing explanatory power through analysis of deep representations, while Peng and Miller [60] suggest integrating traffic theories with deep learning for improved interpretability.

4.3. Critical Analysis of Knowledge Gaps

This systematic review reveals significant knowledge gaps that constrain the practical application of these technologies in sustainable urban mobility. These gaps span technical, methodological, and institutional dimensions, highlighting the need for more comprehensive approaches that address both technological capabilities and real-world implementation challenges.

4.3.1. Limitations of Digital Twins

Digital twin applications face fundamental challenges in data integration and validation. Data realism emerges as a critical concern, with studies consistently reporting difficulties in extracting and integrating information from diverse low-level sources such as sensors [36,69]. These challenges are compounded by scalability issues, as computational demands and maintenance requirements increase exponentially with system complexity and sensor proliferation [31,33]. The need for real-time predictive capabilities to support time-sensitive tasks further intensifies computational challenges [44].

Model validation presents significant barriers, as urban digital twins struggle to maintain simulation accuracy over time due to incomplete real-world information integration [38,40]. The absence of critical datasets—such as socioeconomic and meteorological data—further compromises model utility [44]. Simulating the impact of future technologies, such as autonomous systems, on urban environments presents even greater challenges, while IoT connectivity stability issues compound data gathering difficulties [41,69].

Privacy and implementation limitations create substantial barriers to practical deployment. Fine-grained behavioural data essential for accurate modelling conflicts with data protection requirements and privacy concerns, especially when used for governmental simulations [38,41]. Many digital twins reflect only passive urban infrastructure, requiring development of active systems that can simulate city population activities [36]. The high costs of associated technologies create additional barriers, particularly for smaller municipalities [41].

Technical integration gaps persist despite common use of AI techniques for predictive functions. Several studies highlight suboptimal integration of predictive models with digital twins, suggesting unrealised potential for performance improvements [33,45]. Zhang et al. [34] identify insufficient data support for road visualisation, traffic modelling, and control services. While visualisation technologies improve public participation, technical complexity and resource requirements remain barriers to meaningful citizen involvement, necessitating expansion across multiple urban research levels [32].

4.3.2. Big Data and AI Constraints

Model interpretability represents the most significant challenge for AI applications in policy contexts. The "black-box" nature of deep learning models conflicts with the transparency required for democratic decision-making and public accountability. Understanding how complex interactions between input variables influence mobility patterns may be more valuable for stakeholders than solely focusing on forecasts. Deng et al. [49] propose enhancing explanatory power through analysis of deep representations, while Peng and Miller [60] suggest integrating traffic theories with deep learning for improved interpretability. However, these approaches remain largely theoretical, with limited practical implementation.

Architectural and methodological limitations constrain AI advancement in mobility contexts. Significant gaps exist in applying advanced deep learning architectures, with studies calling for exploration of alternative or hybrid approaches to enhance predictive performance [49,58–60]. The limited exploration of synergies between different traffic parameters—volume, speed, density, and congestion—suggests untapped potential for multi-task prediction models [54,64]. Technical limitations restrict frameworks' ability to capture time-varying mobility semantics such as road closures or complex traffic environments [50,53,66].

Data quality and availability create substantial barriers to enhanced performance. Enhanced predictive capabilities require increased spatial and temporal data granularity [48,52], often necessitating additional sensor deployment with associated costs. Data fusion approaches show promise for comprehensively understanding mobility, including integration of non-mobility data such as environmental factors [51,62]. However, crowdsourced data approaches face participation challenges, often requiring financial incentives for sustained engagement [64]. Performance uncertainties emerge when handling increasing data volumes or sparse-coverage regions [55,57].

Generalisation failures constrain AI model transferability across different urban contexts. Studies consistently report the need for extended evaluation across geographical locations, mobility networks, and varied conditions [51,56,58]. The limited number of evaluation frameworks constrains comparative analysis of different models under varying training scenarios [53]. This limitation particularly affects smaller cities and developing countries, where data infrastructure for model development may be insufficient.

4.3.3. Integration and Implementation Challenges

The gap between technical capabilities and practical implementation represents a critical barrier to the advancement of sustainable mobility. Most reviewed studies focus on technical performance rather than operational integration, with limited evidence of real-world deployment beyond pilot projects. This disconnect between research outputs and policy applications constrains the potential for these technologies to address the mobility challenges identified in Section 3.4.

Research predominantly emphasises algorithmic innovation over practical utility, creating a significant implementation gap. Several studies acknowledge this limitation by speculating on potential applications in optimising personnel allocation and investment strategies [61], business layout and risk prevention in metro operations [61,65], traffic management systems and control strategies [56,59,63], and public transit network performance enhancement [64]. However, these applications remain largely theoretical, with insufficient evidence of sustained real-world deployment beyond pilot studies.

Institutional capacity limitations further complicate system implementation. The technical expertise required for deploying and maintaining these systems substantially exceeds the capabilities of many urban planning agencies, creating significant knowledge and skill gaps. Training requirements, ongoing maintenance costs, and system integration challenges create additional barriers to adoption, particularly for smaller municipalities with limited resources. Advanced visualisation techniques for enhancing model usability among policymakers, planners, and the general public remain underdeveloped, limiting the accessibility of these sophisticated technologies [61].

4.4. Synthesis and Implications

This systematic review reveals that digital twins, big data analytics, and artificial intelligence offer complementary capabilities for addressing sustainable urban mobility challenges. Digital twins excel at stakeholder engagement and scenario visualization, big data analytics enables pattern recognition at scale, and AI provides sophisticated predictive capabilities. However, their individual limitations—data integration challenges, model interpretability issues, and implementation barriers—highlight the need for integrated approaches that leverage the strengths of each technology while mitigating their weaknesses.

This review's findings connect directly to the sustainable mobility challenges identified in Section 3. These technologies can address measurement and evaluation gaps through standardised metrics, enhance public engagement through improved visualization, and support evidence-based policymaking through predictive analytics. Yet their successful implementation requires careful consideration of institutional capacity, stakeholder needs, and the broader urban planning context.

Figure 8 illustrates how these technologies can work synergistically, with digital twins providing the visualization framework, big data analytics supplying the analytical foundation, and AI enabling predictive capabilities. This integration offers pathways for addressing the policy implementation challenges and public engagement deficits identified in the Norwegian case studies while supporting the transition toward more sustainable urban mobility systems.

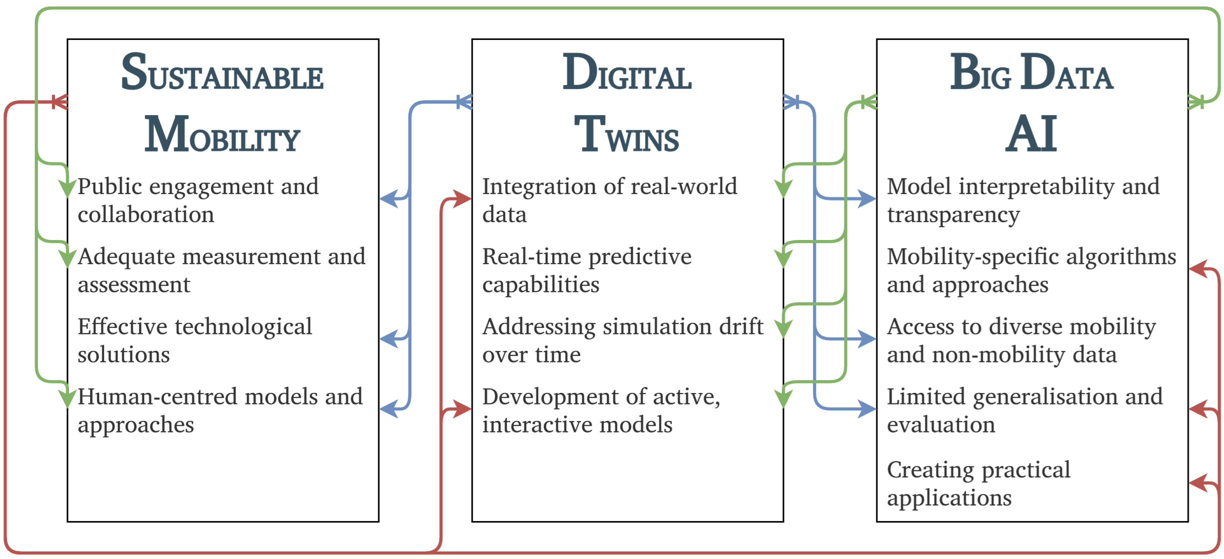

Figure 8. The interplay between digital twin, AI, and big data technologies in sustainable urban mobility. The diagram illustrates how each technology addresses specific challenges and knowledge gaps in urban mobility, and how their integration enables comprehensive, data-driven solutions for sustainable and efficient mobility systems. The arrows indicate the flow of data, insights, and feedback between domains.

The following section examines how these technological capabilities can be synthesised with urban planning theory and policy frameworks to create comprehensive, data-driven solutions for sustainable mobility transitions.

5. Discussion and Proposed Solutions

This section synthesises findings from the previous reviews to examine how emerging technologies can address the challenges and uncertainties faced by policymakers in achieving sustainable urban mobility. Building on the three-stage model of urban transport policy development in Section 3 and the technological applications reviewed in the previous Section 4, we explore how digital twins, big data, and AI can bridge the knowledge gaps and practical challenges identified in sustainable mobility transitions.

Table 5 provides a summary of the identified challenges, current approaches, and knowledge gaps from the sub-reviews, highlighting the interconnected nature of urban planning, technology, and sustainable mobility. The remainder of this section discusses how the challenges identified in one sub-review/domain can be addressed using approaches from other sub-reviews/domains, thereby creating holistic tools and applications for future mobility solutions.

5.1. Bridging Urban Planning Theory and Technological Innovation

The transition from technocratic approaches to sustainable urban mobility requires grounding technological solutions in foundational urban planning concepts. The three-stage model of urban transport policy development (Section 3.1) demonstrates how cities progress from car-centric growth to liveable, accessibility-focused environments. However, as observed in the Norwegian case studies (Section 3.5), this transition faces significant barriers rooted in urban structure, institutional arrangements, and public perception.

5.1.1. Accessibility, Land Use, and Digital Twin Applications

Urban planning theory emphasises accessibility—the ease of reaching destinations—as fundamental to sustainable mobility. Rather than merely facilitating movement, effective mobility policies should enhance access to opportunities while minimising travel demand. The digital twin studies reviewed in Section 4.1 demonstrate how this theoretical foundation can be operationalised through technology.

The Dublin Docklands DT by White et al. [39] exemplifies how digital twins can visualise and test land use–transport integration scenarios, enabling citizens to explore planning proposals and provide feedback on their accessibility impacts. Similarly, the Singapore urban greenway DT by Luo et al. [42] integrates objective environmental analysis with subjective visual perception, supporting human-centric design that prioritises pedestrian accessibility. These applications directly address the measurement and assessment challenges identified in Section 3.4, providing standardised tools for evaluating accessibility outcomes.

The Oslo TOD strategy illustrated in Figure 7 demonstrates how theoretical accessibility principles translate into planning practice, with workplaces within 600 m and housing within 2000 m of transit hubs. DTs can simulate these accessibility thresholds dynamically, testing how different development scenarios affect real-world accessibility patterns. The traffic flow prediction models reviewed in Section 4.2, such as the spatiotemporal frameworks by Wang and Su [67] and Fiorini et al. [50], can provide an analytical foundation for these simulations.

Table 5. Summary of identified challenges, current approaches, and knowledge gaps. *Note: SM—sustainable mobility; DT—digital twin; and AI—artificial intelligence.*

Current Approach	Identified Challenge	Knowledge Gap
SM: Creating Liveable Cities	Transit-oriented development and compact city strategies to reduce urban sprawl and promote sustainable mobility.	Detailed understanding of spatiotemporal dynamics influencing mobility choices.
SM: Smart Mobility Solutions	Technology-driven interventions prioritising efficiency and market opportunities.	Comprehensive, data-driven comparison of smart versus conventional mobility solutions.
SM: Measuring Mobility Initiatives	Lack of clear targets and benchmarks for success, with inconsistent evaluation frameworks.	Standardised indicators for evaluating and comparing mobility initiatives across different scenarios.
SM: Electric and Autonomous Vehicles	Increased vehicle usage and ownership potentially exacerbating urban automobility issues.	Simulating the impact of electric and autonomous vehicles on overall mobility and sustainability.
SM: Public Engagement	Disconnect between policymakers and residents, leading to resistance to sustainable mobility policies.	Enhanced sentiment analysis and collaborative planning tools to align policies with public expectations.
DT: Realism with Real-World Data	Challenges in integrating diverse data sources with varying levels of granularity.	Optimised methods for data collection, preprocessing, and integration for enhanced realism in digital twins.
DT: Robustness of Simulations	Loss of fidelity in simulations over time; lack of comprehensive real-world information.	Integrating non-mobility data and improving representativeness for more realistic simulations.
DT: Data Privacy and Security	Trade-offs between data privacy and the need for granular data for accurate models.	Privacy-preserving techniques that retain spatiotemporal detail without compromising individual privacy.
DT: Scalability of Models	Existing models primarily focus on physical environments, lacking complexity for diverse urban activities.	Developing interactive models that simulate complex urban dynamics beyond physical infrastructure.
DT: AI Integration	Limited use of AI for real-time, predictive functionalities in simulations.	Tailoring AI techniques for predictive accuracy and real-time decision-making within DT models.
AI: Predictive Performance	Use of basic models with limited exploration of synergies between traffic parameters.	Exploration of cutting-edge, hybrid ML/DL models and development of multi-task prediction algorithms.
AI: Data Availability	Limited access to high-quality, granular data for robust analysis and modelling.	Increasing data granularity and combining diverse data sources (mobility and non-mobility) for richer models.
AI: Generalisation and Evaluation	Uncertainty about the transferability of analyses and models to other mobility scenarios.	Improving model generalisation and evaluation to capture time-varying mobility semantics across varying real-world contexts.
AI: Model Interpretability	Limited understanding of how complex interactions between input variables influence mobility predictions.	Enhancing interpretability through analysis of model representations and alignment with traffic theories.
AI: Practical Application	Models used primarily for insights, with limited integration into operational systems.	Advancing visualisation and application of AI models for real-world traffic operations and management tasks.

5.1.2. Equity Implications and Institutional Barriers

The Norwegian case studies also reveal how seemingly progressive mobility policies can exacerbate social inequalities. Bergen's EV subsidies disproportionately benefit wealthier households, while Oslo's compact city strategy contributes to gentrification pressures. These outcomes reflect deeper institutional barriers that technological solutions alone cannot address.

The "anti-toll rhetoric" and resistance to urban planning "elites" documented in both Bergen and Oslo highlight how technocratic approaches alienate residents from mobility transitions. The participatory DT applications reviewed, such as the Herrenberg VR platform by Dembski et al. [40] and the task-based mobility data generation by Papyshev and Yarime [38], offer pathways for more inclusive planning processes that could address these institutional challenges.

However, the AI model interpretability challenges identified in Section 4.3 pose significant barriers to public engagement. The "black-box" nature of deep learning models conflicts with the transparency required for democratic participation in mobility planning. This limitation underscores the need for explainable AI approaches that can bridge the gap between technical sophistication and public understanding.

5.1.3. Technology-Driven Solutions and Sustainability Outcomes

The alignment between current sustainable mobility narratives and the ASI (Avoid–Shift–Improve) framework discussed in Section 3.2 reveals both opportunities and tensions. The European Green Deal's vision of cheaper, more accessible mobility options contrasts with the real-world implementation challenges observed in Norwegian cities, where electromobility policies can undermine broader sustainability goals.

Current sustainable mobility narratives, as extrapolated from existing SSUM solutions in European cities by Gulc and Budna [5], revolve around three central themes:

- Electromobility: Replacing fossil-fuel engines with low-emission alternatives.
- Collective Transport 2.0: Enhancing public transit and shared mobility services.
- Low-Mobility Society: Reducing car-based trips through urban planning.

These themes align with the ASI framework, where "Low-Mobility Society" corresponds to "Avoid," "Collective Transport 2.0" to "Shift," and "Electromobility" to "Improve." However, the Bergen case study demonstrates how the "Improve" strategy can conflict with "Avoid–Shift" approaches, as EV subsidies prompted proposals for new highways that contradict zero-growth targets and undermine public transit investments. The predictive modelling capabilities reviewed in Section 4.2 offer tools for anticipating these policy contradictions, with traffic flow prediction models by Berlotti et al. [48], Deng et al. [49], and Liu et al. [53] simulating how electromobility policies affect overall traffic patterns.

Each mobility strategy presents implementation challenges that require careful consideration. "Electromobility" raises environmental concerns regarding rare metals in EV batteries and cost barriers that may limit access to higher-income groups. "Low-mobility society" approaches often frame car-free cities as banning vehicles from residential, commercial, and work spaces, yet this can neglect individuals' everyday needs and realities. Since residents require reliable travel options, overzealous car-free policies risk alienating the public when infrastructure development lags behind demand, as observed in the Oslo case study.

Research demonstrates clear advantages for sustainable mobility modes over private vehicle use. Investigations into car-dependent compact cities in Greece by Mouratidis et al. [70] found that walking resulted in the highest satisfaction and positive emotions, while public transit scored lowest due to reliability and connectivity issues. Notably, private vehicles rated lower than public transit when travel time was considered. The urban mobility forecasting frameworks by Liu and Dong [66] and Wang and Su [67] can model these long-term impacts on mode choice and travel behaviour.

Supporting evidence from Wang et al. [71] proposes a transit-oriented, multimodal framework integrating ride-hailing, bike-sharing, and fixed-route buses. Their analysis revealed that private car ownership imposes negative social costs, bike-sharing supports bus connections, buses serve longer journeys effectively, and subways prove cost-efficient in high-demand areas. These findings underscore the importance of enhancing public transit services, active mobility infrastructure, and multimodal integration to reduce car dependency and advance sustainability goals.

5.1.4. Integrating Big Data and AI for Mobility Analytics

The transition from survey-based to GPS-enabled mobility data, as documented in Section 3.1, has enabled the fine-grained analysis of mobility patterns, essential for evidence-based policymaking. The consistent time and money budgets that govern mobility behaviour can now be analysed at unprecedented scales, revealing both individual variations and aggregate regularities.

People typically prioritise convenience and cost over sustainability when choosing mobility options. The advanced traveller information systems demonstrated by Ye et al. [72] show how providing real-time data on travel times affects route choices and traffic stability. Similarly, the sustainability information tools proposed by D'Alberto and Giudici [22] can influence mode choices by quantifying emissions for different travel options, enabling individuals to make informed decisions that align with sustainability goals.

The predictive models reviewed in Section 4.2 operationalise these insights through various applications. The metro passenger flow predictions by Che et al. [61] and Zhao and Ma [63] demonstrate how machine learning can anticipate demand variations and optimise service provision. The multimodal integration frameworks by Wang and Su [67] and the graph-based network models by Liu et al. [53] show how AI can capture the complex interactions between different mobility modes.

However, the model interpretability challenges identified in Section 4.3 limit the practical application of these tools in policy contexts. The "black-box" nature of deep learning models conflicts with the need for transparent, accountable decision-making in public policy. This limitation underscores the importance of developing explainable AI approaches that can bridge technical sophistication with policy requirements.

5.1.5. Future Mobility Solutions

Cascetta and Henke [3] and Nguyen [73] identify six major transport revolutions, from animal domestication around 8000 BC to freight containerisation in the 20th century. Cascetta and Henke [3] contend that transportation systems are approaching a seventh revolution simultaneously driven by three ongoing innovations: (i) decarbonised transport, (ii) connected autonomous vehicles, and (iii) transformed mobility services. Figure 9 illustrates how these drivers map onto the ASI framework: "Decarbonised Transport" aligns with "Improve," "Connected Autonomous Vehicles" with "Shift-Improve," and "Transformed Mobility Services" with "Shift."

This imminent revolution reflects two key elements from past revolutions: "the law of unintended consequences" and "super additivity." These manifest in the interactions among drivers, particularly with shared and autonomous electric vehicles (SAEVs). Decarbonisation aligns with EVs and shared mobility to reduce emissions; shared mobility lowers costs and encourages urban EV adoption without significantly increasing traffic volumes; and connected autonomous vehicles enable novel mobility services that enhance safety, reduce operational costs, and improve infrastructure efficiency. Together, these create a cohesive system facilitating on-demand, flexible, and sustainable urban mobility.

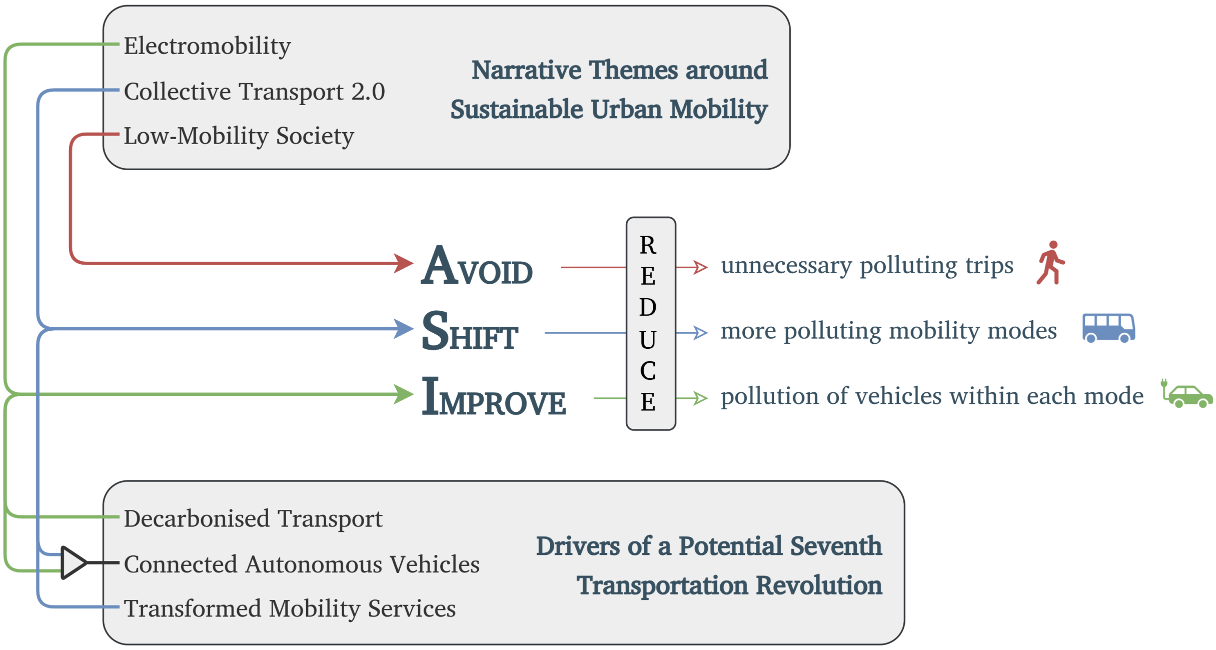

Figure 9. Mapping the Avoid–Shift–Improve (ASI) framework onto sustainable mobility themes and drivers. The figure shows how decarbonised transport, connected autonomous vehicles, and transformed mobility services align with the ASI framework, and how these drivers interact to shape future urban mobility transitions. The mapping highlights the relationships between policy strategies, technological innovations, and sustainability outcomes.

SAEVs simultaneously achieve sustainability, efficiency, and comfort gains by leveraging EV and AV technological advances. They increase vehicle utilisation across trips and maximise seat capacity within trips, significantly reducing traffic congestion and emissions without sacrificing private travel flexibility. Dlugosch et al. [74] analysed car-sharing data from Berlin's human-driven, ICE-powered fleet of 1104 vehicles, finding utilisation rates below one-third due to excessive idle times. The study indicates that this fleet could be replaced by 600 SAEVs and 28 charging points without compromising service quality.

The Berlin findings suggest transformative potential for urban mobility systems. The city's motorised-travel demand, currently served by 1.15 million privately owned cars, could theoretically be met with 264,000 SAEVs supported by 12,320 charging stations. However, these interactions may produce both intended and unintended outcomes, underscoring the complexity of future mobility transitions and the need for careful policy design that anticipates secondary effects while leveraging technological convergence for sustainability goals.

5.1.6. Policymaking and Scientific Research

A seventh transportation revolution would have wide-ranging societal impacts, from reshaping city design to influencing interpersonal dynamics and altering production cycles [3]. These impacts will intensify existing challenges in mobility policy formulation and implementation. Key challenges identified in Section 3.4 include:

- AVs and enhanced mobility services could increase car usage, leading to higher emissions and congestion as travel becomes more affordable and comfortable.
- Environmental benefits of EVs depend on green-energy adoption, while high costs may limit access to higher-income groups and regions.

- Shared mobility might paradoxically increase vehicle kilometres travelled due to fleet rebalancing requirements.
- AV adoption may reduce use of active mobility, public transit, and other sustainable travel modes.
- Existing energy and travel demand models rely on assumptions ill-suited for predicting emerging mobility trends.

Academic and applied research remains crucial for shaping future mobility policies, yet is constrained by outdated, car-centric frameworks rather than demand-oriented approaches focused on activity and accessibility. As Jones [9] observes, evaluation criteria often favour car-related infrastructure, creating biases that neglect the need for sustainable mobility systems. The present era of transformation demands innovative tools and methodologies in mobility research [3,14]. Future research must address system complexity, interactions with broader societal factors, unforeseen impacts from converging technologies, and the potential of technological paradigms to engineer sustainable mobility solutions.

5.2. Limitations and Implementation Challenges

While the reviewed technologies offer substantial potential for advancing sustainable urban mobility, several critical limitations constrain their practical application. Understanding these constraints is essential for developing realistic implementation strategies and managing expectations about technological solutions.

5.2.1. Data Privacy and Interoperability

The fine-grained mobility data required for effective AI models and DT applications raises significant privacy concerns. GDPR and similar frameworks limit the collection of personal location data and constrain data availability for accurate mobility modelling. Privacy-preserving techniques such as differential privacy and federated learning remain largely untested in real-world contexts, compounding the fundamental conflict between data requirements and privacy protection highlighted by Ngadi et al. [41] and Papyshev and Yarime [38].

Data interoperability presents another fundamental challenge, as the diversity of mobility data sources creates integration difficulties that limit the comprehensiveness of analytical models. The DT scalability issues documented in Section 4.3 stem partly from these constraints, with different data formats and collection standards complicating real-time integration. Bauer et al. [69], Clemen et al. [36], and Zhang et al. [34] identify persistent challenges in extracting and integrating information from diverse sources while noting insufficient data support for comprehensive transport system analysis.

5.2.2. Model Validation and Generalisation

The transferability of AI models across different urban contexts remains uncertain. The traffic flow prediction models reviewed in Section 4.2 demonstrate high accuracy in specific cities but show limited evidence of generalisation to other contexts. Peng and Miller [60] note that while multivariate models outperform univariate approaches, generalisation still remains uncertain. Cottam et al. [51] also show that crowdsourced data fusion introduces data quality concerns, limiting model reliability. This particularly affects smaller cities and developing countries, where data infrastructure is less robust.

The “black-box” nature of deep learning models creates additional validation challenges. Planners and policymakers require transparent, interpretable tools, yet accurate AI models often sacrifice interpretability for performance. Deng et al. [49] and Peng and Miller [60] propose enhancing explanatory power through deep representation analysis and integrating traffic theories with deep learning. However, these approaches remain largely theoretical. This accuracy–explainability trade-off constrains AI tool adoption in policy contexts requiring accountability and public trust.

5.2.3. Institutional and Resource Constraints

The implementation of advanced mobility technologies requires significant institutional capacity and financial resources. DT applications typically require substantial upfront investments in data infrastructure, computational resources, and technical expertise. Li and Zhang [31], Tu et al. [33], and Ngadi et al. [41] demonstrate that computational demands increase exponentially with system complexity, while high technology costs create barriers, particularly for smaller municipalities.

Institutional resistance to data-driven approaches also constrains implementation. The Norwegian case studies in Section 3.5 illustrate how entrenched institutional practices and public scepticism can undermine the adoption of innovative mobility solutions. The technocratic criticisms documented by Remme et al. [20] and Wikstrøm and Røe [15] highlight how top-down approaches alienate residents. This creates resistance to policies perceived as disconnected from local realities. Thus, an ongoing challenge in urban governance is balancing technological innovation with democratic accountability.

5.3. Implications for Urban Planning Practice

The integration of digital twins, big data, and AI into urban mobility planning suggests fundamental shifts may be needed in planning practice, institutional arrangements, and professional competencies. This subsection outlines potential implications for urban planners, policymakers, and related stakeholders.

5.3.1. Evolving Planning Methodologies

Traditional transport planning appears to rely heavily on aggregate travel demand models and static infrastructure assessments. However, the technologies reviewed suggest possibilities for more dynamic, responsive approaches that could adapt to real-time conditions and emerging trends. The spatiotemporal prediction frameworks demonstrated by Wang and Su [67] and Liu and Dong [66] may allow planners to move beyond four-stage transport models. These could enable activity-based approaches that better capture urban mobility complexity. Jones [9]'s emphasis that transportation policy should prioritise enhanced accessibility rather than mobility alone appears to align with these advanced analytical capabilities.

Digital twins potentially offer transformative capabilities for scenario planning and public engagement. Participatory applications such as the Dublin Docklands project by White et al. [39], Herrenberg's VR platform by Dembski et al. [40], and Luo et al. [42]'s environmental-perception integration demonstrate how complex planning scenarios might be visualised and communicated to diverse stakeholders. However, implementing these methodologies would likely require substantial changes to existing planning workflows. This is particularly challenging given the assessment difficulties identified by Müller-Eie and Kosmidis [23], who found that most Nordic smart mobility initiatives lacked measurable targets and clear benchmarks for success.

5.3.2. Professional Development and Skills

The integration of Big Data and AI into mobility planning would likely require new professional competencies that bridge the technical and planning domains. This suggests that urban planners may need sufficient understanding of data science methods to critically evaluate AI model outputs and communicate findings to diverse stakeholders. Rather than requiring planners to become data scientists, this might involve developing "data literacy" enabling effective collaboration with technical specialists. This is exemplified by the transition from survey-based to GPS-enabled mobility data documented in Section 3.1.

The interpretability challenges identified in Section 4.3 appear particularly relevant for planning practice. This suggests that planners may need tools that can explain model predictions in terms relevant to planning decisions, such as relationships between land use patterns and mobility outcomes. The challenge of encouraging public participation highlighted by Papyshev and Yarime [38], combined with D'Alberto and Giudici [22]'s demonstration of how sustainability information tools can influence mode choices, suggests that planners might need to bridge technical sophistication with public understanding. They must also address the continued lack of standardised indicators for evaluating initiatives.

5.4. Proposed Solutions

Drawing from this meta-review's investigation into sustainable urban mobility, Table 6 recommends solutions that leverage the Big Data and AI paradigms (hereafter BD/AI) to extract data-driven insights aimed at addressing the existing challenges and uncertainties. These proposed BD/AI solutions integrate advanced analytical, modelling, and visualisation tools to support the formulation and implementation of sustainable and efficient future mobility policies and solutions.

The proposed BD/AI solutions outlined in Table 6 represent pragmatic approaches to addressing the sustainable urban mobility challenges identified in this meta-review. However, their successful implementation depends on overcoming the institutional, technical, and social barriers discussed throughout this analysis. These solutions provide a framework for translating technological capabilities into sustainable mobility outcomes, setting the foundation for the stakeholder recommendations and implementation roadmap presented in the concluding section og this paper.

Table 6. Recommended Big Data and AI (BD/AI) solutions for sustainable urban mobility, detailing key actions and anticipated outcomes.

Proposed Solution	**Action (A) and Outcome (O)**
Promoting Active Mobility	A: Leverage BD/AI in analysing spatiotemporal patterns of active mobility modes. O: Optimised infrastructure design incentivises adoption and increases travel satisfaction.
Enhancing Public Transit Systems	A: BD/AI analysis of ridership data for demand forecasting, route optimisation, and improved scheduling. O: Improved efficiency, reliability, and accessibility of public transit. O: Predict changes to ridership patterns based on various urban development scenarios.
Holistic Mobility Planning	A: Detailed historical analysis of the spatiotemporal dynamics of daily mobility choices. O: Tailored infrastructure planning and policy design eases adoption of sustainable mobility options.
Simulations and "What-If?" Scenarios	A: BD/AI simulation, and analysis of planned policy interventions and mobility solutions. O: Anticipate and mitigate higher-order effects and negative externalities prior to real-world implementation.

Table 6. *Cont.*

Proposed Solution	Action (A) and Outcome (O)
Improving Urban Quality of Life (QoL)	A: BD/AI modelling of the negative QoL effects of urban mobility, such as noise pollution and traffic congestion. O: Deeper understanding of how the built environment interacts with mobility to affect the QoL of residents.
Multimodal Integration	A: Co-optimisation and integration of sustainable mobility modes—public transit, walking, and cycling. O: Reduced use of private cars due to seamless switching and better coverage of first/last-mile travel.
Academic–Policy–Public Collaboration	A: Creation of BD/AI platforms such as digital twins, where researchers, policymakers, and residents can jointly analyse mobility data, trends, and models. O: Integration of academic insights into policy decisions, taking into account public engagement and feedback.

6. Conclusions and Recommendations

6.1. Summary of Key Findings

This paper examines sustainable urban mobility through a meta-review comprising three complementary studies: a review of sustainable mobility with Norwegian case studies, and systematic literature reviews on digital twins and Big Data/AI applications covering the period of 2019–2024. From 72 relevant articles, we identify major trends, limitations, and opportunities in contemporary mobility policy and technology applications.

The mobility narrative has shifted towards prioritising liveable cities, yet implementation faces significant barriers. Cities transitioning to sustainable mobility grapple with technocratic approaches, technocentric solutions, inadequate measurement tools, and unintended negative impacts from technological innovations. Norwegian case studies reveal how EV subsidies disproportionately benefit wealthy households, while compact city strategies contribute to gentrification, illustrating the disconnect between policy intentions and social equity outcomes.

Our findings establish a mobility hierarchy where public transit and active mobility demonstrate clear advantages over private vehicles in terms of travel satisfaction and reduced societal externalities. Digital twins offer dynamic, data-driven virtual representations enabling traffic flow simulation, planning optimisation, and pedestrian network improvement. AI techniques enable traffic forecasting, transit prediction, and multimodal integration through fine-grained mobility data analysis.

We identify persistent challenges, including data interoperability, model validation, insufficient stakeholder engagement, and the "black-box" nature of AI models, that conflict with democratic transparency requirements. Key unresolved tensions include technology–policy disconnect, equity– efficiency trade-offs, democratic participation versus technical expertise, and balancing short-term implementation pressures with long-term sustainability goals.

6.2. Stakeholder Recommendations

In light of the proposed solutions leveraging Big Data and AI paradigms (BD/AI), we outline roles and benefits for various stakeholders in planning, implementing, and assessing sustainable mobility policies:

- Government and Policy

  - National Governments: Create regulatory frameworks supporting BD/AI adoption and allocate funding for infrastructure while mandating equity impact assessments.
  - Municipal Authorities: Utilise BD/AI insights to adapt urban planning and infrastructure while establishing participatory planning processes using digital twins.
  - Urban Planners: Integrate BD/AI insights into city design through interdisciplinary collaboration while developing privacy-preserving frameworks for mobility data collection.
- Industry and Technology
  - Technology Providers: Develop BD/AI technologies and platforms while investing in data interoperability standards and scalable digital twin architectures.
  - Transportation Companies: Implement BD/AI tools to optimise routes, schedules, and multimodal integration while creating open-source tools for mobility analysis.
- Research and Funding
  - Funding Agencies: Invest in BD/AI research that bridges technical innovation with social equity considerations.
  - Research Institutes: Develop advanced BD/AI models and establish validation protocols ensuring transferability across urban contexts.
- Public and Users
  - Urban Residents: Support researchers by contributing crowd-sourced data and participating in digital twin platforms for collaborative mobility analysis.

6.3. Future Research Directions

Despite the comprehensive nature of this meta-review, it is inherently limited in several ways that present opportunities for future research. The review's scope is constrained by its English-language focus, temporal limitations to 2019–2024, potential subjective bias in the quality assessment approach, and exclusive use of Norwegian case studies. Furthermore, the technical background of the authors has led to a focus on technological solutions, resulting in limited engagement with foundational urban planning concepts such as accessibility, land use and transport integration, and social equity.

The technical challenges identified throughout this review suggest significant potential for developing sophisticated forecasting approaches that integrate operational data with machine learning frameworks, spatiotemporal graph-based methodologies for mobility network analysis, and mixed-methods frameworks that combine quantitative big data analytics with qualitative survey insights. These approaches could directly address the persistent gaps between policy intentions and implementation realities observed in the Norwegian case studies, where technocratic planning approaches have struggled to engage citizens and deliver equitable outcomes.

The path forward requires collaborative partnerships among government, industry, research institutions, and citizens to shape emerging technologies towards sustainability outcomes. The technical solutions identified in this review provide a robust foundation for developing data-driven approaches that align policy implementation with empirical evidence of real-world mobility patterns. Success will depend on moving decisively beyond technocratic approaches to embrace participatory, evidence-based planning that prioritises both technological innovation and social equity, enabling cities to achieve sustainable urban mobility systems that serve all residents while addressing pressing environmental challenges.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/urbansci9080301/s1, Table S1: Articles selected for the review on "Sustainable Mobility"; Table S2: Articles selected for the systematic literature review on "Digital Twins"; and Table S3: Articles selected for the systematic literature review on "Big Data and AI". References [75–82] are cited in Supplementary Materials.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ASI	Avoid–Shift–Improve Framework
AV	Autonomous Vehicle
BD	Big Data
CNN	Convolutional Neural Network
CO_2	Carbon Dioxide
DL	Deep Learning
DT	Digital Twin
EV	Electric Vehicle
GRU	Gated Recurrent Unit
ICE	Internal Combustion Engine
ITS	Intelligent Transport System
LSTM	Long Short-Term Memory
MaaS	Mobility as a Service
ML	Machine Learning
PHEV	Plug-in Hybrid Electric Vehicle
PICOC	Population, Intervention, Comparison, Outcome, Context
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QoL	Quality of Life
S.M.A.R.T.	Specific, Measurable, Achievable, Relevant, Time-bound
SAEV	Shared and Autonomous Electric Vehicle
SLR	Systematic Literature Review
SM	Sustainable Mobility
SSUM	Smart and Sustainable Urban Mobility
SUMI	Sustainable Urban Mobility Indicators
SUMP	Sustainable Urban Mobility Plan
TOD	Transit-Oriented Development

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