

AI-Based Dynamic Public Transport Crowding Prediction and Intelligent Route Recommendation System

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Abstract- Public transport in fast-growing cities is under constant pressure, with buses and metro coaches becoming overcrowded at peak hours while remaining underused at other times. Passengers often have no reliable way to know how crowded a vehicle will be before it arrives, while fixed timetables and static journey planners cannot respond effectively to changing demand. Artificial intelligence provides an alternative by treating crowding as a time-series forecasting problem and using predicted occupancy as an input to route recommendation. Research reviewed in this paper reports that recurrent deep-learning models such as Long Short-Term Memory (LSTM) and bidirectional LSTM (BiLSTM), together with tree-based ensembles such as Random Forest and XGBoost, can outperform traditional statistical and schedule-based approaches for occupancy forecasting. Integrated systems that connect prediction with fleet decisions and passenger recommendations are also reported to provide greater operational benefits than isolated prediction models. To confirm that the problem is relevant from the passenger perspective, a primary survey of 123 public transport users was conducted. The survey indicates that overcrowding is regularly experienced by a substantial share of respondents, that many respondents have changed their route because of crowding, and that willingness to trust an AI-based crowding system is divided. These findings support the need for transparent and explainable recommendations rather than an unexplained black-box score. This paper presents the main approaches to AI-based crowding prediction, reports the primary survey findings, explains important feature families and model types, describes a route recommendation method that considers predicted crowding together with travel time, waiting time and transfers, discusses real-time deployment and robustness, and proposes an evaluation plan. The proposed direction combines a data layer, BiLSTM and gradient-boosting prediction models, an ensemble mechanism, and a multi-objective recommendation layer. The overall objective is to support less crowded and efficient journeys while helping transport operators balance capacity. The paper also identifies challenges involving unusual events, new routes, sensor failures, privacy, fairness, passenger behaviour and technology acceptance, and recommends future work on adaptive, lightweight and privacy-aware systems.

Keywords: Public transport; crowding prediction; occupancy forecasting; route recommendation; passenger survey; technology acceptance; LSTM; BiLSTM; Random Forest; XGBoost; real-time systems; smart mobility.

I. INTRODUCTION

Public transport is the backbone of urban mobility, yet most systems still operate on fixed schedules that assume stable demand. In practice, demand varies by hour, weekday, weather, local events and holidays. The result is familiar to every commuter: some buses are packed while the next one is nearly empty. Overcrowding reduces comfort and safety, increases boarding time and delays, and pushes

people toward private vehicles, which worsens congestion and emissions.

Digital services have made real-time data much more available. Vehicles carry GPS units, automatic passenger counters and ticketing systems, and cities publish weather and event information. This makes it possible to move from a reactive, schedule-based service to one that anticipates crowding and informs both passengers and operators.

Traditional journey planners mainly optimise travel time or distance. They generally do not consider how crowded a vehicle will be. A route that is fastest on paper may be an uncomfortable or unusable choice at rush hour. Crowd-aware recommendation fills this gap by treating predicted occupancy as a cost, alongside time and waiting.

Machine learning became an important research direction because occupancy forecasting is a supervised learning problem. A model learns from past occupancy and context, then predicts future load for a route and time. A recent integrated platform in the literature combined BiLSTM occupancy forecasting, reinforcement-learning fleet reallocation and passenger coach recommendations, and reported clear gains over schedule-based and Random Forest baselines [1]. Related work on agent-based fleet simulation shows how demand, dispatching and waiting time can be evaluated together against a wait-time target [7], and urban logistics research shows how routing and environmental indicators can be assessed jointly [4]. Beyond the technical literature, it is important to check whether passengers themselves experience this problem and would accept an AI-based solution. Section 2 of this paper therefore reports a primary survey conducted specifically for this study.

Aim of the Study

The aim is to understand how AI techniques can predict crowding on public transport, what information is useful for prediction, how different models compare, whether passengers actually experience and care about this problem, and how predictions can be turned into route recommendations that reduce passenger discomfort and waiting time.

Importance of the Study

A useful system must do more than achieve low error on a test dataset. It must respond quickly, work on new routes and unusual days, tolerate missing sensor data, protect passenger privacy, and give recommendations that passengers can understand and trust. The primary survey in this paper shows that trust cannot be assumed, which makes this importance concrete rather than theoretical.

II. PRIMARY SURVEY DATASET

To ground the motivation of this study in real passenger experience rather than literature alone, a structured questionnaire was distributed to public transport users and collected through an online form. This section describes the dataset and summarises the findings that are used later in the paper.

Survey Design and Sample

The questionnaire contained 20 questions covering four areas: (i) respondent profile and travel habits, (ii) experience of overcrowding, (iii) route-choice behaviour, and (iv) willingness to use an AI-based crowding-prediction and route-recommendation system. A total of $N = 123$ valid responses were collected. Respondents were reasonably spread across age groups: Below 18 (28), 18–25 (26), 26–35 (28), 36–50 (26) and Above 50 (15). Frequency of public transport use ranged from Daily (30) to Rarely (20), with the remaining respondents using public transport between one and six days a week. The most-used modes reported were a mix of bus, train, metro and share-auto, with train (29) and “Other” (30, mainly mixed-mode users) most common, followed by share auto (23), metro (22) and bus (19). Main travel purposes were fairly evenly split between work/office (27), shopping (25), medical (25), college/education (24) and personal/other (22) trips.

Crowding Experience

Overcrowding is a frequent experience for this sample. Combining the “Often” (28) and “Always” (26) responses, 44% of respondents experience overcrowding at least often, while only 22 respondents (18%) report never experiencing it. Morning peak hours were identified as the highest-crowd period by the largest group of respondents (33), consistent with commuting patterns, followed by afternoon (24) and evening peak (24); interestingly, 23 respondents reported no particular peak time, suggesting that crowding on some routes is not limited to classic rush hours. The most commonly reported effect of overcrowding was difficulty boarding or exiting the vehicle (29), followed by increased waiting time (24) and difficulty getting a seat (23). Waiting times were substantial:

34 respondents typically wait 20–30 minutes and 21 wait more than 30 minutes, together representing 45% of the sample.

Route-Choice Behaviour

Difficulty in choosing a less crowded route was reported by a large share of respondents (“Always” 29, “Often” 28), together 46% of the sample, indicating that passengers frequently lack the information needed to avoid crowded services. When asked what matters most when choosing a route, responses were distributed across less waiting time (28), fewer stops (27), low cost (26), short travel time (24) and less crowd (18), showing that crowding is one factor among several rather than the only priority — which supports a multi-objective scoring approach rather than optimising for crowding alone. Notably, 47 respondents (38%) said they have changed their travel route frequently because of heavy crowding, and a further 15 said they had done so sometimes, together over half the sample, confirming that crowding measurably changes travel behaviour.

Willingness to Use an AI-Based System

Responses on AI adoption were mixed rather than uniformly positive, which is an important and realistic finding for system design. For “Would you use an AI system that predicts public transport crowding?”, 27 said Probably Yes and 26 Definitely Yes (43% combined positive), against 23 Definitely No and 23 Probably No (37% combined negative), with the remainder Not Sure. For the related question on route recommendation specifically, responses skewed more cautious, with 32 respondents saying Definitely No, larger than any single positive category. When asked which feature would be most useful, travel alerts (28) and real-time crowd prediction (26) were the top choices, ahead of alternative-route recommendation (23) and waiting-time prediction (22), suggesting passengers may prefer being informed over being told which route to take. Perceived importance of real-time crowd information was concentrated in the moderate range (Moderately Important 32, Slightly Important 30), rather than at the extremes. Overall usefulness of an AI-based system was rated positively on balance (Very Useful 29, Useful 27, combined 46%, versus

Not Useful 25), though willingness to recommend such a system to others was again split (Probably No 33 and Definitely Yes 31 were the two largest groups).

Interpretation for System Design

Three design implications follow directly from the survey. First, since crowding is a frequent and behaviour-changing problem for a large share of respondents, a crowding-prediction system addresses a real and recurring need rather than an edge case. Second, since willingness to use an AI system is divided and route-recommendation specifically drew more scepticism than crowd prediction alone, the system proposed in this paper (Section 6) is designed to present information (expected crowd level, alternatives) rather than only issuing a single automated instruction, and to explain why a route is recommended, consistent with the explainability direction discussed in Section 9. Third, since travel time, waiting time, cost and fewer stops were all rated close to crowding in importance, the recommendation scoring function in Section 6 is deliberately multi-objective rather than crowding-only.

Table 1: Summary of key survey findings (N = 123)

Survey question	Key finding
Frequency of overcrowding	44% experience it “Often” or “Always”
Highest-crowd period	Morning peak most common (33 of 123)
Difficulty finding a less crowded route	46% report “Always” or “Often”
Changed route due to crowding	51% report doing so “Frequently” or “Sometimes”
Willingness to use crowd-prediction AI	43% positive, 37% negative, remainder unsure
Willingness to use route-recommendation AI	Most common single response was “Definitely No” (32)
Most valued feature	Travel alerts and real-time crowd prediction ranked highest
Perceived overall usefulness of AI system	46% rate it “Useful” or “Very Useful”

Note: the survey is a convenience sample collected through an online form and is used here to motivate and inform system design rather than to make statistically representative claims about the general population. A limitation of self-selecting online surveys is discussed further in Section 9.



Figure 1: Intelligent transportation system architecture illustration.

III. CROWDING PREDICTION USING MACHINE LEARNING

Crowding prediction generally follows a sequence of data collection, preprocessing, feature engineering, model training, testing and deployment.

Basic Prediction Process

- Collect historical and live occupancy data from ticketing, automatic passenger counters, GPS and sensors.
- Clean the data: remove duplicates, fill short gaps and handle outliers.
- Extract time, route, weather and event features.
- Train a forecasting model on sliding windows of past observations.
- Evaluate on later time periods that were not used for training.

Deploy the model to forecast occupancy for the next few hours and update it with live data.

Problem Formulation

Given occupancy observations for a route over the previous T time steps together with contextual features, the model predicts occupancy for the next H steps. Short horizons (for example 15 to 60

minutes) support passenger decisions, while longer horizons (several hours) support fleet positioning. Occupancy may be predicted as a passenger count or as a crowding level such as low, medium or high, which is often easier for passengers to interpret — a preference consistent with the survey finding that respondents most valued simple travel alerts and crowd-level information (Section 2.4).

Data Preprocessing

Raw counts are usually scaled so that routes with very different ridership can be modelled together. Missing values caused by sensor dropout can be filled by forward fill or interpolation, which usually preserves time-series continuity better than mean imputation. Outliers can be detected using rolling statistics and replaced with smoothed estimates. Time is converted into cyclical features so that 23:00 and 00:00 are treated as close together.

IV. FEATURE ENGINEERING AND FEATURE FAMILIES

Feature engineering means choosing the information a model can learn from. Combining several feature families gives a more complete picture of demand.

Temporal Features

Hour of day, day of week, weekday or weekend, and holiday flags capture regular commuting patterns. These features are cheap to compute and often provide most of the predictive signal. This matches the survey finding that morning peak hours were most commonly identified as the highest-crowd period (Section 2.2).

Historical Occupancy Features

Recent occupancy, occupancy at the same time on previous days and weeks, and rolling averages capture both short-term momentum and weekly seasonality.

Spatial and Network Features

Stop or route identifiers, position along the route, neighbouring stop loads, and upstream occupancy describe where crowding is building up. Load at earlier stops is a strong signal for load at later stops.

External Context Features

Temperature, rainfall, public events, exam days and festivals explain demand changes that history alone cannot. Rain, for example, typically raises bus demand on sheltered trunk routes.

Live Operational Features

Current vehicle position, delay and headway (gap to the previous vehicle) show how uneven service is at this moment. A vehicle following a delayed one usually carries a heavier load.

Feature Selection

Large feature sets can contain repetitive information. Correlation filtering, Principal Component Analysis (PCA) and model-based importance ranking can reduce dimensionality, speed up prediction and simplify interpretation.

Table 2: Feature families used for crowding prediction

Feature family	Typical information	Main trade-off
Temporal	Hour, weekday, holiday	Fast, cheap; ignores unusual events
Historical occupancy	Recent and same-time-last-week load	Strong signal; needs clean history
Spatial / network	Stop position, upstream load	Captures propagation; needs stop-level data
External context	Weather, events	Explains anomalies; depends on outside feeds
Live operational	Delay, headway, position	Very current; noisy and needs live GPS

V. MACHINE LEARNING MODELS FOR CROWDING PREDICTION

Several model families have been applied to occupancy forecasting. Performance depends on the data, the features, the training method and the evaluation procedure, so reported results should be

read as representative findings rather than a guarantee that one model is always best.

Baselines: Historical Average and ARIMA

A historical average predicts the typical load for a given route and time slot. ARIMA models the time series statistically. Both are simple and interpretable but handle sudden changes and nonlinear patterns poorly, so they are used mainly as baselines.

Random Forest

Random Forest [2] combines many decision trees. It handles mixed engineered features well, needs little tuning and is a strong classical baseline. It does not model sequences directly, so lagged features must be created manually.

XGBoost

XGBoost [3] builds a strong predictor from a sequence of simpler trees. It is often very accurate on tabular features and is fast at inference, which makes it attractive for real-time use.

LSTM

Long Short-Term Memory networks [5] are recurrent networks designed to learn long-range temporal dependencies. They read a window of past observations and learn daily and weekly patterns directly from the sequence.

BiLSTM

A bidirectional LSTM [8] processes each input window in both forward and backward directions, capturing dependencies in both directions within the window. A stacked BiLSTM with dropout regularisation has been reported to outperform statistical and tree-based baselines on real ridership data [1].

Transformer-Based Models

Attention-based models [9] can relate distant time steps and many routes at once, and are increasingly used for multi-route forecasting. They usually need more data and computation than LSTM models.

Choosing a Model

The literature does not show that one algorithm is universally best. Tree ensembles work well when

engineered features are rich and latency is critical, recurrent models work well on sequential data with strong daily and weekly patterns, and attention-based models become useful when many routes must be forecast together. Comparing several models on the same data is therefore good practice.

VI. HYBRID PREDICTION AND INTELLIGENT ROUTE RECOMMENDATION

Hybrid and Ensemble Prediction

Different models make different errors. An ensemble can average or weight the outputs of a BiLSTM and a gradient-boosted model, so that sequence learning and tabular feature strength are both used. Hybrid systems can also add a live correction step, adjusting a forecast when real-time counts differ strongly from the prediction.

Route Recommendation Method

Once crowding is predicted, each candidate route or vehicle option is given a score. A simple weighted cost is:

$$\text{Cost} = w_1 \cdot \text{Travel Time} + w_2 \cdot \text{Waiting Time} + w_3 \cdot \text{Predicted Crowding} + w_4 \cdot \text{Transfers}$$

Options are ranked by lowest cost. The weights can be fixed defaults or personalised, for example a higher crowding weight for passengers who need a seat, or a higher time weight for urgent trips. This multi-objective design is supported directly by the survey data, where waiting time, fewer stops and low cost were each rated close in importance to crowding itself (Section 2.3), rather than crowding dominating passenger choice on its own. The system can then present the top options with a short explanation such as "second bus is 25% less crowded, 4 minutes later", which reflects the survey preference for informative alerts over an unexplained single recommendation (Section 2.4).

Operator-Side Use

The same predictions help operators. Forecast overload on a segment can trigger an extra vehicle, a short-turn, or a change in headway. Reported integrated systems connect forecasting to fleet reallocation so that insights flow both to passengers

and to dispatchers [1]. Agent-based simulation of demand and dispatching, with a target such as a 15-minute maximum wait, is a useful way to test such policies before real deployment [7].

Advantages and Limitations

The main advantage is that passengers spread across vehicles and times, which reduces peak crowding without adding capacity. The limitation is cost and complexity: more data sources, more computation and the need for stable live feeds. Recommendations that ignore passenger behaviour can also fail, since if everyone is told to take the same emptier bus, it becomes the crowded one.

VII. REAL-TIME DETECTION AND DEPLOYMENT

A crowding system meant for daily use must respond within seconds. A model with excellent accuracy is still unsuitable if each prediction takes too long or depends on data that arrives late.

Data Pipeline

Live GPS, passenger counter and ticketing streams are timestamp-aligned, validated and passed through a message broker to the prediction service. Data-quality monitoring flags sensor dropouts and activates fallback imputation so the pipeline keeps running.

Low-Latency Inference

Forecasts for all routes can be computed periodically (for example every few minutes) and cached, while passenger requests only read the cache and run the route scoring. This keeps response time low even at peak load.

Fast-Slow Architecture

- Step 1: Receive the passenger's origin, destination and time.
- Step 2: Look up cached crowding forecasts and rank options with the fast scoring rule.
- Step 3: If the best options are clearly separated, return the answer immediately.
- Step 4: If options are close or data is uncertain, run a deeper analysis with fresher data or a heavier model.

- Step 5: Return the recommendation with a confidence indication.

Passenger Interface

A mobile or web application shows live vehicles on a map, a colour-coded crowding level per vehicle, and recommended alternatives. Updates should be pushed over persistent connections so that changes appear without manual refresh. Given the survey's mixed trust results (Section 2.4), the interface should let passengers see the underlying crowd level and travel-time estimate, not only a final ranked recommendation.

VIII. ROBUSTNESS, COLD START AND PRIVACY

Benchmark accuracy is not the same as real-world reliability. Transport demand is affected by events that models rarely see, and the system must remain useful when conditions change.

Unusual Events and Distribution Shift

Festivals, strikes, sports events and severe weather create demand that differs from the training data. Post-pandemic changes in commuting habits, new routes and timetable revisions cause gradual distribution shift. Adding event calendars and weather features helps, and simulation of event scenarios with demand multipliers can help operators prepare in advance [1].

Cold Start

New routes and new stops have no history. Transfer of patterns from similar routes, use of static features such as land use and stop type, and rapid updating as data arrives can reduce this problem.

Sensor Failure and Data Quality

Counters can drop out or miscount, and GPS can drift. Robust systems detect anomalies, fall back to imputed or model-only estimates, and report reduced confidence rather than silently giving wrong values.

Privacy

Crowding can be estimated without tracking individuals. Aggregated counts, anonymised

ticketing data and on-device processing reduce risk. Continuous passenger tracking and video-based counting need clear policy and technical anonymisation, an issue also noted in earlier integrated transit work [1].

Fairness and Feedback Effects

Recommendations should not systematically push vulnerable or low-income areas toward worse service. Monitoring of route-level outcomes and of feedback effects, where recommendations themselves change demand, is needed.

IX. RESEARCH GAPS AND FUTURE DIRECTIONS

Dataset Quality

Public, multi-city occupancy datasets that include events, weather and anomalies are scarce. Larger, time-aware and diverse benchmarks are needed so that results from different studies can be compared fairly. The primary survey in this paper is a convenience sample of 123 respondents collected through an online form; it is useful for motivating design choices but is not a statistically representative sample of the general commuting population, so its findings should be validated with a larger and more demographically balanced sample in future work.

Long-Term Adaptation

Models need continual learning to keep up with changing ridership without a full rebuild each time. Online updating and drift detection are promising directions.

Explainability and Trust

The survey found that willingness to trust an automated route recommendation was lower than willingness to simply receive crowd information (Section 2.4). This suggests explainability is not only a technical nicety but a precondition for adoption, and future systems should evaluate trust and adoption directly, not only prediction accuracy.

Behaviour-Aware Recommendation

Future systems should model how passengers respond to advice, so that recommendations spread

demand instead of shifting the crowd from one vehicle to another.

Multi-Modal Integration

Combining buses, metro, and first- and last-mile options in one recommendation, together with cost and emissions, would give a fuller picture of sustainable travel.

Recommended Research Direction

- Use time-based splits and include event and holiday days in evaluation.
- Combine sequence models with gradient-boosted models in ensembles.
- Use cached forecasts with a fast-slow decision path for low latency.
- Report accuracy together with latency, robustness to sensor failure and fairness.
- Use aggregated, privacy-preserving data wherever possible.
- Provide simple explanations with each recommendation, and validate adoption with larger passenger surveys.

X. PROPOSED SYSTEM AND EVALUATION PLAN

System Overview

The proposed system has four layers: (1) a data layer collecting occupancy, GPS, ticketing, weather and event data; (2) a prediction layer with a BiLSTM forecaster, a gradient-boosting model and an ensemble combiner; (3) a recommendation layer that scores routes by time, waiting, transfers and predicted crowding; and (4) an interface layer for passengers and operators, designed around the informative-alert preference found in the primary survey (Section 2.4).

Evaluation Metrics

Prediction quality is measured by Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and R^2 . For crowding levels, accuracy, precision, recall and F1 are also used. Recommendation quality is measured by average crowding experienced, average waiting time, share of passengers shifted to less crowded options, and latency of the response. In addition, following the survey findings on adoption, user-facing evaluation should include a follow-up trust and satisfaction survey after a pilot deployment. Evaluation should use time-based splits, training on earlier periods and testing on later ones, and should separately report results on peak hours, holidays and event days.

Comparison Design

Table 3: Proposed model comparison and evaluation measures

Model	MAE	RMSE	R^2	Inference time
Historical average	to be measured	to be measured	to be measured	to be measured
ARIMA	to be measured	to be measured	to be measured	to be measured
Random Forest	to be measured	to be measured	to be measured	to be measured
XGBoost	to be measured	to be measured	to be measured	to be measured
LSTM	to be measured	to be measured	to be measured	to be measured
BiLSTM (proposed)	to be measured	to be measured	to be measured	to be measured
BiLSTM + XGBoost ensemble	to be measured	to be measured	to be measured	to be measured

Note: the table is a template. The values must be filled from the experiments actually carried out on the chosen dataset.

XI. CONCLUSION

AI-based crowding prediction turns public transport from a fixed, reactive service into one that anticipates demand. The primary survey conducted for this study (N = 123) confirms that overcrowding is a

frequent, behaviour-changing problem for real passengers, that they currently lack good tools for choosing less crowded routes, and that their trust in an automated system is not automatic, particularly for route recommendation rather than simple crowd information. This makes the design choices in this paper — multi-objective scoring, informative rather than purely prescriptive output, and explainability — directly evidence-based rather than assumptions.

Time, history, network, weather and live operational features give models the information they need, and recurrent networks such as BiLSTM, tree ensembles such as Random Forest and XGBoost, and hybrids of these provide strong forecasting performance in the literature. Predicted crowding can then be used as a cost in route recommendation, helping passengers choose less crowded and faster options while helping operators place capacity where it is needed.

The most important challenge is real-world reliability and adoption. Unusual events, new routes, sensor failures, privacy concerns, passenger behaviour and, as the survey shows, passenger trust can all reduce the real-world value of a technically accurate system. A fast-slow architecture with cached forecasts, confidence reporting, fallback handling and clear, explainable output is a practical way to balance speed, accuracy, robustness and adoption.

Future work should focus on realistic and time-aware datasets, a larger and more representative passenger survey, continual adaptation, explainability, behaviour-aware recommendation and privacy-preserving data collection. The goal is not simply a model with a low error score, but a passenger-information system that stays useful, trusted and used when demand changes.

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