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Original Article

SMART MULTIMODAL PUBLIC TRANSPORT ANALYTICS AND DECISION SUPPORT SYSTEM

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ABSTRACT

Public transport faces several challenges, such as delays, overcrowding, uncertain bus arrival times, and difficulties in changing routes. This paper proposes a Smart Multimodal Public Transport Analytics and Decision Support System. The system mainly focuses on buses while also supporting trains, metro services, and walking. It uses transport-related data to estimate arrival times, predict delays, identify crowd levels, and forecast passenger demand. It also helps passengers select suitable routes and supports transport authorities in monitoring transport services. The system uses publicly available, historical, and simulated data. This paper describes the proposed system and presents a plan for its evaluation.

Keywords: Smart Public Transportation, Multimodal Trans Portation, Transport Analytics, Machine Learning, ETA Prediction, Delay Prediction, Passenger Demand, Decision Support System

INTRODUCTION

Public transport is an essential part of urban mobility, particularly in growing cities where many people rely on buses and other forms of transportation. However, passengers often experience problems such as uncertain bus arrival times, overcrowding, difficult transfers, and insufficient information during delays or service disruptions.

Transport authorities also face challenges in managing buses, routes, schedules, passenger demand, and service delays efficiently. In many systems, passenger-oriented services and transport management functions are handled separately, limiting the ability to use transport information in a coordinated way. Existing research has explored several areas, including arrival-time prediction, crowd estimation, multimodal route planning, disruption management, passenger-demand forecasting, and electric bus management.

This paper proposes a Smart Multimodal Public Transport Analytics and Decision Support System to bring these functions together within a common framework. The system mainly focuses on bus transportation while also considering local trains, metro services, and walking. It uses information such as vehicle locations, routes, schedules, passenger demand, and other transport-related data to support predictions and operational analysis.

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Transparency: The authors affirm that this manuscript presents an honest, accurate, and transparent account of the study. All essential aspects have been included, and any deviations from the original study plan have been clearly explained. The writing process strictly adhered to established ethical standards.
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The proposed system offers passenger services such as live bus tracking, estimated time of arrival (ETA) prediction, delay prediction, crowd estimation, multimodal journey planning, and journey recovery. It also supports transport authorities through demand forecasting, route performance assessment, crowd analysis, and fleet management.

The main objective is to improve the passenger travel experience while providing transport authorities with data-based insights for planning and operational decision-making.

RELATED WORK

1) ETA and Delay Prediction

Reich et al. (2019) reviewed bus arrival-time prediction methods using Automatic Vehicle Location (AVL) data. They highlighted differences in input data and evaluation methods, which make it difficult to compare prediction accuracy across studies. Liu et al. (2020) introduced BusTime, a framework for evaluating bus arrival-time prediction methods using GPS data from Dublin. It includes LSTM-based models and several statistical approaches. While these studies focus mainly on arrival-time prediction, Ibarra-Rojas et al. (2015) provide a broader review of bus network planning, operation, and control. These studies highlight the need to consider arrival times alongside passenger crowding and other journey-related factors when developing more comprehensive transport systems.

2) Crowding Estimation

Crowding has a direct effect on public transport operations and passenger comfort. It can affect vehicle speed, waiting times, service reliability, and passengers' travel choices. Therefore, considering crowding is important for estimating passenger demand accurately Tirachini et al. (2013).

Arabghalizi and Labrinidis (2020) used regression models to predict bus loads and classification methods to identify crowding levels. Their study relied on smart-card and GPS data collected by a transport agency in Pittsburgh. Shrivastava et al. (2024) grouped transit segments according to passenger numbers and developed time-series models to forecast ridership for each group. Their research used three months of ticketing data from Bhubaneswar. The study also describes using the predictions in a passenger information system, allowing passengers to compare travel options based on crowding levels

3) Multimodal Journey Planning

RAPTOR Delling et al. (2015) finds suitable public transport routes by considering arrival times and the number of transfers required. It does not require graph preprocessing and can be adapted to changing transport conditions. The method can also be extended to consider factors such as fare zones and transfer reliability.

Reference Bast et al. (2016) provides a review of route-planning methods used in transportation networks. The General Transit Feed Specification (GTFS) Wong (2013) offers a standard format for sharing public transport schedules and service information. Although these methods support route planning, a complete journey planning system should also consider passenger needs, including crowding, service disruptions, and the specific requirements of visitors.

4) Disruption Handling and Tourist Needs

When public transport services are disrupted, passengers may need to change their travel plans, particularly when alternative routes have limited capacity. Research on capacity-aware passenger rerouting Bachmann et al. (2024) examines how suitable alternatives can be provided during such incidents. This requires identifying affected passengers, checking the available capacity on alternative routes, and sharing timely updates as conditions change.

The effectiveness of travel information also depends on the overall state of the transport network Cats and Jenelius (2014). This is especially important for visitors who may be unfamiliar with local routes and transport services. A study of newcomers using public transport in Dublin Kinsella and Caulfield (2011) highlights the importance of information that helps people understand and use the system. These findings underline the need to provide practical, dependable travel guidance, particularly to passengers who have limited knowledge of the local network.

5) Demand Forecasting and Authority Analytics

DeepPF Liu et al. (2019) uses deep learning to forecast passenger entry and exit flows in metro systems. Its predictions take into account several factors, including external conditions, time, location, and operational characteristics. Considering these factors helps the model identify changes in passenger demand across

different periods and areas. However, DeepPF was developed primarily for metro networks, and its forecasting process does not directly link predicted demand to fleet-allocation decisions. As a result, although the framework supports passenger-flow forecasting, further integration is needed to connect demand predictions with fleet management in bus-based public transport systems.

6) Electric Bus Management

The reviews in Perumal et al. (2022), Zhang et al. (2023) discuss key challenges involved in planning and operating electric bus fleets. Their coverage includes investment decisions, charging infrastructure, vehicle scheduling, and the coordination of charging times. These issues are closely related to the limited distance electric buses can travel on a single charge and the time needed to recharge their batteries.

Both reviews mainly examine optimization techniques for improving fleet planning and scheduling. They also identify the need to make these processes more robust as an important area for future research.

7) LLM-Based Transit Assistants

Jonnala et al. (2024) investigated how large language models (LLMs) perform information retrieval and comprehension tasks using General Transit Feed Specification (GTFS) data from San Antonio. ChatPlanner Yang et al. (2026), on the other hand, combines fine-tuned LLMs with retrieval-augmented generation (RAG) to identify relevant route parameters and interpret users' travel preferences.

Despite these capabilities, ChatPlanner uses a separate routing algorithm to calculate journeys. This design choice addresses the limitations of tool-augmented LLMs, which may produce inconsistent results or inaccurate travel-time estimates. The proposed system follows a similar principle by separating language-based understanding of passenger requests from deterministic route calculations.

RESEARCH GAPS AND PROPOSED APPROACH

The existing literature reveals five key research gaps that the proposed system aims to address.

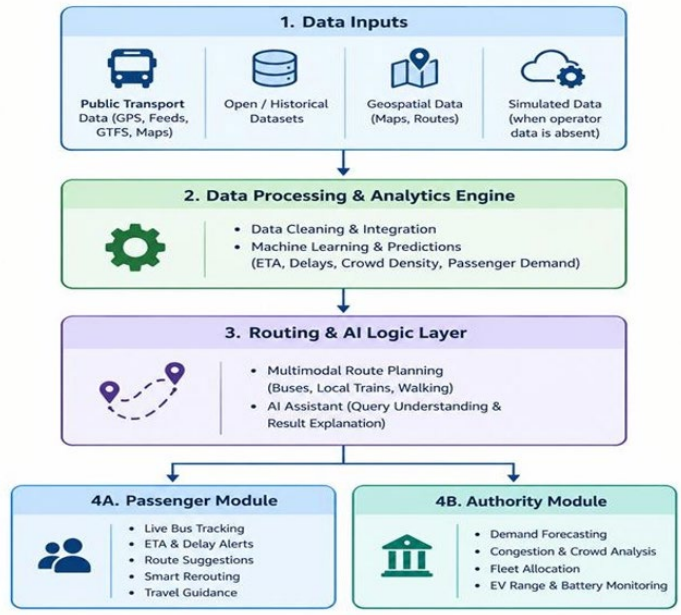
- First, ETA and delay prediction studies use different evaluation metrics, making their results difficult to compare. The proposed system uses MAE, RMSE, and a schedule-based baseline for consistent evaluation.
- Second, crowd-prediction methods often depend on smart-card or ticketing data that may not be publicly available. The proposed system uses available data, load-related proxy features, and simulated data when necessary, although simulation remains a limitation.
- Third, disruption management requires information about passenger demand and alternative transport capacity. Therefore, the proposed system integrates crowd prediction with disruption recovery.
- Fourth, tourists and unfamiliar passengers need clear guidance when planning journeys or responding to disruptions. The system addresses these needs through tourist-oriented journey planning and disruption-recovery support.
- Finally, LLM-based transport assistants may provide unreliable route calculations or transport information. The proposed system uses the AI assistant to understand queries and explain results, while deterministic methods handle route planning and transport-data retrieval.

PROPOSED SYSTEM

The proposed system introduces a conceptual framework for smart multimodal public transportation. It primarily focuses on bus services while also incorporating local trains, metro services, and walking as additional modes to support multimodal journeys.

The framework is designed to function without relying on private databases maintained by transport operators. Instead, it can use publicly available information and simulated data when required, particularly when access to private transport data is limited.

The system gathers information about bus locations, routes, schedules, passenger demand, crowding levels, and other relevant transport parameters. The collected information is then processed and analyzed to produce useful predictions and recommendations that support passenger travel and transport-related decision-making.



PROPOSED ARCHITECTURE

The proposed architecture combines transport data collection, data processing, machine learning, passenger services, and authority-level analytics within a common framework. It gathers information about bus locations, routes, schedules, passenger demand, crowding levels, and other relevant transport parameters. The collected data are then processed and analyzed to generate predictions and recommendations that support passenger travel and transport management.

The passenger module offers a range of services, including live bus tracking, estimated time of arrival (ETA) prediction, delay prediction, crowd estimation, multimodal journey planning, and journey recovery. These services aim to help passengers make informed travel choices and respond more effectively to unexpected changes, delays, or disruptions during their journeys.

The authority module focuses on analyzing transport operations and supporting management decisions. Its main functions include passenger demand forecasting, route performance assessment, crowd-level analysis, and fleet management. These capabilities help transport authorities understand overall system performance and make better-informed operational decisions.

From the passenger's perspective, the system is designed to make everyday travel more convenient and reliable. Services such as live bus tracking, ETA and delay predictions, crowd estimates, multimodal journey planning, and journey recovery can help passengers plan their trips and adjust their travel choices when unexpected delays or service disruptions occur.

From the transport authority's perspective, the architecture supports demand forecasting, route performance analysis, crowd monitoring, and fleet-management decisions. By bringing passenger-oriented services and authority-level analytical functions together, the proposed system aims to create a more coordinated, responsive, and data-driven public transportation service.

Paper	Year	Main Focus	Methodology	Key Contribution	Main Limitation
Proposed System (Adhau et al.)	Active (2027)	Unified passenger travel assistance & authority decision support.	React.js + Python Flask + MySQL; Scikit-learn ML; Leaflet/OSM mapping; public GTFS/simulated feeds.	Integrates multimodal routing (Bus/Metro/Train/Walk), AI ETA/crowd prediction, Journey Recovery, & E-Bus fleet monitoring.	Must operate on open APIs, public feeds, and simulated data due to restricted private agency databases.
ChatPlanner (Yang et al.)	2026	Personalized, preference-based transit route planning.	LangGraph (LLaMA-3/Qwen-2.5) + RAG for intent/preferences; MC-RAPTOR for path search.	Eliminated routing hallucinations (99% feasibility vs. 35% for GPT-5) via decoupled NLP and search.	MC-RAPTOR runtime grows exponentially when optimizing more than 2 preferences simultaneously.
Encoder-Decoder	2024	Multi-step bus arrival time	Spatially mapped Seq2Seq GRU with	Captured backward-propagating congestion	Complex data preprocessing across

RNNs (Bhutani et al.)		prediction under mixed traffic.	bidirectional decoder (EDB) and headway synchronization.	waves in heterogeneous, undisciplined traffic (Delhi).	historical trips; limited to single corridors.
LLMs in Transit (Jonnala et al.)	2024	Evaluating LLM understanding of GTFS transit data.	Benchmarked zero-shot GPT-3.5 and GPT-4o on GTFS schema reasoning and tabular retrieval.	Showed LLMs succeed on simple lookups but fail (less than 50% accuracy) on complex multi-table joins.	Context token limits prevent full-network feeds; prone to hallucinating trip connections.
PFP-XPOI (Lv et al.)	2022	Short-term bus passenger flow & boarding prediction.	Extreme Gradient Boosting (XGBoost) fused with Point-of-Interest (POI) buffer categories.	Showed 300 m POI radius best captures land-use demand, outperforming standard SVM and LSTM.	Static POI data cannot capture sudden real-time transit disruptions or unexpected delays.
Electric Bus Scheduling (Perumal et al.)	2022	Electric vehicle scheduling (E-VSP) and charging management.	Operations Research survey of MIP, column generation, and metaheuristics for electric fleets.	Formulated constraints for battery SOC, driving range, degradation, and time-of-use tariffs.	Computationally heavy static formulations; real-time disruption recovery remains scarce.
BusTime (Liu et al.)	2020	Accuracy vs. latency trade-offs for urban bus ETA models.	KD-tree stop-based GPS interpolation; compared Delay, k-NN, Kernel Regr., and LSTM.	Stop-based interpolation reduced data size and runtime by approximately 5× with negligible accuracy loss.	Deep models (LSTM) require intensive tuning and struggle with real-time scaling on non-GPU setups.

DATA AND ANALYTICS

The proposed system uses publicly available real-time bus and GPS data, open and historical datasets, free public APIs, OpenStreetMap, and GTFS-style schedule information. When private transport operator data are unavailable, simulated data are used where necessary and clearly labelled as simulated. Python, Pandas, NumPy, and scikit-learn support the system's transport analytics and machine learning tasks Pedregosa et al. (2011). The system generates predictions for estimated time of arrival (ETA), delays, crowd levels, passenger demand, peak-hour conditions, and route performance. Crowd levels are estimated using historical and simulated load-related features rather than direct passenger-count data. Jasani (2024)

PASSENGER MODULE

The passenger module provides real-time bus tracking, smart route suggestions, travel alerts, and journey planning across multiple transport modes. It also includes tourist- and visitor-oriented planning for passengers who are unfamiliar with the transport network.

The journey-recovery service generates an alternative route from the passenger's current location when a delay occurs or a connection is missed. The system also provides NCMC mobility information and carbon-saving estimates.

The AI travel assistant focuses on understanding user queries and explaining results. Route planning and transport-data retrieval are handled by dedicated deterministic services.

AUTHORITY MODULE

The authority module helps transport authorities understand passenger demand and monitor overall system performance. It provides information on passenger demand, peak-hour conditions, route performance, crowd levels, and congestion at bus stops. This information can support better operational decisions, including the allocation of buses and fleet resources Ibarra-Rojas et al. (2015), Cats and Jenelius (2014).

For electric buses, the system displays basic information such as bus number, battery percentage, estimated driving range, battery condition, charging status, and maintenance status. The dashboard is mainly intended to support fleet monitoring and maintenance activities Perumal et al. (2022), Zhang et al. (2023). It does not assign labels such as "unsafe bus" or "accident risk" unless there is sufficient supporting evidence.

PERFORMANCE EVALUATION

The proposed system will be evaluated using different metrics for its main functions. ETA and delay prediction will be assessed using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), and the results will be compared with a schedule-based baseline.

Crowd-level prediction will be evaluated using accuracy and F1-score, while passenger demand forecasting will be assessed using Mean Absolute Percentage Error (MAPE). The journey planner will be evaluated based on travel time and the quality of the recommended journeys.

CHALLENGES AND LIMITATIONS

The main challenges include estimating crowd levels in the absence of direct passenger-load data, validating simulated transport data, maintaining reliable real-time data feeds, and ensuring that the AI assistant provides information based on accurate and reliable transport data.

CONCLUSION

This paper reviewed key studies across several areas of public transportation, including bus ETA prediction, crowd estimation, multimodal journey planning, disruption management, tourist travel, demand forecasting, electric bus management, and LLM-based transit assistants. The review suggests that most existing studies focus on only a few of these areas, with limited integration between them. This indicates the need for a more comprehensive framework that brings together multiple transport services and analytical capabilities.

To address this gap, we proposed a Smart Multimodal Public Transport Analytics and Decision Support System. The system primarily focuses on bus transportation while also considering local trains, metro services, and walking. It brings together real-time transport information, multimodal journey planning, predictive analytics, and decision-support functions to support a more integrated approach to public transportation.

The proposed system is designed to use publicly available data, historical datasets, and simulated data when real-world information is unavailable. Future work will focus on completing the system implementation, integrating real-time transport data, assessing its performance using the defined evaluation metrics, and validating its effectiveness in real-world public transportation settings.

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