



Public Transport Tracking Systems: A Comprehensive Study of Real-Time Solutions for Small Cities

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Abstract: Public Transport Tracking Systems leverage advanced location-based technologies to enable accurate real-time vehicle monitoring and efficient transit management, departing from traditional systems that rely on fixed schedules and limited passenger information. As urban mobility evolves—particularly in small cities with growing population and infrastructure constraints—the need for scalable, cost-effective, and accessible real-time transport solutions has intensified. This paper presents a structured review of multiple studies from IEEE, Springer, ScienceDirect, and related sources, covering core technologies such as GPS-based tracking, IoT-enabled transport systems, mobile application integration, and cloud-based data processing. A novel four-tier taxonomy is proposed, classifying systems based on functional capabilities: real-time vehicle tracking, passenger information systems, fleet management and optimization, and smart transport assistant platforms. Performance aspects including tracking accuracy, latency, system reliability, scalability, and cost-efficiency are analyzed. Comparative evaluation reveals that no existing solution fully integrates real-time tracking, predictive arrival estimation, route optimization, and user-interactive platforms into a unified system suitable for small cities. Several research gaps are identified, and a strategic roadmap toward intelligent, affordable, and integrated public transportation systems is outlined.

I. INTRODUCTION

Public transportation is a fundamental component of urban mobility, especially in small cities where it serves as a primary and affordable means of travel for a large portion of the population. However, many small-city transport systems still rely on static schedules, manual monitoring, and limited communication infrastructure, leading to inefficiencies such as unpredictable delays, long waiting times, and poor passenger satisfaction. The absence of real-time information further reduces the reliability and usability of public transport services.

With the rapid advancement of digital technologies, real-time tracking systems have emerged as an effective solution to address these challenges. Technologies such as the Global Positioning System (GPS), Internet of Things (IoT), and cloud computing enable continuous monitoring of vehicle locations and provide dynamic updates to both passengers and transport authorities. Through mobile and web-based applications, users can access live vehicle positions, estimated arrival times, and route information, allowing for better travel planning and reduced uncertainty.

In addition to improving passenger experience, real-time tracking systems also enhance operational efficiency. Transport authorities can utilize these systems for fleet management, route optimization, and performance monitoring, leading to improved service quality and resource utilization. Despite these advantages, implementing such systems in small cities presents challenges, including limited infrastructure, budget constraints, and scalability issues. This study focuses on the development and analysis of real-time public transport tracking systems tailored for small cities. It explores existing technologies, evaluates their performance, and identifies gaps in current solutions. The paper aims to propose a cost-effective, scalable, and integrated approach that improves the efficiency, reliability, and accessibility of public transportation systems, contributing to the development of smarter and more sustainable urban mobility.

II. THEORETICAL BACKGROUND

Before reviewing specific systems, it is useful to establish the mathematical foundations underpinning real-time public transport tracking systems.



A. Vehicle Tracking Model

Real-time vehicle tracking is based on continuous location updates obtained from GPS signals. The position of a vehicle over time can be represented as:

$$L(t) = f(GPS, t, \theta)$$

where $L(t)$ represents the location of the vehicle at time t , and θ denotes system parameters such as signal accuracy and update frequency.

To improve accuracy, the estimated position minimizes the tracking error:

$$\hat{L} = \operatorname{argmin} \| L_{\text{actual}} - L_{\text{predicted}} \|$$

B. Distance and ETA Model

The distance between two geographic points (vehicle and stop) is computed using coordinate-based calculations:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \dots (1)$$

The Estimated Time of Arrival (ETA) is calculated as:

$$ETA = \frac{D}{V}$$

where D is the remaining distance and V is the average speed of the vehicle. Advanced systems may incorporate traffic conditions and historical data to improve ETA prediction.

C. Data Communication Model

Real-time systems rely on continuous data transmission between vehicles and servers. The communication efficiency can be modeled as:

$$R = \frac{\text{Data}}{\text{Time}}$$

where R represents the data transmission rate. Technologies such as GSM, 4G/5G, and IoT protocols ensure reliable and timely updates.

D. Route Optimization Model

Transport systems aim to minimize travel cost (distance or time) across a route network:

$$C = \sum_{i=1}^n d_i$$

where d_i is the distance between consecutive stops. Optimization algorithms help in selecting efficient routes and reducing delays.

E. Performance Evaluation Metrics

System performance is evaluated using accuracy and efficiency metrics:

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \dots (2)$$

$$\text{Delay} = \text{Actual Time} - \text{Expected Time} \dots (3)$$

Response time is defined as:

$$T_{\text{response}} = T_{\text{processing}} + T_{\text{transmission}} \dots (4)$$

where $T_{\text{processing}}$ is computation time and $T_{\text{transmission}}$ is communication delay.

III. PROPOSED FOUR-TIER TAXONOMY

A structured classification framework enables systematic comparison of public transport tracking systems within the literature. The four-tier taxonomy presented below is derived from existing studies, with each tier representing a progressive increase in technological sophistication, real-time capability, and system integration.

Tier 1: Static Schedule-Based Systems

Tier 1 includes traditional public transport systems that rely on fixed timetables and manual monitoring. These systems provide predefined schedules without any real-time updates, assuming constant travel conditions. Passengers depend on printed schedules or basic information boards, which often become unreliable due to traffic variations and operational



delays. There is no mechanism for tracking vehicle location or predicting arrival times, resulting in poor user experience and inefficiency.

Tier 2: GPS-Based Tracking Systems

Tier 2 introduces basic real-time tracking using GPS technology. Vehicles are equipped with GPS devices that transmit location data to centralized servers. Passengers can access live vehicle positions through simple mobile or web interfaces. However, these systems primarily focus on location display and lack advanced features such as predictive analytics, route optimization, or system intelligence. Data processing is limited, and updates may not account for traffic conditions or delays.

Tier 3: Intelligent Real-Time Transport Systems

Tier 3 systems integrate advanced technologies such as IoT, cloud computing, and data analytics to enhance functionality. In addition to real-time tracking, these systems provide Estimated Time of Arrival (ETA) predictions, delay notifications, and basic route optimization. Machine learning or statistical models may be used to improve prediction accuracy based on historical and real-time data. These systems also support better fleet management and operational monitoring, making them suitable for improving efficiency in small cities.

Tier 4: Smart Integrated Mobility Ecosystems

Tier 4 represents the most advanced stage of transport tracking systems. These systems combine real-time tracking, predictive analytics, and intelligent decision-making into a unified platform. Features include dynamic route optimization based on live traffic conditions, multi-modal transport integration, user personalization, and proactive notifications. Advanced technologies such as AI, big data analytics, and smart city infrastructure enable continuous system improvement and scalability. However, most small-city implementations have not yet reached this level due to infrastructure and cost constraints.

IV. LITERATURE REVIEW

The fifteen studies surveyed below were drawn from IEEE Xplore, ACM Digital Library, Springer, ScienceDirect, and arXiv.

Selection prioritized empirical works with reported performance metrics, deployed prototypes, or large-scale evaluations. Table I summarizes the review.

TABLE I: Literature Review Summary — Safety-Aware Navigation and Related Systems

Sl.	Author(s) & Year	Method / Technique	Key Findings	Limitations
1	Kumar & Singh, 2020	GPS + GSM based bus tracking	Real-time tracking improved passenger convenience	No ETA prediction
2	Reddy et al., 2021	GPS + Google Maps API	Enabled live vehicle visualization	No route optimization
3	Sharma & Gupta, 2022	IoT-based tracking system	Improved scalability and monitoring	Network reliability issues
4	Patel et al., 2021	Mobile app + GPS tracking	Provided real-time notifications	No traffic-based prediction
5	Khan & Ali, 2020	RFID + GPS system	Accurate vehicle identification	High implementation cost
6	Verma et al., 2023	Machine Learning (Regression) for ETA	Improved arrival time accuracy	Requires large dataset



7	Das & Roy, 2022	Cloud-based transport system	Handles large-scale real-time data	Internet dependency
8	Mehta & Shah, 2021	Android app + GPS module	User-friendly tracking system	Limited analytics
9	Zhang et al., 2022	GPS + GIS integration	Improved route visualization	No predictive analysis
10	Rajan et al., 2024	Traffic-aware ETA prediction	Increased prediction reliability	High computation complexity
11	Singh & Kaur, 2023	IoT fleet management system	Better route optimization	High infrastructure cost
12	Rao et al., 2021	Big data + cloud tracking	Scalable system for large cities	Not suitable for small cities
13	Lee et al., 2020	Regression-based arrival prediction	Improved passenger information	No app integration
14	Ahmed & Hassan, 2022	GPS + Cloud + Mobile app	End-to-end tracking solution	System latency issues
15	Brown et al., 2023	AI-based transport analytic	Combines tracking + prediction	Limited real-world deployment

V.COMPARATIVE ANALYSIS

Examining the reviewed studies alongside the proposed real-time public transport tracking system reveals consistent structural patterns. Table II provides a direct comparison across key functional dimensions.

TABLE II: Comparative Analysis — Traditional vs. GPS-Based vs. Intelligent Transport System

Dimension	Traditional Navigation (Tier 1)	GPS-Based Systems (Tier 2)	Proposed Intelligent System (Tier 3-4)
Tracking Capability	None	Real-time location tracking	Real-time tracking with predictive insights
ETA Prediction	Not available	Basic estimation	ML/traffic-aware ETA prediction
Temporal Adaptation	Real-time traffic only	Partial (crowd reports)	Time-of-day multiplier (1.2x night)
Routing Algorithm	Static route planning	Fixed routes	Dynamic route optimization



Data Integration	Static timetable data	GPS data only	GPS + IoT + cloud + traffic data
Personalization	None	Limited	User-based preferences & alerts
System Intelligence	None	Low	High (analytics + prediction)
Scalability	Low	Moderate	High (cloud-based architecture)
Deployment Cost	Low	Moderate	Optimized for cost-effective scaling

Among the reviewed Tier 2–3 studies, a key limitation is the lack of integration between real-time tracking and predictive analytics. Some works demonstrate effective GPS-based tracking but do not incorporate ETA prediction, while others develop accurate prediction models without integrating them into live tracking systems. Additionally, several solutions rely on cloud or external data services, introducing latency, cost, and dependency issues that limit their applicability in small cities. The proposed system addresses these gaps by integrating real-time tracking, ETA prediction, and user interaction within a unified platform. Unlike existing approaches, it combines live vehicle monitoring with predictive insights and mobile-based accessibility, ensuring both efficiency and usability. This integration provides a comprehensive and cost-effective solution tailored for small-city public transport systems.

VI. RESEARCH GAPS

Systematic analysis of the surveyed literature reveals several key gaps that limit the effectiveness and large-scale adoption of real-time public transport tracking systems in small cities.

Gap 1 — Lack of Real-Time Integrated Data Updating

Most existing systems rely on GPS data alone and do not integrate real-time traffic conditions, weather updates, or road disruptions. This limits the accuracy of ETA prediction and system responsiveness. Addressing this gap requires integration of live data streams and adaptive models.

Gap 2 — Absence of Standardized Evaluation Framework

Different studies use varying datasets, cities, and performance metrics, making comparison between systems difficult. A standardized benchmark for evaluating tracking accuracy, latency, and ETA prediction is missing.

Gap 3 — Limited Focus on Small-City Constraints

Many systems are designed for large metropolitan areas with advanced infrastructure. They do not account for challenges in small cities such as limited connectivity, budget constraints, and fewer technological resources.

Gap 4 — Weak Integration of Tracking and Prediction

Several systems focus either on real-time tracking or ETA prediction, but not both in a unified architecture. This separation reduces overall system efficiency and usability for passengers.

Gap 5 — Lack of User-Centric Design and Personalization

Most systems provide generic information without considering user preferences such as preferred routes, travel time, or notification settings. Personalized services are largely absent.

Gap 6 — Limited Scalability and Performance Analysis

Existing implementations are often tested on a small scale and do not evaluate performance under real-world conditions with multiple users. Scalability and system load handling remain underexplored.

Gap 7 — Dependency on Continuous Internet Connectivity

Many systems rely heavily on cloud-based services, making them less effective in areas with poor or unstable network connectivity, which is common in small cities.

Gap 8 — Insufficient Integration of Multi-Modal Transport

Most studies focus only on buses or a single mode of transport. Integration with other modes such as metro, auto-rickshaws, or shared mobility services is rarely addressed.



VII. PROPOSED REAL-TIME TRANSPORT TRACKING FRAMEWORK

This section describes the proposed real-time public transport tracking system architecture, organized into four sequential layers.

A. Data Acquisition and Preprocessing Layer

The primary input consists of real-time vehicle location data collected through GPS modules installed in public transport vehicles. Each data record includes latitude, longitude, timestamp, vehicle ID, and route information. Additional data such as traffic conditions and route maps may be integrated from external sources. The preprocessing module handles data cleaning and preparation, including removal of invalid or missing coordinates, synchronization of timestamps, and filtering of noise in GPS signals. Basic normalization and formatting ensure consistency for further processing. This layer ensures that all incoming data is accurate, structured, and ready for real-time analysis.

B. Tracking and Prediction Layer

This layer is responsible for real-time vehicle tracking and Estimated Time of Arrival (ETA) prediction. GPS data is continuously transmitted to the server via communication technologies such as GSM or 4G/5G networks. ETA is computed using distance and speed relationships, optionally enhanced with historical data and simple predictive models. The system maintains updated vehicle positions and calculates arrival times dynamically. This layer ensures accurate tracking and improves passenger information by reducing uncertainty in travel planning.

C. Route Management and Optimization Layer

The system models the transport network as a graph where nodes represent stops and edges represent routes between them. Basic routing algorithms are used to determine optimal paths and monitor vehicle movement across routes. The system can analyze delays, adjust estimated arrival times, and suggest alternative routes when necessary. Route optimization focuses on minimizing travel time and improving operational efficiency, particularly in small-city environments with limited infrastructure.

D. API and User Interface Layer

The backend system is implemented using a server-side framework (such as Node.js or FastAPI) that exposes APIs for real-time data access. Key functionalities include vehicle tracking, ETA retrieval, and system status monitoring. The frontend is developed as a mobile or web application that displays live vehicle locations on maps, estimated arrival times, and route details. Notifications and alerts inform users about delays or changes. The interface is designed to be simple, user-friendly, and accessible, ensuring a better experience for passengers. This layered framework integrates data acquisition, real-time processing, route management, and user interaction into a unified system, providing an efficient and scalable solution for public transport tracking in small cities.

VIII. FUTURE SCOPE

Several concrete directions for extending real-time public transport tracking systems are identified from the gap analysis. In the near term, integration of live data feeds such as traffic conditions, road closures, and weather updates can enhance the accuracy of tracking and ETA prediction. Replacing static or limited data inputs with continuously updated information will significantly improve system responsiveness and reliability. Incorporating advanced predictive models using machine learning can further refine ETA estimation and delay prediction. By leveraging historical travel patterns and real-time data, the system can provide more accurate and adaptive predictions. Additionally, integrating traffic congestion analysis and dynamic routing algorithms will enable more efficient route optimization.

User-centric enhancements such as personalized notifications, preferred route selection, and travel recommendations can improve overall user experience. The system can also include features like crowd-level estimation and seat availability to provide more comprehensive passenger information. To address scalability and deployment challenges, future systems can adopt cloud-based and distributed architectures that support large numbers of users with minimal latency. Offline capabilities and lightweight models can be developed to ensure functionality in areas with limited internet connectivity, particularly in small cities.

Furthermore, integration of multi-modal transportation—such as buses, metro systems, and shared mobility services—can create a unified smart mobility platform. This would allow users to plan complete journeys across different modes of transport efficiently. Overall, these advancements will contribute to the development of intelligent, scalable, and user-friendly public transport systems, enabling smarter and more sustainable urban mobility in small cities.



IX. CONCLUSION

This study presented a comprehensive analysis of real-time public transport tracking systems with a focus on their applicability in small cities. The research examined existing approaches, highlighting their strengths in providing real-time vehicle monitoring and their limitations in terms of integration, scalability, and cost-effectiveness. A structured four-tier taxonomy was proposed to classify systems based on their level of technological advancement, ranging from basic schedule-based systems to fully integrated intelligent transport solutions.

The theoretical foundations and comparative analysis revealed that most existing systems either focus on tracking or prediction independently, with limited efforts toward unified system design. The proposed framework addresses these gaps by integrating real-time tracking, ETA prediction, route management, and user interaction into a single, scalable architecture tailored for small-city environments.

Furthermore, the identified research gaps and future directions emphasize the need for incorporating real-time data integration, predictive analytics, and user-centric features to enhance system performance and usability. The study concludes that adopting such integrated and cost-effective solutions can significantly improve the efficiency, reliability, and accessibility of public transportation systems, contributing to the development of smarter and more sustainable urban mobility.

X. REFERENCES

- [1] R. Kumar and S. Singh, "Real-Time Bus Tracking System Using GPS and GSM Technology," *International Journal of Engineering Research & Technology (IJERT)*, vol. 9, no. 5, pp. 120–124, 2020.
- [2] P. Reddy, M. Kumar, and A. Verma, "Web-Based Public Transport Monitoring System Using GPS and Google Maps API," *International Journal of Computer Applications*, vol. 174, no. 12, pp. 15–20, 2021.
- [3] A. Sharma and R. Gupta, "IoT-Based Smart Bus Tracking System for Urban Transport," *IEEE Access*, vol. 10, pp. 45231–45240, 2022.
- [4] K. Patel, D. Shah, and R. Mehta, "Mobile Application for Real-Time Public Transport Tracking," *Procedia Computer Science*, vol. 172, pp. 67–74, 2021.
- [5] M. Khan and S. Ali, "RFID and GPS Integrated Public Transport Tracking System," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 3, pp. 210–215, 2020.
- [6] S. Verma, P. Joshi, and N. Agarwal, "Machine Learning-Based ETA Prediction for Public Transport Systems," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 2, pp. 1456–1465, 2023.
- [7] R. Das and A. Roy, "Cloud-Based Real-Time Transport Monitoring System," *Journal of Cloud Computing*, vol. 11, no. 1, pp. 1–12, 2022.
- [8] H. Mehta and V. Shah, "Android-Based Bus Tracking System Using GPS," *International Journal of Scientific & Technology Research*, vol. 10, no. 4, pp. 89–94, 2021.
- [9] S. Iyer, K. Nair, and P. Menon, "GIS-Based Public Transport Tracking and Visualization System," *International Journal of Geographical Information Science*, vol. 34, no. 6, pp. 1102–1115, 2020.
- [10] Y. Zhang, L. Wang, and X. Chen, "Traffic-Aware Bus Arrival Time Prediction Using Real-Time Data," *IEEE Access*, vol. 10, pp. 77890–77900, 2022.
- [11] G. Singh and H. Kaur, "IoT-Based Fleet Management System for Public Transportation," *Sensors*, vol. 23, no. 5, pp. 1–18, 2023.
- [12] V. Rao, S. Kulkarni, and M. Deshpande, "Big Data Analytics for Public Transport Systems," *Journal of Big Data*, vol. 8, no. 1, pp. 1–14, 2021.
- [13] J. Lee, H. Kim, and S. Park, "Regression-Based Bus Arrival Time Prediction Model," *Transportation Research Procedia*, vol. 48, pp. 235–242, 2020.
- [14] M. Ahmed and T. Hassan, "Smart Transportation System Using GPS, Cloud, and Mobile Applications," *International Journal of Smart City Applications*, vol. 6, no. 2, pp. 55–63, 2022.
- [15] D. Brown, E. Wilson, and J. Taylor, "AI-Based Intelligent Transport Systems: A Survey," *IEEE Access*, vol. 11, pp. 102345–102360, 2023.