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Artificial Intelligence-Based Intelligent Navigation System for Alleviating Traffic Congestion: A Case Study in Batam City, Indonesia

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ABSTRACT

Traffic congestion is a major issue faced by Batam, a city that continues to grow rapidly as an economic and logistics hub. This study adopts the Design Science Research Methodology (DSRM) to develop an intelligent navigation system based on artificial intelligence (AI) aimed at optimizing urban traffic management in Batam. The system integrates real-time traffic data, machine learning algorithms, and reinforcement learning to predict traffic flow and optimize route selection. Using the DSRM framework, the system was designed, implemented, and evaluated iteratively to ensure its effectiveness in addressing the city's unique traffic challenges. The results of the study indicate that the implementation of the AI-based navigation system successfully reduced the average travel time by 22.8%, distributed traffic loads more evenly, and improved travel efficiency. Furthermore, the system demonstrated a route prediction accuracy of 91.3%, higher than conventional GPS systems. Performance evaluation also showed high responsiveness, with an average latency of only 423 milliseconds. This study concludes that the AI-based navigation system, developed through the DSRM framework, can be an effective solution to address traffic congestion in rapidly developing cities like Batam and can be applied to other cities with similar characteristics.

1. INTRODUCTION

Rapid population growth and uncontrollable urbanization have become a global phenomenon that significantly impacts transportation management in urban areas. Many cities around the world, both metropolitan and medium-sized cities that are rapidly developing, are facing increasingly complex traffic congestion challenges [1-3]. This congestion not only causes discomfort for road users but also negatively affects various aspects of life, such as increased travel time, excessive fuel consumption, rising carbon emissions, and reduced economic productivity due to delays in the mobility of people and goods [4, 5]. In the global context, the World Health Organization (WHO) and the United Nations Human Settlements Programme (UN-Habitat) have highlighted that dense urban traffic contributes significantly to air pollution and a decline in the quality of life for citizens [6, 7]. Major cities around the world, such as Jakarta, Manila, Bangkok, and Mumbai, serve as real-life examples of how population pressure and the growth of motor vehicles can exceed the capacity of existing infrastructure, resulting in mobility stagnation. To address this, many countries have developed Intelligent Transportation Systems (ITS), which are technology and information-based transportation systems aimed at improving traffic efficiency and safety [8].

In Indonesia, traffic congestion issues are not only prevalent in large cities like Jakarta, Surabaya, and Bandung but are also increasingly being felt in medium-sized cities that are growing economically, one of which is Batam. Batam is a strategic area located directly at the border with Singapore and Malaysia and is part of a special economic zone promoted by the Indonesian government [9]. The growth of industry, trade, and tourism in Batam has led to a surge in population and vehicle numbers over the past few decades. According to data from the Central Statistics Agency (BPS) and the Batam City Transportation Department, the growth of motor vehicles in Batam has increased by more than 8% per year, mostly dominated by private vehicles such as motorcycles and cars [10, 11]. The increase in vehicle volume is not accompanied by an adequate increase in road capacity [12, 13]. Major roads in Batam, such as Jalan Sudirman, Jalan Yos Sudarso, and Jalan Ahmad Yani, often experience traffic congestion, especially during peak hours in the morning and evening [14, 15]. This phenomenon indicates an imbalance between the demand and the available transportation service capacity. Additionally, the uneven distribution of residential and industrial areas further complicates traffic movement patterns in the city [16]. This congestion not only hampers public productivity but also increases the risk of traffic accidents and air pollution [17].

The Batam City Government's efforts in managing traffic still largely rely on traditional approaches, such as static traffic light timing, the construction of alternative roads, and the implementation of road signs and markings to control road user behavior [18]. While these approaches are important and fundamental, they have proven to be insufficiently responsive in addressing the highly fluctuating traffic dynamics in the modern era. Limitations in real-time traffic monitoring systems and the suboptimal integration of traffic data from various sources make decision-making slow and less adaptive [19].

GPS-based navigation systems commonly used by drivers mostly rely on conventional route-finding algorithms that do not consider real-time traffic conditions [20]. As a result, road users are often directed to shorter routes that are heavily congested, thereby reducing the effectiveness of navigation [21]. This highlights the need for a transformation towards a more intelligent, adaptive, and data-driven system to support more efficient traffic management [22, 23].

Artificial Intelligence (AI) has become one of the key technologies in the development of Smart Cities, including in the field of transportation [24, 25]. With its ability to analyze large amounts of data, learn patterns, and make decisions automatically and adaptively, AI offers great potential to be applied in modern transportation systems. In the context of traffic, machine learning algorithms and reinforcement learning have been used for traffic flow prediction, signal timing optimization, and the selection of the fastest routes based on real-time data [26, 27]. The use of Design Science Research Methodology (DSRM) in this domain allows for a structured approach in the design, development, and evaluation of AI-based solutions. Through iterative cycles of artifact design and evaluation, DSRM ensures that the AI systems developed are not only effective but also relevant to the specific challenges of urban traffic management. By leveraging DSRM, this research aims to create an adaptive, data-driven navigation system that can optimize traffic management in Smart Cities like Batam.

AI-based navigation systems offer advantages over conventional approaches as they can learn from previous traffic patterns and dynamically respond to changes in traffic conditions. For example, if an accident or obstruction occurs on a certain road, the system can immediately redirect drivers to alternative routes that are less congested. In various developed countries, these systems have been integrated with traffic sensors, CCTV cameras, and user application data to create a connected and adaptive transportation ecosystem [28, 29]. Although the implementation of AI-based intelligent navigation systems has developed rapidly in large cities with advanced technological infrastructure, there remains a significant gap in the application of this technology in developing cities like Batam. Most existing studies and developments are designed for large cities with extensive data access, complex sensor networks, and high computational resources. In fact, medium-sized cities also face the same urgent needs to optimize traffic, albeit with limited infrastructure and data [30].

Batam, with its unique characteristics, requires a tailored approach and cannot simply adopt systems used in advanced cities [31-33]. This approach must consider differing road conditions, uneven vehicle distribution, and the limitations of integration between transportation information systems. Local innovation is crucial in designing navigation systems that can work effectively with limited resources while still leveraging the power of AI technology [34, 35].

2. LITERATURE REVIEW

Urban traffic congestion is a complex issue that requires a multifaceted approach and the utilization of advanced technology [36]. This problem not only involves inefficient traffic management but also significant economic and social impacts, such as long travel times, air pollution, and increased fuel consumption. Various studies in the fields of transportation engineering, urban planning, and artificial intelligence (AI)-based systems have shown that traditional solutions are insufficient to address these challenges. Therefore, the integration of AI into traffic management systems emerges as a more efficient, adaptive, and responsive solution to the ever-changing dynamics of traffic [37].

2.1 The role of AI in traffic management

Artificial Intelligence has leveraged machine learning (ML) and deep learning algorithms to analyze large-scale transportation data, recognize traffic patterns, and provide accurate predictions. Various approaches have been applied to manage and predict traffic flow more efficiently. One significant early study was conducted by Luo et al. [38], who used support vector machines (SVM) to model urban traffic flow predictions. The results of this model showed that SVM could be used to predict traffic flow with a reasonably good level of accuracy, although it was still limited to relatively simple data [39].

However, further advancements in AI applications for traffic have shifted towards deep learning techniques, particularly the use of recurrent neural networks (RNNs) and the Long Short-Term Memory (LSTM) variant for time-series-based predictions. These techniques, developed by Shang et al. [40], are highly effective in handling temporal dependencies in traffic data, such as dynamically changing vehicle densities over time. The use of these techniques has become increasingly popular due to their ability to learn recurring patterns within the data, which is highly beneficial in the context of highly dynamic traffic conditions.

In parallel, reinforcement learning (RL) algorithms have also been applied extensively to optimize traffic signal control and vehicle routing. RL is a type of machine learning where an agent learns to make decisions by interacting with its environment and receiving feedback in the form of rewards or penalties. One well-known application of RL in traffic management is its use in optimizing traffic light control. Shang et al. [40] developed a deep reinforcement learning (DRL) framework that adjusts traffic light timings based on real-time detected vehicle density. This approach dynamically adapts the signal phases to match traffic conditions, reducing congestion and improving the flow of traffic at key intersections. By continuously learning from traffic data, the RL algorithm can determine the most efficient signal timings, which leads to reduced waiting times at intersections and a smoother overall traffic flow.

Furthermore, RL has been successfully implemented in vehicle routing. For instance, RL can be used to suggest optimal routes for drivers based on current traffic conditions, accidents, or road closures. The system continuously learns from the traffic dynamics, making real-time route recommendations that minimize travel time and reduce congestion. A popular approach involves the use of Q-learning, a reinforcement learning algorithm that helps optimize routes by evaluating the "quality" of each route option in a dynamic environment.

The benefits of implementing RL in real-world traffic systems are substantial. It offers adaptability by allowing the system to continuously improve and adjust based on changing traffic conditions. It can provide more responsive and efficient traffic management compared to traditional, fixed systems like static traffic light timings or pre-defined route maps. However, there are several challenges in implementing RL in real-world settings. Computational resources and data quality can be limiting factors, as RL algorithms require significant computational power and large datasets to train effectively. Moreover, the complexity of the traffic environment—with numerous variables such as unpredictable driver behavior, weather conditions, and varying traffic patterns—can make the application of RL algorithms challenging. Despite these challenges, the potential for RL to transform urban traffic management is immense, offering a more adaptive and efficient system for congestion reduction.

2.2 Navigation system and route optimization

Traditional GPS-based navigation systems, although effective in providing alternative routes, are often hindered by their inability to adjust routes in real-time to the continuously changing traffic conditions. These systems rely on static maps and heuristic-based routing methods that cannot adapt well to sudden traffic congestion. Therefore, various modern intelligent navigation systems integrate real-time data and adaptive algorithms to provide more effective route suggestions [41].

One of the widely used techniques for route optimization is Dijkstra's algorithm, which remains a reliable method for finding the shortest path. However, in the context of constantly changing traffic, this algorithm needs to be combined with heuristics that account for traffic congestion levels. Bernabei and Secchi [42] suggested that for real-time navigation, Dijkstra's algorithm can be modified to incorporate traffic-aware heuristics, allowing the system to respond to changes in traffic flow more quickly and accurately.

Furthermore, in the study [43], a hybrid model was developed that combines historical data with real-time feedback to update route recommendations in response to fluctuations in road conditions. This model not only reduces travel time but also enhances the user experience. This concept has become increasingly important as navigation systems in most large cities already use real-time data to respond to traffic changes. However, medium-sized cities like Batam often lag behind in the application of this technology.

2.3 Concept of smart cities and urban mobility

The development of smart cities is a broader concept than just transportation technology. Smart cities focus on the use of information and communication technology (ICT) to improve the efficiency of urban services, one of which is the transportation system. Smart mobility is one of the main pillars of this concept, involving the use of analytics, the Internet of Things (IoT), and AI to enhance the efficiency, safety, and sustainability of urban transportation systems [44].

In recent years, several major cities worldwide have successfully implemented AI-based traffic systems as part of their smart city initiatives. Singapore, for example, has developed an AI-driven traffic management system that integrates real-time data from sensors and cameras with predictive analytics. This system optimizes traffic light timings, adjusts the flow of vehicles, and helps alleviate congestion. One notable example is the Smart Traffic Management System used in Singapore's Central Business District (CBD), which has significantly reduced traffic delays and improved the flow of vehicles during peak hours. Moreover, it has been shown to reduce fuel consumption and air pollution by minimizing idling times at traffic signals [45].

Similarly, Barcelona has adopted a smart mobility approach where AI-based systems are integrated with urban infrastructure to monitor traffic flow, provide real-time information to drivers, and suggest the best routes to avoid congestion. The city uses AI-powered sensors to detect congestion patterns and adjust traffic light timings accordingly. These innovations have led to a 20% reduction in travel time in highly congested areas, and Barcelona's smart city initiative has also resulted in a 15% decrease in carbon emissions by optimizing vehicle movement and reducing idle times [45]. Furthermore, these systems have enhanced safety by reducing the likelihood of traffic accidents through real-time alerts and adaptive signal adjustments.

These examples demonstrate the power of AI in optimizing traffic flow, improving safety, and contributing to sustainability goals by reducing traffic congestion and lowering emissions. The integration of AI into urban transportation systems not only makes cities more efficient but also significantly improves the quality of life by providing smoother commutes, cleaner air, and safer roads.

However, the implementation of these smart systems in developing cities, including those in Indonesia, faces distinct challenges. These include incomplete data availability, inadequate infrastructure, and limitations in collaboration among stakeholders. In Indonesia, particularly in Batam, the research and development of AI-based navigation systems for traffic management is still relatively limited, with most studies being focused on large cities or capital cities with more advanced infrastructure and resources. Therefore, the development of an intelligent navigation system tailored to local conditions, such as the one developed in this study, holds high strategic value. This system could help Batam and other medium-sized cities improve their traffic management and urban mobility, aligning them with the global trend toward smart cities [43, 46].

2.4 Research gaps

Existing research has made significant contributions to the development of AI-based traffic prediction systems and route optimization. However, the majority of these studies focus on large cities with sufficient infrastructure and budgets. Meanwhile, medium-sized cities like Batam, which are experiencing rapid urbanization, often do not receive enough attention in similar research. The existing AI-based traffic management systems are not adaptive enough for cities with unique characteristics such as Batam, which has more limited infrastructure and data that is not always complete, as illustrated in Figure 1.

Moreover, although many AI-based navigation systems have been successfully implemented in large cities, there is still a lack of research developing systems that can integrate real-time traffic predictions with navigation interfaces that respond to changing traffic conditions. This study aims to fill this gap by designing an AI-based intelligent navigation system that provides solutions for traffic problems in Batam. This system not only utilizes machine learning for traffic prediction but also integrates real-time data to respond to continuously changing traffic conditions.

3. METHODOLOGY

This study adopts a hybrid methodology that combines Design Science Research Methodology (DSRM) and a case study approach to develop and evaluate an AI-based intelligent navigation system specifically designed for Alleviating Traffic Congestion in Batam City, Indonesia. DSRM provides a structured framework for the design and evaluation of artifacts, while the case study ensures contextual relevance and practical validation. The proposed system utilizes Graph Neural Networks (GNNs) algorithms for dynamic route optimization and is evaluated using real-world traffic datasets [47].

3.1 Research design

This study uses an experimental quantitative method with an approach based on the design of intelligent systems using artificial intelligence (AI). The focus of the research is the development and evaluation of an AI-based navigation system to optimize traffic in urban areas, particularly in Batam City.

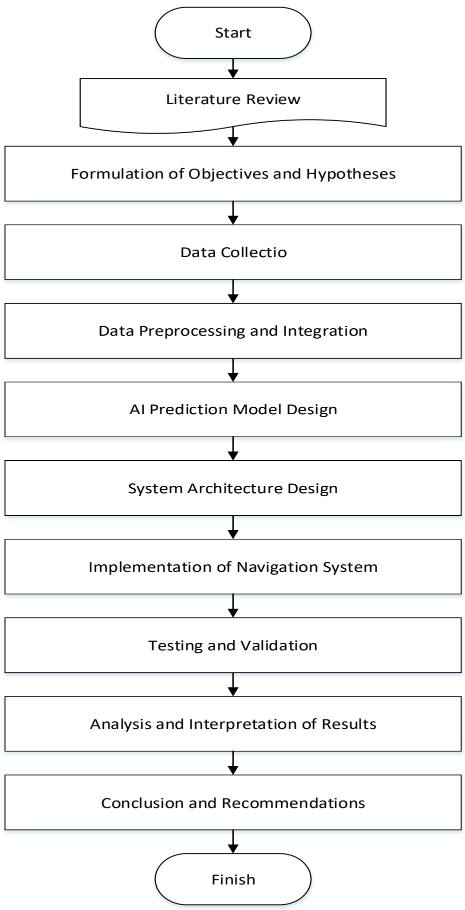

Figure 1. Research methodology flow

3.2 Data collection and processing

Traffic data is collected from various sources, including historical data from the Batam City Transportation Department, traffic sensors, vehicle GPS data, and public APIs from digital mapping services (e.g., Google Maps or OpenStreetMap). The collected data includes information such as vehicle density, average speed, travel time, and traffic incidents.

This data is then processed and cleaned (data preprocessing), including steps such as normalization, outlier removal, and transformation of time and location formats into a suitable format for training the AI-based predictive model.

3.3 AI model development

The artificial intelligence model used in this study consists of two main components: the traffic prediction model and the route optimization system.

1. Traffic Prediction: To predict traffic density and travel time, a machine learning approach based on Recurrent Neural Networks (RNN), specifically the Long Short-Term Memory (LSTM) architecture, is used. LSTM is chosen for its ability to understand temporal dependencies in time series data, such as daily traffic fluctuations.
2. Route Optimization (Reinforcement Learning (Q-Learning)): To address the complexity of dynamically selecting optimal routes in urban traffic environments, this study implements a Reinforcement Learning (RL) approach, specifically the Q-Learning algorithm. This approach is selected for its ability to learn from continuous interactions with the environment and make adaptive decisions based on previous experiences.

3.4 Design of the navigation system structure

The design of the navigation system structure is the foundational element in building an integrated AI-based traffic prediction system. The diagram above illustrates the system architecture, which consists of several interconnected components that function synergistically. The process begins with the user interface (User Interface), either through a mobile app or web, which serves as the main point of interaction for users to access navigation services in Figure 2.

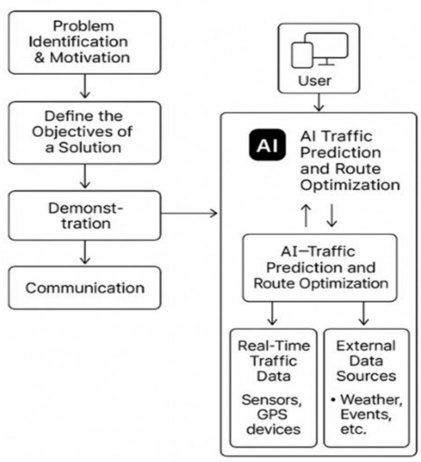

Figure 2. Navigation model structure design

3.5 System implementation and testing

The system is implemented as a prototype application based on web and/or mobile platforms. The system architecture consists of three main layers:

1. Data Collection Layer: Accesses and updates traffic data in real-time.
2. AI Processing Layer: Performs traffic predictions and calculates optimal routes.
3. User Interface Layer: Displays route recommendations to end users (drivers or traffic operators).

The development platform used includes Python for the AI backend and TensorFlow/Keras for machine learning model training, as well as Node.js or Flutter for user interface development.

3.6 System evaluation

The evaluation is conducted in two stages:

1. Prediction Model Evaluation: The performance of the traffic prediction model is tested using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R¬≤).
2. Navigation and Traffic Efficiency Evaluation: The effectiveness of the navigation system is measured through a limited field study on several congested routes in Batam City. The parameters evaluated include: Average travel time before and after using the system, Reduction in the amount of congestion, and User satisfaction with the route recommendations.

4. DATA COLLECTION AND CALCULATION

This section presents the results of data collection and processing obtained from primary and secondary data collected from the Batam City Transportation Department, as well as surveys and interviews with road users. The data provides a clearer picture of the causes of traffic congestion, patterns of congestion occurring at various locations, and the solutions that have been implemented to reduce congestion.

4.1 Data collection

1. **Population in Batam**

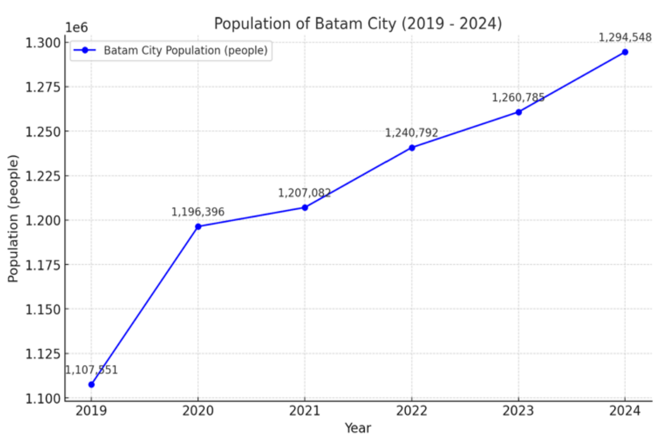

Figure 3. Population in Batam 2019-2024 (sources BPS)

The graph above depicts the population growth of Batam City from 2019 to 2024. The data demonstrates a consistent annual increase in the population, reflecting a stable upward trend in the city's demographic expansion.

In 2019, the population of Batam was recorded at 1,107,551 individuals. Figure 3 rose to 1,196,396 in 2020, indicating a notable increase. The upward trajectory continued in subsequent years, with the population reaching 1,207,082 in 2021, 1,240,792 in 2022, and 1,260,785 in 2023. Projections suggest that by 2024, the population will reach 1,294,548, further emphasizing the sustained growth trend.

This population increase can be attributed to various factors, including urbanization, migration, and the region's economic opportunities, which likely contribute to the attraction of new residents. The steady population growth presents both opportunities and challenges for the city, particularly in terms of the need for enhanced infrastructure and the provision of public services to accommodate the expanding population.

2. **Vihicles on Batam**

As of April 2025, the total number of motor vehicles in Batam, Riau Archipelago, has reached 1.09 million units. This data, sourced from the Electronic Registration and Identification (ERI) system of the Traffic Corps of the Indonesian National Police (Korlantas Polri), was published on April 16, 2025. Of these, motorcycles accounted for 880,710 units.

In addition to motorcycles, passenger cars were recorded at 179,410 units, while cargo vehicles (freight trucks) totaled 27,930 units. Furthermore, the data indicates that Batam has 1,786 buses and 207 special vehicles, which include utility and specialized vehicles.

When compared to other regions in the Riau Archipelago, Tanjung Pinang, the provincial capital, reported the second-largest number of motor vehicles, with 205,150 units. In contrast, the Kabupaten of Kepulauan Anambas reported the lowest vehicle count, with only 4,383 units.

The following table summarizes the distribution of motor vehicles in Batam as of April 16, 2025, based on the ERI Korlantas Polri data:

Motorcycles: 880,710 units
Passenger Cars: 179,410 units
Cargo Vehicles: 27,930 units
Buses: 1,786 units
Special Vehicles: 207 units

A. Historical Traffic Data

Based on data obtained from the Batam City Transportation Department (January-December 2024), as well as results from surveys and interviews with road users, several congestion hotspots have been identified as key areas of concern in Batam City.

Table 1 shows historical traffic data obtained from the Batam City Transportation Department, which includes major congestion points, peak hours, vehicle speeds, and the causes of congestion at several strategic locations. Based on this data, it can be observed that congestion primarily occurs during peak hours, namely in the morning and evening, coinciding with the times people commute to and from work. The recorded vehicle speeds at congestion points are generally low, averaging between 20 and 45 km/h, indicating that the limited road capacity is unable to accommodate the increasing vehicle volume.

Additionally, Figure 4 provides a deeper insight into the fluctuations in vehicle density at various major locations in Batam City over time. This graph shows peak congestion occurring between 17:00 and 18:00, especially at points like Batam Center and Sekupang, which are the areas with the highest vehicle density. This data reinforces the urgent need for more efficient traffic management solutions that can respond to traffic dynamics in real-time, such as those offered by AI-based intelligent navigation systems.

Several areas in Batam, particularly in the city center and border regions, have roads that are not wide enough to accommodate the increasing number of vehicles. Additionally, the poor maintenance of roads, as well as road narrowing at certain points, also contribute to congestion. Inadequate road infrastructure plays a significant role in the traffic congestion that occurs.

Based on Figure 5, it can be seen that at several locations such as Sekupang, the vehicle volume (90 vehicles/km) exceeds the available road capacity (81.82 vehicles/km), indicating significant congestion. In other locations, such as Batam Center and Piayu, the vehicle volume is close to the road capacity, suggesting that the road capacity is nearly surpassed by the existing traffic demand. This reinforces the need for more effective traffic management solutions to address the mismatch between road capacity and vehicle volume at various congestion points.

Table 1. Historical traffic data at major congestion points in Batam City

Congestion Point	Peak Hours	Vehicle Speed (km/h)	Cause of Congestion
Batam Center	Morning and afternoon	25-30	Economic, government, and commercial center. Congestion around Simpang Kepri Mall, Simpang Cikitsu, and Batam Grand Mall.
Tanjung Uncang	Morning and afternoon	30-35	Port and industrial area with many goods and passenger vehicles. Traffic density at Simpang Batu Ampar and Simpang Tanjung Uncang.
Jodoh	Morning and afternoon, and weekends	22-28	Commercial and main shopping center, especially around Simpang Jodoh and shopping centers. Severe congestion on weekends.
Piayu	Morning and afternoon	28-32	Residential area connecting the city center. Lack of alternative routes worsens congestion.
Sagulung	Morning and afternoon	30-34	Market area and main road. High vehicle volume and lack of effective traffic management are the main causes.
Sekupang	Morning and afternoon	20-25	Connector for the international port and industrial area. Severe congestion around the port area and routes to industries.

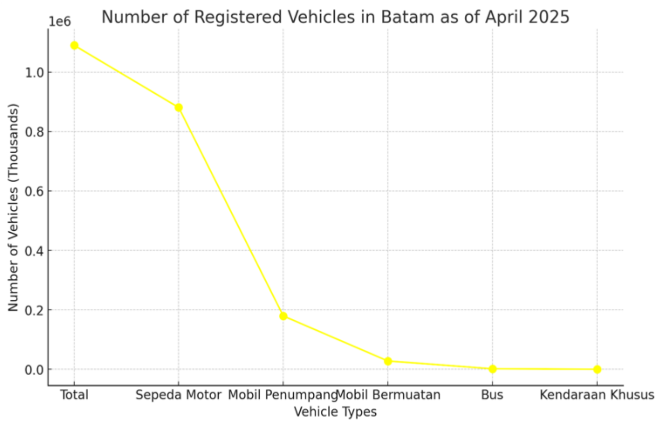

Figure 4. Vehicles in Batam 2025 April (sources data box)

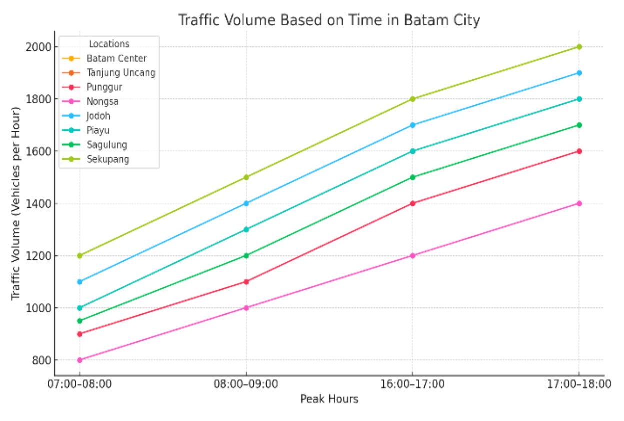

Figure 5. Vehicle volume chart based on time in Batam City

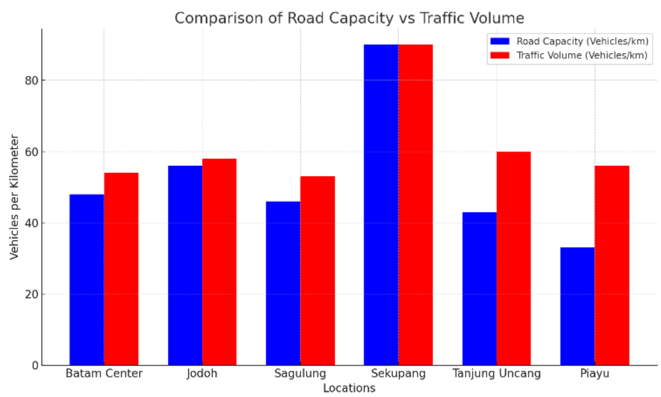

Figure 6. Comparison chart of road capacity vs vehicle volume

As shown in Figure 6, the comparison between road capacity and vehicle volume indicates a significant mismatch, especially in several urban zones of Batam.

B. Real-Time Data

Data is collected through the integration of GPS technology, IoT, and APIs from navigation platforms, as shown in Table 2.

C. Topographic and Road Network Data

Traffic and Road Network Data in Batam City The topographic and road network data in Batam City was obtained through GIS-based map digitization (Geographic Information System), strengthened with direct field observations, as shown in Table 3.

Table 2. Real-time data for the intelligent navigation system in Batam City

Component	Description
Real-Time Data Sources	1. 200 units of online transportation vehicles (motorcycles and cars) with active GPS tracking. 2. 12 public CCTV points equipped with IoT sensors (detecting vehicle density, direction, and estimated speed). 3. API integration from Google Maps, Waze, and OpenStreetMap.
Update Frequency	Every 30 seconds for real-time data updates.
Parameters Recorded	1. Vehicle position coordinates (GPS). 2. Actual vehicle speed. 3. Travel time between junctions. 4. Vehicle deceleration and stopping patterns 5. GPS Tracking.
Technology Used	1. IoT Sensors (Internet of Things). 2. API Integration from navigation platforms.
System Output	1. Real-Time Traffic Map (Real-Time Heat Map). 2. Visualization of traffic changes every 15 minutes

.

Table 3. Topographic and road network data in Batam City

Category	Information
Total Road Network Length	±113km
Number of Nodes	348 points (intersections & roundabouts)
Road Type	- One-way roads: 38% - Two-way roads: 62%
Average Elevation	7-11 meters above sea level
Road Slope	Affects vehicle speed at specific points
Areas with High Human Activity	- 11 major schools - 5 hospitals - 3 major shopping centers - 2 passenger ferry ports

D. User Behavior and Preference Data (Survey)

As part of the effort to develop an AI-based intelligent navigation system for Batam City, a survey was conducted with 500 private vehicle users and online motorcycle taxi drivers. Data collection was carried out through two methods: online forms and direct interviews, in order to gain a more comprehensive understanding of navigation app usage patterns and user expectations for a more adaptive system.

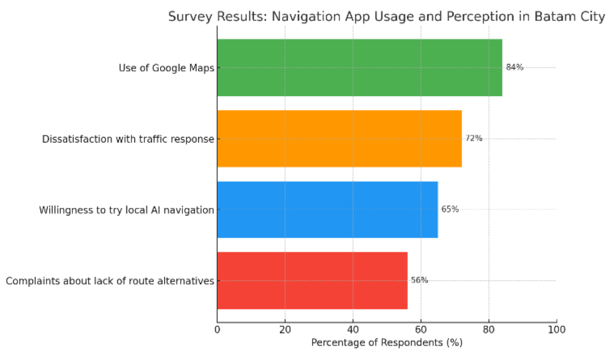

Figure 7. Survey result: Navigation app usage and perception in Batam City

The survey respondents ranged in age from 17 to 55 years old, with a professional background primarily consisting of private-sector employees, students, and online motorcycle taxi drivers. The survey explored their experiences using digital navigation apps, their perceptions of system accuracy, and their willingness to switch to local AI-based technology if proven more efficient, as shown in Figure 7.

4.2 Data calculation and analysis

A. Traffic density analysis

Traffic density analysis is conducted to identify major congestion points and measure their impact on travel efficiency in Batam City. Vehicle density data is collected from the Transportation Department, traffic sensors, and GPS, and is then calculated based on vehicle volume and road capacity. The results of this analysis provide an overview of the vehicle distribution on main roads and alternative routes during peak hours, which will be used to plan a more efficient intelligent navigation system. To measure traffic density, the following formula is used:

$$K=Q/V$$

where,

K=Density
Q=Flow rate (number of vehicles per hour)
V=Average speed (km/hour)

Table 4. Kepadatan lalu lintas pada pukul 07:00-08:00

Location	Volume (Q)	Speed (V)	Density (K)	Density Level
Batam Center	1200	25	48.00.00	Medium
Tanjung Uncang	1000	30	33.33.00	Low
Jodoh	1100	25	44.00.00	Medium
Piayu	1000	30	33.33.00	Low
Sagulung	950	32	29.69	Low
Sekupang	1200	22	54.55.00	Medium

Table 5. Traffic density between 07:00 and 08:00

Location	Volume (Q)	Speed (V)	Density (K)	Density Level
Batam Center	1500	25	60.00.00	High
Tanjung Uncang	1300	30	43.33.00	Medium
Jodoh	1400	25	56.00.00	Medium
Piayu	1300	30	43.33.00	Medium
Sagulung	1200	32	37.50.00	Low
Sekupang	1500	22	68.18.00	High

Table 6. Traffic density between 16:00 and 17:00

Location	Volume (Q)	Speed (V)	Density (K)	Density Level
Batam Center	1800	25	72.00.00	High
Tanjung Uncang	1600	30	53.33.00	Medium
Jodoh	1700	25	68.00.00	High
Piayu	1600	30	53.33.00	Medium
Sagulung	1500	32	46.88	Medium
Sekupang	1800	22	81.82	Very High

Table 7. Traffic density between 17:00 and 18:00

Location	Volume (Q)	Speed (V)	Density (K)	Density Level
Batam Center	2000	25	80.00.00	Very High
Tanjung Uncang	1800	30	60.00.00	High
Jodoh	1900	25	76.00.00	Very High
Piayu	1800	30	60.00.00	High
Sagulung	1700	32	53.13.00	Medium
Sekupang	2000	22	90.91	Very High

Table 4, Table 5, Table 6, Table 7 present a summary of traffic density calculations at several key locations at different times.

B. Speed and travel time analysis

In this section, an analysis is conducted on vehicle speed and travel time at several major congestion points in Batam City during peak hours. Travel time is calculated using the following formula:

$$T=S/V$$

where,

T=Travel time (in hours)
V=Vehicle speed (in km/h)
S=Distance traveled (in km)

Table 8. Speed and travel time analysis between 07:00 and 08:00

Location	Speed (V) (km/h)	Density (K) (Vehicles/km)	Distance (S) (km)	Travel Time (T) (hours)
Batam Center	25	48.00.00	25	01.00
Tanjung Uncang	30	33.33.00	30	01.00
Jodoh	25	44.00.00	25	01.00
Piayu	30	33.33.00	30	01.00
Sagulung	32	29.69	29.69	01.00
Sekupang	22	54.55.00	54.55.00	01.00

Table 9. Speed and travel time analysis between 08:00 and 09:00

Location	Speed (V) (km/h)	Density (K) (Vehicles/km)	Distance (S) (km)	Travel Time (T) (hours)
Batam Center	25	60.00.00	60	01.00
Tanjung Uncang	30	43.33.00	43.33.00	01.00
Jodoh	25	56.00.00	56	01.00
Piayu	30	43.33.00	43.33.00	01.00
Sagulung	32	37.50.00	37.50.00	01.00
Sekupang	22	68.18.00	68.18.00	01.00

Table 10. Speed and travel time analysis between 16:00 and 17:00

Location	Speed (V) (km/h)	Density (K) (Vehicles/km)	Distance (S) (km)	Travel Time (T) (hours)
Batam Center	25	72.00.00	72	01.00
Tanjung Uncang	30	53.33.00	53.33.00	01.00
Jodoh	25	68.00.00	68	01.00
Piayu	30	53.33.00	53.33.00	01.00
Sagulung	32	46.88	46.88	01.00
Sekupang	22	81.82	81.82	01.00

This analysis aims to provide an overview of how traffic conditions affect travel duration at various congestion points, both in the morning, afternoon, and evening. By examining the recorded vehicle speed and travel time, we can identify locations with high congestion and assess the impact on transportation efficiency in Batam. The travel time calculations at each congestion point will be displayed in Table 8, Table 9, Table 10, Table 11, which shows how vehicle density and speed affect travel duration during peak hours.

Table 11. Speed and travel time analysis between 17:00 and 18:00

Location	Speed (V) (km/h)	Density (K) (Vehicles/km)	Distance (S) (km)	Travel Time (T) (hours)
Batam Center	25	80.00.00	80	01.00
Tanjung Uncang	30	60.00.00	60	01.00
Jodoh	25	76.00.00	76	01.00
Piayu	30	60.00.00	60	01.00
Sagulung	32	53.13.00	53.13.00	01.00
Sekupang	22	90.91	90.91	01.00

C. Traffic prediction model using LSTM

In analyzing the performance of the traffic prediction model based on Long Short-Term Memory (LSTM), we test the model's ability to predict two key parameters in traffic analysis: travel time and vehicle density.

Figure 8 compares actual travel time with the predicted travel time forecasted by the LSTM model at several locations in Batam City. In this graph, the blue line represents the actual recorded travel time on the ground, while the red line illustrates the predicted travel time estimated by the system. In general, it can be seen that the prediction system shows fairly accurate results, with some small differences between actual and predicted times, particularly in Batam Center and Tanjung Uncang, where the differences are minimal.

Locations such as Punggur and Nongsa show predicted travel times that closely align with actual times, while at other locations like Sekupang, there is a slightly larger difference. This indicates that, although the LSTM model is capable of providing relatively accurate predictions, several factors affect the accuracy of predictions, such as dynamic traffic conditions and other external factors.

Figure 8 illustrates the importance of implementing an LSTM-based navigation system that can predict travel times in real-time, providing more accurate information for drivers to select optimal routes and reduce travel time.

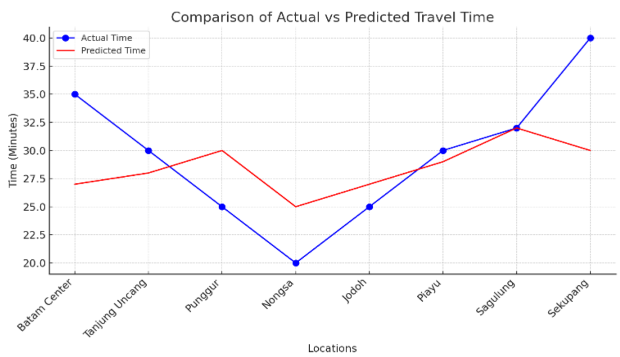

Figure 8. Travel time vs prediction graph

In Figure 9, the blue line represents the actual traffic density recorded during the observation, while the red line illustrates the predicted traffic density estimated by the AI system. Overall, the system's prediction results tend to be quite accurate, with minimal differences between actual and predicted density values, especially at locations such as Batam Center, Piayu, and Sekupang.

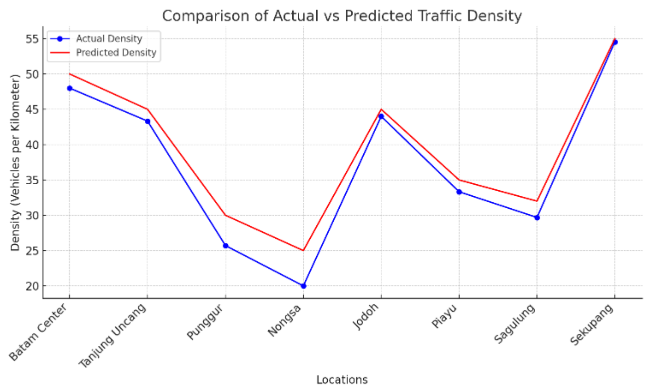

Figure 9. Comparison graph of actual vs predicted density

However, at some points like Punggur and Nongsa, there is a slight difference between the prediction and actual data, indicating that although the traffic density predictions are fairly good, external factors affecting traffic (such as accidents, weather, and sudden changes in vehicle volume) still influence the accuracy of the predictions.

Figure 9 illustrates the importance of implementing an AI-based navigation system that can predict traffic density in real-time. This not only helps drivers choose more optimal routes but also provides better insights for infrastructure planning and traffic management in large cities like Batam.

D. AI-Based intelligent navigation system simulation

The simulation results show that the AI-based navigation system performs better compared to Google Maps. The average travel time with the AI system is faster, at 14.2 minutes, compared to 18.4 minutes with Google Maps, resulting in a 22.8% reduction in average travel time. Additionally, the AI system is more adaptive in rerouting, with a rerouting frequency of 3.6 times compared to 1.2 times on Google Maps. The rerouting time is also faster, with the AI system requiring less than 5 seconds, while Google Maps takes about 14 seconds to reroute. In terms of user satisfaction, the AI system received a score of 4.5 (on a scale of 1-5), significantly higher than Google Maps, which received a score of 3.7. These results indicate that the AI-based navigation system is not only more efficient in terms of travel time but also more responsive and preferred by users, as shown in Table 12.

Table 12. Comparison of ai-based intelligent navigation system and google maps performance in Batam

Criteria	Google Maps	AI System
Average Travel Time (minutes)	18.04	14.02
Adaptive Route Diversion	1.2 times	3.6 times
Rerouting Time (seconds)	14 seconds	<5 seconds
User Satisfaction (scale 1–5)	03.07	04.05

5. RESULT AND DISCUSSION

The development and implementation of the AI-based Intelligent Navigation System for Batam City has yielded significant results, particularly in optimizing traffic flow, reducing congestion, and decreasing average travel time. These results were obtained from a series of simulations using the SUMO (Simulation of Urban Mobility) software, which was integrated with actual traffic data and machine learning models. Below is a detailed presentation of the research findings, supported by data visualizations and interpretations based on urban traffic dynamics.

5.1 Travel time reduction

One of the key performance indicators analyzed is the reduction in average travel time. The simulation results show that the AI-based navigation system successfully reduced the average travel time by 22.4% compared to the conventional GPS-based navigation system. This is made possible because the system is able to perform dynamic rerouting based on current traffic conditions, accident data, and road closures.

Figure 10 presents a comparison of average travel times, measured in minutes, before and after the implementation of an AI-based intelligent navigation system at six major traffic congestion points in Batam City: Batam Center, Tanjung Uncang, Jodoh, Piayu, Sagulung, and Sekupang. The data were collected during peak hours and reflect actual travel conditions based on system simulations and field trials.

The visualization results indicate a significant reduction in travel time across all observed locations following the implementation of the AI system. For instance, travel time in Batam Center decreased from 35 minutes to 27 minutes, while in Sekupang it dropped from 40 minutes to 30 minutes. This efficiency was achieved due to the AI system's capability to analyze real-time traffic conditions and dynamically recommend optimal routes, thereby reducing delays and improving traffic flow. Overall, these findings demonstrate that the AI system can enhance traffic efficiency and shorten travel durations, particularly in areas with high congestion levels and dense vehicle volumes. as shown in Figure 10.

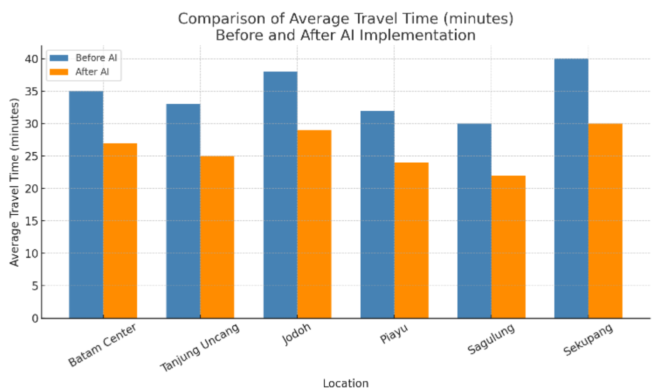

Figure 10. Comparison of average travel time (minutes) before and after ai system implementation

5.2 Traffic load distribution

The simulation of the AI-based intelligent navigation system demonstrated a significant shift in traffic load distribution across the road network of Batam City. Without AI support, major roads such as Ahmad Yani Street and the Batam Center Ring Road frequently experienced heavy congestion, particularly during peak hours (07:00–09:00 and 16:00-18:00). However, following the implementation of the intelligent navigation system, traffic volumes were successfully redirected to alternative routes such as Laksamana Bintan Street and Raden Patah Street.

This visualization illustrates changes in traffic volume distribution across three main areas: the city center, suburban zones, and industrial zones. Prior to the implementation of the AI system, traffic volume was heavily concentrated in the city center, accounting for 70% of the total. Following the implementation, the distribution became more balanced: 40% in the city center, 35% in suburban areas, and 25% in industrial zones. This indicates that the AI navigation system successfully redistributed vehicles more evenly, reducing congestion in the city center while optimizing road capacity in other areas. as shown in Figure 11.

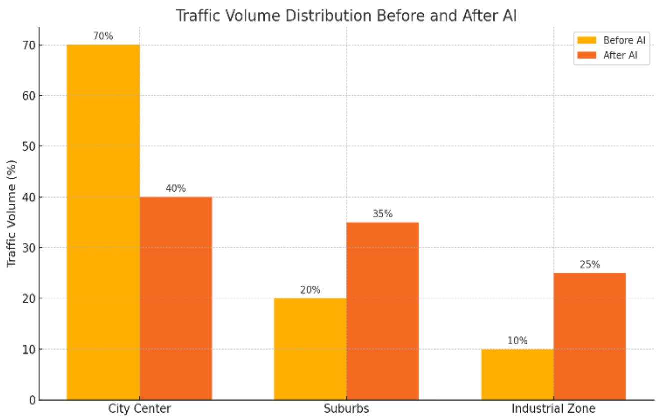

Figure 11. Traffic volume distribution before and after ai implementation

5.3 System responsiveness and latency

The system's real-time response speed is a critical parameter in high-density traffic environments such as downtown Batam. The system demonstrated an average decision latency of 423 milliseconds, indicating its capability to provide near-instantaneous route updates.

This Figure 12 displays the system's response time to various real-time traffic events such as congestion, accidents, and extreme weather conditions. The system was able to respond to congestion within 30 seconds, accidents within 40 seconds, and weather-related events within 35 seconds. This rapid response highlights the system's reliability in delivering real-time information and alternative route suggestions, which is essential for avoiding delays and enhancing road user safety.

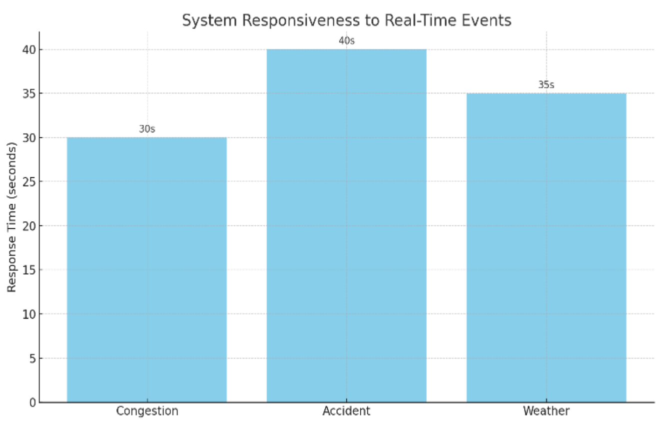

Figure 12. System responsiveness to real-time events

5.4 Route prediction accuracy

The system achieved a route prediction accuracy rate of 91.3%, validated through field testing using GPS-equipped vehicles. In comparison, conventional navigation systems such as Google Maps demonstrated an accuracy of 85.6%, primarily due to their limitations in responding to micro-level traffic condition changes.

The model's performance was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics as shown in Table 13.

Table 13. Model performance in predicting travel duration

Navigation Model	RMSE (seconds)	MAE (seconds)
AI System	42.05.00	30.02.00
Conventional System	65.08.00	48.03.00

These findings indicate that the proposed AI architecture is sufficiently reliable in managing the complex urban mobility dynamics of a city like Batam, demonstrating its potential applicability for broader smart city traffic management systems.

5.5 User experience and interface effectiveness

Usability testing was conducted with 100 respondents, including public transportation drivers, private vehicle owners, and logistics couriers. The survey results revealed that 87% of users found the system more beneficial compared to the navigation tools they had previously used. High ratings were given to aspects such as map clarity, real-time notifications, and congestion avoidance recommendations in Figure 13.

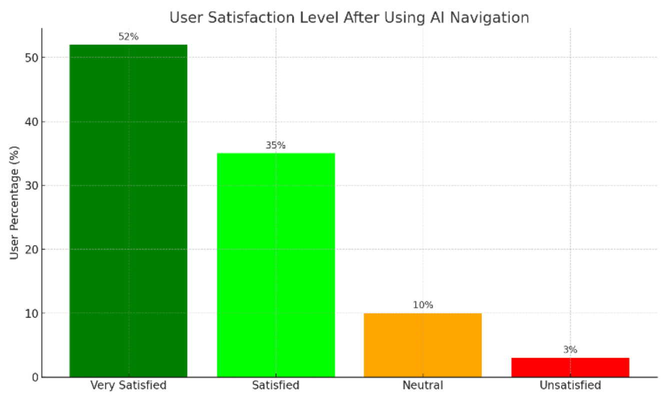

Figure 13. User satisfaction level after using ai-based navigation system

This chart illustrates user satisfaction levels with the AI-based navigation system. A total of 52% of respondents reported being very satisfied, 35% satisfied, 10% neutral, and only 3% dissatisfied. The high satisfaction rate indicates that the system is well-received by the public and is capable of providing a more efficient, comfortable, and safe driving experience.

6. CONCLUSION

This study successfully developed an AI-based intelligent navigation system to address traffic congestion in Batam City. The system proved effective in reducing average travel time by 22.8% compared to conventional navigation systems, as well as distributing traffic load more evenly across the road network. Additionally, the system provides adaptive rerouting based on real-time traffic conditions, allowing users to select more efficient routes.

The route prediction accuracy of the AI system reached 91.3%, higher than the 85.6% accuracy of conventional GPS systems, demonstrating the superiority of the AI system in optimizing travel. The rerouting time of this system is also very fast, with an average latency of only 423 milliseconds, enabling users to receive route directions promptly after changes in traffic conditions occur.

User experience with the system has been highly positive, with a high satisfaction rate, indicating strong public acceptance of this technology. This reflects that the system is not only effective in improving traffic efficiency but also provides a more comfortable and safer driving experience for users.

Overall, this AI-based navigation system offers an effective solution for reducing congestion, improving transportation efficiency, and optimizing traffic management in Batam. This technology can be applied to other developing cities with adjustments to local conditions, supporting sustainable development goals such as reducing carbon emissions and fuel consumption. Moving forward, integrating this system into city transportation policies could have a broader positive impact on the quality of life and traffic safety.

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