Future Generation Computer Systems 180 (2026) 108379

Contents lists available at ScienceDirect

Future Generation Computer Systems

journal homepage: www.elsevier.com/locate/fgcs

Digital twins in public bus transport: A systematic literature review of architectures, intelligence, and interaction

Manuel Andruccioli, Giovanni Delnevo *, Roberto Girau, Paola Salomoni

Department of Computer Science and Engineering - Alma Mater Studiorum, Università di Bologna, Cesena, Italy

A R T I C L E I N F O

Keywords:
Digital twin
Public transportation
Bus transit systems
Smart mobility
Digital sustainability

A B S T R A C T

The adoption of Digital Twin (DT) technologies in public transport systems, particularly bus networks, is gaining momentum as cities seek smarter, more responsive, and efficient mobility solutions. Enabled by advances in IoT, AI, and Big Data Analytics, DTs offer real-time monitoring, simulation, and optimization of transit operations. However, despite their potential, the application of DTs in bus-based public transport remains relatively underexplored and fragmented across the literature. This study presents a Systematic Literature Review (SLR) aimed at synthesizing current research on DT technologies in this domain. Specifically, it investigates architectural models, technological frameworks, and platform designs; examines how AI and machine learning models are integrated to support operational tasks; and analyzes the role of Human-Computer Interaction (HCI) in the design and usability of such systems. By identifying key trends, challenges, and research gaps, this work provides a structured overview of the current landscape . Furthermore, it outlines directions for future research in DT-enabled public transportation systems.

1. Introduction

The rapid evolution of technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Big Data Analytics has catalyzed the emergence and proliferation of Digital Twins (DTs) as a foundational paradigm in the engineering of Cyber-Physical Systems (CPSs) [1]. DTs, dynamic, digital replicas of physical entities [2], are increasingly utilized for real-time monitoring, analysis, simulation, and optimization of their real-world counterparts [3]. These capabilities hold particular promise in domains characterized by complexity, dynamism, and infrastructure-intensive operations, such as public transportation [4]. The integration of IoT infrastructures, through vehicle-embedded sensors, roadside devices, and V2X connectivity, provides the real-time data streams necessary for synchronizing physical assets with their DTs, enabling live simulations and proactive control in urban mobility contexts [5]. While DT applications have gained significant traction in sectors like manufacturing [6], healthcare [7], and smart cities [8], their application in public transportation systems, especially bus-based transit, has only recently begun to gain scholarly and industrial attention [9].

Public transport systems, and bus networks in particular, present unique operational challenges that align well with the capabilities of DTs [10]. These systems involve continuously moving assets, heterogeneous sensor data streams, human interaction, and a need for predictive maintenance and dynamic optimization [11]. In this context, DTs offer a means to simulate, monitor, and manage transit operations more effectively. The integration of a DT of the infrastructure itself, encompassing road networks and bus lanes, is crucial for simulating traffic flows and managing asset synchronization in a holistic urban mobility context [12]. This enables enhanced service reliability, reduced downtime, and improved passenger experience [13]. Furthermore, the increasing availability of edge computing, 5G connectivity, and AI/Machine Learning (ML) algorithms has enabled the development of intelligent, responsive, and scalable DT solutions for public transit systems [14,15].

Despite this growing interest, the body of knowledge surrounding the design, implementation, and evaluation of DT technologies in bus-based transportation remains fragmented. There is a lack of comprehensive understanding regarding the architectural designs, data integration models, AI/ML components, and Human-Computer Interaction (HCI) strategies underpinning these systems. Moreover, as DT systems scale beyond individual deployments to interconnected ecosystems, the challenges of interoperability, standardization, and real-time responsiveness become even more pronounced.

To address this knowledge gap, this paper presents a Systematic Literature Review (SLR) focused on the application of DT technologies in public transport systems, with a particular emphasis on bus and similar

* Corresponding author.
E-mail addresses: manuel.andruccioli@unibo.it (M. Andruccioli), giovanni.delnevo@unibo.it (G. Delnevo), roberto.girau@unibo.it (R. Girau), paola.salomoni@unibo.it (P. Salomoni).

https://doi.org/10.1016/j.future.2026.108379
Received 26 May 2025; Received in revised form 17 December 2025; Accepted 16 January 2026
Available online 19 January 2026

transit modes. The objective is to synthesize current research, identify prevailing trends, and highlight open challenges in the engineering of DT systems within this domain. Specifically, we investigate the models, architectures, components, frameworks, and platforms adopted or proposed in such systems. Then, we examine how artificial intelligence and machine learning models are integrated and what functionalities they support. Finally, we explore the role of human-computer interaction, particularly how user interaction is designed, evaluated, or conceptualized. Through this lens, our study contributes a more targeted understanding of the DT landscape in urban bus transit, highlighting both current practices and open research challenges.

The remainder of the paper is structured as follows. Section 2 illustrates the background and several related works. Section 3 details our approach. The main findings are presented in Section 4 together with a discussion of them. Section 5 discusses the implications and provides concrete recommendations for future research. Finally, Section 6 concludes the paper, highlighting some final remarks and future works.

2. Background and related work

DT technology emerged as a transformative approach within the broader context of smart city development, with numerous studies examining its applications across various urban functions. Comprehensive surveys by Utku et al. [16] and Whig et al. [17] have explored DT implementations in city planning, public transportation, energy management, healthcare, and waste management. Urban planning applications have been particularly notable, with Mal et al. [18] developing a comprehensive DT of Lyon, France, while Orsini and Piras [19] proposed interconnected DT networks for Italy's transport infrastructure management and renewable energy optimization.

The application of DTs in Intelligent Transportation Systems (ITSs) has shown significant promise for improving operational efficiency and sustainability. DT in public transportation can optimize performance, enhance passenger experience, and support sustainable urban mobility through improved operational accuracy and energy efficiency [20,21]. Specialized applications have extended to commercial and freight vehicles [22], bicycle systems [23], and railway structural health monitoring [24]. The intersection of DTs with urban energy systems has been explored by Szpilko et al. [25] and Golinska-Dawson and Sethanan [26], emphasizing smart grids, renewable integration, and energy-efficient urban freight systems.

A central research theme in transportation DTs is the design of their architectures, which determine how heterogeneous data, models, and services are orchestrated. Several works have proposed reference frameworks to address the complexity of ITS. Bao et al. [27] outlined a three-layer architecture–data access, calculation/simulation, and management/application–highlighting the transition from traditional traffic simulations to DT-enabled predictive and optimization capabilities. Instead, Irfan et al. [28] introduced a hierarchical reference architecture for transportation DTs, spanning the physical space, communication gateways, and digital space. Similarly, Faliagka et al. [29] proposed an open DT framework for smart mobility, with the goal of evolving toward city-wide deployments.

On high-level reference models, more specialized architectures target data and computational challenges. Zhang et al. [30] designed a multi-source data collaboration framework for ITS, aimed at overcoming data redundancy and enabling dynamic/static data fusion across heterogeneous sources. In large-scale contexts, DTUMOS [31] is introduced, an open-source framework optimized for scalability and simulation speed in metropolitan areas such as Seoul and New York. At the system level, Bhatt et al. [32] recently proposed DigIT, a modular and scalable DT platform leveraging a domain concept model to integrate predictive simulations into ITS operations, demonstrating real-time adaptability to evolving traffic patterns.

Beyond architecture, the value of DT in public transport lies in their ability to embed AI and ML to support prediction, optimization, and decision-making. Studies show that AI enhances classification, anomaly detection, and operational optimization in transport infrastructures [33], while also enabling the integration of heterogeneous data sources to predict travel behavior and evaluate policy scenarios [34]. Recent frameworks combine multi-source data fusion and predictive analytics to provide congestion forecasts, and safety heatmaps [35], demonstrating the role of AI in supporting real-time decision-making for sustainable mobility. Hierarchical models are also introduced to improve traffic safety and mobility across different system levels [28].

A variety of implementations adopt classical regression and ensemble models for demand forecasting and traffic state prediction, while others rely on deep learning for spatiotemporal analysis, anomaly detection, or computer vision tasks [27,30]. Adaptive machine learning pipelines have been proposed to continuously update predictive models in DT environments [32], and AI-based routing and arrival-time estimation have been shown to improve scalability and accuracy in large metropolitan simulations [31].

Moving to interaction dimension, the role of HCI in DT is still emerging and underdeveloped. While AI and architectural approaches have attracted significant attention, human interaction with DT systems has been addressed only marginally. Systematic reviews highlight that HCI contributions to DTs are limited and fragmented [36,37]. These studies emphasize that DTs are often conceived as technological artifacts without accounting for interaction paradigms that make them accessible and usable for diverse stakeholders. In public transport, human-centered methods such as surveys, prototyping, and user studies are increasingly applied [38], but their integration into DTs is still scarce.

In summary, prior work illustrates that DTs for urban mobility have advanced through increasingly sophisticated yet fragmented architectures that orchestrate heterogeneous data and models, through embedded intelligence that enable predictive and adaptive decision-making, and, to a lesser extent, through interaction mechanisms that shape how stakeholders can access and act upon these capabilities. This fragmentation highlights the need for a systematic review that synthesizes these diverse contributions, identifies common patterns, and exposes critical research gaps. While general applications of DT in urban planning and transportation are well documented, our focus on these three dimensions is motivated by their central role in determining both the technological feasibility and the practical adoption of DTs for public bus transport. By examining architectures, intelligence, and interaction aspects together, we address the core enablers that bridge system-level design with real-world usability, thereby aligning with the pressing challenges of deploying scalable, adaptive, and human-centered DT solutions in public bus transport.

3. Methods

This Section outlines the Research Questions that motivated the study, describes the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) methodology and details the process of data collection and analysis.

3.1. Research questions

The primary Research Question that guide this study is:

RQ: How are DT technologies applied in public transport systems, with a particular focus on bus and similar modes of transit?

Specifically, this work aims to investigate the following questions to provide insights into three main aspects:

- **RQ1**: What are the common architectures, components, frameworks, and platforms used or proposed in DT implementations of bus and similar modes of transit?
- **RQ2**: How are AI and ML models integrated into DTs of bus and similar transit systems, and what types of tasks do they support or enable?

Table 1
Database-specific query strings.

Database	Query string
ACM DL	(“digital twin*” OR “virtual twin*” OR “digital replica*” OR “digital shadow*”) AND (“bus” OR “buses” OR “busses” OR “trolleybus*” OR “public transport*” OR “transit system*”)
IEEE Xplore	(“All Metadata”:”digital twin*” OR “virtual twin*” OR “digital replica*” OR “digital shadow*”) AND (“bus” OR “buses” OR “busses” OR “trolleybus*” OR “public transport*” OR “transit system*”)
ScienceDirect	(“digital twin”) AND (“bus” OR “buses” OR “busses” OR “public transportation” OR “public transport” OR “transit system” OR “transit systems”)
Scopus	TITLE-ABS-KEY(“digital twin*” OR “virtual twin*” OR “digital replica*” OR “digital shadow*”) AND TITLE-ABS-KEY(“bus” OR “buses” OR “busses” OR “trolleybus*” OR “public transport*” OR “transit system*”)
SpringerLink	(“digital twin*” OR “virtual twin*” OR “digital replica*” OR “digital shadow*”) AND (“bus” OR “buses” OR “busses” OR “trolleybus*” OR “public transport*” OR “transit system*”)

- **RQ3**: What is the role of HCI in DTs of bus and similar transit systems, and how is user interaction designed or studied?

In this work, when we refer to “similar modes of transit” alongside bus systems, we mean ground-based public transport modes that share comparable operational characteristics with traditional bus networks. These include, but are not limited to, trolleybuses, trams and streetcars, light rail transit systems, bus rapid transit, guided bus systems, and other bus-like vehicles such as minibuses.

In addition, while DTs in public bus transportation encompass a broad spectrum of applications and implementations, this systematic literature review focuses on addressing the core operational and management challenges of bus-based transit systems. Our study specifically examines DT applications that model one or more of the following entity categories (described in Section 4.2): bus infrastructure, traffic flows and trips, passengers and their behavior, bus physical models, and fleet management systems.

3.2. PRISMA methodology

A SLR is a structured and methodical approach to identifying, analyzing and synthesizing all existing research on a particular topic [39]. Its purpose is to provide a comprehensive and unbiased summary of current knowledge, highlight gaps in the literature and offer a foundation for future research. By following a clear and replicable process, a SLR ensures that conclusions are based on a thorough evaluation of all relevant studies rather than on a selective or subjective sample. The search for relevant studies is often carried out across various databases and sources.

In this study, we took advantage PRISMA methodology [40,41]. It provides a standardized framework for conducting and reporting systematic reviews and meta-analyses. Its purpose is to enhance transparency, rigor, and reproducibility by guiding researchers through the process of data extraction, study selection, and synthesis. In addition, following the PRISMA guidelines ensures that the review process is systematically and clearly documented.

3.3. Data collection

We searched for published studies available online through major digital libraries and databases in the field of computer science, including the *ACM Digital Library (ACM DL)*, *IEEE Xplore*, *ScienceDirect*, *Scopus*, and *SpringerLink*.

To guide our search, we established a set of keywords intended to capture studies related to DT technologies in public transport, with a particular focus on bus systems. These keywords were combined using boolean logic to construct a comprehensive search string. To further enhance the inclusion of terms and to account for variations in word endings or phrasing, we employed wildcards. The search strategy was designed to cover a broad spectrum of terms, ensuring the inclusion of relevant studies despite variations in terminology and application areas.

The query string was entered into the search fields of each selected database. Where supported, we restricted the search to specific metadata fields–namely, the title, abstract, and keywords–to improve the relevance and precision of the retrieved results. To ensure reproducibility, Table 1 presents the exact query string used for each database, including any modifications required to fit the platform’s search syntax.

All searches were conducted in April 2025, ensuring consistency and temporal alignment across data sources and search strategies. To ensure the quality and relevance of the reviewed literature, we included only publications written in English. Furthermore, we limited our selection to peer-reviewed journal articles and conference papers for which the full text is available. Other sources, such as book chapters, were excluded from the review. It is important to note that the focus of this review is on the application of DT technologies in public transport, specifically bus systems, concerning architectures, frameworks, use cases (e.g., demand forecasting), and HCI. The other inclusion and exclusion criteria are listed in Table 2. Additionally, we included only research articles, excluding other literature reviews and meta-analyses.

3.4. Data processing

The process of selecting the relevant literature was carried out in accordance with the PRISMA guidelines and consisted of four main phases:

1. identification of relevant studies,
2. screening based on title and abstract,
3. eligibility assessment of the full text, and
4. data extraction and synthesis.

The inclusion and exclusion criteria defined in Table 2 were systematically applied throughout these phases, ensuring a transparent and reproducible selection process. A detailed overview of the number of records included and excluded at each stage–also together with the reasons for exclusion–is illustrated in Fig. 1, which follows the PRISMA methodology and directly reflects the application of these criteria.

In the identification phase, a comprehensive search was conducted across multiple academic databases, including ACM DL, IEEE Xplore, ScienceDirect, Scopus, and SpringerLink. The initial query retrieved a total of 2066 records. Then, 132 duplicate records were identified and removed, resulting in a refined pool of 1934 unique papers.

During the screening phase, we applied inclusion and exclusion criteria to filter the papers. Specifically, we excluded 1816 records for the following reasons:

1. studies were not peer-reviewed, or
2. the full text was not available in English, or
3. the titles clearly indicated that the subject matter did not pertain to the application of DT technologies in public transport, or
4. the abstracts indicated that the studies were not focused on DT technologies for public transport, or
5. papers could not have been retrieved from the database.

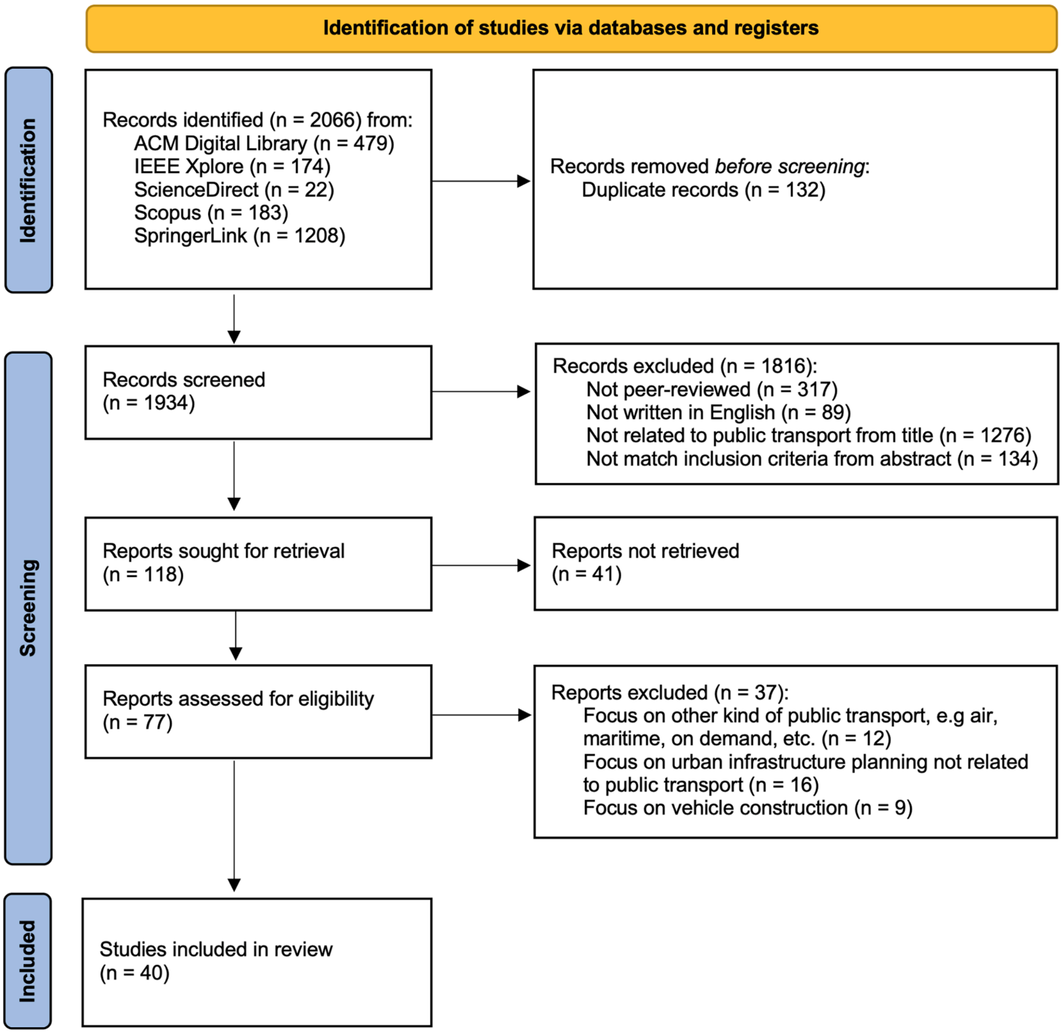

Fig. 1. PRISMA 2020 flow diagram for new systematic reviews which included searches of databases.

Table 2
Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
Written in English	Written in other languages
Peer-reviewed articles	Non peer-reviewed articles
Full text available	No full text available
Empirical studies	Literature reviews and meta-analyses
Focus on DT applications for public transportation, specifically on busses or similar transit systems.	Focus DT technologies for different kind of public transport systems, such as air, maritime, last mile, etc.
Focus on DT architectures, frameworks, applications, use cases, and HCI.	Focus on DT applications for other goals, such as infrastructure planning or vehicle design.

This left us with 77 papers for further evaluation. In the eligibility phase, we conducted an in-depth review of the full texts of these papers. We excluded 37 papers for the following reasons:

- 12 papers were not focused on technologies for public transport, but rather on other types of transportation systems, such as air, maritime, or last-mile and on demand transport, etc.;
- 16 papers were focused on DT technologies for urban infrastructure planning, that are not directly related to public transport;
- 9 papers focus on DT technologies for vehicle design and construction.

After this rigorous filtering process, a total of 40 studies met all predefined inclusion criteria and were retained for in-depth analysis. These studies are listed and referenced in Table A.1, in the Appendix.

3.5. Critical assessment

Subsequently, in addition to the collection and screening process described respectively in Sections 3.3 and 3.4, an evaluation of the studies based on their coverage was conducted. The results are summarized in Table 3, which presents a matrix with columns corresponding to the Research Questions (RQ1, RQ2, and RQ3) and rows representing each included article. Each article was evaluated for whether it addressed each Research Question, with a ✓mark indicating that the study pro-

Table 3
Critical assessment of research questions on reviewed papers.

Ref	RQ1	RQ2	RQ3	Total
[42]	×	✓	×	1
[43]	✓	×	×	1
[44]	✓	×	×	1
[45]	✓	×	×	1
[46]	✓	✓	×	2
[47]	✓	✓	✓	3
[48]	✓	×	✓	2
[49]	✓	✓	×	2
[50]	✓	✓	×	2
[51]	✓	×	×	1
[52]	✓	✓	×	2
[53]	✓	✓	✓	3
[54]	✓	✓	×	2
[55]	✓	×	✓	2
[56]	✓	✓	×	2
[57]	✓	✓	×	2
[58]	✓	✓	×	2
[59]	×	✓	×	1
[60]	✓	×	×	1
[61]	✓	×	✓	2
[62]	✓	×	×	1
[63]	✓	×	✓	2
[64]	✓	×	×	1
[65]	✓	×	×	1
[66]	✓	✓	✓	3
[67]	✓	×	×	1
[68]	✓	×	×	1
[69]	✓	×	×	1
[70]	✓	×	×	1
[71]	✓	×	×	1
[72]	✓	×	×	1
[73]	×	✓	×	1
[74]	✓	✓	×	2
[75]	✓	✓	×	2
[76]	✓	✓	✓	3
[77]	✓	×	×	1
[78]	✓	×	✓	2
[79]	✓	×	✓	2
[80]	✓	×	×	1
[81]	✓	×	✓	2
Total	**37**	**17**	**11**	

vided an answer to the question, and a ×mark indicating that it does not provide any information about the topic.

With respect to RQ1, which focuses on system architectures and technological infrastructure, 37 out of the 40 studies provided sufficiently detailed descriptions. These studies commonly reported on the software and hardware components involved, the platforms adopted, and the frameworks used to implement or prototype their systems. Then, RQ2 concerns the integration of AI and ML models within the systems. We found 17 studies that include information on the types of algorithms used, their functional roles, and how they were incorporated into the system. Regarding RQ3, which examines the role of HCI, 11 studies explicitly addressed how users can interact with the system, including aspects such as User Interfaces (UIs) and interaction modalities.

Overall, 4 out of the 40 studies met aspects of all three Research Questions, providing comprehensive coverage of system architecture, AI/ML integration, and user interaction. A larger group of 17 studies addressed two of the three Research Questions, demonstrating partial alignment with the assessment criteria, while the remaining 19 studies covered one of the three dimensions. These findings highlight a significant heterogeneity in how the different aspects of system design are addressed across the literature. They suggest that the development of DT systems often focuses selectively on certain technical components, while neglecting equally critical dimensions like AI/ML integration or user interaction. This pattern indicates that a comprehensive approach is not consistently adopted and that, in many cases, essential aspects for

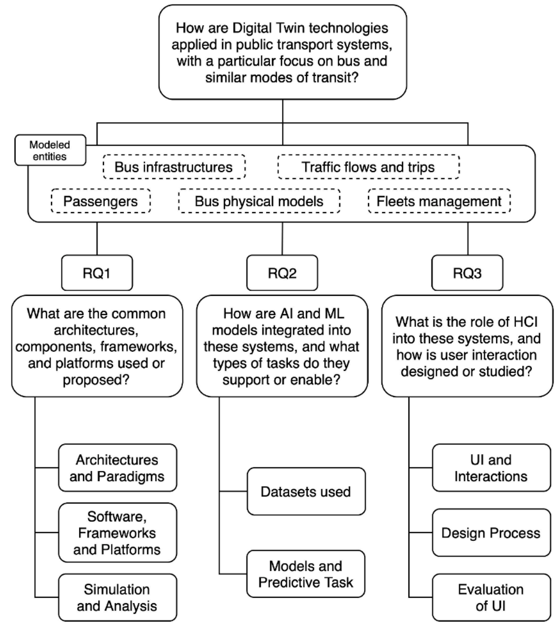

Fig. 2. Overview of the research questions.

the deployment, usability, and effectiveness of DT solutions are poorly explored or insufficiently documented.

3.6. Extraction of relevant fields

The final step of the methodology involved identifying and summarizing relevant information from the selected studies. This process was carried out manually through a comprehensive reading of the full texts, extracting data that addresses the predefined Research Questions. Table 4 report all of the fields that were compiled to compose the final dataset of the selected articles, enabling further analysis. In particular, three key fields were compiled to directly correspond to the Research Questions guiding the review and a "Countries" field was added to indicate a list of countries where the case studies were conducted.

4. Findings and discussion

This Section begins with a preliminary quantitative analysis of the retrieved studies, followed by a discussion about how studies model the entities within DT systems. Then, we present the answers to the three Research Questions outlined in Section 3. Fig. 2 offers a visual synthesis of the main findings across the three Research Questions, helping to contextualize the discussions that follow.

4.1. Quantitative analysis

In this Section, we provide a quantitative analysis of key attributes from the selected studies, including the geographic origin of the datasets and the locations where DT systems were physically implemented or where real-world transport data was collected and utilized for modeling purposes.

As previously mentioned, the systematic review identified 40 relevant studies focusing on the application of DTs in public transport, specifically within bus systems. From these studies, we extracted information about the countries where the DT systems were implemented or where the associated transport data was collected and applied. This results in a total of 32 case studies that utilized datasets or described implementations from 16 different countries across 3 continents. Table 5 presents the distribution of these studies based on the country where the DT was implemented or where the associated transport data was

Table 4
Extracted fields from the selected studies for data analysis.

#	Field	Description
1	ID	Unique identifier for the article.
2	Title	Title of the article.
7	Abstract	Abstract of the article.
3	Authors	Authors of the article.
4	Year	Year of publication.
5	Source title	Title of the journal or conference.
6	Publisher	Publisher if the article is a journal.
6	DOI	DOI of the article.
7	Keywords	Keywords of the article.
8	Objective	Objective and key findings of the article.
9	Countries	List of countries where the case studies were conducted.
10	RQ1	Description how the architecture, components, frameworks, and platforms are used in the article.
11	RQ2	Description how AI and ML models are used in the article and what tasks they support.
12	RQ3	Description how HCI is used in the article and how user interact with the system.

Table 5
Number of case studies per country conducted from each article.

Country	Count	Case Studies
Spain	6	[53,61,64,68,75,77]
Italy	4	[48,53,56,69]
France	3	[52,74,76]
Russia	3	[43,55,57]
United States	3	[46,51,58]
China	2	[44,73]
Norway	2	[42,79]
Finland	1	[53]
Germany	1	[68]
Japan	1	[78]
Mexico	1	[45]
Netherlands	1	[53]
South Korea	1	[65]
Sweden	1	[68]
Turkey	1	[59]
United Kingdom	1	[66]

collected. From the total, the most frequently represented country was Spain (n = 6), followed by Italy (n = 4), and 3 case studies each from France, the United States, and Russia, respectively.

Of the 40 studies included in the review, 26 were published in the proceedings of conferences focused on transport systems, smart cities, or computer science. The remaining 14 studies appeared in peer-reviewed journals. Table 6 provides an overview of the journals in which these studies were published. Both conference papers and journal articles were predominantly situated within the engineering and computer science domains, but also included areas such as energy systems, urban studies, and intelligent transportation, further reflecting the interdisciplinary nature and broad applicability of the research.

4.2. Entities in public transport DT systems

DT systems should be able to create a virtual representation of the physical system they are “twinning”, which includes not only the physical assets but also connections and interactions among them. In the context of public transport, this means that DT systems can take into account any entity related to the entire system, both analyzing static aspects and dynamic behavior. We have identified the following categories of entities that are commonly modeled in the reviewed studies:

1. *bus infrastructure*, which includes the modeling of bus stops, bus lanes, bus stations, and other physical assets that are part of the bus system,
2. *traffic flows and trips*, which includes the modeling of traffic flows, trip generation, trip distribution, and other aspects related to the movement of buses and passengers,
3. *passenger*, which includes the modeling of passenger behavior, preferences, and interactions with the bus system,
4. *bus physical model*, which includes the bus dynamic model, including its acceleration, deceleration, braking, and other mechanical and physical characteristics that govern its motion and operational performance on the road,
5. *fleets management*, which includes the modeling of bus fleets, including their size, composition, and operational characteristics.

Table 7 summarizes the number of studies that model each entity. It is important to notice that some studies may model multiple category entities, and the same entity may be modeled in different ways. For example, bus infrastructure can be modeled as a static representation of the physical assets, or as a dynamic representation that takes into account the interactions between buses and passengers, leading to a double categorization of the study.

As shown in the table, bus infrastructure is the most frequently modeled entity, which is present in 34 studies. This importance can be attributed to the fundamental role that infrastructure components–such as bus stops, lanes, and stations–play in the functioning of bus transit systems. These physical elements serve not only as the primary interfaces between passengers and the transit network but also as critical determinants of service reliability, travel time, and overall system performance. Consequently, accurate representation and analysis of bus infrastructure are essential for evaluating operational strategies, optimizing network design, and supporting transportation planning. Furthermore, infrastructure tends to be more predictable and subject to direct control, making it a particularly viable target for intervention and optimization within transportation models and to work on them.

Then, traffic flows and trips are modeled in 22 studies and passenger behavior in 13 studies. The modeling of traffic flows and trips is crucial for understanding the dynamics of bus operations, including route performance, congestion patterns, and service frequency. This modeling enables transit agencies to make data-driven decisions regarding scheduling, capacity planning, and resource allocation. Moreover, individuals are not just passive passengers–they are dynamic agents whose decisions and interactions play a fundamental role in shaping transport demand and performance. Accurately modeling user behavior, when possible, is essential for understanding how they engage with the bus system, understanding their travel patterns, preferences, and reactions to changes in service. This information is critical for the development of user-centered transit solutions that effectively address passenger needs and enhance overall service satisfaction.

Finally, bus physics and fleet management are modeled in 8 and 7 studies, respectively. The modeling of bus physics is essential for accurately simulating vehicle behavior, including not only acceleration, deceleration, and braking characteristics but also steering dynamics. A comprehensive physical model enables realistic reproduction of bus motion under various operational scenarios, accounting for factors such as

Table 6
List of Journals and corresponding Publishers for the selected articles.

Publisher	Journal
Elsevier	Sustainable Energy Technol. Assess. ([44]) Energy ([51]) Applied Energy ([58])
IEEE	IEEE Access ([47]) Transactions on ITS ([70,80])
Istanbul University	Electrica ([59])
MDPI	Smart Cities ([53]) Applied Sciences ([57,68]) Electronics ([62])
River Publishers	Journal of Web Engineering ([61])
Springer	Multimedia Tools and Applications ([48]) Software and Systems Modeling ([52])

Table 7
Classification of studies per each modeled entities in DT.

Entity	Count	Papers
Bus infrastructure	34	[43–45,47,48,50–53,55–61,64–73], [74–77], [78–81]
Traffic flows and trips	22	[42,43,45,47,51,52,56,57,60,61,63,65–69,73–78]
Passengers	13	[45,53,56,59–61,63,64,66,67,69,77,78]
Bus physical model	8	[44,46,49,54,58,62,68,73]
Fleets Management	7	[45,46,50,51,53,58,72]

vehicle mass distribution, suspension response, and tire-road interaction. This level of detail is critical for evaluating safety, performance, and operational efficiency. Similarly, the modeling of bus fleets is important for understanding the operational characteristics of multiple vehicles within a transit system, such as fleet size, composition, and runtime utilization. This enables agencies to analyze and optimize fleet management strategies, paving the way for vehicle assignment, runtime rescheduling, and resource allocation. In addition, the modeling of both individual buses and entire fleets plays a crucial role in assessing energy consumption and emissions, which is increasingly important in the context of sustainability and environmental impact evaluation. As cities strive to reduce their carbon footprint and promote greener transportation solutions, understanding the energy dynamics of bus systems is essential for evaluating the effectiveness of operational strategies and technologies. These insights can inform the development of more energy-efficient vehicle designs, route planning approaches, and energy management systems, contributing not only to reduced operational costs but also to lower environmental impact and improved overall system performance.

4.3. Architecture, components, and frameworks in DT systems for public transport

This Section provides an overview of the actors and architecture for DT in public transport, answering the first Research Question **RQ1**, "*What are the common architectures, components, frameworks, and platforms used or proposed in DT implementations of bus and similar modes of transit?*". As anticipated in Table 3, the majority of the selected studies (37 out of 40) provided sufficiently detailed descriptions that allowed us to analyze the software aspects of the proposed DT systems.

4.3.1. Software architectures and paradigms

The software architecture is a critical aspect that defines how the system components interact, communicate, and collaborate to achieve the desired functionality. In the context of DT for public transport, the architecture must address various data sources from all components with different natures and properties, processing units, and interfaces to provide a view of the system's performance and behavior. The reviewed literature reveals several recurring architectural styles, patterns, and paradigms, with 14 of the selected studies explicitly detailing the architecture of their proposed systems.

Many of the proposed architectures in the reviewed studies adopt a *Client-Server* communication model to facilitate the interaction between system components, both in terms of machine to machine communication, but also for creating end user applications. This model is particularly flexible, allowing for the integration into various scenarios and use cases. For instance, in [47] authors present a platform for creating DTs and distributing them through the cloud, allowing communication to the system from both IoT devices and end users. Similarly, in [48] authors present a web-based client-server platform for creating 3D representations of modeled entities. In addition, key advantages include the ability to distribute computational load effectively between the client and server components, enabling the offloading of intensive processing tasks to the server or, when appropriate, to the client. Also notable is the possibility of decoupling the client and server components, allowing for independent development and deployment of each part, as illustrated in the implementation proposed by [79].

To understand how different software layers interact with each other, the *Multi-layer architecture* is a common approach. This architecture is particularly effective in managing the complexity of DT systems, such as public transport ones, as it allows for the separation of concerns and the organization of components into distinct layers, each with its own responsibilities as proposed in [66,72,78]. Typically, these architectures include layers such as the presentation layer, the application layer, and the data layer. This separation of concerns allows different components of the system to evolve independently and facilitates integration with external services. For example, in [56], the proposed architecture includes additional layers beyond those previously mentioned. These layers address the following aspects: acquisition, ingestion and processing, storage, simulation, service, as well as security and both intra- and inter-twin communication.

Furthermore, the concept of the *compute continuum* [82] has emerged as a new trend for enabling scalable, efficient, and context-aware DT systems. It refers to the seamless distribution of computational tasks across a spectrum of resources–from constrained edge devices to fog nodes and centralized cloud platforms–based on workload requirements, latency constraints, and energy efficiency considerations. However, due to the absence of a standardized structure for implementing the compute continuum, many authors propose their own tailored architectural interpretations. In [55] fog computing is used to increase performance near embedded devices. In [60,64,77], the authors propose the compute continuum in a 3-tier architecture, including the cloud, fog, and edge nodes that are used to distribute computational tasks based on their proximity to data sources and processing needs. Instead, Campolo et al. [69] also proposes a 3-tier architecture, but with a different focus. In this design, the ground layer is used to collect data from the physical system, while the edge layer is used to virtualize DT components and the remote layer is used to access the system from the cloud. Finally, García-Luque et al. [61] proposes a 4-tier architecture that extends the traditional cloud-fog-edge model by introducing an additional mist layer. This layer includes devices that lie outside the direct authority and control of the DT system–such as end user devices–enabling the delivery of personalized information tailored to individuals.

In addition, *microservices* architectural style has gained traction in recent years as a way to build scalable and maintainable systems. In the context of DTs, they can be used to create modular components that can be easily integrated into existing systems or replaced with new ones as needed. This is particularly relevant in public transport applications, where different subsystems (e.g., traffic flow, energy consumption, passenger behavior) must evolve and operate concurrently. In [61,76], the

Table 8
Classification of DT implementation for *architecture type*, *implementation stage*, and *data update*.

Paper	Type	fStage	Update
[47]	Client-Server	Lab	Batch
[48]	Client-Server	Real	Online
[55]	Cloud continuum	Lab	–
[56]	Multi-Layer	Lab	Online
[60]	Cloud continuum	Concept	–
[61]	Cloud continuum, Microservice	Lab	Online
[64]	Cloud continuum	Concept	–
[66]	Multi-Layer, Streaming	Lab	Online
[69]	Cloud continuum	Lab	Online
[72]	Multi-Layer	Concept	–
[76]	Microservice	Real	Online
[77]	Cloud continuum	Lab	Online
[78]	Multi-Layer	Lab	–
[79]	Client-Server	Lab	Batch

authors propose a microservices-based architecture for the DT of a transport system, which allows for the independent development and deployment of each component. In parallel, the adoption of *streaming architectures* has become increasingly important for enabling the continuous processing of real-time data streams from sensors and IoT devices. In [66] it's proposed a streaming data platform that integrates with a DT for real-time system analysis and monitoring. Such architectures are essential for handling time-sensitive information, such as vehicle telemetry or passenger flow, and allow the system to react promptly to changes in the physical environment.

Among the studies, some DT proposals remain at the conceptual level (*Concept*) [60,70,72], while the majority of implemented systems are realized in controlled lab environments (*Lab*) [47,55,56,61,66,69,77–79] or through deployments in real-world scenarios (*Real*) [48,76]. In real-world deployments, DTs updates are *online* and acquire data in real time from the environment, ensuring that the virtual counterpart remains continuously synchronized with the physical system. In many cases, lab-based DTs rely on real-time data publicly available through operators web-server on the scheduling and current position of vehicles. Instead, in others–such as DTs focused primarily on simulation [47] or interaction aspects [79]–data are updated in batches using pre-collected datasets or not updated at all [55,78]. Finally, conceptual DTs do not integrate any data source, as they remain at a design or architectural level. Table 8 details the architecture type of the DT, the implementation stages, and synchronization approaches observed across the reviewed studies.

In summary, the architectural approaches reviewed in the literature reflect the complexity and adaptability required to build effective DT systems for public transport. From the flexible client-server to a more advanced microservices or compute continuum paradigms, each architecture aims to address specific system requirements, such as scalability, real-time data processing, and efficient task distribution across heterogeneous computational resources. In addition, the integration of multi-layer architectures further enhances the system's modularity and separation of concerns.

4.3.2. Software, frameworks and platforms

Among the 37 reviewed studies, 27 provide detailed descriptions of the software, frameworks, and platforms used to support the development and implementation of DT systems in this context. These tools range from programming languages and simulation engines to specialized frameworks for data processing and visualization.

A recurrent theme across the studies is the use of simulation frameworks, particularly Simulation of Urban MObility (SUMO). It appears in several works [45,51,65,75] as a foundational tool for traffic modeling, offering open-source support for simulating road networks, vehicle movement, and traffic control. These models are often combined with other platforms to provide optimization capabilities. For instance, in [51], SUMO is embedded within the TransitMo framework, which supports origin-destination demand modeling, traffic prediction, and behavior analysis.

AnyLogic is another notable software used. In [67] author proposes a simulation model of the bus route using it, modeling passenger boarding and alighting, stop dwell time, boarding refusal probability, and passenger waiting time cost. Furthermore, [65] integrates SUMO with AnyLogic to enhance the simulation fidelity and allow for advanced traffic light optimization strategies. In addition to traffic-focused tools like PTV Visum [57] and Vissim [61], general-purpose simulation engines such as MATLAB [62,68] and COMSOL [72] are also used-primarily for physical modeling in scenarios involving energy systems, battery dynamics, and control mechanisms.

To complement these simulation capabilities, 3D modeling and immersive visualization technologies–such as Unity [63,79,81]–are increasingly integrated into DT frameworks. Unity, often combined with live data streams, enables dynamic scenario simulation and virtual prototyping within public transport environments. Similarly, platforms like Snap4City [48] support smart city integration through web-based interface, offering features such as IoT connectivity and 3D visualization.

Modeling architectural components is also a critical aspect of DT development. In this context, FIWARE [83] serves as a robust open-source framework to manage context information and integrate heterogeneous data sources, enabling high interoperability and scalability. For example, in [56], FIWARE is employed to build a DT public transport system using a multi-layer architecture that emphasizes data interoperability. The implementation leverages FIWARE's Smart Data Models to ensure standardized and consistent data representation across system components. Similarly, Eclipse Ditto [61] is an open-source framework for managing digital representations of physical entities through a unified *digital twin* abstraction, supporting real-time synchronization, device connectivity, and scalable integration with IoT platforms.

In terms of programming environments, Python is the dominant language used in DT system implementations across studies [45,46,48,51,56–58,75,76,79,80], due to its extensive ecosystem for data processing, simulation, and machine learning. Many frameworks are built directly in Python or use it as a glue language between simulation tools and analytical engines. Other languages such as C# [55], Java [61,69], JavaScript [55,78], and Scala [52,74] are also used, but to a lesser extent.

Streaming technologies and pub/sub services also play a crucial role, leveraging tools and protocols such as Kafka, MQTT, AMQP, and CoAP to enable real-time, low-latency data exchange between devices and central systems. For instance, Van Den Berghe [66] integrates Kafka into the DT architecture for real-time streaming, monitoring, and forecasting of passenger flows in public transport systems. Additionally, data processing frameworks like Apache Spark [52,74] are employed to manage large-scale data, particularly graph-based structures for transit networks in real time, enabling fine-grained event tracking and forecasting.

Regarding data storage technologies, the studies show a preference for NoSQL databases, particularly MongoDB [56,61,77]. Time-series databases such as CrateDB [56], InfluxDB [61], and TimescaleDB [56] are also mentioned. This preference is likely due to their flexibility and scalability, which are well-suited for handling the large volumes of heterogeneous and time-series data commonly generated by devices in public transport systems, such as passenger counters, vehicle telemetry systems, and environmental sensors.

Furthermore, blockchain has been explored as a supporting platform in [70], which proposes a DT-as-a-Service model for decentralized market interactions, such as service pricing negotiations. While still emerging, such approaches show promise for secure and transparent operations. Additionally, Prajapat et al. [80] presents a quantum-secure authentication protocol for DT-based transportation systems, using quantum key distribution and related principles to enhance communication security between vehicles, DTs, and central authorities.

Table 9
Classification of DT type, with *framework*, and *dataset* used.

	Framework		Dataset	
Type	Open	Scratch	Open	Closed
Simu-lation	[45,51,65,75]	[76]	[65]	[51,68,75,76]
Math model	[51]	[46,70,80]	[46]	[51,58,62]
Visua-lization	[48,63]	[55,79]	[48,79]	[63]
Data-driven	[52,61,74]		[52,61,74]	[57,58]
Arch. model	[56,61,66]	[67,69,72,76–79,81]	[61,66,79]	[76]

Table 10
Classification of simulation usage within DT implementation.

Usage type	Papers
DT	[49,54,76]
Validation with simulation	[44,47,50,51,58,62,75]
Simulation only	[43,45,46,53,57,65,67,68,71]

To complement this analysis, we classified the reviewed DTs by type, framework, and dataset openness (Table 9). The identified types include *simulation*, *mathematical*, *visualization*, *data-driven*, and *architectural models*. Simulation DTs are often used for what-if scenarios, typically rely on open-source tools (e.g., SUMO) but employ closed, non-public datasets when studies use real-world data. Visualization DTs use 2D/3D and immersive platforms (e.g., Unity) to support interactive exploration. Mathematical and data-driven DTs frequently depend on proprietary datasets to optimize specific variables or validate hypotheses. Works on defining architecture for DTs sometimes leverage open frameworks, though the majority propose novel architectures developed from scratch. While most works use exclusively open-source technologies, a few studies employ commercial tools for targeted development phases like dataset acquisition [57] or implement hybrid approaches combining open and proprietary solutions [63,65].

The reviewed studies highlight a rich ecosystem of software tools, frameworks, and platforms supporting DT development for public transport systems. Tools like SUMO, AnyLogic, and Unity enable detailed simulation and visualization, while platforms such as FIWARE support integration and scalability. Python is widely adopted due to its versatility in data handling and modeling. Additionally, real-time streaming, and NoSQL/time-series databases demonstrate a clear focus on flexibility and responsiveness in managing complex and heterogeneous transport environments.

4.3.3. Simulation and analysis

Simulation plays a central role in the development, validation, and application of DT systems in public transport. Simulations are used to replicate the behavior of physical systems under various operational and environmental conditions. These simulation activities often serve as a bridge between real-world data with virtual models to forecast outcomes, evaluate performance, and test strategies. In the review of the literature, we identify 19 studies within selected ones that incorporate simulation as part of their DT systems. However, it is crucial to distinguish between traditional simulation approaches and true DT implementations. While DT has become a widely adopted term in recent literature, many studies claiming to develop DT systems actually implement enhanced simulations without the bi-directional synchronization to physical systems and continuous real-time update loops that characterize DTs. As shown in Table 10, our analysis reveals that among the studies incorporating simulation, only few papers truly implement DT functionality, while the majority employ either standalone simulations or use simulation primarily for validation purposes.

A primary aspect of simulation in DT systems for public transport is the scale at which the simulation is conducted, as it significantly affects the level of detail, computational requirements, and the type of insights that can be obtained. Traffic simulation can be broadly categorized into microscopic, mesoscopic, and macroscopic, models. *Microscopic* models, used in studies [51,53,65,75], provide the most granular view by modeling individual agents (vehicles, passengers) and their interactions in high detail. These are ideal for evaluating traffic control strategies, passenger behavior, or energy consumption patterns at the vehicle level. *Mesoscopic* models strike a balance between detail and computational efficiency by simulating individual vehicle movements or flows while using simplified behavioral assumptions. Finally, *Macroscopic* models, as demonstrated in [57], focus on aggregated system behavior, modeling traffic flow or transit operations at a high level using statistical or flow-based equations. The choice of simulation scale often depends on the system's objectives: strategic planning favors macro models, operational optimization leans toward micro or hybrid approaches, and mesoscopic models are chosen for scalable yet behaviorally rich scenarios.

People and their travel patterns are central to the functioning and design of public transport systems. Passengers behaviors not only influences system performances but also offers critical insights for data-driven decision-making. The simulation of passenger behavior can be conducted through various modeling approaches, depending on the level of detail required and the specific aspect under investigation. For example, in [67] authors employs a discrete-event, agent-based simulation to model bus movements, passenger boarding and alighting, and waiting times at stops, enabling detailed analysis of route efficiency and service quality. In contrast, Chainikov et al. [57] utilizes a macroscopic city transport model to examine how factors such as travel time and transport mode affect passenger behavior at a broader scale. Instead, simulations related to traffic, as seen in [43,47,65], focus on analyzing flow and congestion patterns to support urban mobility decisions, such as relocating bus stops, creating bus bays, or optimizing traffic signal timing, with the aim of improving overall system performance. Other works, such as [75,76], integrate real-time data to develop DTs that support operational decisions during runtime, such as dynamic bus rescheduling to mitigate disruptions and improve service reliability. It is crucial to clearly define the objective of a simulation, which may range from improving operational efficiency and service reliability [43,76], to minimizing operational costs [44], or supporting strategic planning [57,65].

Another aspect of simulation in DT systems for public transport lies in modeling energy consumption, vehicle dynamics, and operational optimization. Several studies incorporate high-fidelity simulations to assess and enhance the energy efficiency of electric and hybrid bus systems. For example, in [45], simulation involves detailed parameters such as vehicle speed, weight, road gradient, and aerodynamic drag to evaluate how operational choices–like bus stop distance–affect overall energy consumption. Similarly, other works [46,50,58] leverage DT for the optimization of electric fleets, involving battery charging strategies, also using solar energy. Simulations also address in-vehicle energy behavior: [49] models consumption in fuel-cell buses using AI-enhanced predictions, while [62,68] explore physical properties like traction torque and driving profiles to improve battery usage and regenerative braking. These simulation-based DTs not only forecast consumption under variable real-world conditions but also inform intelligent control strategies and predictive maintenance (e.g., [54,71]). Such energy-focused simulation efforts are essential for supporting low-carbon mobility policies and ensuring the long-term sustainability and efficiency of public transport systems.

In summary, simulation plays a key role in DT systems for public transport, enabling detailed analysis, predictive modeling, and operational optimization. The reviewed studies employ a variety of simulation scales and methods, from microscopic traffic models to macroscopic city-level evaluations, chosen according to specific system objectives. Simulations also support applications such as energy management, passenger behavior analysis, and real-time decision-making, highlighting their importance in enhancing performance, sustainability, and resilience in bus-based transport systems.

4.3.4. Discussion

The analysis of the literature reveals a highly fragmented technological landscape for DT systems in public transport, particularly in bus-based networks. While many systems share similar architectural goals-modularity, scalability, and real-time operation-their implementations vary widely.

To answer the **RQ1**, client-server models, multi-layered architectures, and compute continuum paradigms (cloud-fog-edge) are all present, but there is no common framework across all the studies. Instead, custom, ad hoc solutions dominate, often tailored to very specific use cases and local constraints.

This diversity extends to the components and technologies employed. Modules such as real-time data ingestion, simulation engines, and visualization dashboards are frequently included, but they are assembled using a wide array of frameworks and tools, including SUMO, AnyLogic, Unity, and FIWARE. The predominance of Python as a programming language reflects its suitability for rapid prototyping and integration, but also underscores the absence of standardized platforms or reusable software stacks. The use of NoSQL/time-series databases and streaming platforms for real-time data handling further demonstrates the technical variety, while experiments with technologies like blockchain remain isolated and exploratory.

Such technological heterogeneity reflects the field's immaturity. There is no uniformity or consensus on best practices, reference architectures, or common frameworks. This limits the interoperability, replicability, and scalability of DT systems, especially when trying to extend or adapt solutions beyond their original context.

Nevertheless, this fragmentation is not entirely negative. The reviewed systems are largely problem-driven, aiming to address real operational and planning challenges, such as traffic optimization, passenger flow forecasting, or energy management. Although these tasks may appear common, their implementation often reveals real-world constraints that necessitate ad hoc solutions. These application-specific requirements often justify the use of tailored, non-standard approaches, especially in the absence of mature, general-purpose DT frameworks for public transport.

One consistent insight across studies is that effective DT development is fundamentally data-driven. Most systems rely on existing operational data, as adding new sensors or monitoring systems is often impractical in the short term, particularly in large and complex transit networks. The ability to leverage available data, whether from AVL, ticketing, or external APIs forms the starting point for most DT initiatives, dictating the scope, structure, and capabilities of the resulting system.

In sum, while the field currently lacks standardization and exhibits a proliferation of technologies, it demonstrates a strong alignment with real-world needs. Future efforts should aim to balance local customization with shared design principles, moving toward more unified and interoperable DT architectures without compromising the flexibility required to solve diverse and context-specific transport problems.

4.4. Integration of AI and ML in digital twin systems

To address **RQ2**, "*How are AI and ML models integrated into DTs of bus and similar transit systems, and what types of tasks do they support or enable?*", we analyzed the selected studies according to three dimensions: (1) the datasets used to train or support the models, (2) the algorithms employed, and (3) the specific tasks these models are designed to address within DT systems for public transportation. Just 17 studies presented some information about the integration of AI and ML models [42,46,47,49,50,52–54,56–59,66,73–76].

4.4.1. Dataset employed

The majority of studies integrate real-world operational data, primarily sourced from public transportation systems, that include information on passenger flow, bus locations, travel speeds, and service disruptions. This data supports applications such as demand forecasting, incident analysis, and route optimization [42,52,53,66,74,76]. While others took advantage of specific operational datasets from universities [46,58] or transit agency logs related to charging behavior [50] or electric bus usage [73]. Historical vehicle data, such as powertrain performance, also contributes to predictive maintenance and energy consumption modeling [54]. Synthetic datasets are occasionally employed to simulate specific conditions or augment real data, often in combination with public data sources [52]. Finally, in some cases, the dataset source is not specified [49], or not used in the context of conceptual or architecture-focused studies [56,57,75].

4.4.2. AI and ML models and predictive task

The reviewed studies integrate a diverse range of AI and ML models to support predictive and optimization tasks within DT systems. These models serve functions such as forecasting demand, estimating energy use, predicting traffic or transit conditions, and enabling simulation-based decision support.

Predictive models for energy and powertrain performance were employed in multiple works. Gaussian Processes were used to predict energy consumption in electric university bus systems [46,58], while models such as KNN, RF, MLP, and Adaptive Neuro-Fuzzy Inference Systems supported powertrain fault prediction and fuel use estimation [49,54,73]. Similarly, custom learning algorithms were developed to forecast charge consumption and time-to-charge for electric buses [50].

Time-series and demand forecasting were addressed using models like LSTM, ARIMA, and PROPHET to predict ridership or mobility demand across urban areas [56,59]. LASSO regression was used for estimating passenger arrivals at stops [66]. While traffic and transit state prediction was tackled through various regression and ensemble models. LASSO, SVR, CART, and gradient boosting were used for bus line speed prediction [52], while another study applied Random Forest to estimate station load and incident durations [76]. Travel time estimation and network load analysis were supported via MLP models [57], and one study employed a Genetic Algorithm to optimize traffic simulation configurations [75].

Multi-domain KPI prediction was explored using a comprehensive suite of models-including LR, SVR, GBR, RF, and KNN-to predict indicators related to air quality, mobility, and transit usage from city-wide data [53]. Then, computer vision and simulation support was demonstrated by a model based on ResNet18 for mesh reconstruction in 3D environments [47]. A few papers did not specify any ML model, despite addressing analytic tasks such as temporal pattern detection or speed prediction, suggesting either manual or heuristic-based approaches [42,74].

4.4.3. Discussion

To answer **RQ2**, the analysis shows that AI/ML integration in DT systems for public transportation is primarily task-specific and data-driven, supporting a range of predictive, diagnostic, and optimization functions.

The dataset analysis highlights a reliance on operational mobility data, reflecting the data-intensive nature of DT systems. However, several studies lack transparency regarding data provenance, granularity, or preprocessing steps, which limits reproducibility. Moreover, the absence of data in some studies suggests that certain DT implementations are still at an early or theoretical stage. To strengthen future research, clearer documentation and broader access to high-quality, annotated, and multimodal transit datasets are essential.

Moreover, the diversity of models reflects the heterogeneous nature of tasks within DT systems, from energy and mobility forecasting to anomaly detection and optimization. However, many studies rely on classical or off-the-shelf models without detailed discussion of their selection, tuning, or validation. Furthermore, deep learning remains underutilized, and few works integrate multiple models into comprehensive pipelines. Future work should emphasize comparative evaluations, explainability, and integration into user-facing applications to enhance interpretability and decision support in real-world transport contexts.

Future research should move beyond isolated predictive modules toward more integrated, transparent, and user-aware AI components within DT systems. This includes the adoption of multimodal datasets, more rigorous evaluation protocols, and a stronger emphasis on explainability and human-in-the-loop configurations to improve both technical performance and real-world usability.

4.5. The role of HCI in DT systems for public transport

To address the **RQ3**, "*What is the role of HCI in DTs of bus and similar transit systems, and how is user interaction designed or studied?*", we analyzed the selected studies according to three dimensions: (1) the user interfaces and interactions supported, (2) the design processes underlying the development of these interfaces, and (3) the methods used to evaluate user interaction. As anticipated in Table 3, out of the 40 analyzed papers, only 11 exhibit at least one of these aspects [47,48,53,55,61,63,66,76,78,79,81].

4.5.1. UI and interactions

Among the 11 papers, each one outlines the presented interface, specifying the functionalities offered and the primary interactions designed. The UIs in the analyzed DT systems for public transport vary widely in form and complexity, reflecting the diversity of stakeholders they aim to support, from operators and planners to citizens and policymakers.

Several systems employ interactive dashboards and map-based interfaces to facilitate real-time monitoring and decision-making [61,66,76] and to simulate events such as rerouting buses and assess their projected outcomes in real-time [66]. Advanced visualization techniques are used to enhance comprehension and support non-technical users, such as multi-dimensional views of traffic scenarios [48,53]. While some interfaces include 3D and VR environments to support immersive interaction for real-time vehicle inspection [47] or to explore urban areas and simulate operational trade-offs [63,79,81]. Certain systems encourage citizen engagement by providing congestion data [78] while some interfaces are designed specifically for transit personnel and supervisors [55,76].

The reviewed systems generally utilize visually rich, map-centric dashboards and increasingly incorporate multi-dimensional and immersive environments. Interaction complexity ranges from basic monitoring to advanced simulation and user input. Citizen-facing interfaces are less common but indicate a growing awareness of non-operational users. Despite active development of HCI components in DT systems, their design often prioritizes technical aspects over user-centered design.

4.5.2. Design process

Among the reviewed works, only [63] explicitly discusses the methodology adopted during the design phase of the DT system. In this case, the authors employed the Design Research Methodology (DRM), a structured approach that emphasizes iterative development through cycles of analysis, design, evaluation, and refinement.

This study highlights the value of aligning technical development with user needs through iterative design and early stakeholder involvement, a contrast to reviewed works lacking documented design processes. This absence suggests an ad hoc or technology-driven approach to user interaction design in many public transportation DT systems. Despite the complexity of human-system interaction, the limited adoption of established HCI methodologies reveals a critical research gap, underscoring the need for a more systematic integration of design principles to ensure system effectiveness and usability.

4.5.3. Evaluation of user interfaces

The evaluation of UIs within the reviewed studies is limited to two studies [47,63] and primarily focused on system-level or design-concept validation rather than on human-centered usability testing. In [47], a Virtual Reality (VR)-based system was evaluated by engaging 10 users, each tasked with performing 100 interactions within the immersive environment. The evaluation regarded quantitative metrics, with no qualitative feedback or usability metrics (e.g., user satisfaction). A simulation-based approach is used also in [63] where target users assessed the conceptual validity and the system effectiveness through the EVOKE model. Similarly, just a quantitative analysis is carried out.

This tendency toward performance- and system-centric assessments rather than comprehensive human-centered one fall short in capturing user experience dimensions, highlighting a gap in the current literature.

4.5.4. Discussion

The analysis reveals that HCI plays a limited but emerging role in the development of DT systems for public transportation. Interfaces commonly support visualization, monitoring, and scenario analysis through dashboards, 3D/VR environments, and mobile applications. However, most are technology-driven, with minimal grounding in established HCI practices.

To answer **RQ3**, the role of HCI is primarily functional, enabling data access and system control, rather than methodological. User interaction is seldom shaped by structured design processes or evaluated with usability metrics. Only one study [63] employed a formal design methodology, underscoring the broader absence of systematic HCI integration. Key challenges include the lack of documented design processes and user involvement, raising concerns about usability across diverse user groups. Evaluations tend to be performance-focused, with little attention to user satisfaction or experience [84]. Nonetheless, some systems show promise by enabling interactive simulations, user-generated data, and multidimensional exploration [85,86]. These features suggest potential for more participatory and inclusive platforms.

Future work should adopt structured HCI approaches such as participatory design, co-design, and usability testing, to ensure that DT systems are not only technically robust but also user-centered and effective in real-world public transport contexts [87].

5. Implications and recommendations

The recommendations summarized in Table 11 outline a concrete research agenda for advancing DT systems in bus-based public transport. They emphasize the urgent need for standardization of architectures and interoperability, scalable and secure data acquisition, and the embedding of cybersecurity by design. Equally important are the definition of benchmarks for evaluation, the integration of AI/ML into real-time operational contexts, the promotion of open datasets to ensure reproducibility, and the systematic adoption of user-centered design processes. Taken together, these directions provide a balanced roadmap that addresses technical, methodological, and socio-technical dimensions, ensuring that future DT for bus public transport solutions are robust, interoperable, and aligned with the needs of both operators and passengers.

5.1. Limitations

While this SLR offers a structured synthesis of DT applications in bus public transport, several limitations should be acknowledged. First, the search strategy was explicitly based on the presence of the terms "digital twin", "virtual twin", "digital replica", and "digital shadow" in titles, abstracts, or keywords. As a result, relevant studies that employ similar concepts or technologies but do not explicitly use this terminology may have been excluded. This could lead to an underrepresentation of functionally equivalent systems that are not labeled as DTs.

Second, the review considered only peer-reviewed publications. While this ensures a certain level of scientific rigor, it also excludes non-peer-reviewed sources such as preprints, technical reports, white papers, or project deliverables. These types of documents-especially in a rapidly evolving and applied domain like smart mobility-may contain

Table 11
Implications and concrete recommendations for advancing DT research in bus-based public transport systems.

Focus Area	Recommendations for Future Work
Reference Architectures	Establish a standardized reference architecture and shared design patterns that explicitly cover data ingestion, model integration, simulation, and user interaction, ensuring comparability across deployments.
Interoper-ability and Standards	Contribute to the definition of interoperability standards for DT components, enabling seamless integration across heterogeneous vendors, transport modes, and urban infrastructures.
Scalable Data Acquisition	Define modular and scalable data acquisition components capable of integrating heterogeneous sources, including sensors, vehicle telemetry, and crowd-sourced passenger data, while ensuring data quality and reliability.
Embed cybersecurity by design	Incorporate robust security mechanisms and patterns into all layers of DT systems, including secure data ingestion, encrypted communication across IoT and cloud infrastructures, and access control.
Evaluation and Benchmarks	Define common performance benchmarks and evaluation metrics for DT systems in public transport, including latency, scalability, and passenger satisfaction.
AI/ML Integration	Advance the deployment of AI/ML beyond predictive analytics to real-time control, adaptive scheduling, and optimization of routes, explicitly integrating models with live data streams from IoT infrastructures.
Open Datasets and Reproducibility	Promote the sharing of benchmark datasets for public transport DTs, ensuring reproducibility of ML experiments and enabling evaluation of training strategies that account for non-IID data sources.
User-Centered Design Processes	Establish systematic design and development methodologies grounded in user-centered design, involving both operators and passengers throughout the lifecycle to ensure usability, inclusivity, and trust in DT systems.

innovative or ongoing DT implementations that have not yet reached formal publication but are still highly relevant.

Additionally, the scope of the study focused primarily on academic literature, which may not fully capture industry practices, proprietary systems, or pilot projects deployed by transit agencies and technology providers. As such, the insights presented here reflect primarily the academic perspective and may not encompass the full range of developments in real-world DT applications.

Moreover, a further limitation lies in the uneven distribution of contributions across the three Research Questions. Specifically, RQ1 was addressed in 37 out of the 40 reviewed studies, whereas RQ2 and RQ3 received significantly less attention, with only 17 and 11 papers respectively offering insights. This disparity reflects a broader imbalance in the current research landscape, where system-level technical details are more frequently described and documented than the integration of AI/ML techniques or the design of human-centered interfaces. Consequently, the findings related to RQ2 and RQ3 may be less comprehensive and should be interpreted with this limitation in mind.

6. Conclusion

This SLR explored the state of the art in DT technologies applied to public transport systems, with a particular focus on bus-based networks. Through a structured analysis of the existing literature, we investigated the prevailing architectural designs, technological components and frameworks, the integration of AI/ML models, and the role of HCI in DT systems. Our findings reveal a technologically diverse but fragmented ecosystem, where a wide variety of architectures are used to meet domain-specific requirements. Similarly, the choice of components, simulation tools, and platforms is largely ad hoc and tailored to individual cases, resulting in a lack of uniformity and standardization across the field. This heterogeneity, while reflective of the early stage of DT adoption in public transit, poses challenges for interoperability, scalability, and applicability. On the positive side, these systems are often built around available operational data, underscoring a pragmatic and data-driven approach to DT development. This is particularly crucial in large and complex transport networks where retrofitting with new sensors and infrastructure is not always feasible.

However, most of the reviewed works tend to focus on isolated aspects of DT systems, such as simulation or AI/ML, without addressing the full spectrum of required elements, from architecture and data integration to real-time analytics and human-computer interaction. This partial approach limits the development of truly holistic and integrated DT solutions for public transport. To move toward more mature and interoperable solutions, future research should focus on establishing reference architectures and standard components to guide system design and improve interoperability, while also developing reusable, modular frameworks to reduce reliance on bespoke implementations. Further efforts are needed to deepen the integration of AI/ML in real-time control and decision-making processes, enhance the role of HCI by adopting user-centered design principles and rigorously evaluating usability, and explore strategies for scalable data acquisition, especially in environments where sensor infrastructure is limited.

CRediT authorship contribution statement

Manuel Andruccioli: Writing – original draft, Visualization, Investigation; **Giovanni Delnevo:** Writing – review & editing, Writing – original draft, Methodology, Investigation; **Roberto Girau:** Writing - review & editing, Supervision; **Paola Salomoni:** Writing – review & editing, Supervision, Project administration, Conceptualization.

Data availability

No data was used for the research described in the article.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT in order to improve language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement N. 101095882 (EBRT2030).

Appendix A. Papers details

Table A.1
Details of the reviewed papers, including Title and Publication Year.

Ref	Title	Year
[42]	Unveiling Urban Mobility Patterns: A Data-Driven Analysis of Public Transit	2024
[43]	Features of development of a digital twin of the transport system of an urban area using simulation modeling methods	2024
[44]	Sustainable and robust route planning scheme for smart city public transport based on multi-objective optimization: Digital twin model	2024
[45]	Introducing fine grained energy consumption variables into a public passenger transport simulation in SUMO	2024
[46]	Towards a 24/7 Carbon-Free Electric Fleet: A Digital Twin Framework	2024
[47]	Toward the Creation of a Digital Twin Authoring Tool: A Smart Mobility Perspective in Smart Cities	2024
[48]	Implementing integrated digital twin modelling and representation into the Snap4City platform for smart city solutions	2024
[49]	Digital Twin Framework for Powertrain Energy Consumption of Fuel Cell Electric Bus	2024
[50]	Increasing Electric Vehicles Utilization in Transit Fleets using Learning, Predictions, Optimization, and Automation	2023
[51]	Energy-efficient multimodal mobility networks in transportation digital twins: Strategies and optimization	2025
[52]	Reasoning over time into models with DataTime	2023
[53]	Enhancing Urban Sustainability: Developing an Open-Source AI Framework for Smart Cities	2024
[54]	Advanced Powertrain Fault Diagnosis for Electric Buses: An IoV Approach	2024
[55]	Using Applied Computing on Embedded Computers to Build Digital Twins in a Fog Computing Environment	2023
[56]	A Digital Twin Architecture for Intelligent Public Transportation Systems: A FIWARE-Based Solution	2024
[57]	Studying Spatial Unevenness of Transport Demand in Cities Using Machine Learning Methods	2024
[58]	Optimal coordination of electric buses and battery storage for achieving a 24/7 carbon-free electrified fleet	2025
[59]	Comparison of Time Series Forecasting for Intelligent Transportation Systems in Digital Twins	2024
[60]	Towards an Urban Digital Twins Continuum Architecture	2024
[61]	Integrating Citizens' Avatars in Urban Digital Twins	2023
[62]	A Digital Twinning Approach for the Internet of Unmanned Electric Vehicles (IoUEVs) in the Metaverse	2023
[63]	Exploration of the Digital Twin for Prototyping the Product-Service System Design in a Bus Manufacturing Company	2024
[64]	Deploying Digital Twins over the Cloud-to-Thing Continuum	2023
[65]	Adaptive Traffic Signal Control for a Mixed Autonomous and Traditional Vehicles by Agent-Based Digital Twin Simulation	2023
[66]	A processing architecture for real-time predictive smart city digital twins	2021
[67]	Simulation Modeling of a Bus Route	2021
[68]	Parameter Optimization and Tuning Methodology for a Scalable E-Bus Fleet Simulation Framework: Verification Using Real-World Data from Case Studies	2023
[69]	Digital Twins at the Edge to Track Mobility for MaaS Applications	2020
[70]	Digital Twin Consensus for Blockchain-Enabled Intelligent Transportation Systems in Smart Cities	2022
[71]	Employing LIVE Digital Twin in Prognostic and Health Management: Identifying Location of the Sensors	2022
[72]	Analysis of digital twin application of urban rail power supply system for energy saving	2021
[73]	Digital-Twin-Driven Driving Range Prediction of Electric Vehicles	2023
[74]	DataTime: A Framework to smoothly Integrate Past, Present and Future into Models	2021
[75]	A Digital Twin for Bus Operation in Public Urban Transportation Systems	2023
[76]	Architecture of a Public Transport Supervision System Using Hybridization Models Based on Real and Predictive Data	2020
[77]	Modeling Urban Digital Twins over the Cloud-to-Thing Continuum	2022
[78]	Digital Twin Configuration Method for Public Services by Citizens	2023
[79]	GENOR: A Generic Platform for Indicator Assessment in City Planning	2022
[80]	Quantum Secure Energy-Efficient Authentication Protocol for Digital Twins-Enabled Transportation Cyber-Physical Systems	2025
[81]	Computer Vision-Based Method for Digital Twin Modelling in Railway	2024

References

[1] A. Parnianifard, S. Jearavongtakul, P. Sasithong, N. Sinpan, S. Poomrittigul, A. Bajpai, P. Vanichchanunt, L. Wuttisittikulkij, Digital-twins towards cyber-physical systems: a brief survey, Eng. J. 26 (9) (2022) 47–61. https://doi.org/10.4186/ej.2022.26.9.47

[2] A. Sharma, E. Kosasih, J. Zhang, A. Brintrup, A. Calinescu, Digital twins: state of the art theory and practice, challenges, and open research questions, J. Ind. Inf. Integr. 30 (2022) 100383. https://doi.org/10.1016/j.jii.2022.100383

[3] M. Attaran, B.G. Celik, Digital twin: benefits, use cases, challenges, and opportunities, Decis. Anal. J. 6 (2023) 100165. https://doi.org/10.1016/j.dajour.2023.100165

[4] K. Kušič, R. Schumann, E. Ivanjko, A digital twin in transportation: real-time synergy of traffic data streams and simulation for virtualizing motorway dynamics, Adv. Eng. Inf. 55 (2023) 101858. https://doi.org/10.1016/j.aei.2022.101858

[5] H. Xu, A. Berres, S.B. Yoginath, H. Sorensen, P.J. Nugent, J. Severino, S.A. Tennille, A. Moore, W. Jones, J. Sanyal, Smart mobility in the cloud: enabling real-time situational awareness and cyber-physical control through a digital twin for traffic, IEEE Trans. Intell. Transp. Syst. 24 (3) (2023) 3145–3156. https://doi.org/10.1109/tits.2022.3226746

[6] M. Soori, B. Arezoo, R. Dastres, Digital twin for smart manufacturing, a review, Sustainable Manuf. Serv. Econ. 2 (2023) 100017. https://doi.org/10.1016/j.smse.2023.100017

[7] M.D. Xames, T.G. Topcu, A systematic literature review of digital twin research for healthcare systems: research trends, gaps, and realization challenges, IEEE Access 12 (2024) 4099–4126. https://doi.org/10.1109/access.2023.3349379

[8] R.F. El-Agamy, H.A. Sayed, A.L.A. Arwa M, M. Aljohani, M. Elhosseini, Comprehensive analysis of digital twins in smart cities: a 4200-paper bibliometric study, Artif. Intell. Rev. 57 (6) (2024). https://doi.org/10.1007/s10462-024-10781-8

[9] C. Ge, S. Qin, Digital twin intelligent transportation system (DT–ITS)-a systematic review, IET Intel. Transport Syst. 18 (12) (2024) 2325–2358. https://doi.org/10.1049/itr2.12539

[10] S. Werbińska-Wojciechowska, R. Giel, K. Winiarska, Digital twin approach for operation and maintenance of transportation system-systematic review, Sensors 24 (18) (2024) 6069. https://doi.org/10.3390/s24186069

[11] M. Ahmad Jan, M. Adil, B. Brik, S. Harous, S. Abbas, Making sense of big data in intelligent transportation systems: current trends, challenges and future directions, ACM Comput. Surv. 57 (8) (2025) 1–43. https://doi.org/10.1145/3716371

[12] X. Chang, R. Zhang, J. Mao, Y. Fu, Digital twins in transportation infrastructure: an investigation of the key enabling technologies, applications, and challenges, IEEE Trans. Intell. Transp. Syst. 25 (7) (2024) 6449–6471. https://doi.org/10.1109/tits.2024.3401716

[13] D. Wu, A. Zheng, W. Yu, H. Cao, Q. Ling, J. Liu, D. Zhou, Digital twin technology in transportation infrastructure: a comprehensive survey of current applications, challenges, and future directions, Appl. Sci. 15 (4) (2025) 1911. https://doi.org/10.3390/app15041911

[14] A. Matei, M. Cocoşatu, Artificial internet of things, sensor-based digital twin urban computing vision algorithms, and blockchain cloud networks in sustainable smart city administration, Sustainability 16 (16) (2024) 6749. https://doi.org/10.3390/su16166749

[15] N.A. Khan, J.-C. Nebel, S. Khaddaj, V. Brujic-Okretic, Scalable system for smart urban transport management, J. Adv. Transp. 2020 (2020) 1–13. https://doi.org/10.1155/2020/8894705

[16] D.H. Utku, F.O. Catak, M. Kuzlu, S. Sarp, V. Jovanovic, U. Cali, N. Zohrabi, Digital Twin Applications for Smart and Connected Cities, Springer Nature Singapore, 2023, p. 141–154. https://doi.org/10.1007/978-981-99-0252-1_6

[17] P. Whig, B.Y. Kasula, A.B. Bhatia, R.R. Nadikattu, P. Sharma, Digital Twin-Enabled Solution for Smart City Applications, Springer Nature Switzerland, 2024, p. 259–280. https://doi.org/10.1007/978-3-031-58523-4_13

[18] C. Malé, T. Lagier, Simulating the Interactions of Environmental and Socioeconomic Dynamics at the Scale of an Ecodistrict: Urban Modeling of Gerland (Lyon, France), Elsevier, 2021, p. 299–321. https://doi.org/10.1016/b978-0-12-818215-4.00011-0

[19] G. Orsini, G. Piras, Digital Construction and Management the Public's Infrastructures, Springer International Publishing, 2023, p. 93–110. https://doi.org/10.1007/978-3-031-29515-7_10

[20] B. Manandhar, K. Dunkel Vance, D.B. Rawat, N. Yilmaz, Leveraging digital twin technology for sustainable and efficient public transportation, Appl. Sci. 15 (6) (2025) 2942. https://doi.org/10.3390/app15062942

[21] K. Sreenivas Rao, P. Harini, S.K. Mohapatra, J. Mohanty, Power Energy System Consumption Analysis in Urban Railway by Digital Twin Method, 2024, . 10.1002/9781394257003.ch13

[22] V.F. de Oliveira, G. Matiolli, C.J.B. Júnior, R. Gaspar, R.G. Lins, Digital twin and cyber-physical system integration in commercial vehicles: latest concepts, challenges and opportunities, IEEE Trans. Intell. Veh. 9 (4) (2024) 4804–4819. https://doi.org/10.1109/tiv.2024.3378579

[23] S. Helms, Y. Rauch, M. Bejarano, M. Kettner, J. Eckert, Investigation of the performance of electric bicycles in interaction with cyclists' driving behaviour in driving cycles on a chassis dynamometer, in: SAE Technical Paper Series, SETC, SAE International, 2023, pp. 1–8. https://doi.org/10.4271/2023-01-1816

[24] M.O. Adeagbo, S.-M. Wang, Y.-Q. Ni, Revamping structural health monitoring of advanced rail transit systems: a paradigmatic shift from digital shadows to digital twins, Adv. Eng. Inf. 61 (2024) 102450. https://doi.org/10.1016/j.aei.2024.102450

[25] D. Szpilko, X. Fernando, E. Nica, K. Budna, A. Rzepka, G. Lăzăroiu, Energy in smart cities: technological trends and prospects, Energies 17 (24) (2024) 6439. https://doi.org/10.3390/en17246439

[26] P. Golinska-Dawson, K. Sethanan, Sustainable urban freight for energy-efficient smart cities-systematic literature review, Energies 16 (6) (2023) 2617. https://doi.org/10.3390/en16062617

[27] L. Bao, Q. Wang, Y. Jiang, Review of digital twin for intelligent transportation system, in: 2021 International Conference on Information Control, Electrical Engineering and Rail Transit (ICEERT), IEEE, 2021, p. 309–315. https://doi.org/10.1109/iceert53919.2021.00064

[28] M.S. Irfan, S. Dasgupta, M. Rahman, Toward transportation digital twin systems for traffic safety and mobility: a review, IEEE Internet Things J. 11 (14) (2024) 24581–24603. https://doi.org/10.1109/jiot.2024.3395186

[29] E. Faliagka, E. Christopoulou, D. Ringas, T. Politi, N. Kostis, D. Leonardos, C. Tranoris, C.P. Antonopoulos, S. Denazis, N. Voros, Trends in digital twin framework architectures for smart cities: a case study in smart mobility, Sensors 24 (5) (2024) 1665. https://doi.org/10.3390/s24051665

[30] X. Zhang, D. Han, X. Zhang, L. Fang, Design and application of intelligent transportation multi-source data collaboration framework based on digital twins, Appl. Sci. 13 (3) (2023) 1923. https://doi.org/10.3390/app13031923

[31] H. Yeon, T. Eom, K. Jang, J. Yeo, DTUMOS, Digital twin for large-scale urban mobility operating system, Sci. Rep. 13 (1) (2023). https://doi.org/10.1038/s41598-023-32326-9

[32] H. Bhatt, Sahil, K. Vaidhyanathan, R. Biju, D. Gangadharan, R. Trestian, P. Shah, Architecting digital twins for intelligent transportation systems, in: 2025 IEEE 22nd International Conference on Software Architecture Companion (ICSA-C), IEEE, 2025, p. 215–223. https://doi.org/10.1109/icsa-c65153.2025.00041

[33] J. Wu, X. Wang, Y. Dang, Z. Lv, Digital twins and artificial intelligence in transportation infrastructure: classification, application, and future research directions, Comput. Electr. Eng. 101 (2022) 107983. https://doi.org/10.1016/j.compeleceng.2022.107983

[34] M. Aghaabbasi, S. Sabri, Potentials of digital twin system for analyzing travel behavior decisions, Travel Behav. Soc. 38 (2025) 100902. https://doi.org/10.1016/j.tbs.2024.100902

[35] K. Long, C. Ma, H. Li, Z. Li, H. Huang, H. Shi, Z. Huang, Z. Sheng, L. Shi, P. Li, S. Chen, X. Li, AI-enabled digital twin framework for safe and sustainable intelligent transportation, Sustainability 17 (10) (2025) 4391. https://doi.org/10.3390/su17104391

[36] B.R. Barricelli, D. Fogli, Digital twins in human-computer interaction: a systematic review, Int. J. Hum. Comput. Inter. 40 (2) (2022) 79–97. https://doi.org/10.1080/10447318.2022.2118189

[37] F. Vainionpää, M. Kinnula, A. Kinnula, K. Kuutti, S. Hosio, HCI and digital twins – a critical look: a literature review, in: Proceedings of the 25th International Academic Mindtrek Conference, Academic Mindtrek 2022, ACM, 2022, p. 75–88. https://doi.org/10.1145/3569219.3569376

[38] C.R. Lengkong, C. Mayas, H. Krömker, M. Hirth, The Development of Human-Centered Design in Public Transportation: A Literature Review, Springer Nature Switzerland, 2024, p. 40–62. https://doi.org/10.1007/978-3-031-60480-5_3

[39] A. Nightingale, A guide to systematic literature reviews, Surgery 27 (9) (2009) 381–384. https://doi.org/10.1016/j.mpsur.2009.07.005

[40] D. Moher, A. Liberati, J. Tetzlaff, D.G. Altman, Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement, PLoS Med. 6 (7) (2009) e1000097. https://doi.org/10.1371/journal.pmed.1000097

[41] M.J. Page, J.E. McKenzie, P.M. Bossuyt, I. Boutron, T.C. Hoffmann, C.D. Mulrow, L. Shamseer, J.M. Tetzlaff, E.A. Akl, S.E. Brennan, R. Chou, J. Glanville, J.M. Grimshaw, A. Hróbjartsson, M.M. Lalu, T. Li, E.W. Loder, E. Mayo-Wilson, S. McDonald, L.A. McGuinness, L.A. Stewart, J. Thomas, A.C. Tricco, V.A. Welch, P. Whiting, D. Moher, The PRISMA 2020 statement: an updated guideline for reporting systematic reviews, BMJ 372 (2021) n71.

[42] O. Yusuf, A. Rasheed, F. Lindseth, M. Slaastuen, Unveiling urban mobility patterns: a data-driven analysis of public transit, in: 2024 International Conference on Control, Automation and Diagnosis (ICCAD), IEEE, 2024, p. 1–6. https://doi.org/10.1109/iccad60883.2024.10553660

[43] A. Krasnikov, V. Simonov, S. Boykov, Features of development of a digital twin of the transport system of an urban area using simulation modeling methods, E3S Web Conf. 535 (2024) 04004. https://doi.org/10.1051/e3sconf/202453504004

[44] M. Xiao, L. Chen, H. Feng, Z. Peng, Q. Long, Sustainable and robust route planning scheme for smart city public transport based on multi-objective optimization: digital twin model, Sustainable Energy Technol. Assess. 65 (2024) 103787. https://doi.org/10.1016/j.seta.2024.103787

[45] G.-C.C. Angelina, H.R. Manuel, I.F. de la Mota, Introducing fine grained energy consumption variables into a public passenger transport simulation in SUMO, Procedia Comput. Sci. 232 (2024) 1890–1899. https://doi.org/10.1016/j.procs.2024.02.011

[46] M. Ribeiro, J. Luke, S. Martin, E. Balogun, G. Cezar, M. Pavone, R. Rajagopal, Towards a 24/7 carbon-free electric fleet: a digital twin framework, in: Energy Proceedings, Applied Energy Innovation Institute (AEii), 2024, pp. 1–10. https://doi.org/10.46855/energy-proceedings-11033

[47] M. Umair Hassan, S. Abdel-Afou Alaliyat, I.A. Hameed, Toward the creation of a digital twin authoring tool: a smart mobility perspective in smart cities, IEEE Access 12 (2024) 111280–111292. https://doi.org/10.1109/access.2024.3442079

[48] L. Adreani, P. Bellini, C. Colombo, M. Fanfani, P. Nesi, G. Pantaleo, R. Pisanu, Implementing integrated digital twin modelling and representation into the Snap4City platform for smart city solutions, Multimed. Tools Appl. 83 (12) (2023) 37121–37146. https://doi.org/10.1007/s11042-023-16838-0

[49] H.A. Taha, A. Mammeri, Digital twin framework for powertrain energy consumption of fuel cell electric bus, in: 2024 IEEE 10th World Forum on Internet of Things (WF-IoT), IEEE, 2024, p. 607–612. https://doi.org/10.1109/wf-iot62078.2024.10811123

[50] J. Guanetti, Y. Kim, X. Shen, J. Donham, S. Alexander, B. Wootton, F. Borrelli, Increasing electric vehicles utilization in transit fleets using learning, predictions, optimization, and automation, in: 2023 IEEE Intelligent Vehicles Symposium (IV), IEEE, 2023, p. 1–6. https://doi.org/10.1109/iv55152.2023.10186570

[51] W. Li, B. Wang, R. Sun, L. Ai, Z. Lin, Energy-efficient multimodal mobility networks in transportation digital twins: strategies and optimization, Energy 318 (2025) 134587. https://doi.org/10.1016/j.energy.2025.134587

[52] G. Lyan, J.-M. Jézéquel, D. Gross-Amblard, R. Lefeuvre, B. Combemale, Reasoning over time into models with datatime, Softw. Syst. Model. 22 (5) (2023) 1689–1712. https://doi.org/10.1007/s10270-023-01080-x

[53] M. Shulajkovska, M. Smerkol, G. Noveski, M. Gams, Enhancing urban sustainability: developing an open-source AI framework for smart cities, Smart Cities 7 (5) (2024) 2670–2701. https://doi.org/10.3390/smartcities7050104

[54] H.A. Taha, A. Mammeri, S. Yacout, Advanced powertrain fault diagnosis for electric buses: an IoV approach, in: 2024 IEEE 10th World Forum on Internet of Things (WF-IoT), IEEE, 2024, p. 1–7. https://doi.org/10.1109/wf-iot62078.2024.10811251

[55] N. Zhukova, A. Subbotin, Using applied computing on embedded computers to build digital twins in a fog computing environment, in: 2023 12th Mediterranean Conference on Embedded Computing (MECO), IEEE, 2023, p. 1–6. https://doi.org/10.1109/meco58584.2023.10154931

[56] A. De Benedictis, F. Rocco di Torrepadula, A. Somma, A digital twin architecture for intelligent public transportation systems: a FIWARE-based solution, in: Web and Wireless Geographical Information Systems, Springer Nature Switzerland, 2024, p. 165–182. https://doi.org/10.1007/978-3-031-60796-7_12

[57] D. Chainikov, D. Zakharov, E. Kozin, A. Pistsov, Studying spatial unevenness of transport demand in cities using machine learning methods, Appl. Sci. 14 (8) (2024) 3220. https://doi.org/10.3390/app14083220

[58] J. Luke, R.M.G. de Castro, S. Martin, E. Balogun, G.V. Cezar, M. Pavone, R. Rajagopal, Optimal coordination of electric buses and battery storage for achieving a 24/7 carbon-free electrified fleet, Appl. Energy 377 (2025) 124506. https://doi.org/10.1016/j.apenergy.2024.124506

[59] M.A. Ertürk, Comparison of time series forecasting for intelligent transportation systems in digital twins, ELECTRICA (2024). https://doi.org/10.5152/electrica.2024.23200

[60] S. Laso, L. Toro-Gálvez, J. Berrocal, J. Troya, C. Canal, J. Manuel Murillo, Towards an urban digital twins continuum architecture, in: Software Architecture. ECSA 2023 Tracks, Workshops, and Doctoral Symposium, Springer Nature Switzerland, 2024, p. 272–286. https://doi.org/10.1007/978-3-031-66326-0_17

[61] R. García-Luque, L. Toro-Gálvez, N. Moreno, J. Troya, C. Canal, E. Pimentel, Integrating citizens' avatars in urban digital twins, J. Web Eng. (2023). https://doi.org/10.13052/jwe1540-9589.2264

[62] M. Ebadpour, M.B. Jamshidi, J. Talla, H. Hashemi-Dezaki, Z. Peroutka, A digital twinning approach for the internet of unmanned electric vehicles (ioUEVs) in the metaverse, Electronics 12 (9) (2023) 2016. https://doi.org/10.3390/electronics12092016

[63] Z. Yan, T. Larsson, Exploration of the digital twin for prototyping the product-service system design in a bus manufacturing company, in: Design, User Experience, and Usability, Springer Nature Switzerland, 2024, p. 390–400. https://doi.org/10.1007/978-3-031-61362-3_28

[64] S. Laso, L. Tore-Gálvez, J. Berrocal, C. Canal, J.M. Murillo, Deploying digital twins over the cloud-to-thing continuum, in: 2023 IEEE Symposium on Computers and Communications (ISCC), IEEE, 2023, p. 1–6. https://doi.org/10.1109/iscc58397.2023.10218052

[65] H. Lim, M. Go, T. Lim, D.Y. Kim, Adaptive traffic signal control for a mixed autonomous and traditional vehicles by agent-based digital twin simulation, in: Advances in Production Management Systems. Production Management Systems for Responsible Manufacturing, Service, and Logistics Futures, Springer Nature Switzerland, 2023, p. 603–618. https://doi.org/10.1007/978-3-031-43670-3_42

[66] S. Van Den Berghe, A processing architecture for real-time predictive smart city digital twins, in: 2021 IEEE International Conference on Big Data (Big Data), IEEE, 2021, pp. 2867–2874. https://doi.org/10.1109/bigdata52589.2021.9671660

[67] A.I. Zhukov, D.G. Moroz, Simulation modeling of a bus route, in: 2021 Intelligent Technologies and Electronic Devices in Vehicle and Road Transport Complex (TIRVED), IEEE, 2021, p. 1–5. https://doi.org/10.1109/tirved53476.2021.9639219

[68] M.M. Hasan, N. Avramis, M. Ranta, M. El Baghdadi, O. Hegazy, Parameter optimization and tuning methodology for a scalable E-bus fleet simulation framework: verification using real-world data from case studies, Appl. Sci. 13 (2) (2023) 940. https://doi.org/10.3390/app13020940

[69] C. Campolo, G. Genovese, A. Molinaro, B. Pizzimenti, Digital twins at the edge to track mobility for maas applications, in: 2020 IEEE/ACM 24th International Symposium on Distributed Simulation and Real Time Applications (DS-RT), IEEE, 2020, p. 1–6. https://doi.org/10.1109/ds-rt50469.2020.9213699

[70] S. Liao, J. Wu, A.K. Bashir, W. Yang, J. Li, U. Tariq, Digital twin consensus for blockchain-enabled intelligent transportation systems in smart cities, IEEE Trans. Intell. Transp. Syst. 23 (11) (2022) 22619–22629. https://doi.org/10.1109/tits.2021.3134002

[71] A.E. Bondoc, M. Tayefeh, A. Barari, Employing LIVE digital twin in prognostic and health management: identifying location of the sensors, IFAC-PapersOnLine 55 (2) (2022) 138–143. https://doi.org/10.1016/j.ifacol.2022.04.183

[72] Y. Wang, G. Zhang, R. Chen, Z. Liu, R. Qiu, Analysis of digital twin application of urban rail power supply system for energy saving, in: 2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI), IEEE, 2021, p. 29–32. https://doi.org/10.1109/dtpi52967.2021.9540127

[73] S. Zhuo, Z. Wang, H. Jin, Z. Zhao, Y. Zhao, R. Peng, H. Li, Digital-twin-driven driving range prediction of electric vehicles, in: Proceedings of International Conference on Image, Vision and Intelligent Systems 2022 (ICIVIS 2022), Springer Nature Singapore, 2023, p. 793–801. https://doi.org/10.1007/978-981-99-0923-0_79

[74] G. Lyan, J.-M. Jézéquel, D. Gross-Amblard, B. Combemale, Datatime: a framework to smoothly integrate past, present and future into models, in: 2021 ACM/IEEE 24th International Conference on Model Driven Engineering Languages and Systems (MODELS), IEEE, 2021, p. 134–144. https://doi.org/10.1109/models50736.2021.00022

[75] P. Ruiz, M. Seredynski, A. Torné, B. Dorronsoro, A digital twin for bus operation in public urban transportation systems, in: Big Data Intelligence and Computing, Springer Nature Singapore, 2023, p. 40–52. https://doi.org/10.1007/978-981-99-2233-8_3

[76] A. Amrani, H. Arezki, D. Lellouche, V. Gazeau, C. Fillol, O. Allali, T. Lacroix, Architecture of a public transport supervision system using hybridization models based on real and predictive data, in: 2020 23rd Euromicro Conference on Digital System Design (DSD), IEEE, 2020, p. 440–446. https://doi.org/10.1109/dsd51259.2020.00076

[77] N. Moreno, L. Toro-Gálvez, J. Troya, C. Canal, Modeling urban digital twins over the cloud-to-thing continuum, in: CEUR Workshop Proceedings, 3620, CEUR-WS, 2022, pp. 1–5.

[78] T. Kobayashi, H. Hata, K. Fukae, H. Sato, S. Tanimoto, A. Kanai, Digital twin configuration method for public services by citizens, in: 2023 IEEE International Conference on Consumer Electronics (ICCE), IEEE, 2023, p. 01–03. https://doi.org/10.1109/icce56470.2023.10043426

[79] L. Leplat, R. da Silva Torres, D. Aspen, A. Amundsen, GENOR: A generic platform for indicator assessment in city planning, in: 36th International ECMS Conference on Modelling and Simulation, ECMS 2022, 2022-May, European Council for Modelling and Simulation, 2022, p. 245 – 253.

[80] S. Prajapat, D. Kumar, P. Kumar, M. Wazid, A.K. Das, M.S. Hossain, Quantum secure energy-efficient authentication protocol for digital twins-enabled transportation cyber-physical systems, IEEE Trans. Intell. Transp. Syst. (2025) 1–15. https://doi.org/10.1109/tits.2025.3546432

[81] S. Zhang, B. Leromancer, C. Nicodeme, Computer vision-Based method for digital twin modelling in railway, in: 2024 IEEE 27th International Conference on Intelligent Transportation Systems (ITSC), IEEE, 2024, p. 2737–2742. https://doi.org/10.1109/itsc58415.2024.10919750

[82] V. Cardellini, P. Dazzi, G. Mencagli, M. Nardelli, M. Torquati, Scalable compute continuum, Future Gener. Comput. Syst. 166 (2025) 107697. https://doi.org/10.1016/j.future.2024.107697

[83] F. Cirillo, G. Solmaz, E.L. Berz, M. Bauer, B. Cheng, E. Kovacs, A standard-based open source IoT platform: FIWARE, IEEE Internet Things Mag. 2 (3) (2019) 12–18. https://doi.org/10.1109/iotm.0001.1800022

[84] M.W. Lauer-Schmaltz, P. Cash, D.G.T. Rivera, ETHICA: designing human digital twins-a systematic review and proposed methodology, IEEE Access 12 (2024) 86947–86973. https://doi.org/10.1109/access.2024.3416517

[85] F. Bonetti, A. Bucchiarone, J. Michael, A. Cicchetti, A. Marconi, B. Rumpe, Digital twins of socio-technical ecosystems to drive societal change, in: Proceedings of the ACM/IEEE 27th International Conference on Model Driven Engineering Languages and Systems, MODELS Companion '24, ACM, 2024, p. 275–286. https://doi.org/10.1145/3652620.3686248

[86] K.S. Lee, J.-J. Lee, C. Aucremanne, I. Shah, A. Ghahramani, Towards democratization of digital twins: design principles for transformation into a human-building interface, Build. Environ. 244 (2023) 110771. https://doi.org/10.1016/j.buildenv.2023.110771

[87] W. Kemkomnerd, C. Tirapas, The digital twin immersive design process and its potential disruption to healthcare design through a user-centered approach, Buildings 14 (9) (2024) 2839. https://doi.org/10.3390/buildings14092839