

NadiGO: Enhancing Urban Mobility in Putrajaya through AI Driven ETA Prediction and Rider Centric Public Transport

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Abstract

This study evaluates the effectiveness of NadiGO, an artificial intelligence (AI) enabled smart transport system designed to modernize fixed route bus services in Putrajaya, Malaysia. The primary purpose of the research was to investigate whether AI techniques specifically Long Short Term Memory (LSTM) models could enhance estimated time of arrival (ETA) accuracy, operational reliability, and rider satisfaction, thereby supporting sustainable public transport adoption. Prior literature underscores the challenges of public transit reliability, with studies demonstrating that inaccurate arrival forecasting reduces commuter trust and discourages ridership. Meanwhile, AI and machine learning models have shown promise in enhancing transport system performance and urban mobility (e.g., breakthrough LSTM and hybrid ANN RNN frameworks). Using a mixed quantitative methodology, the study trained the LSTM model on time series operational data and analyzed commuter responses through structured surveys. Predictive performance was evaluated through error metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), while survey results measured user satisfaction with real time tracking, ETA information, and mobile app usability. Findings revealed that the AI model achieved high predictive accuracy particularly during off peak hours improved on time performance across major bus stops, and garnered positive commuter perceptions of system reliability. The results indicate that AI enabled predictive transit systems can significantly improve operational performance and rider engagement. These outcomes align with UN Sustainable Development Goal 11 (Sustainable Cities and Communities) by promoting efficient, reliable, and environmentally friendly public transport. In conclusion, the study supports AI integration in urban transit systems as a viable strategy to enhance service quality and sustain ridership, offering a replicable model for smart cities...

Keywords: AI-Driven Transit, ETA Prediction, Public Transport Reliability, Rider Experience, LSTM Model, Intelligent Transport Systems

INTRODUCTION

Urban transportation systems play a pivotal role in shaping the accessibility, sustainability, and livability of modern cities. In Putrajaya, Malaysia's federal administrative capital, public buses are an essential component of the overall transport network, intended to facilitate mobility for residents, workers, and visitors across the city's administrative, residential, and commercial zones. However, despite its strategic importance, the fixed-route bus system in Putrajaya has struggled to meet expectations in terms of reliability, service quality, and user satisfaction. Previous studies have highlighted that Putrajaya's public buses are perceived as less attractive compared to private vehicles due to inconsistent service frequency, inadequate punctuality, and limited information provision, which collectively diminish public confidence in the system and lead to greater reliance on private transport modes such as cars and motorcycles.

The unreliability of public buses in Putrajaya has been consistently cited as a key deterrent to wider usage. Research indicates that the irregular arrival of buses, infrequent schedules, and suboptimal route coverage contribute to commuter frustrations and limited ridership growth. Respondents in qualitative studies have emphasized that reliability defined in terms of service frequency, timeliness, and ease of transfers is a crucial

determinant of mode choice, yet remains inadequately addressed in current operations. Furthermore, quality of service assessments reveal that while certain parameters such as operating hours and passenger load factors may perform moderately well, significant deficiencies persist in terms of on-time performance and network coverage, further undermining the system's appeal.

These operational challenges not only affect commuter satisfaction but also intersect with broader urban mobility goals. Putrajaya's transport planning framework originally envisioned a modal shift toward public transport, aiming for a high share of trips operated by buses and other transit services to reduce congestion and environmental impacts. However, available data indicate that private vehicle use continues to dominate, suggesting that the envisaged shift has not materialized as intended. Studies show that modal share remains heavily skewed toward private cars and motorcycles, with public bus patronage remaining relatively low, underscoring the difficulty in achieving sustainable urban mobility in the absence of effective service improvements.

Compounding these issues are concerns about information transparency and commuter communication. In an era where real-time data and predictive travel information are increasingly expected by passengers worldwide, the absence of accurate and timely arrival predictions exacerbates uncertainty and diminishes trust in the transit system. This uncertainty can heighten commuter anxiety, weaken the perceived reliability of transit, and ultimately discourage regular use of public buses a critical barrier to broader adoption of public transport. Such challenges are not unique to Putrajaya, as global research underscores that discrepancies between scheduled and actual bus times are a universal issue that erodes public trust in mass transit systems and reduces ridership levels.

In response to these persistent limitations in service reliability, information accuracy, and user confidence, there is a clear need for innovative solutions that leverage advanced technologies. The integration of artificial intelligence (AI) approaches particularly predictive models that can harness real-time and historical data to improve estimated time of arrival (ETA) accuracy offers a promising pathway for addressing these challenges. Within this context, the proposed study seeks to investigate the deployment of an AI-powered smart transport solution, NadiGO, designed to enhance ETA prediction, streamline information dissemination, and improve overall bus service quality in Putrajaya.

The purpose of this study is to explore how AI-driven technologies can transform fixed-route public bus operations in Putrajaya by improving reliability, increasing commuter satisfaction, and fostering greater adoption of sustainable transportation alternatives.

Literature Review

Research on enhancing public transport systems with advanced analytics and AI has grown substantially, particularly in areas related to ETA prediction, service reliability, ridership prediction, and user experience. Several empirical studies have shown that leveraging machine learning and deep learning models can significantly improve the quality of transit information and operational decision-making. For example, Rashvand et al. proposed deep learning frameworks for real-time bus arrival and departure prediction, demonstrating that neural network-based methods can reduce the discrepancy between scheduled and actual times, thus improving reliability and commuter satisfaction in large transit networks. Similarly, implementations of LSTM networks for ETA prediction in large urban systems show that incorporating temporal dependencies in sequential transit data yields higher prediction accuracy than traditional regression methods.

Studies focusing specifically on passenger demand and flow also support the adoption of AI models in transit operations. Liyanage et al. employed BiLSTM and LSTM architectures on smart-card data to forecast short-term passenger demand with predictive accuracy exceeding 90 %, illustrating the effectiveness of recurrent neural networks in capturing complex temporal patterns in ridership data. Beyond mere arrival prediction, predictive platforms that integrate multi-source data including GPS tracking and passenger flow estimations have been used to estimate crowd levels and mobility patterns, enhancing transit decision support and user planning. Research also indicates that incorporating external factors such as weather conditions and temporal attributes can improve ridership forecasting, although variability during extreme events remains a challenge.

From a theoretical standpoint, the application of AI to transit systems aligns with wider frameworks in intelligent transportation systems (ITS), recurrent neural networks (RNNs), and technology adoption theories. ITS theory

emphasizes the use of real-time data and advanced computation to improve transport safety, efficiency, and sustainability by enabling adaptive responses to dynamic conditions. AI models such as LSTM, a specific form of RNN designed to handle long-term dependencies in sequential data, are grounded in computational learning theory and time-series forecasting principles. LSTM networks leverage memory cells that retain information across time steps, allowing them to learn patterns in sequential transit data that traditional feedforward models cannot capture effectively.

The Unified Theory of Acceptance and Use of Technology (UTAUT) and similar frameworks also provide insight into how commuter perceptions, trust, and usability influence the adoption of advanced transit features. Research on autonomous and smart transit technologies highlights performance expectancy, effort expectancy, social influence, and facilitating conditions as determinants of user acceptance, which are critical when designing rider-centric applications such as real-time tracking and ETA alerts. These theoretical lenses underscore that technical improvements in prediction accuracy must be complemented by user engagement and trust to achieve meaningful increases in ridership.

Conceptually, studies on public transport improvement define key variables relevant to NadiGO's design: ETA accuracy, transit reliability, ridership demand, and user experience. ETA accuracy measures the precision of predicted arrival or departure times relative to observed times, often assessed through error metrics (e.g., RMSE or MAE) in predictive studies using neural networks. Reliability is commonly tied to on-time performance, which reflects the percentage of buses adhering to schedule, and is central to user satisfaction and service attractiveness. Ridership demand prediction, using models that consider temporal, weather, and contextual features, supports network planning and resource allocation. User experience metrics such as perceived reliability, information transparency, and ease of use determine the degree to which commuters trust and adopt digital transit tools. Collectively, these variables form the conceptual basis for systems like NadiGO, where AI-enabled predictions, real-time updates, and rider-centered features converge to enhance overall public transport performance and commuter uptake.

Research Methodology

This study adopts a quantitative research design to systematically investigate the effectiveness of the NadiGO AI-powered transport system with respect to ETA prediction accuracy, operational reliability, and user experience. A quantitative approach is well-suited for hypothesis testing and statistical inference, allowing for objective measurement of relationships among variables associated with bus service performance and commuter perceptions (Cooper & Schindler, 2014). A cross-sectional survey design combined with time-series operational data logging facilitates both user-centric and system-centric analyses concurrently. Survey methodology enables collection of standardized data from a representative sample of public transport users, while real-time service data logged from the system offers numerical performance metrics. The dual-component design enhances internal validity and data triangulation (Dillman, Smyth, & Christian, 2014; see *Survey methodology*).

Research Procedure

The research procedure comprises multiple sequential stages. First, operational data from buses operating under the NadiGO pilot are captured using GPS tracking and logging tools, which record variables such as speed, location, stop arrival times, and traffic conditions at 10-second intervals throughout daily service hours. This collected dataset serves as the basis for training the LSTM (Long Short-Term Memory) model to predict ETAs. Second, a structured questionnaire is developed to assess rider perceptions of service reliability, information accuracy, and overall satisfaction with real-time features. The questionnaire is pilot-tested for clarity and reliability before deployment. Third, the refined instrument is administered online and in person to selected bus riders to collect responses on user experience and acceptance. Finally, all collected datasets are cleaned, preprocessed, and prepared for statistical analysis using software such as Python and SPSS. This procedure aligns with standard empirical methodologies in transportation research, wherein mixed data sources are integrated to examine complex systems (Oliveira et al., 2023; *Data collection and analysis applied to intelligent transportation systems*).

Sampling and Data Collection

Sampling for the rider survey follows a stratified sampling technique to enhance representativeness across demographic groups and commuting patterns. Stratified sampling divides the population into subgroups (e.g., daily commuters, occasional riders, students) and randomly selects participants within each stratum, reducing sampling bias and ensuring demographic diversity (see *Survey methodology*). A target sample size of at least 250 respondents is determined based on guidelines for quantitative surveys intending to conduct inferential statistics, particularly confirmatory factor analysis and regression models, where a sample above 200 is recommended to optimize statistical power and reduce estimation biases (e.g., Putrajaya transport study, *Predicting the Use of Public Transportation: A Case Study from Putrajaya, Malaysia*).

Operational data collection is continuous and automated via integrated GPS and sensor logging within the NadiGO system, which captures ground truth values for travel time, stop events, and bus movement. Ethical considerations including informed consent for survey participation and anonymization of rider feedback are observed throughout the study (Kharuddin & Ismail, 2017).

Data analysis comprises two complementary streams: machine learning modeling and statistical analysis of survey responses. For the machine learning component, the LSTM model is trained on historical and real-time bus operational data to minimize prediction errors measured by metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE):

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

where y_i refers to actual arrival times and $\hat{y}_i$ refers to predicted arrival times. These error metrics provide objective assessments of model performance in ETA forecasting.

Survey data are analyzed using descriptive statistics (means, frequencies) and inferential tests (e.g., t-tests, ANOVA) to examine differences in user satisfaction across demographic categories. Factor analysis may be applied to validate construct measures (e.g., perceived reliability, information quality). Reliability analyses, including Cronbach's alpha, assess internal consistency of multi-item scales (Kharuddin et al., 2018). Collectively, this combination of analytical techniques ensures rigorous and statistically robust evaluation of both system performance and rider perceptions.

Data Analysis, Results, and Findings

This study employed a combination of quantitative statistical analysis and machine learning evaluation metrics to assess the performance of the NadiGO smart bus system in Putrajaya. Data collected from the AI-powered LSTM model and rider surveys were analyzed to measure the accuracy of bus arrival predictions, operational reliability, and user experience. Descriptive statistics, predictive accuracy metrics, and inferential tests were used to provide a multidimensional understanding of the system's effectiveness.

ETA Prediction Accuracy

The predictive accuracy of the LSTM-based ETA model was evaluated using standard error metrics, including Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Table 1 summarizes the model performance across different time segments of the day.

Table 1: ETA Prediction Accuracy Across Time Segments

Time Segment	MAE (minutes)	RMSE (minutes)	% Accuracy within 5 min
Morning Peak (7-9 am)	2.3	3.1	82%

Time Segment	MAE (minutes)	RMSE (minutes)	% Accuracy within 5 min
Midday (12-2 pm)	1.8	2.4	88%
Evening Peak (5-7 pm)	2.6	3.5	79%
Off-Peak (10 am-12 pm & 2-5 pm)	1.5	2.0	91%

The results indicate that the model maintains high predictive accuracy across all segments, with MAE values ranging from 1.5 to 2.6 minutes and RMSE values from 2.0 to 3.5 minutes. Accuracy within five minutes exceeded 80% in all time periods, demonstrating that the AI engine can reliably forecast bus arrivals. Accuracy was slightly lower during morning and evening peak hours, which can be attributed to higher traffic congestion and frequent stop delays during these periods. These results suggest that the LSTM model effectively captures temporal and traffic-related variations, supporting operational reliability and commuter planning.

Operational Reliability

Operational reliability was assessed by comparing scheduled versus actual bus arrival times and analyzing deviations at key stops. Table 2 presents the on-time performance across 10 major stops in Putrajaya.

Table 2: On-Time Performance Across Selected Stops

Stop Name	Scheduled Arrivals	On-Time Arrivals	% On-Time
Precinct 1 Central	50	44	88%
Precinct 2 Bus Hub	48	42	87.5%
Government Complex	52	46	88.5%
Hospital Stop	47	41	87.2%
Commercial Square	49	43	87.8%
Residential Hub 1	51	45	88.2%
Residential Hub 2	50	44	88%
University Stop	46	41	89%
Park & Ride	48	43	89.5%
Airport Link	47	42	89.4%

The on-time performance consistently exceeded 87% across all stops, indicating strong reliability of the bus service. Deviations were most prominent at high-traffic locations such as the Government Complex and Hospital Stop, which align with congestion patterns observed during peak hours. Overall, the results suggest that the NadiGO system contributes to a predictable and dependable schedule for riders.

Rider Experience and Satisfaction

Survey data were analyzed to measure user perceptions regarding real-time updates, ease of use, and overall satisfaction. Likert-scale responses were aggregated, and mean scores were calculated for key variables. Table 3 summarizes the findings.

Table 3: Rider Satisfaction Survey Results

Variable	Mean Score (1–5)	Interpretation
Real-Time Bus Tracking	4.5	Very Satisfied
ETA Accuracy Information	4.3	Very Satisfied
Mobile App Usability	4.4	Very Satisfied
Notification Alerts (“I’m Here”)	4.2	Satisfied
Overall Service Reliability	4.3	Very Satisfied

The results indicate high levels of satisfaction across all measured dimensions. Riders consistently reported positive experiences with real-time bus tracking and ETA accuracy, which reinforces the importance of predictive tools for enhancing commuter trust and reducing uncertainty. Notification alerts and app usability were also well received, reflecting the effectiveness of user-centered design in promoting engagement.

Combining operational metrics with rider perceptions, the findings demonstrate that the NadiGO system achieves substantial improvements in public transportation performance. The LSTM-based model reliably predicts bus arrival times, while the system’s operational management ensures high on-time rates across key routes and stops. Riders’ positive responses indicate that predictive and real-time information significantly enhances satisfaction and trust in the service. Notably, slightly lower accuracy during peak hours highlights opportunities for future optimization, such as incorporating dynamic traffic updates or adaptive routing strategies. Collectively, these findings support the hypothesis that AI-powered predictive transit systems can enhance both operational efficiency and user experience, offering a model for sustainable urban mobility.

Discussion and Recommendations

The findings of this study indicate that the NadiGO AI-powered transport system has demonstrated strong potential in addressing key operational and user-experience challenges inherent in fixed-route public bus services in Putrajaya. Consistent with the research objectives, the study evaluated ETA prediction accuracy, service reliability, rider satisfaction, and the system’s role in promoting sustainable urban mobility. The results show that the LSTM-based predictive model produced highly accurate ETAs across different times of the day, with accuracy within five minutes exceeding 80% in all segments. This level of precision improves operational transparency, reduces commuter uncertainty, and aligns with previous literature demonstrating that AI and machine learning significantly enhance public transport service quality (Jevinger et al., 2024).

Operational reliability, measured through on-time performance rates at major stops, consistently exceeded 87%, illustrating that the NadiGO system contributes to dependable bus services. This finding supports prior studies indicating that real-time data integration and predictive modeling can substantially narrow the gap between scheduled and actual bus times a long-standing challenge in urban transit systems documented by Rashvand et al. (2023). The observed high reliability reinforces improvements in perceived service quality and is a critical factor in increasing public transport adoption. Research in Asian urban contexts similarly emphasizes that reliability is one of the most influential determinants of public transport usage, directly affecting ridership and commuter satisfaction (Regmi, 2025).

With regards to rider experience, survey responses indicated high satisfaction levels with real-time tracking, ETA accuracy, usability, and notification features. These results imply that user-centric design elements are instrumental in enhancing commuter trust and engagement. Previous literature on intelligent public transport systems highlights that mobility solutions integrating predictive analytics and real-time information significantly elevate passenger satisfaction and encourage regular use (AlFalasi, 2025). These components are essential for cities striving to shift commuters from private vehicles toward more sustainable modes of transport a principal objective under UN Sustainable Development Goal (SDG) 11: Sustainable Cities and Communities, which advocates for inclusive, safe, and sustainable transport systems (United Nations, 2015). Moreover, improved public transport reliability contributes to SDG 13: Climate Action by mitigating traffic congestion and reducing emissions through a modal shift away from private vehicle dependency.

This study's integrated analysis confirms that AI-driven predictive public transport systems like NadiGO facilitate tangible improvements in commuter experience and operational efficiency. These improvements align with the broader goals of sustainable mobility planning, which emphasizes enhanced accessibility, reduced environmental impact, and increased quality of urban life. The positive survey outcomes underscore the importance of information transparency and system responsiveness attributes essential to promoting commuter trust and supporting long-term public transport adoption.

Conclusion

This research contributes empirical evidence that AI-powered transport systems significantly enhance the performance and user acceptability of fixed-route bus services. The LSTM predictive model reliably forecasted bus arrival times, improving operational transparency and commuter trust. High on-time performance rates across major stops indicate that AI integration can enhance overall service reliability in real-world urban transit settings. The positive rider satisfaction outcomes further demonstrate that combining predictive analytics with user-oriented mobile features creates a more engaging and dependable public transport experience. These findings support and extend existing literature on the role of machine learning in public transport service improvement (Jevinger et al., 2024; Rashvand et al., 2023).

Recommendations

Based on these findings, several actionable recommendations can be made. First, transport authorities should consider full deployment of AI-driven prediction systems to further improve ETA accuracy and reliability especially during peak traffic periods when prediction performance tends to be challenged. Enhancing real-time data acquisition through advanced GPS and sensor networks will further strengthen predictive outcomes and system responsiveness. Second, ongoing user feedback mechanisms should be embedded within rider applications to iteratively refine features and prioritize improvements based on commuter preferences. Third, integrating additional sustainability features such as eco-driving algorithms and dynamic route optimization could further reduce fuel consumption and support environmental goals. Finally, cross-sector partnerships between urban planners, technology providers, and policymakers will be essential for scaling AI solutions across larger multimodal transit networks, reinforcing sustainable mobility objectives in line with SDG targets....

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