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A Comprehensive and Systematic Review of Performance Evaluation of Public Transit

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Abstract

Public transit plays a crucial role in urban transportation systems, providing an efficient and sustainable mode of public transportation. Performance evaluation of public transit is essential for achieving sustainable, efficient, and user-centric urban mobility systems. Despite numerous studies on transit performance, there remains a lack of comprehensive frameworks that consolidate diverse indicators, data sources, and evaluation techniques. This study conducts a systematic literature review using the PRISMA method to synthesize 162 peer-reviewed articles on public transit performance published between 2001 and 2023. Key performance indicators (KPIs) are categorized into five dimensions: safety and security, customer satisfaction, traffic, finance, and environment. The study highlights the increasing adoption of data-driven tools–such as Automatic Vehicle Location (AVL), Automatic Passenger Counting (APC), GTFS, and AI-based analytics–and identifies methodological trends across different transit modes. A visual mapping of KPIs and data sources is presented to assist transit agencies, researchers, and policymakers. This review makes a unique contribution to a unified, multi-dimensional framework for performance evaluation that aligns with current urban mobility challenges such as digital transformation, resilience, and inclusivity.

Keywords

analysis of public transport, performance evaluation, key performance indicators, route planning, PRISMA

1 Introduction

In an era of rapid urbanization and climate change, public transit systems are under increasing pressure to perform efficiently, sustainably, and equitably. Evaluating transit performance is essential for achieving these goals, as it helps policymakers and operators improve service delivery, allocate resources, and enhance user satisfaction. However, the field lacks a consolidated framework that integrates traditional performance indicators with emerging tools and data sources. This study addresses that gap by conducting a systematic review of the literature to identify, categorize, and analyze key performance indicators (KPIs), data collection techniques, and evaluation methodologies across various dimensions of transit performance. By mapping 163 studies from the past two decades, this review offers a comprehensive reference for understanding how public transit performance has evolved and where future efforts should be directed.

Due to the different forms of transportation, the large number of origins and destinations, and the volume and variety of traffic, urban transportation is incredibly complicated. Mobility includes a substantial amount of urban transportation, especially in densely populated areas (Remi et al.,2009; Rodrigue, 2016; Yang and Tang, 2018). The transport sector has a big impact on a nation's overall development (Agarwal, 2009; Pradhan and Bagchi, 2013). A strong economy depends heavily on transportation, which is primarily responsible for moving people and goods (Iles, 2005; Adinata et al., 2021; Kim et al., 2024). Additionally, the quickly expanding population, urbanization, and extensive use of motor vehicles have made it difficult for people to travel around in developing nations due to issues like traffic jams, air, and sound pollution, and extreme energy consumption. To deal with these changes and problems, developing nations must have effective transport planning. Utilizing more environmentally friendly modes of transportation, particularly public transportation, is emphasized. Measurement of performance indicators of transit systems is useful in planning, implementation, and review of these systems (Dajani and Gilbert, 1978; Gwilliam, 1999; Zolfaghari et al., 2002; Venigalla and Ali, 2005; Wiley et al., 2011; Ramli et al., 2012; Poister et al., 2013; Shaik and Abdul-Kader, 2013; Anderson

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and Khan, 2014; Liu and Moini, 2015; Pojani and Stead, 2015; Pathak et al., 2019; Singer et al., 2023).

While several reviews have addressed specific dimensions of public transit performance, such as environmental impact, service reliability, or customer satisfaction, this review distinguishes itself by offering a holistic and multi-dimensional synthesis. Using the PRISMA approach, it categorizes 162 studies across five key domains–safety and security, customer satisfaction, traffic, finance, and environment–and systematically maps the diversity of Key Performance Indicators (KPIs) and data-driven methodologies employed in the literature. In contrast to earlier reviews that typically focus on one performance aspect or technology, this work integrates traditional and emerging methods (e.g., GPS-based AVL, GTFS, APC, big data analytics, and AI tools) to provide a unified framework for performance evaluation. This comprehensive scope and the visual mapping of KPIs and methodologies serve as a practical reference for researchers and transit authorities seeking to benchmark, improve, or innovate in urban transit performance evaluation. In this article, literature related to the performance measurement of public transit is reviewed. The main key performance indicators are fetched from the literature, and the same are tabulated and categorized. Then, in subsequent sections, performance measure methodologies of public transit are given.

2 Methodology

Citation chaining, also known as snowballing, is the process of finding cited references (Boland et al., 2014; Bettany-Saltikov and McSherry, 2016). To conduct a thorough assessment, specialists in the field should be contacted for any unpublished or newly submitted works relevant to the review issue. This extensive search retrieves all relevant material, a crucial aspect of a systematic review. To present the aforementioned process, a Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) flow chart with four sections: identification, screening, eligibility, and inclusion is given in Fig.1.

This figure illustrates the systematic review process using the PRISMA framework, showing the number of records identified, screened, assessed for eligibility, and included in the final review. A total of 163 studies were selected from an initial pool of 520 records.

2.1 Literature search strategy

The systematic review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. The literature search was conducted across major

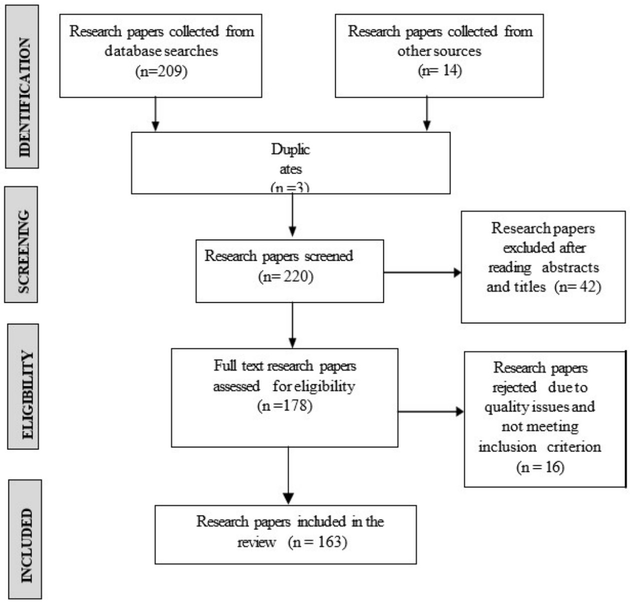

Fig. 1 PRISMA flow diagram for study selection process

databases, including Scopus, Web of Science, ScienceDirect, IEEE Xplore, and Google Scholar, covering peer-reviewed articles published between 2001 and 2023. Search strings combined terms related to public transit and performance evaluation (e.g., "public transport performance", "transit key performance indicators", "urban mobility", "transit data sources", "AVL", "GTFS", "APC", "machine learning in transit") using Boolean operators.

2.2Inclusion and exclusion criteria

Studies were included if they:

1. addressed public transit system performance,
2. used or discussed measurable KPIs,
3. involved real-world data or data-driven methods,
4. were published in English.

Exclusion criteria included: conference abstracts, editorials, purely conceptual papers without empirical support, and studies focused solely on non-transit mobility (e.g., ride-hailing or personal vehicles).

2.3 Study selection and quality assessment

After duplicate removal, a two-stage screening process was applied: first, titles and abstracts were reviewed, followed by full-text assessment. Of 520 initially retrieved records, 163 met all inclusion criteria. Although formal quality scoring (e.g., GRADE or CASP) was not applied due to methodological diversity, each selected study was assessed for clarity of objectives, relevance of performance measures, methodological rigor, and data transparency.

3 Review of performance measure KPIs

Transit city buses play a crucial role in urban transportation systems, offering residents and commuters a convenient and efficient travel option. To evaluate and enhance their performance, it is essential to establish Key Performance Indicators (KPIs). These KPIs provide a structured framework for assessing service quality, operational efficiency, and sustainability, enabling transit authorities to make data-driven decisions for better service delivery.

Among the most critical KPIs are on-time performance, which measures adherence to published schedules, and headway adherence, which evaluates the consistency of bus intervals to reduce irregularities. Passenger load is another important measure, assessing average occupancy during peak and off-peak hours to prevent overcrowding and optimize frequency. Operational efficiency is further captured by dwell time, which reflects the duration buses spend at stops, and travel-time deviation, which compares actual versus scheduled travel times. Additionally, bus bunching highlights inefficiencies when multiple buses arrive together, while waiting time measures the typical duration passengers spend at stops, directly influencing customer perception.

Broader measures of service quality and sustainability include service reliability, which accounts for breakdowns, disruptions, and operational resilience, and customer satisfaction, gauged through passenger surveys on comfort, safety, cleanliness, and communication. Finally, environmental impact is an increasingly vital KPI, assessing fuel efficiency, emissions reduction, and the adoption of greener technologies. Together, these indicators provide a holistic understanding of bus system performance and guide strategies for delivering reliable, passenger-focused, and environmentally sustainable transit services.

A comprehensive review of the literature enabled the categorization of KPIs into five groups, with corresponding references presented in Table 1.

This categorization and the corresponding KPIs are presented in Fig. 2 to Fig. 6, with their respective unit of measurement indicated in brackets. The quantitative and qualitative KPIs for transit systems identified in this study have been established through a detailed review of the relevant literature (Krynauw and Cameron, 2003; McKinnon, 2007; McKinnon et al., 2009; Toledo, 2011). These references provide the foundation for defining indicators that capture both operational efficiency and service quality in transit performance assessment. Moreover, detailed summary of KPIs are given in Appendix A.

Establishing and monitoring such KPIs is crucial for evaluating the performance of city bus transit systems and for ensuring efficient, reliable, and sustainable public transportation services. By systematically tracking these indicators, transit authorities and operators can identify shortcomings, make evidence-based decisions, optimize resource allocation, and enhance the overall passenger experience. Furthermore, the continuous measurement and analysis of KPIs enable transit systems to adapt to changing travel demands, promote long-term sustainability, and contribute to the development of smart and connected urban mobility solutions.

Table 1 KPI categories and references

KPI Category	Key References
Safety & Security	Hess (2006); Zimmerman and Simonoff (2008); Iweze (2011); Aderamo, (2012); Polunsky (2017); Charly and Mathew (2020); Reddy et al., (2020); Ceccato et al., (2022); Chai et al., (2022); Fan and Yang (2022); Pulugurtha and Srirangam (2022); Singh et al., (2022); Zuo (2022)
Customer Satisfaction	Aydin et al., (2015); Huo et al., (2015); Olivková (2015); Gao et al., (2016); El-Diraby et al., (2019); Zhang et al., (2019); Askari et al., (2021); Choi et al., (2021); Zheng et al., (2021); Silveira et al., (2022); Chuenyindee et al., (2022); Shabani et al., (2022); Shbeeb (2022); Luo et al., (2023)
Traffic	Alkhatib et al., (2022); Bolaños et al., (2022); Lee and Miller (2022); Nævestad et al., (2022); Ahmad et al., (2023); Coulombel et al.,(2023); Zhang and Wu (2023)
Finance	Lee (1989); Karlaftis and Mccarthy (1997); Li and Wachs (2004); Kennedy et al., (2005); Kiggundu (2009); Tang and Lo (2010); Min et al., (2015); Estrada et al., (2021); Goodman et al., (2021); Krelling and Badami (2022); Spernbauer et al., (2022); Awad et al., (2023); Coulombel et al., (2023); Deng et al., (2023); Klar et al., (2023)
Environment	Donnelly et al., (2007); Paget-Seekins (2012); Jamil et al., (2015); Abbasi and Nilsson, (2016); Kang et al., (2017); Di Vaio et al., (2018); Abbasi et al., (2020); C. C. Kang et al., (2020); Fulzele and Shankar (2023); Kumar et al., (2021); Motlagh et al., (2021); Purnell et al., (2022); Severino et al., (2022); Zhang et al. (2023)

4 Review of performance measure strategies

The gathering and examination of data from diverse sources is a necessary step in the performance evaluation of transportation. Data collection techniques include automatic vehicle positioning systems, passenger counters, and onboard surveys. The obtained data is then subjected to statistical analysis methods, benchmarking, and simulation modeling to produce actionable insights. These methodologies provide a comprehensive understanding of bus performance and enable data-driven decision-making. The summary of these methodologies and the outcomes are given in Appendix B.

Security and safety KPIs

Utilization of pedestrian crossing infrastructure (%)	wearing seatbelts (%)	Minutes spent responding to an emergency	The frequency of driving while intoxicated (numbers)
Road traffic accidents resulted in fatalities or serious injuries.	Percentage of experienced, skilled, and certified drivers (%)	Road signs and safety precautions (number)	Insufficient headroom (%)
Use of fire extinguishers and other firefighting equipment	Utilization of luminous gear, especially for cyclists (%)	The frequency of failing to stop or yield at intersections or pedestrian crossings	Evaluating a vehicle's ability to withstand a crash and its effectiveness
Overloading occurrence (number)	frequency of going over the speed limit (numbers)	The number of traffic accidents	The frequency of running red lights at intersections (number)
Utilization of crash helmets (%)	Deteriorated roads containing potholes	Vehicles with mechanical issues that are still in operation (%)	Older cars still on the road (%)
Number of illegal transportation providers	Number of times that armed robbers have attacked commuters	The amount of efficient police patrol squads	

Fig. 2 KPIs related to safety and security

Customer satisfaction KPIs

Effective complaint resolution and complaint handling	Average number of days needed to handle claims	Minutes/hours spent responding to emergencies	satisfaction with the state of the road system
Customer satisfaction with projects that have been completed	Total percentage of complaints	the actions of drivers and conductors	Vehicle maintenance
Personal safety at parking lots/stops	Vehicle safety at parking lots/stops	Personal safety on board	Accessibility to parking lots/stops
Vehicle accessibility	Cost of the trip	Frequency of vehicles	Punctuality (departure times and arrival times)
Experience during the entire trip	Customer service	The availability of seats at the motor park or stop	Crowding during peak hours
The ease of the journey facilities at the motor park or stop	The cleanliness of the vehicle	The temperature of the vehicle	The cleanliness of the motor park or stop

Fig. 3 KPIs related to customer satisfaction

4.1 Fixed sensor and vehicular sensor networks

Traditionally, traffic data has been collected through stationary devices such as loop detectors, traffic cameras, and weather stations installed at key intersections and corridors to

Traffic related KPIs

Number of kilometers (km) of non-motorized amenities	Median speed (km/hr)	Average/total distance traveled	Minutes/Hourly Delay (Congestion)
Public transportation use	Modal split	Public transportation trips	Travel time on the road network to pertinent sites of interest (in minutes or hours)
Public transportation facility access times (in minutes or hours)	Duration (in minutes or hours) of the typical parking hunt	Roads with damage and potholes (%)	The level of service provided by bicycle and walking paths potholes (%)
the age distribution of public transportation vehicles	Vehicles with mechanical issues that are still in operation (%)	Older cars still on the road (%)	Bridges with damage or collapse (%)

Fig. 4 KPIs related to traffic

Finance KPIs

Cost of travel ($)	Total commercial revenue/operating costs ($)	Fare income ($)	Public transport investment expenditure as a percentage of GDP (%)
Road network spending as a percentage of GDP (%)	Private transportation expenses ($)	Governmental transportation costs ($)	Urban public transportation system cost per passenger ($)

Fig. 5 KPIs related to finance

Environment KPIs

Air pollution levels from urban transportation I. carbon dioxide (CO2), II. sulfur dioxide (SO2), III. carbon monoxide (CO), IV. particulates (PM10) V. Volatile organic compounds (VOCs)	The number of old vehicles still on the road	The amount of fuel used by vehicles	The decibel level of noise from urban transportation

Fig. 6 KPIs related to environment

measure variables like vehicle count, density, and road conditions. These fixed sensors are purpose-built, widely used, and provide reliable data with known error levels. However, their coverage is limited to immediate locations, and installation is costly, time-consuming, and often disruptive to traffic (Zhang et al., 2007).

Fixed sensor networks often fall short for advanced traffic control in urban environments, where conditions are more complex than highways. In contrast, vehicles dispersed across road networks now carry sensors and communication tools that can provide valuable real-time measurements, with taxis and public transport vehicles often serving as centralized probe fleets. Although initially limited to local deployments, efforts have been made to scale probe vehicle networks (Young, 2007). Over recent decades, increasing interest has focused on connected vehicle systems, exemplified by the IEEE 802.11p WAVE standard (2010) and the U.S. DoT's push for mandatory V2V/V2I radios. These initiatives converge toward the Internet of Vehicles (IoV), integrating probe cars, VANETs, and telematics to connect people, vehicles, and environments.

4.2 User mobility/ mobile location services

Vehicle sensor data is largely controlled by the automotive industry, limiting external access. Most probe vehicle systems rely on Global Navigation Satellite System (GNSS) receivers with communication equipment for data transmission, though passenger mobile devices equipped with GNSS, accelerometers, WLAN, and cellular radios also enable positioning and context sensing. Biagioni et al., (2011) introduced EasyTracker, a smartphone-based system designed for smaller transit agencies to implement transit tracking and arrival time prediction. By equipping vehicles with smartphones running a dedicated app, the system autonomously detects stops, identifies routes, infers schedules from GPS traces, and predicts arrival times through online algorithms. Similarly, Chen et al., (2014) proposed a method to model and compare user mobility profiles by applying frequent sequential pattern mining, incorporating both location and temporal semantics, and validating their approach on datasets from Yonsei University and Microsoft Research Asia, showing improved performance over prior works.

The availability of third-party mobility data services further expands transportation analysis. The Google Distance Matrix API provides detailed information on car trip times, enabling large-scale modeling. Dumbliauskas et al., (2017) used free and open-source software (Python and QGIS) to build the spatial framework and extract data for the full city of Kaunas and its surroundings. Their study produced relative trip time graphs, examined travel time variability, and developed a mean journey time matrix suitable as a skim matrix for validating the Kaunas city macro model.

4.3 GPS-based Automatic Vehicle Location (AVL)

Aoki et al., (2018) developed the BusBeat early event detection method, which leverages GPS trajectory data from periodic vehicles—such as buses, shuttles, garbage trucks, and police cars—that routinely operate on pre-planned routes. By incorporating a Time-dependent Congestion Network (TCN), BusBeat enables real-time identification of geospatial events without compromising privacy, as slow traffic patterns around event venues can signal occurrences even before participants arrive. Complementary research by Mazloumi et al., (2010) analyzed travel time distributions, highlighting their role in urban transit planning. Traditional applications of Automatic Vehicle Location (AVL) data, such as displaying arrival and departure estimates on digital boards, have now extended to smartphone-based trip planners, offering passengers information on missed connections, alternate routes, and delays. More advanced Intelligent Transport Systems (ITS) even provide connection assurance, holding services briefly to facilitate passenger transfers when delays occur. However, the accuracy and reliability of data remain critical to building user trust. In developing contexts, Kumar and Singh (2010; 2012) explored the construction of Advanced Traveler Information Systems (ATIS), discussing system architecture, development, and key features. Meanwhile, the growing use of probe vehicles equipped with GPS and sensors has expanded possibilities for traffic monitoring. To enhance absolute location estimation, Upadhyay et al., (2020) proposed a sensor fusion model based on an extended Kalman filter, integrating GPS and inertial measurement unit (IMU) sensor inputs.

Beyond real-time monitoring, GPS trajectory data supports predictive and classification applications in urban mobility and planning. Petersen et al., (2019) introduced a method exploiting non-static spatiotemporal correlations in metropolitan bus networks to forecast journey times, capturing patterns often overlooked by conventional models. For transportation planning and traffic management, identifying travel modes (e.g., bicycles, walking, cars, trains) is essential. While surveys once dominated, the Global Positioning System now enables more precise data collection, avoiding underreporting biases; however, raw GPS traces lack explicit travel mode labels. To address this, researchers have applied segmentation techniques to infer transportation modes from trajectories (Biljecki et al., 2013; Dabiri et al., 2020). Similarly, trajectory data can facilitate land-use classification, with Pan et al., (2013) demonstrating its potential through analysis of year-long traces from 4,000 taxis to understand the social function of urban spaces. GPS data also supports identification of potential bus stops, as shown in studies by Biagioni et al., (2011), Stenneth and Yu (2013), and Garg et al., (2018), further emphasizing its versatility in mobility and urban research.

4.4 Big data/data mining

Applications of trajectory data mining span across path-finding, location or destination prediction, movement behavior analysis of single or multiple moving objects, trajectory interpretation, and a variety of urban service applications. Despite its potential, the management, processing, and mining of trajectory data present significant challenges (Baraniuk, 2011; Liu et al., 2013). The vast amount of trajectory data generated at high speed is difficult to store, and discrepancies in sampling methods or sampling rates make it nearly impossible to establish reliable similarity scores for comparison. The spatial and temporal complexity of these datasets further complicates query processing. Mobility data itself exists in multiple forms, depending on the underlying recording technology. Spinsanti et al., (2012) classified trajectory data into three primary types–GPS-based, GSM-based, and geo-social network-based–while Pelekis and Theodoridis (2014) added RFID- and Wi-Fi-based formats. GPS data are composed of chronologically ordered sequences of geographic coordinates captured by GPS-enabled devices, GSM data consist of ordered cell identification sequences, and geo-social data are derived from geographic metadata attached to social media. Data mining, as a critical step in the knowledge discovery process, enables the extraction of meaningful information from such massive datasets (Fayyad et al., 1996; Maimon and Rokach, 2009). In addition to conventional relational and transactional databases, spatial data mining tasks have also been reviewed (Mennis and Guo, 2009; Miller and Han, 2009). Andrienko et al. (2011) proposed a conceptual framework for categorizing movement analysis methods into tasks, while Castro et al. (2013) specifically analyzed taxi traces under operational, traffic, and social dynamics.

Primary trajectory mining approaches focus on clustering and classification. Modern clustering algorithms extend traditional clustering approaches by incorporating trajectory similarity measures (Han et al., 2011), with distance and similarity functions explained in detail by Rokach (2009). Numerous clustering techniques exist (Fraley and Raftery, 1998; Han et al., 2009; Han et al., 2011), though boundaries between categories remain ambiguous. Classification, on the other hand, seeks to assign objects to predefined classes using labeled training sets (Han et al., 2011). Beyond these primary tasks, secondary mining approaches examine spatial, temporal, or spatio-temporal arrangements to reveal hidden movement patterns. For example, Dodge et al., (2008) provided an integrated survey of movement pattern mining, while outlier detection has been applied at both sub-trajectory (Lee et al., 2008; Liu et al., 2012; Yuan et al., 2011) and full-trajectory levels (Zhang et al., 2011). Trajectory data also support predictive applications, such as forecasting future locations using Markov models or trajectory patterns. These prediction methods are categorized into three groups: those using only individual moving object data (Gidófalvi and Dong, 2012; Jeung et al., 2008; Krumm and Horvitz, 2006;), those incorporating other moving objects (Backstrom et al., 2010), and hybrid approaches (Monreale et al., 2009; Morzy, 2006; Ying et al., 2011).

4.5 General Transit Feed Specification (GTFS)

General Transit Feed Specification (GTFS) data, widely produced and shared by agencies, provides schedules, stop and route locations, and service details, and has become the de facto standard for transit data despite being underutilized (Wong, 2013). Visualization approaches, such as PubtraVis (Prommaharaj et al., 2020), highlight its potential, while conformance analyses (Queiroz et al., 2019) reveal discrepancies between GTFS routes and bus GPS trajectories, exposing data inconsistencies. Complementing this, Nissimoff (2016) developed a C# tool integrating static GTFS data with the "Olho Vivo" real-time API and machine learning to predict bus arrival times.

4.6 Automatic passenger counters (APC) /Automated Fare Collection (AFC)

Automatic passenger counting (APC) employs technologies such as infrared (IR) door sensors, cameras, and fare collection data, with automated fare collection (AFC) systems–including mobile apps, validators, and electronic fareboxes–providing both passenger counts and a seamless travel experience across modes. APC accuracy focuses on the error distribution between measured and actual passenger activity; Kimpel et al., (2003) evaluated Tri-Met's APC system using video surveillance as a reference, while Siebert and Ellenberger (2020) introduced a revised t-test to address type I and II errors in assessing APC precision.

4.7 Manual surveys

Manual surveys remain a simple yet effective method for collecting transit performance data (Putra, 2013; Putra et al., 2014; Randheer et al., 2011). For instance, Girma (2022) used questionnaires to interview frequent bus users in Addis Ababa, while market research has long emphasized customer satisfaction as a measure of perceived service quality. Eboli and Mazzulla (2009) developed a customer-perspective index and later proposed the Heterogeneous Customer Satisfaction Index to account for differences in user perceptions across service components. Similarly, Islam et al. (2014) examined links between service quality and user satisfaction in Sintok, Malaysia, through questionnaire surveys, finding that service quality significantly shapes perceptions. In Ghana, Sam et al., (2018) surveyed over 100 public transport users in Kumasi and, using multiple regression and paired-sample t-tests, revealed notable gaps between expectations and perceptions, highlighting overall dissatisfaction with bus services.

4.8 Clustering of trajectories/GPS coordinates

In urban settings, taxi supply and demand are often imbalanced; Chang et al. (2010) addressed this by forecasting demand distributions using time, weather, and location contexts through data filtering, grouping, semantic annotation, and hotness computation, demonstrating via a web mash-up that context-aware clustering improves fleet management. Similarly, Liu et al. (2018) applied Affinity Propagation (AP) clustering to taxi OD points to optimize depot locations, refining hierarchical clustering with administrative segmentation and adjusting input parameters for low similarity matrices. Beyond clustering, transit performance can be assessed through service/garage reports, onboard surveys, Bluetooth, fuel, and emission data, analyzed statistically to identify correlations, trends, and significance. Benchmarking against industry standards or peer systems highlights performance gaps, while simulation modeling tests schedule, route, or fleet adjustments virtually before real-world application. Cost-benefit analysis evaluates financial efficiency in terms of operations, revenues, and investment priorities. Finally, stakeholder engagement–*via* passenger, driver, authority, and community feedback–provides qualitative insights on satisfaction, accessibility, and impact, ensuring a holistic evaluation framework for enhancing efficiency, reliability, and service quality in public transit systems.

To enhance the real-world relevance and utility of the reviewed KPIs and methodologies, some key practical applications and case studies are tabulated in Table 2. These case studies underscore the practical application of KPIs and performance methodologies, supporting evidence-based planning, monitoring, and evaluation of public transit systems.

5 Conclusion and future scope

This review synthesized findings from 163 studies to provide a comprehensive framework for evaluating public transit performance across five domains: safety and security, customer satisfaction, traffic, finance, and environment. By integrating traditional indicators with emerging data sources and methodologies–including GPS-based AVL, GTFS, APC, and big data analytics–the study highlights how performance assessment has evolved toward more real-time, data-driven, and user-focused approaches.

While notable progress has been made, challenges remain in standardizing data, ensuring accessibility, and incorporating equity and resilience into evaluation frameworks. The review serves as a consolidated reference for researchers and practitioners, offering guidance for benchmarking, planning, and advancing sustainable, efficient, and user-centric transit systems.

Despite increasing attention to public transit performance evaluation, this review highlights three key gaps. First, standardized multi-dimensional KPI frameworks that combine service-level and system-level indicators are still lacking, especially in developing cities. Second, the integration of real-time and big data sources (e.g., GPS, APC, GTFS, mobile sensing) with qualitative dimensions such as equity and user satisfaction remains limited. Third, resilience is underexplored—few studies examine performance under atypical conditions like pandemics or extreme weather, and emerging tools such as AI and machine learning remain experimental with limited validation. Moreover, performance assessments are often disconnected from policy and funding outcomes, reducing their practical impact.

To address these gaps, future research should focus on:

1. studying modal shift behavior to encourage car-to-transit adoption;
2. enhancing first-/last-mile connectivity through integrated hubs and micromobility;
3. incorporating climate resilience into transit planning;
4. developing AI-driven real-time decision support systems;
5. embedding spatial and demographic equity indicators into evaluation frameworks;
6. adopting mixed methods to capture user experiences alongside quantitative data.

Together, these priorities can support the development of adaptive, equitable, and data-driven public transit systems.

Table 2 Mapping of methodologies to practical Applications

Methodology	Applied in	Utility
AVL & GPS trajectory analysis	Kaunas, Lithuania (Dumbliauskas et al., 2017)	Travel-time reliability, skim matrices
Smartphone-based tracking	EasyTracker (Biagioni et al., 2011)	Real-time prediction, low-cost transit tracking
Manual surveys	Addis Ababa, Ethiopia (Girma, 2022)	Customer satisfaction, quality benchmarking
GTFS data visualization	Calgary, Canada (Prommaharaj et al., 2020)	Route compliance, schedule analysis

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Appendix A

A1 Summary of key performance indicators (KPI) and findings from the literature

Ref.	KPI's	Objectives	Findings
Oruganti et al. (2016)	Bus schedule datasets Real-time transit feeds Time-point feed Traffic flow feed Weather condition feed	Effects of local events and other environmental factors on travel delay	Created a model that forecasts how weather and traffic will affect transportation system delays.
Valdés et al. (2017)	Frequency or Interval Percent Person- Minutes Served Transit Service Accessibility Index Index of Transit Service Availability On-Time Performance (Fixed-Route) Headway Regularity or Adherence Run-Time Ratio Travel Time	To create a way for obtaining real-time data from huge databases produced by deployed GPS- based AVL systems, and to suggest new metrics for service improvement using "Big Data"	High variations in running time were observed. A new performance measure "inflated headway score (IHS)" is proposed. Routes have a morning peak, an afternoon peak, and a low point at noon.
Harsha et al. (2020)	Travel time Running time	To comprehend the distribution of journey times on the varied flow of traffic in developing nations.	When compared to other distributions, the Generalized Extreme Value (GEV) distribution performs comparably better in both temporal and geographic aggregation. At both the route and segment levels, the Generalized Extreme Value (GEV) distribution fits trip timings the best.
Coghlan et al. (2019)	Transit Delays Arrival Time Prediction Stop arrival times	To determine the best way to pre-process or filter the huge quantity of AVL data that a transit bus generates. And to identify useful classification criteria for the condition of the bus at any given time and the length of any delays.	A reusable system was developed for the delay assignment analysis that will: 1. Filter out incorrect trips. 2. Calculate the amount of delay brought on by the three primary sources by dissecting a trip into its component pieces. 3. Offer delay values by DoW, ToD, and pattern.
Aoki et al. (2018)	Bus speed Vehicle speed changes avg. of tweets per day avg. of check- ins per day	Predicting the likelihood of a major event is crucial for reducing accide nts. People who lack a desire for the event may adjust their plans or take a diversion when they are aware of it in advance in order to prevent getting stranded in heavy traffic.	Developed a technology that collects GPS data from frequent vehicles and is also capable of early identification of events without violating anyone's privacy. By utilizing an essential attribute of periodic cars–which routinely go along a pre-planned route with a predetermined departure time–his interpolation technique recovers the lost GPS data before the participants arrive.
Prommaharaj et al. (2020)	mobility speed flow density headway	This study intends to show the potential of GTFS data by describing the design and development of a tool for displaying GTFS data that shows the spatial and temporal patterns of transit services and allows the extraction of qualitative data and insights.	Using six visualization modules–mobility, speed, flow, density, headway, and analysis. To measure and visualize the performance of the public transit system from various perspectives, this study develops a brand-new interactive visual analytics tool called PubtraVis that makes use of the GTFS data that carries schedule information
Mazloumi et al. (2010)	Travel time variability	With the help of a GPS data set for a bus route, this research aims to examine the day-to-day variability in trip times on public transportation.	For different departure time windows at different times of the day, this study examined the kind and form of travel time distributions.
Nguyen et al. (2018)	Travel-time reliability on-time performance travel-time estimation.	The authors process and analyze trajectory data in real-time to evaluate the effectiveness of Los Angeles' public transportation system.	Through an interactive web-based application, the authors show how the results of data analysis can be visualized. The created algorithms and systems offer strong tools to find problems and boost the effectiveness of public transportation networks.

A1 Summary of key performance indicators (KPI) and findings from the literature (continued)

Ref.	KPI's	Objectives	Findings
Petersen et al. (2019)	Travel time variability	Traditional approaches struggle with congestion, and as a result, travel time variability rises in cities, making it difficult to anticipate travel times in metropolitan regions. This study's goal is to create a system for forecasting bus travel times that takes advantage of the non-static spatiotemporal correlations seen in metropolitan bus networks, allowing the identification of detailed patterns that are overlooked by traditional methods.	They used the long short-term memory (LSTM) and convolutional layers to develop a deep neural network model with numerous outputs and time steps. The method is empirically evaluated and compared to other well-known techniques for predicting trip times. They find that their model outperforms every other method they compare it with, by a significant margin
Dumbliauskas et al. (2017)	Travel time fluctuation during the day calculation of travel time variability estimation of origin-destination (OD)	This study aims to analyze data on car travel times that Google Company has gathered from smartphone users.	In this study, the initial framework was established using GIS tools, and data extraction, analysis, and visualization were all done automatically using Python programming language. The evaluation led to the calculation of these KPIs.
Zhou et al. (2019)	Bus journey time Route distance Deviation degree	To identify the covered road sequence for a particular bus route, this article aims to develop an algorithm that makes use of bus stop information and historical bus positions, or places where buses have previously been.	They construct a high- quality GPS trajectory for the bus route before using a cutting-edge map-matching algorithm to the resulting packed trajectory to determine the road sequence. Their suggested approach is examined using actual bus line data from more than 400 bus services in Singapore.
Dabiri et al. (2020)	Maximum speed Mean speed Mean moving speed Average proximity to some infrastructure	This study aims to create a mechanism for classifying movement data into single-modal segments and dividing them into groups based on the mode of transportation.	A seventeen-million- point data set gathered in Europe was used to evaluate their new methodology. When the classified results are compared to the reference data produced via manual classification, the accuracy of the classification using the prototype is calculated to be 91.6%.
Ismail and Said (2015)	Total distance Total traveled time	This study attempts to demonstrate how Kuala Lumpur's multi- mode transportation concept was used to determine the best path in the city's highly developed and intricate transportation system. More specifically, it combines all modes of urban transportation into one intelligent data model.	The result enables users to better understand outcomes in terms of visualization, total distance traveled, and total time spent traveling and produces a directional map to choose the best path based on either time or distance as impedance.
Tiznado-Aitken et al. (2021)	Travel speed acceleration and braking temporal spacing between vehicles buffer times space within the vehicle share of dedicated rights-of-way density within the vehicle on-time performance headway adherence service duration	This study outlines a framework for examining opportunities' accessibility via public transportation. It takes into account how highly the user values factors that affect the level of service during his journey and the amount of competition for urban prospects.	They find that the introduction of competition has a more significant impact than the addition of a purely arbitrary grading system for service quality.
Fadaei and Cats (2016)	Vehicle running time and rest time Reliability Demand patterns total vehicle trip time layover and recovery times passenger waiting time passenger in- vehicle time passenger travel time monetary values operator costs	This article outlines an evaluation framework and a step-by-step process for measuring the effects of operational and design changes on public transportation.	In a field experiment in Stockholm, they apply the suggested evaluation framework. The comprehensive evaluation of the effects of design and operational measures allows for the comparison of various implementations, the evaluation of their efficacy, the prioritization of alternative measures, and the creation of a solid foundation for investment motivation.
Barabino et al. (2020)	Offer of services Accessibility information Attention is given to passengers Comfort safety and security effects on the environment	This research aims to create a comprehensive approach that identifies a large number of KQI, describes their characteristics, enlists the help of experts to elicit opinions for each KQI, assesses the large number, and identifies the most promising set.	An application built using a Monte Carlo simulation method and data from an international survey serves as a demonstration of this integrated approach. Additionally, by connecting these results with those acquired from two separate techniques, a constrained and pertinent set of 9 overlapping KQI is generated.

A1 Summary of key performance indicators (KPI) and findings from the literature (continued)

Ref.	KPI's	Objectives	Findings
Curtis and Scheurer (2017)	Minimum service standard travel impediment, weekday inter peak	To evaluate the level of accessibility in current public transportation systems and as a potential criterion for future planning and investment, this article discusses the usage of accessibility performance measures.	The results demonstrate a relationship between accessibility performance indicators of network and service designs and the prevalence of successful urban public transport systems, as evaluated by patronage.
Oña et al. (2016)	Availability Accessibility customer care time, safety and security	Through the use of cluster analysis, this study assesses the metropolis of Seville's (Spain) quality of service for a variety of customer profiles.	Six user profiles were discovered, and it was discovered that each of them has a unique perspective on the service, with varying gaps between those perspectives.

Appendix B

A2 Summary of methodologies/datasets and outcomes

Ref.	Methodologies	Outcomes
Biagion et al. (2011)	User mobility/ mobile location services	Their model is robust enough to anticipate future travel with an acceptable error and can explain the variation in the bus trip time.
Valdés et al. (2017)	Vehicular Sensor Networks GPS based AVL	Developed a method that successfully collected real-time data from enormous databases created by GPS-based AVL systems installed in public transit vehicles, combined that data with information on transportation demand available from other sources, including the Census, and proposed new metrics to help improve service using "Big Data"
Harsha et al. (2020)	GPS based AVL	It is discovered that the GEV distribution, both at the route and segment levels, better suits the journey time under varied traffic conditions. This distribution performed generally substantially better than every other one of the chosen distributions.
Coghlan et al. (2019)	GPS based AVL	Produced instruments for organizations and planners to evaluate and enhance the effectiveness of transportation services using big data analytics and in-the-moment forecasts.
Aoki et al. (2018)	GPS based AVL	Developed a technology that gathers GPS information from random cars and can identify events before they happen without violating people's privacy. His interpolation technique recovers the lost GPS data event before the participants arrive by making use of the primary feature of periodic-cars, which regularly go on a pre-scheduled route with a pre-determined departure time.
Chen et al. (2014)	User mobility/ mobile location services	They put forth a fresh approach to building users' movement patterns. They offered a solution for how user similarity comparison may include location semantics and temporal semantics.
Prommaharaj et al. (2020)	General Transit Feed Specification (GTFS)	This research builds on past findings and creates PubtraVis, a new public transit system operating visualization tool. Public transportation operators, local politicians, and the general public can all communicate more easily about the design and operation of public transportation by using PubtraVis, which can be a useful tool to demonstrate the dynamic nature of transit vehicles from the entire transit network at a glance.
Berkow et al. (2009)	GPS based AVL Automatic passenger counters Vehicular Sensor Networks	Based on an analysis of one year's worth of historical data for all routes and stops, a visualization tool is produced. A number of statistical models are also developed to demonstrate how the statistical analysis may result in new and relevant transit performance measures (TPMs) in addition to those previously provided by the transit sector as a whole.
Queiroz et al. (2019)	General Transit Feed Specification (GTFS)	They showed that buses running in various cities do not always follow the predetermined route, highlighting a flaw in the GTFS. Some discrepancies, like the inaccurate GPS route label, are more problematic and need to be addressed right once. With a more effective strategic strategy in the GTFS design and real-time monitoring of bus GPS data, additional inconsistencies could be prevented.
Chang et al. (2010)	Clustering of trajectories/GPS coordinates	The taxi demand analysis problem is solved in this paper using a four-step methodology. Records of taxi requests are filtered based on the context. The spatial distance is used to group these records. Finding related roads for each detected cluster allows for the association of the cluster with the semantic significance of the representative roads. Then, using the cluster's characteristics and the distance between it and the taxi driver, the hotness index is determined.
Liu et al. (2018)	Clustering of trajectories/GPS coordinates	To solve the extremely complicated challenge posed by the massive data collection, they provide an efficient AP clustering method based on administration region segmentation. Any city can use the methodological framework if the data gathering is feasible.

A2 Summary of methodologies/datasets and outcomes (continued)

Ref.	Methodologies	Outcomes
Dabiri et al. (2020)	GPS based AVL Fixed Sensor Networks User mobility/ mobile location services	To determine the class of the vehicle (bus, car, etc.) from its trajectory, a neural network is advised. This study introduces a novel type of GPS trajectory that not only works with deep learning models but also considers both the road parameters and the vehicle velocity.
Pan et al. (2013)	GPS based AVL Land-use classification	The classification results with the optimal feature combination have a 95% recognition accuracy. The classification results also identified areas that transitioned from one land-use class to another. These areas' dynamics of land-use class transitions showed peculiar real-world social events.
Nissimoff (2016)	General Transit Feed Specification (GTFS)	The method described in this article uses telemetry from public vehicles to find trends and provide accurate, real-time arrival time estimates at any location along well-known routes. The outcomes show a convincing forecast accuracy and are encouraging.