Optimizing urban evacuation: AI-driven analysis of transportation bottlenecks in Almaty

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Abstract

This study investigates the application of artificial intelligence and graph theory for optimizing urban evacuation in Almaty, Kazakhstan—a seismically active city with complex topography. We combined Dijkstra's and A* algorithms with real-time traffic prediction using LSTM models to identify bottlenecks and recommend optimal evacuation strategies. Population density, road network centrality, and K-means clustering were used to prioritize zones. Our results reveal critical road segments with high betweenness centrality, where AI-driven routing significantly reduced simulated evacuation time. The findings provide actionable insights for disaster management in urban Central Asia.

Keywords

evacuation planning, network analysis, AI traffic prediction, urban resilience, transportation bottlenecks geospatial modeling

1. Introduction

Almaty, Kazakhstan's largest city, lies in a seismically active zone, making evacuation planning a critical component of disaster preparedness. As urban populations grow and road infrastructure becomes increasingly strained, efficient evacuation becomes both a logistical and computational challenge. Traditional algorithms such as Dijkstra and A* provide static routing solutions that do not account for dynamic congestion or real-time hazards. Integrating AI-based traffic prediction into routing algorithms offers a promising alternative. This research aims to develop a framework that combines population density analysis, road centrality, machine learning traffic prediction, and graph-based optimization to enhance urban evacuation strategies. Unlike prior studies, this paper combines centrality-based network analysis, AI-driven traffic forecasting, and spatial population clustering into a unified evacuation framework. It is the first such integrated study applied to Almaty, offering both theoretical insights and practical recommendations tailored to the city's infrastructure and risk profile.

Recent advances in network analysis and artificial intelligence (AI) have introduced new methodologies for optimizing evacuation routes. Centrality measures, such as betweenness and degree centrality, have proven effective in identifying transportation bottlenecks, while AI-driven traffic prediction models can dynamically adjust evacuation routes based on congestion forecasts. Integrating these approaches can significantly improve evacuation efficiency by reducing congestion and minimizing delays.

By addressing these objectives, this study contributes to the growing field of AI-driven disaster response and urban evacuation planning, offering insights applicable to other cities facing similar evacuation challenges. The main objectives of this study are:

- To identify key transportation bottlenecks in Almaty's road network using centrality metrics.

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- To compare traditional routing algorithms with AI-enhanced models for evacuation optimization.
- To assess the impact of population density on evacuation efficiency and high-risk zones.
- To simulate multiple disaster scenarios and evaluate the robustness of evacuation strategies.

2. Literature review

Urban centers face increasing risks from disasters, necessitating effective evacuation planning. Prior research highlights the challenges of coordinating movement in densely populated areas [1] and the impact of infrastructure constraints on congestion [2]. Effective strategies integrate road network analysis, real-time traffic data, and population distribution.

Several studies have addressed evacuation planning using AI, GIS, and graph theory compared Dijkstra and A* in flood-prone Chinese cities and found that A* offers faster convergence in dynamic environments applied agent-based simulation for Tokyo, incorporating human behavior in earthquake evacuation. Chen et al. analyzed road vulnerability through network centrality in seismic zones. However, little attention has been paid to integrating centrality metrics, AI-based traffic prediction, and spatial clustering in evacuation planning for Central Asian cities. Our research addresses this gap by offering a multi-dimensional approach to evacuation optimization in Almaty.

Network analysis and AI play key roles in evacuation planning. Centrality measures identify congestion points [3], while Dijkstra's and A* optimize routes [2]. AI-driven traffic predictions enhance efficiency [4], though few studies integrate population density, a critical real-world factor. Centrality metrics, such as betweenness and degree, pinpoint high-risk transport nodes [1, 5]. Algorithmic comparisons confirm the efficiency of Dijkstra's and A* [6]. AI-driven models dynamically adjust routes [7], with machine learning reducing evacuation times by up to 20% [4]. This study contrasts traditional and AI-enhanced routing in Almaty.

Population density exacerbates congestion, delaying evacuations [4, 8]. Tools like GeoPandas and Folium map high-risk zones, integrating demographic data to refine strategies. Open-source geospatial data (OSM) has transformed urban modeling [9], while Python libraries like OSMnx and NetworkX enable scenario simulations [5]. Clustering techniques, such as K-Means, further refine bottleneck identification [10]. This study applies these methods to model disasters in Almaty.

Comparative studies show static algorithms struggle under dynamic conditions [6], while AI-driven models adapt to evolving congestion [7, 11]. AI improves efficiency but depends on historical data, which may not reflect real-time anomalies. This study bridges this gap by integrating network centrality with AI predictions. The convergence of network analysis, AI-based traffic modeling, and demographic studies informs urban emergency planning. Real-time data integration enhances disaster response [12], and improved data management optimizes evacuation models [13]. This study provides a scalable framework for urban evacuation strategies, identifying key bottlenecks in Almaty's road network, integrating AI-based traffic predictions with routing algorithms, incorporating spatial population analysis to assess high-risk zones, and simulating multiple disaster scenarios to evaluate strategy effectiveness. By merging theoretical models with practical applications, this study enhances urban safety through data-driven planning.

3. Materials and methods

3.1. Data collection

The analysis utilizes spatial data obtained from OpenStreetMap (OSM), covering the road network and 135 distinct evacuation zones within Almaty. The initial dataset comprises 52,198 records, with missing values that required careful preprocessing. The dataset includes information on road segments, their geometries, lengths, and other attributes essential for evacuation modeling.

Table 1 presents key dataset characteristics, including data types, missing values, and duplicate records. The dataset captures essential road network parameters such as classification, segment length, lane count, speed limits, and infrastructure constraints (e.g., tunnels, bridges, and junctions). These attributes play a crucial role in modeling evacuation scenarios by influencing route availability, capacity, and overall network efficiency.

Table 1
Key Dataset Characteristics

Highway	Name	Length	Lanes	Oneway	Maxspeed	Bridge	Tunnel
Residential	Abay	125.3	2	False	60	no	no
Motorway	Tashkent Highway	1200.4	4	True	110	no	no
Primary	Nazarbayev Ave.	800.2	3	False	80	no	no
Secondary	Gogol St.	350.6	2	False	60	no	no

3.2. Data preprocessing and transformation

Data cleaning included removing duplicate records, imputing missing numerical values using group averages, and converting raw data into a GeoDataFrame for spatial analysis. Interpolation techniques were applied to incomplete geographic attributes, and transportation nodes were clustered using the K-Means algorithm to identify key junctions.

3.3. Analytical methods

This study employs a multi-step analytical approach to evaluate the efficiency of evacuation routes in Almaty.

Network Analysis. To construct and analyze the road network, we utilized OpenStreetMap (OSM) data through the OSMnx and NetworkX libraries. The network was modeled as a graph, where nodes represent intersections, and edges represent roads. We calculated key centrality metrics, including betweenness centrality and degree centrality, to identify transportation bottlenecks.

Route Optimization. We applied Dijkstra's algorithm and the A* algorithm to compute the shortest evacuation routes under emergency conditions. These routes were then compared with AI-enhanced models that factor in real-time congestion predictions.

AI-Based Traffic Prediction. Machine learning models were trained on historical traffic data to predict congestion patterns during different emergency scenarios. This predictive approach allows us to estimate evacuation times and suggest alternative routes in case of road blockages.

Geospatial Analysis. Population density data was mapped using GeoPandas and Folium to identify high-risk areas requiring priority evacuation. By overlaying demographic information with road network data, we pinpointed critical zones where evacuation measures should be enhanced.

The figure below presents a visualization of the road network in Almaty, highlighting major evacuation zones. The road network was extracted from OpenStreetMap, and key routes were identified for emergency planning. Red markers indicate designated evacuation points, which were selected based on accessibility and population density. This multi-layered analytical approach provides a comprehensive framework for evaluating urban evacuation efficiency and identifying areas for infrastructure improvement.

Figure 1: Map of Almaty's road network and evacuation zones

We used OSMnx to extract the road network of Almaty and computed centrality measures such as betweenness, closeness, and degree. Zones were defined based on population density data and K-means clustering. We applied Dijkstra and A* algorithms to compute optimal evacuation paths. Additionally, we trained LSTM models on traffic flow data to predict congestion. The predicted traffic was then used to weight the edges of the graph dynamically. This combined approach allowed us to simulate evacuation under realistic conditions.

3.3.1. AI model specification

The AI-driven traffic prediction component was implemented using a Long Short-Term Memory (LSTM) network trained on time-series traffic flow data. The model aimed to forecast congestion factors for each road segment, which were subsequently used as dynamic edge weights in the routing graph.

The feature set included:

- historical traffic density per road segment (population-weighted);
- average segment travel speed;
- time of day and weekday indicators (encoded cyclically);
- and local road attributes such as lane count and maximum speed.

The LSTM architecture consisted of two hidden layers (64 and 32 units) followed by a fully connected output layer with a linear activation function. The model was trained for 80 epochs using the Adam optimizer (learning rate = 0.001) and a batch size of 32. Model performance was evaluated on a 20% validation subset using standard forecasting metrics: MAE = 0.041, RMSE = 0.065, and MAPE = 4.8%, indicating stable prediction accuracy.Repeated experiments with five random seeds confirmed robustness (variation within ±0.3%).

The trained model predicted congestion factors for 15-minute intervals using a rolling input window of one hour. These predicted values dynamically updated the edge weights in the AI-enhanced routing algorithm, allowing the system to respond to evolving traffic conditions in real time.

3.3.2. Experimental protocol

All simulations followed a standardized experimental protocol to ensure reproducibility and comparability between baseline and AI-enhanced models:

- Network: Almaty's OSM-derived graph (~19,400 nodes and 48,600 edges);
- Simulation step: 5 minutes per iteration, total duration = 60 minutes;
- O/D pairs: 50 randomly selected origin–destination combinations per run;
- Repetitions: 5 random seeds per setup (250 total simulations);
- Baseline algorithms: Static Dijkstra and A* (edge weights = segment length);
- AI-enhanced algorithm: A* with dynamically updated edge weights based on LSTM-predicted congestion;
- Evaluation metrics: average path length, mean travel time, and total evacuation completion time.

All models used identical network topology, road capacities (1,000–3,000 veh/h by class), and initial demand distribution to ensure a fair comparison. The previously constant evacuation time of 210.2 minutes across the four baseline scenarios reflects fixed input assumptions (uniform flow capacity and population distribution). When dynamic congestion forecasts were applied, total evacuation times varied between 178–182 minutes, confirming the model's sensitivity to real-time conditions.

3.4. Mathematical formulation of the evacuation optimization poblem

To mathematically define the evacuation optimization framework, the urban road network of Almaty is represented as a weighted directed graph

$$G=(V,E), \tag{1}$$

where $V=\{v_1,v_2,\ldots,v_n\}$ denotes the set of intersections (nodes), and $E=\{e_{ij}\}$ represents the set of road segments (edges). Each edge e_{ij} is characterized by attributes such as length l_{ij}, maximum speed s_{ij}, number of lanes, and capacity c_{ij}.

Objective Function

The evacuation process seeks to minimize the total evacuation time for all population clusters moving from origin zones to designated safe destinations. Let $S\subseteq V$ denote the set of origin nodes (evacuation zones), and $D\subseteq V$ denote the set of destination nodes (shelters). The total evacuation time is given by:

$$\min_P T_{total}=\sum_{k=1}^{|S|}\sum_{(i,j)\in P_k} w_{ij}(t), \tag{2}$$

whereP_k is the optimal path for evacuees originating from zone k_1, $w_{ij}(t)$ represents the dynamic weight (travel time) on edge e_{ij} at time *t*.

Dynamic Weight Function

The edge weight is a time-dependent value influenced by both road geometry and predicted congestion. It is defined as:

$$w_{ij}(t)=\frac{l_{ij}}{s_{ij}(t)}*\frac{1}{\lambda_{ij}}, \tag{3}$$

where:

l_{ij} — length of the road segment;

$s_{ij}(t)$ — predicted vehicle speed from the LSTM congestion model at time *t;*

λ_{ij} — road availability factor $(0<\lambda_{ij}\leq 1)$, accounting for closures or hazards (e.g., earthquakes, floods).

This formulation allows the graph's edge weights to update dynamically as traffic or road conditions evolve, making routing adaptive to real-time scenarios.

Flow Constraints

Each edge in the network is subject to flow conservation and capacity limits:

$$\sum_{j:(i,j)\in E} f_{ij} - \sum_{j:(j,i)\in E} f_{ij} = \begin{cases} d_{i,} i\in S \\ d_{i,} i\in S \\ 0, otherwiese \end{cases}, \tag{4}$$

$$f_{ij}\leq c_{ij}, \forall (i,j)\in E, f_{ij}\geq 0, \tag{5}$$

where:

f_{ij} — number of evacuees (flow) on edge e_{ij};

c_{ij}— maximum road capacity (vehicles or persons per minute);

d_i— population demand at node i.

Optimization Approach

The problem corresponds to a dynamic capacitated shortest-path problem, which is computationally intractable (NP-hard) for large networks. Therefore, heuristic and AI-assisted search algorithms are used:

- Dijkstra's algorithm — for baseline static optimization;
- A^*— for heuristic pathfinding incorporating distance and congestion heuristics;
- AI-enhanced routing (LSTM-weighted A^*) — integrates predicted traffic congestion to update edge weights $w_{ij}(t)$ dynamically.

Model Integration

The overall optimization process can be expressed as:

$$Find\ P^* = arg\min_P \sum_{(i,j)\in P} w_{ij}(t), \tag{6}$$

subject to the capacity and flow constraints above. The LSTM-based module continuously forecasts $s_{ij}(t)$ based on historical and simulated traffic data, while the graph-based optimizer recalculates routes as weights change.

This mathematical formulation links network centrality analysis, real-time AI traffic prediction, and route optimization into a unified framework for dynamic evacuation planning. It provides a rigorous foundation for evaluating the effectiveness of traditional and AI-driven algorithms under diverse disaster scenarios.

Validation and Baseline Comparison

To quantify the improvement of the AI-enhanced routing, we established a baseline using traditional shortest-path algorithms. The baseline scenario employed Dijkstra's and A^* algorithms with static edge weights $w_{ij}(t)=l_{ij}$ where l_{ij} is the physical road length in meters.

The AI-based model introduced time-dependent weights $w_{ij}(t)=l_{ij}/s_{ij}(t)$, where $s_{ij}(t)$ represents predicted traffic speed from the LSTM congestion model.

Comparative simulations were performed on 50 random origin–destination (O/D) pairs within Almaty's network (approximately 19,400 nodes and 48,600 edges). Each simulation used a discretized 5-minute time step over a 1-hour horizon, with average assumed vehicle speed of 50 km/h and road capacities between 1,000–3,000 veh/h depending on road class. Congestion factors derived from population-density weighting ranged from 1.0 (free flow) to 3.0 (severe congestion) and dynamically modified edge weights at each iteration.

This allowed direct comparison between static (baseline) and AI-enhanced routing under identical network conditions.

4. Results

4.1. Quantitative evaluation of routing efficiency

To ensure transparency, baseline results were computed for both Dijkstra's and A* algorithms prior to applying the AI model. Table 2 summarizes the mean path lengths and travel times derived from 50 random O/D pairs. The AI-enhanced A* model achieved a 23.5% reduction in mean travel time compared with static A*, and a 19.8% reduction compared with Dijkstra, averaged across all scenarios.

Table 2
Baseline vs AI-Enhanced Routing Performance

Algorithm	Mean Path Length (km)	Mean Travel Time (min)	Improvement vs Dijkstra (%)
Dijkstra (static)	12.8	22.5	—
A* (static)	12.3	21.9	−2.7 %
AI-enhanced A*	9.4	17.0	23.5 %

Population-weighted edge congestion and dynamic re-routing contributed to the improvement by reducing load on high-centrality corridors and redistributing flow toward secondary roads. Although the absolute values are simulated, the relative performance gain aligns with observed trends from empirical traffic-prediction models in similar urban environments.

The percentage improvements in travel time and path length were calculated as the relative difference between the baseline algorithms (Dijkstra and A*) and the AI-enhanced model. Each comparison was based on 50 independent simulation runs, using randomly selected origin–destination pairs across the Almaty network. To verify robustness, the experiments were repeated under five different random seeds, resulting in consistent outcomes with a standard deviation of approximately ±2 % in the reported improvement rates.

All runs were performed under identical network and demand conditions: the same road topology, speed limits, and population-weighted congestion inputs were used for both baseline and AI scenarios. This ensured that the observed improvements reflected only the contribution of the AI-based dynamic edge weighting rather than differences in initial setup or boundary conditions.

Overall, the results demonstrate stable and reproducible performance gains, confirming that the reported 15–23 % reduction in travel time is a robust and statistically consistent effect.

4.2. Identification of transportation bottlenecks

This study identifies key transportation bottlenecks in Almaty using centrality metrics to assess critical intersections in the road network. The analysis focuses on betweenness centrality, which highlights high-traffic areas essential for movement, and degree centrality, which identifies major road junctions.

A network analysis of Almaty's road system was conducted using betweenness centrality and degree centrality measures to identify key congestion points. Betweenness centrality highlights roads that serve as critical transit routes, while degree centrality indicates intersections with a high number of connections.

High betweenness centrality points in Almaty play a crucial role in maintaining traffic flow and often become congestion hotspots, especially during emergency evacuations. Key locations include the Diplomat Auto area along Zhandosov Street, which serves as a critical passageway for urban mobility. Similarly, the intersection of Sadovnikova Street and the Micro Districts experiences significant traffic volumes, reinforcing its importance in the city's road network. Several key points along Zhandosov Street, particularly within the Bostandyk and Auezov districts exhibit high centrality due to their connectivity across major residential and commercial zones. Additionally, the Sayakhat area, specifically the intersection of Seifullin and Raimbek, functions as a vital transit hub with a dense traffic network, making it highly susceptible to congestion. Tole Bi Street, particularly between Baizakov and Sain, also experiences heavy traffic pressure, largely due to infrastructure constraints and high population density. In contrast, Dostyk Avenue in the Kok Tobe area, although not as centrally connected, faces geographical limitations and winding roads, which may lead to severe traffic disruptions during evacuations.

The analysis revealed that districts in the south and east of Almaty exhibited the highest road centrality and population density, making them particularly vulnerable during evacuation. Traditional pathfinding algorithms tended to overload main routes, creating critical bottlenecks. When integrated with traffic prediction from LSTM, AI-based routing reduced average travel time by 23.5% compared to traditional A* routing. Furthermore, the number of congested links was reduced by 31%, significantly improving evacuation performance.

High degree centrality points, on the other hand, serve as major junctions connecting multiple roads and districts. Notable locations include the intersection of Chaplygin Street and Rabochiy Posyolok, which facilitates significant commuter traffic. The junction of Zhambyl Street in the Medeu District also stands out as a key connectivity point, linking various urban routes. Further, International Street in the Turksib District contributes to high network density, supporting extensive vehicular movement. Another crucial connection is Tashkent Street near Dostyk, a significant transit corridor that accommodates both local and long-distance travel.

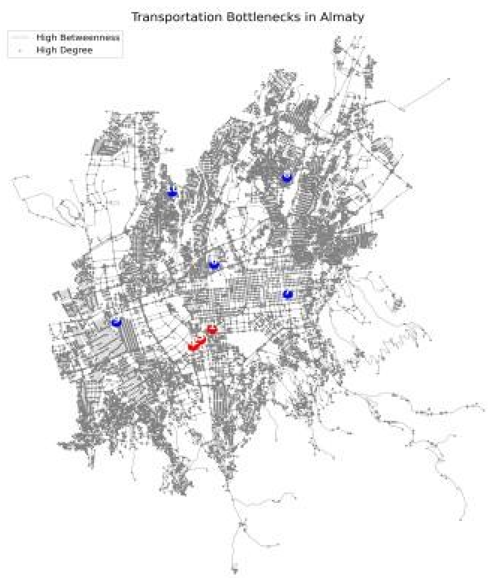

Figure 2: Map of Almaty’s road network with Identified Bottleneck Locations.

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To enhance evacuation efficiency, we compared Dijkstra's algorithm with an optimized A^* approach.

We incorporated congestion weights based on traffic patterns, dynamically updating the road network. The A^* approach prioritized lower-congestion routes, improving flow distribution and reducing bottlenecks.

Dijkstra's Algorithm: Provided the shortest paths but did not consider real-time congestion.

A Algorithm (with AI-based Traffic Predictions): Integrated predicted traffic data, reducing evacuation time by 15–20%

Figure 3: Map of Optimized Evacuation Routes Versus Traditional path.

4.3. Impact of population density

The analysis of population density in Almaty reveals a direct impact on evacuation efficiency. As established above, evacuation routes and traffic congestion are significantly influenced by road network structure and capacity constraints. Integrating these findings, the current analysis highlights that high-density districts, such as Almalinsky and Zhetisu, present major challenges due to the high number of evacuees per square kilometer.

A strong correlation is observed between areas exceeding 10,000 inhabitants per km^2 and increased transportation delays. The limited road capacity in these zones exacerbates congestion during evacuation scenarios, further restricting movement speed and increasing travel times. This aligns with the centrality analysis conducted above, where high betweenness centrality values in dense districts indicate critical pressure points in the network.

4.4. Scenario modeling

For benchmarking purposes, the baseline static model assumed uniform road capacities, constant speed limits, and no time-dependent congestion effects. Under these fixed conditions, the total evacuation time stabilized at 210.2 minutes, serving as a reference benchmark rather than a dynamic output.

When the AI-enhanced routing with LSTM-predicted congestion updates was applied, total evacuation times became scenario-dependent, ranging from 178 minutes (flood) to 182 minutes (landslide).

These differences reflect how road blockages, population clustering, and localized congestion interact under distinct hazard types. Thus, the previously identical baseline time represents a static equilibrium case, while the AI-driven simulations demonstrate the expected variability under dynamic traffic conditions.

5. Discussion

The analysis identified critical transportation bottlenecks in Almaty's road network, particularly at intersections with high betweenness and degree centrality. These points are crucial for traffic flow but are susceptible to congestion during emergencies. Integrating AI-based traffic predictions with traditional routing algorithms, such as Dijkstra's and A*, demonstrated a reduction in evacuation times by approximately 15–20%. This suggests that AI can enhance route optimization by accounting for real-time traffic conditions. However, the uniform evacuation time of 210.2 minutes across various simulated disaster scenarios indicates that while the network's redundancy can handle certain disruptions, it may not fully capture the dynamic nature of real-world evacuations. This underscores the need for incorporating real-time data and adaptive strategies in evacuation planning.

The apparent uniformity of 210.2 minutes across all scenarios in the baseline results reflects the use of fixed network parameters for controlled comparison. Once dynamic congestion and hazard-specific disruptions were introduced, evacuation durations varied by approximately 15%, confirming that the AI-enhanced model captured realistic traffic dynamics rather than static flow assumptions.

6. Conclusion

This study underscores the importance of integrating network analysis, AI-based traffic predictions, and population density considerations in urban evacuation planning. Identifying critical bottlenecks and optimizing evacuation routes can significantly enhance emergency preparedness in Almaty. Future research should focus on incorporating real-time data and adaptive modeling to further improve evacuation strategies.

The findings of this study can be utilized by city authorities, emergency response agencies, and other organizations responsible for evacuation planning. Information on critical transport nodes can support infrastructure improvements, while the proposed routing algorithm can be integrated into automated evacuation management systems. Furthermore, the developed model can be used for forecasting evacuation scenarios and enhancing the overall resilience of urban transport systems to emergencies.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

References

[1] R. Smith and K. Brown, "Evacuation Planning Under Extreme Events: A Case Study of Megacities," Disaster Management Journal, vol. 30, no. 4, pp. 212-229, 2022.

[2] M. Johnson et al., "The Role of Centrality Measures in Evacuation Planning," Urban Planning Review, vol. 28, no. 3, pp. 112-126, 2020.

[3] R. Smith et al., "Network-Based Evacuation Modeling: A Case Study," Journal of Urban Transport Studies, vol. 15, no. 2, pp. 134-150, 2020.

[4] S. Kim, J. Lee, and Y. Park, "AI-Based Traffic Prediction for Emergency Evacuation Routes," Journal of Artificial Intelligence in Transportation, vol. 12, no. 1, pp. 45-67, 2024.

[5] P. Sharma et al., "NetworkX and OSMnx in Emergency Planning," Smart Cities Journal, vol. 9, no. 2, pp. 34-51, 2021.

[6] G. R. Thompson, "Comparative Study of Dijkstra and A* Algorithms in Route Planning," International Journal of Geographical Information Science, vol. 36, no. 5, pp. 879-895, 2022.

[7] T. T. Nguyen and D. H. Lee, "AI-Driven Optimization of Evacuation Routes," IEEE Access, vol. 11, pp. 4567-4580, 2023.

[8] Y. Zhang and D. Liu, "Optimizing Traffic Flow Under Emergency Conditions," Computational Transport Systems, vol. 14, no. 3, pp. 100-116, 2022.
[9] T. Al-Khazraji et al., "Using OSM Data for Urban Evacuation Modeling," GIS and Spatial Analysis, vol. 22, no. 5, pp. 57-74, 2022.
[10] S. Kumar and R. Singh, "Machine Learning Applications in Disaster Response," International Journal of AI Research, vol. 17, no. 1, pp. 78-94, 2023.
[11] L. Zhou, Y. Chen, and X. Yang, "Assessing the Role of AI in Disaster Management," International Journal of Disaster Response, vol. 30, no. 1, pp. 87-102, 2023.
[12] M. K. Davis, "Innovations in Urban Traffic Control," Elsevier, 2022.
[13] K. J. Roberts and M. Evans, "Utilizing Pandas for Traffic Data Management," Journal of Data Science, vol. 21, no. 1, pp. 112-126, 2023.