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Weighted Multi-Objective Enriched Navigation using Slender Loris Optimization Algorithm

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Abstract

Urban mobility remains a major concern in smart city environments, as most navigation systems optimize routes primarily based on distance or travel time while overlooking safety factors such as crime patterns, environmental conditions, and population presence. This limitation exposes travellers particularly women, tourists, and other vulnerable groups to increased risk in unfamiliar or isolated areas. To address this issue, this paper proposes Weighted Multi-Objective Enriched Navigation using Slender Loris Optimization Algorithm (WOMEN_SLOA), a multi-objective routing framework that integrates safety indicators with conventional routing metrics for secure urban travel. Inspired by the cautious behaviour of the slender loris, the SLOA based model balances travel distance, travel time, and risk exposure during route selection. Historical crime and accident records, spatial points of interest, and mobility patterns are fused through a weighted safety-scoring scheme to estimate segment-level safety and guide path optimization. A perception-oriented component is further examined to analyse how subjective safety awareness may influence routing behaviour. Experimental results show that the proposed system reduces exposure to high-risk areas while maintaining competitive routing efficiency compared with traditional shortest-path approaches. These findings demonstrate the potential of WOMEN_SLOA for safety-aware navigation in smart city transportation systems.

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1 Introduction

Ensuring personal safety during travel has become a growing concern in modern urban environments, particularly within rapidly developing smart cities and intelligent transportation systems. Existing navigation tools, such as Google Maps and similar routing services, typically prioritize the shortest distance or minimum travel time, often overlooking user safety. However, the fastest route may not always be the safest, especially in areas characterized by high crime rates, poor lighting, or low pedestrian activity. As urban mobility becomes more dynamic, the demand for safety-aware navigation systems continues to rise (Lakshmi & Joseph, 2022). Women experience heightened vulnerability during travel, especially when navigating unfamiliar or poorly monitored areas at night (Stark & Meschik, 2018). Consequently, many women deliberately choose longer but perceived safer routes to avoid potential harassment or unsafe environments. Supporting this concern, a 2014 survey by Cornell University and Hollaback reported that 85% of 4,872 American women altered their routes to avoid harassment, and 67% adjusted their travel times to reduce risk (ILR & Hollaback!, 2023). These findings clearly indicate the gap between conventional route optimization and real-world safety needs. Native residents often develop implicit knowledge about safer areas and time-sensitive risk patterns. In contrast, visitors and new residents lack such contextual awareness and may unknowingly travel through unsafe streets due to insufficient information regarding local crime trends and environmental risks (Harms et al., 2021).

With increasing urbanization, rising crime rates, and evolving social conditions, travelers frequently conduct independent research, such as reviewing crime reports or seeking local advice before exploring unfamiliar areas. These approaches are time-consuming and unsuitable for real-time decision-making. Moreover, crime patterns fluctuate depending on time of day, events, and seasonal variations, rendering static safety information inadequate (Makariye, 2017; Kim et al., 2023). Although some cities, such as New York, provide safety heat maps that visualise crime intensity, these representations are often coarse and limited to district-level summaries. To enhance urban mobility and personal security, navigation systems must incorporate additional dimensions such as environmental context, user preferences, and perceived safety indicators (Jiang et al., 2022).

Urban safety remains a major concern in contemporary city planning. According to the Ministry of Road Transport and Highways (MoRTH), India reports over 170,000 road fatalities annually, with pedestrians and two-wheeler riders accounting for a significant proportion of victims (Ministry of Road Transport and Highways, 2023). These figures emphasize the need for navigation systems that extend beyond temporal or spatial optimization to incorporate safety-aware decision-making.

The expansion of smart city initiatives offers opportunities to integrate diverse urban data sources for addressing safety challenges. Despite advancements in computational routing methods, most navigation systems continue to prioritize shortest-path or fastest-route strategies without explicitly incorporating contextual safety indicators (Li et al., 2017). This limitation becomes critical in environments where crime distribution, infrastructure quality, and environmental conditions vary significantly. Smart city platforms leverage sensing technologies, cloud infrastructure, and data-driven decision frameworks to enhance urban services (Doolan & Muntean, 2017; Garip et al., 2015). However, a persistent gap exists between large-scale data collection and meaningful data utilization. Although municipal authorities promote open data initiatives, researchers often face limited access to structured, actionable datasets. Understanding dataset characteristics and limitations is therefore essential for advancing safety-aware routing solutions (Mobasheri et al., 2017).

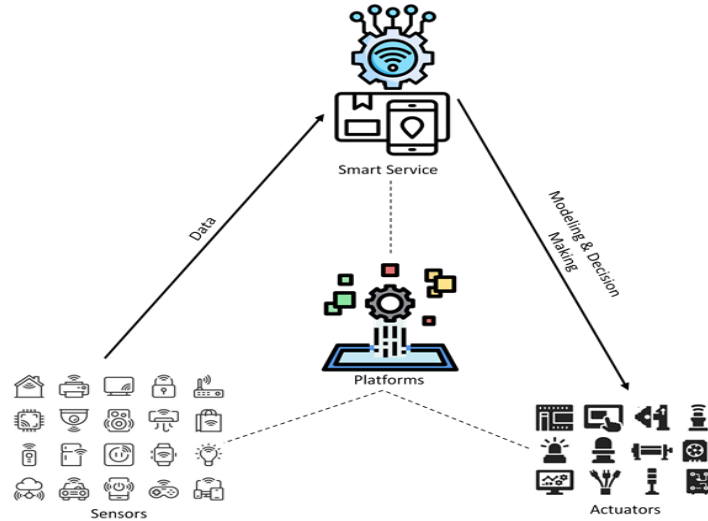


Figure 1. Data, modelling, and decision making in smart cities

To quantify urban risk, several studies have introduced safety indices within navigation frameworks. Consequently, route planning has been formulated as a multi-objective optimization problem over a road network, aiming to minimize travel distance while maximizing safety levels. As a variant of the Multi-Objective Optimization Problem (MOOP), this problem is computationally complex and NP-complete. Due to this complexity, traditional exact methods become impractical for real-time applications, leading researchers to adopt meta-heuristic optimization techniques for efficient route discovery (Song et al., 2020).

Advancements in Intelligent Transportation Systems (ITS) have enhanced the ability to analyze traffic and pedestrian behavior. Machine learning techniques enable the detection of anomalies such as unusual crowd patterns or recurring incidents, facilitating proactive identification of risk-prone regions (Zhou et al., 2025). Mobile and wearable technologies further enable real-time alerts, dynamic rerouting, and location-based risk notifications. Crowdsourced feedback enriches safety perception layers with community-driven insights, improving system adaptability and contextual awareness (Su et al., 2014). Safety-aware navigation contributes to social inclusion by reducing fear and travel avoidance behavior, particularly among women and other vulnerable groups. Such systems promote equitable access to essential services and foster more resilient urban mobility environments.

To enhance commuter safety, the Q-learning-based S-Nav framework was proposed to avoid high-risk zones through dynamic risk classification (Misra et al., 2021). Despite such progress, several challenges remain. Data availability and quality vary across cities, creating coverage gaps and reliability concerns. Additionally, privacy protection is critical when utilizing geo-location and surveillance-based data. Defining universally applicable safety metrics is also complex due to subjective perceptions and dynamic urban conditions (Zhang et al., 2014).

Advances in computational infrastructure now enable integration of diverse safety indicators within routing models. Modern travelers increasingly expect navigation systems that ensure both efficiency and safety. Consequently, recent research emphasizes integrating crime statistics and accident data into routing decisions to support risk-aware mobility (He et al., 2017), (Lakshmi et al., 2024).

To address these limitations, a novel multi-objective path-planning framework based on the Slender Loris Optimization Algorithm (SLOA) (Vijaya Lakshmi et al., 2024) is proposed. The model integrates safety-critical parameters to generate secure and efficient route recommendations while balancing competing objectives under uncertain conditions.

This research develops a system that recommends safe routes, particularly for women travelers, by identifying paths with higher safety index values between the source and destination. The contributions have been made as follows:

- **Specialized Focus on Late-Night Travel Safety:** Unlike existing systems, this paper identified the special challenges brought about during the late hours; this work focuses on analyzing data specific to late-night travel.
- **Comprehensive human mobility insights** can be drawn from the integration of POI data, route preferences, and social check-in data. The innovative methodology of the research brings forth the identification of the routes secured and much frequented by the community at night; it then suggests pathways to reduce the dangers associated with being alone at night.
- A perception-based recommendation component is introduced to analyze how experiential awareness may influence route selection, enabling personalized guidance according to user familiarity levels.
- The Slender Loris Optimization Algorithm is employed as a multi-objective optimizer to simultaneously balance travel distance, travel time, and safety risk, enabling the generation of efficient and safer navigation paths.

In this personalized recommendation system, community knowledge and shared experiences are leveraged to provide safety tips tailored to individual user needs, resulting in more effective and relevant guidance. The following section explains the framework for discovering the safest route using optimization algorithms for road travelers. A comprehensive review of related research is presented in Section 2. The proposed architecture of WOMEN_SLOA, along with the methodology for calculating the safety index and its associated factors, is described in Section 3. Section 4 details the datasets used, visualization procedures, and implementation framework. Section 5 presents the results and comparative performance analysis, followed by a discussion of the findings. Finally, Section 6 concludes the study by summarizing the key outcomes related to safe route discovery for urban travelers using WOMEN_SLOA.

2 Related work

Vehicular Navigation Systems (VNS) primarily optimize traffic efficiency by recommending the fastest routes based on current traffic conditions. Similarly, Intelligent Transportation Systems (ITS) focus on congestion detection and rerouting strategies (Pan et al., 2017). However, these systems often overlook safety-related risks, potentially directing vehicles through unsafe areas to avoid congestion. To address this limitation, recent studies have explored safety-aware and personalized routing approaches. The SafePath (Galbrun et al., 2016) system recommends secure routes using publicly available crime records to estimate street-level risk and balance safety with travel efficiency. Similarly, Crowdsafe leverages crowdsourced crime reports to generate safer navigation paths (Shah et al., 2011). However, reliance solely on user-reported incidents may introduce noise and underreporting issues. A safe-routing system for Mexico City employs Naïve Bayes classification to process official crime data and crime-related tweets for route guidance (Mata et al., 2016). Another approach utilizes sentiment analysis of geocoded tweets to identify high-risk areas and adjusts routing decisions accordingly (Kim et al., 2014). Despite these advancements, many systems lack adequate consideration of late-night travel risks and do not incorporate personalized safety perception into route selection. Multi-objective route planning has been widely applied in communication networks, transportation systems, and robotics. As an NP-complete problem, it requires balancing multiple conflicting objectives simultaneously. Two primary approaches exist: the *a priori* method, which converts multiple objectives into a single weighted objective, and the *a posteriori* method, which generates a set of trade-off solutions without predefined priorities (Emmerich & Deutz, 2018; Chagas & Wagner, 2022). Several multi-objective evolutionary algorithms have been proposed, including NPGA (Horn et al., 1994), MOGA (Murata

et al., 1996), SPEA2 (Zitzler et al., 2001), and NSGA-II (Deb et al., 2002). Although NSGA-II demonstrates strong performance, GA-based route planning faces practical limitations. Genetic operators may produce infeasible routes, and high-dimensional Pareto fronts complicate evaluation and visualization. Small variations in one objective may also significantly influence others, increasing decision complexity.

To address these challenges, this study adopts a weighted-sum formulation in conjunction with the proposed SLOA-based optimization framework. The weighted sum approach simplifies multi-objective routing into a single-objective formulation, while SLOA enhances exploration capability and convergence efficiency.

3 System architecture

The higher-level architecture of the proposed WOMEN_SLOA system consists of three primary components: (i) data pre-processing, (ii) safety index computation at the road-segment level, and (iii) multi-objective optimization-based routing. Figure 1 presents the overall framework, and Figure 2 illustrates the operational workflow of the proposed system.

At the input layer, the system collects essential user information such as origin, destination, and travel profile (e.g., gender, tourist status), along with dynamic contextual data, including traffic updates, incident reports, and environmental conditions. These inputs are integrated with heterogeneous smart-city datasets, including historical crime data, accident records, point-of-interest (POI) information, frequently preferred routes, human mobility patterns, and a prototype-level Peer Recommendation Score (PRS) module.

During the pre-processing stage, raw datasets are spatially aligned with road segments, temporally weighted, normalized, and aggregated to derive meaningful segment-level attributes. A weighted safety scoring framework then computes a safety index for each road segment by combining crime intensity, lighting availability, pedestrian density, emergency accessibility, and other contextual urban safety factors. The PRS component provides experiential feedback-based insights and is currently implemented as a prototype module to enhance the segment-level safety assessment.

The computed safety indices are passed to the multi-objective optimization engine based on the Slender Loris Optimization Algorithm (SLOA). This engine simultaneously balances travel distance, travel time, and aggregated safety risk to generate optimized safety-aware routes. Candidate routes are ranked according to user-defined preference weights to support personalized navigation decisions.

The final recommended routes are delivered through a web-based interface designed for interactive visualization, route comparison, and safety-aware navigation support. The overall architecture ensures that routing decisions are guided not only by efficiency but also by dynamic urban safety intelligence, with particular emphasis on safer mobility for women, especially during late-hour travel.

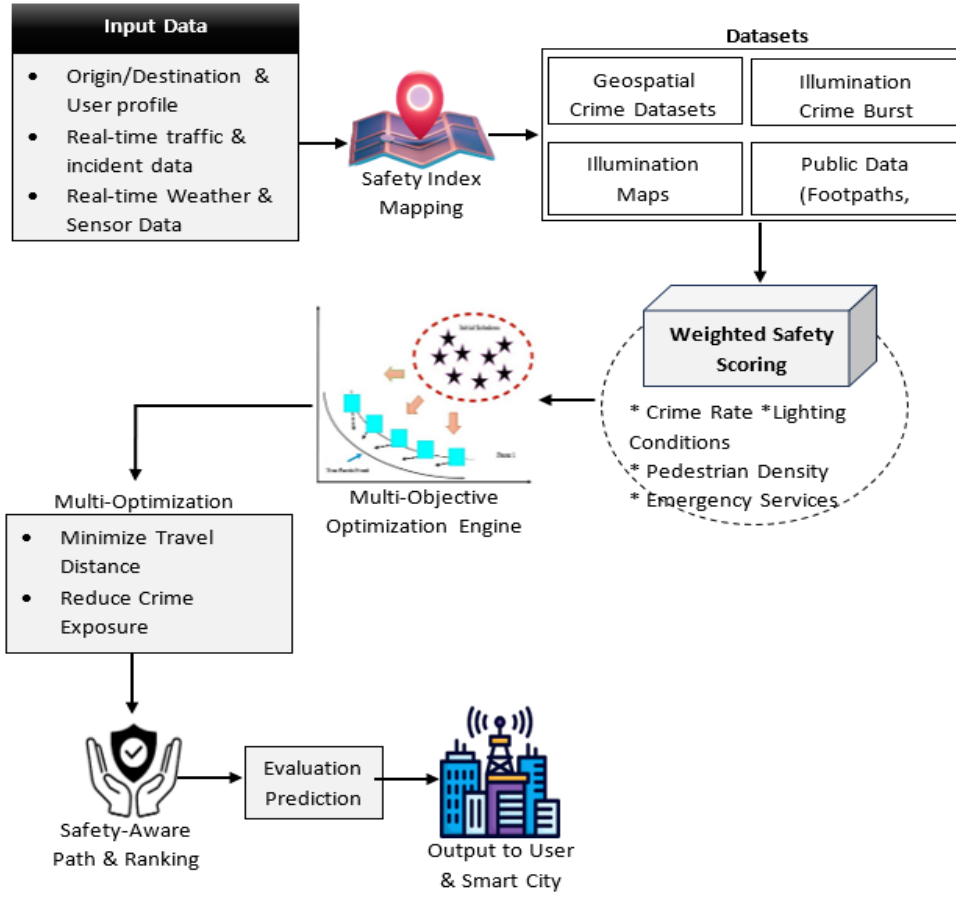


Figure 2. Proposed system architecture

3.1 Dataset description

The objective of this section is to develop a methodology to assign a safety index value to a road network by considering various safety metrics obtained from multiple sources. The data used for safety assessment in this work are classified into historical crime and accident data, POI spatial data, and traffic-related data used to identify frequently preferred routes and human mobility.

Crime data and accidental data

Safe routing has been widely explored in the literature, with numerous studies proposing algorithms that optimize travel paths based on safety, traffic conditions, and accident-prone areas. In our work, we considered both static and dynamic safety based on crime and accident datasets. For the static safety score computation, accident and crime data are first geo-coded and map-matched to the road network. Then, the safety score of each road segment is calculated based on the accumulated number of crime and accident incidents. A higher number of crime incidents in a road segment indicates a greater likelihood of crime occurrence, and similarly, a higher number of accumulated accident cases indicates an increased probability of collision risk.

Equation (1) defines the Safety Index for Crime and Accidents ($SI_{C,A}$):

$$SI_{C,A} = \alpha \cdot cip + \beta \cdot crp \quad (1)$$

Where: cip = Crime Incident Probability; crp = Collision Risk Probability; α and β are weighting factors such that $\alpha + \beta = 1$

Both probabilities are derived from real-world incident frequency relative to population and spatial density:

$$cip = \frac{N_c}{P} \quad (2)$$

$$crp = \frac{N_a}{T_e} \quad (3)$$

Where: N_c = number of crimes reports in the grid/region; N_a = number of reported accidents/collisions; P = total population of the region; T_e = traffic volume of road segment e).

These raw probabilities may exceed 1 due to high incident density - hence normalization is required.

To ensure values lie between 0 and 1, min-max normalization is applied:

$$cip_{norm} = \frac{cip - cip_{min}}{cip_{max} - cip_{min}} \quad (4)$$

$$crp_{norm} = \frac{crp - crp_{min}}{crp_{max} - crp_{min}} \quad (5)$$

$$\text{Thus: } cip := cip_{norm} \in [0,1] \quad (6)$$

$$crp := crp_{norm} \in [0,1] \quad (7)$$

Normalization transforms them into a dimensionless scale between 0 and 1, enabling fair integration into the overall safety index.

For the dynamic safety score (DSS), LSTM_AM [19] is used to predict the safe route availability score for the road segment. This study was conducted with the objective of constructing a prognostic framework that uses LSTM networks in conjunction with attention mechanisms for the examination of accident and crime data, ultimately offering precise and evolving assessments of route availability. The LSTM receives time-series features for each grid/node, as detailed in Table 1.

Table 1. Temporal features and their description

Temporal Feature	Description
Crime frequency trend	Hourly reports mapped to the road segment
Accident trend	Time-dependent collision density
Traffic flow	Number of taxis/vehicles available per hour
Lighting/Active POIs	Level of human activity & illumination at night

These features are encoded in hourly sequences over several weeks/months to capture seasonal and periodic variations.

$$DSS_t = \sigma(W_h \cdot h_{t-1} + W_z \cdot I_t + b) \quad (8)$$

Where: I_t = input vector of temporal features at time t; h_{t-1} previous hidden state of the LSTM; W_h, W_z, b learnable parameters; σ = activation function ensuring score normalization in [0,1]. DSS varies based on actual day-night conditions, seasonal fluctuations, and real-time signals where available.

The Route Availability Score (RAS) incorporates DSS to ensure that unsafe or less-active routes during late-night hours are penalized:

$$RAS(r, t) = \frac{1}{|r|} \sum_{x \in r} DSS_{x,t} \quad (9)$$

Here: r = selected route; t = time of travel; $DSS_{x,t}$ time-specific safety value of each node/segment

This ensures:

- Different route outputs for the same origin-destination pair depending on travel time.
- Improved safety for women by prioritizing well-lit, high-activity late-night paths.

- sClear separation between algorithm logic and dataset-driven temporal risk estimation

The proposed work involves compiling comprehensive accident and crime datasets, encompassing detailed information on road accidents (timestamps, locations, severity, weather conditions, traffic volume) and crime incidents (types of crimes, timestamps, locations, severity). The LSTM model takes multiple input variables that influence road safety and traffic conditions. These include real-time traffic volume (vehicles per hour), population density (people/km²), road spatial features (area, lane count), and environmental factors such as weather conditions (temperature, precipitation, visibility, and wind speed). Each variable is normalized and temporally aligned to ensure proper sequence modeling, allowing the LSTM to capture complex temporal dependencies in safety and incident prediction. The datasets undergo meticulous pre-processing to guarantee uniformity and precision. Numeric attributes such as traffic volume and severity are standardized, while categorical variables like weather conditions and crime types are transformed into numerical values through one-hot encoding. Accident and crime data are synchronized to ensure consistent time granularity (e.g., hourly or daily). The core of the system is an LSTM-based model integrated with an attention mechanism. Data are structured into sequences to capture temporal trends, with each sequence encompassing features including accident occurrences, crime reports, weather conditions, and traffic volume. The LSTM layers analyze these sequences to detect long-term relationships and patterns in the data. An attention layer is incorporated to enable the model to focus on the most pertinent time intervals within each sequence, thereby enhancing prediction accuracy. The final output layer produces an availability score RA for each road segment, indicating the probability of the route being unobstructed and secure, as depicted in Figure 3.

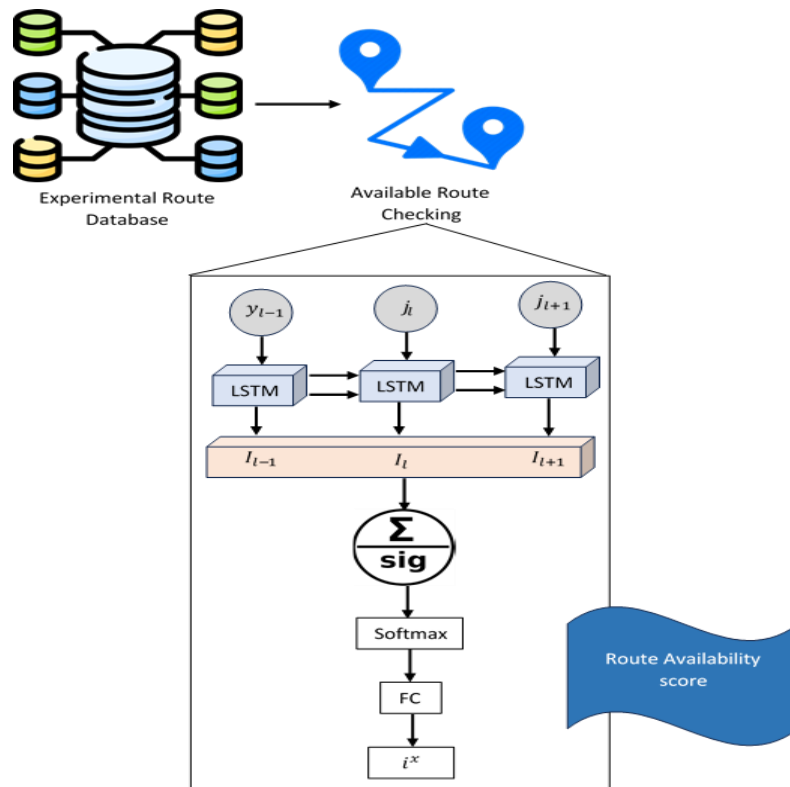


Figure 3. LSTM-AM- based safest route score prediction (Adapted from (Lakshmi et al., 2024)).

POI data

This metric considers the presence and proximity of significant points of interest (POIs) along a route. These include locations such as hospitals, hotels, restaurants, gas stations, pharmacies, schools, and police stations. POIs possess various characteristics that are beneficial for location-based services. In navigation systems, identifying nearby services and incorporating POIs and landmarks enhances the efficiency of route planning. The presence of certain POIs, such as police stations, may reduce the likelihood of crime, while POIs in general influence human mobility patterns. Roads with a higher density of POIs typically experience greater human activity compared to isolated roads with few or no POIs. This increased activity can contribute to improved perceived safety.

The safety index based on POI is formulated in Equation (10).

$$S_{IPOI} = \sum_{i=1}^N POIfs(i) \quad (10)$$

Where:

- S_{IPOI} = Safety index contribution based on POIs
- $POIfs(i)$ = familiarity score of the i-th POI, calculated as:

$$POIfs(i) = \frac{\text{Number of visits to } POI_i}{\text{Maximum number of visits among all } POIs}$$

This formula normalizes POI visits between 0 and 1. A POI that is frequently visited receives a higher familiarity score, indicating greater public awareness and better monitoring, which can contribute positively to road safety evaluation. Less-visited POIs have lower scores, reflecting potential safety risks.

Frequently preferred route (FPR)

Big trajectory data has emerged because of the increase in mobile devices with GPS. The objective of this metric is to import the common navigation preference route of the earlier travelers. When visiting an unfamiliar place, travelers, especially women, preferred to follow the most commonly used route for several reasons, such as to avoid risk and dangerous spots. At first footmark graph is constructed from the trajectory data for the user-specified destination for the given time period. From that path, the frequency is calculated based on the number of trips for the path. Footmark graph is also indirectly connected to the human mobility pattern, so that the route with more footmarks is considerably safer compared to deserted routes. The road segment safety value is measured based on the footmark by Equation (11).

$$SI_{FPR} = \sum_{s \rightarrow d, e \in E} X \cdot \log \left(\frac{fpr_i}{fpr_{\max}} + Y \right) \quad (11)$$

Where X, Y are scaling and logarithmic constant

fpr_i represent the frequency of road segment i

$fpr_{\max}$ represent the maximum frequency of usage among all road segments

Human mobility

Road safety is influenced by traffic flow and human mobility. From the trajectory data, we analyze and derive insights about human mobility patterns, such as identifying popular routes, common destinations, and areas with high pedestrian traffic. These insights can be useful for urban planning, transportation management, and other applications. The number of individuals entering the region and the number of persons leaving the region are therefore the two attributes that we identify for each grid. These characteristics are taken from taxi trajectories that track the pick-up and drop-off points for every journey. Even though much of the work is concentrated on avoiding

traffic congestion in rerouting, in safe routing, roads with considerable human mobility are preferred to reduce the fear and anxiety of traveling alone during late hours. The safety index based on human mobility is calculated based on Equation (12).

$$SIHM = \sum_{e \in E} [n(H_A) + n(H_D)] \quad (12)$$

Where, H_A is the number of pickup and drop-off for the particular source grid; H_D no of pick-up and drop-off for the particular destination grid

Peer recommendation score

The information required to calculate the safety index of a road segment can be sourced from official crime records and individual travel encounters gathered through crowdsourcing. The latter is particularly valuable due to its recentness and broader coverage. Crowd-sourced knowledge is commonly utilized in route recommendation systems, where the experiences of local travelers are directly applied to identify safer routes (Islam et al., 2021). To explore this aspect, the proposed work introduces a peer recommendation mechanism that considers driver experience levels. A Peer Recommendation Score (PRS) is formulated to differentiate route suggestions for novice and experienced users, enabling personalized navigation based on familiarity and comfort. This PRS is incorporated as a prototype extension of the framework to examine how experiential feedback could be integrated with computed safety indicators. The components and characteristics of the PRS are summarized in Table 2.

Within the WOMEN_SLOA framework, the PRS complements the safety index by representing perceived safety conditions alongside statistical environmental indicators such as crime records and illumination. The weighted formulation allows subjective awareness to influence route preference while maintaining consistency with the data-driven safety evaluation. The score models experiential perception for specific locations or routes, enabling the system to account for potential human judgement in addition to static environmental data. Each value contributes to a combined framework that balances perception with objective safety indicators, allowing WOMEN_SLOA to adapt route selection according to both measured risk and perceived comfort, particularly in areas with limited historical incident information.

Table 2. Aspects and details

Aspect	Details
Feature	Peer Recommendation Score (PRS)
Purpose	Enhances route safety by integrating user/community feedback on the safety of specific locations or routes.
Dataset Used	User feedback inputs in a prototype setting
Data Type	User generated inputs and dynamically updated contextual safety information
No. of Feedback Entries	Variable depending on participation
Geographic Coverage	Applicable to urban navigation regions.
Temporal Span	Continuously updated as new feedback is received
Calculation Method	Weighted scoring framework integrating peer feedback with crime data, illumination, and infrastructure related features to compute the overall safety index.

To ensure that the proposed safety-aware routing model genuinely caters to the specific needs of women travelers, this work integrates multiple heterogeneous datasets with explicit emphasis on women-centric safety indicators shown in Table 3. The safety index assigned to each road segment is derived using historical crime and accident records, spatial Point-of-Interest (POI) data, and human mobility information. Unlike general crime data used in previous works, the crime dataset in this study includes a distinct subset dedicated to Crimes Against Women (CAW), such as harassment, stalking, kidnapping, and sexual assault, enabling the model to estimate female-specific risk levels more accurately. POI features such as police stations, hospitals, and well-lit public establishments are incorporated to reflect increased surveillance and social presence, which

have proven to reduce women's vulnerability in public spaces. Mobility data, including pick-up/drop-off activity and temporal travel patterns, allow the system to differentiate between high-risk isolated routes and safer, highly populated ones, especially during night-time hours when the risk to women is significantly higher. By incorporating these gender-focused parameters into the safety index computation, the WOMEN_SLOA model becomes more aligned with the practical safety needs of women, ensuring that routing recommendations are socially responsible, inclusive, and statistically grounded.

3.2 Pre-processing

Raw data alignment & map-matching: GNSS trajectories are map-matched to corresponding road segments to ensure segment-level feature alignment. For each positioning point p and candidate road edge e , the nearest projection onto the road network is computed. The projected point p' on edge e , is obtained as:

$$p' = \text{proj}_e(p) \quad (13)$$

Each point is then assigned to the most probable road segment based on spatial proximity and trajectory continuity. Subsequently, the mapped points are aggregated at the edge level to obtain segment-wise representations.

Temporal weighting/decay for events: A temporal weighting scheme was applied to event records so that recent incidents exerted greater influence than older ones. For each event k on edge e occurring at time t_k , its time-weighted contribution at the current time t is defined as

$$w_{t,k} = \exp\left(-\frac{t-t_k}{\tau}\right) \quad (14)$$

Where τ represents the temporal decay constant (in hours or days). The time-weighted crime score for each edge e is:

$$C_e = \sum_{k \in \varepsilon_e} s_k \cdot w_{t,k} \quad (15)$$

Where s_k denotes the severity of event k (e.g. 1 = petty, 3 = violent) and ε_e represents the set of events associated with edge e .

This formulation reduces the influence of outdated observations while preserving the significance of recent safety conditions for subsequent modeling.

Spatial smoothing/kernel density estimate (KDE): To capture the spatial distribution of crime incidents, kernel density estimation (KDE) is employed to estimate the local crime intensity around a location or road-segment centroid. The continuous density function is defined as:

$$\hat{f}(i) = \frac{1}{nh} \sum_{x=1}^n K\left(\frac{\|i-i_x\|}{h}\right) \quad (16)$$

where h denotes the bandwidth parameter, i_x represents the location of observed events, and $K(\cdot)$ is the kernel function. A Gaussian kernel is adopted, defined as: $K(u) = \frac{1}{\sqrt{2\pi}} e^{-u^2/2}$.

The estimated density $\hat{f}(i)$ provides a continuous representation of local crime intensity. This density is subsequently integrated over a spatial buffer surrounding each road segment to obtain the segment-level smoothed crime intensity $\hat{C}_e$. This transformation ensures that nearby incidents contribute proportionally to the safety characterization of each road segment, thereby improving spatial robustness.

Table 3. Dataset Description

Dataset Type and Feature	Description	Format	Source Example	Utilization in Safety Index	Women-Safety Relevance
Crime Data					
Crime Incident Reports	Location, time, crime type, severity	Point GeoJSON / CSV	City Police / NCRB	Used to compute crime probability (cip)	High*
Crimes Against Women Subset (CAW)	Filtered subset of sexual harassment, stalking, abuse, kidnapping, etc.	CSV	Women Safety Cell / NCRB	Weighted more in safety index	Critical
Accident Data					
Road Accident Records	Location, timestamp	GIS / CSV	Road Transport Authority Dataset	Used for collision risk score: crp	Indirect
Accident Severity	Injury levels and accident intensity	Numeric	Traffic Dept.	Input feature for dynamic risk modelling (LSTM-AM)	Indirect
POI Spatial Data					
Hospitals, Pharmacies	Emergency service availability	GIS POI Layer	OpenStreetMap / Govt. Portal	Improves safety confidence score	Indirect
Police Stations	Law enforcement proximity	GIS POI Layer	Public datasets	Reduces crime risk contribution	High
Market, Restaurants, Schools	Indicators of human activity	GIS POI Layer	Open data sources	Supports mobility-based safety estimation	Moderate
Mobility & User Behavior Data					
Human Mobility	Movement patterns across locations	Numeric / Aggregated	Taxi trajectories and Transport datasets	Reduces isolation-based risk	Moderate
Temporal Patterns	Time-based travel behavior	Time-series	Historical Mobility data	Input to LSTM-AM for dynamic safety	High
Environmental Data					
Street Lighting	Illumination level of road segments	Categorical / Raster	Municipal data	Used in nighttime safety scoring	High
CCTV Coverage	Surveillance availability	Categorical	Smart City data / Public safety data	Strongly reduces perceived crime risk	High

* includes crimes against women (harassment, assault)

Feature extraction per road segment: Feature extraction is performed at the road-segment level by computing normalized attributes for each edge e . The considered features include:

- Distance/length d_c (in meters), obtained from GIS data.
- Crime intensity $\hat{C}_e$, obtained from spatial smoothing of time-weighted crime scores.
- Lighting score L_e , representing streetlight density or luminance.
- Pedestrian density P_e , estimated as the average number of pedestrians per unit time (derived from mobility or sensor/cellular data where available)
- Camera/CCTV coverage V_e , defined as the proportion of the segment under surveillance.
- Emergency access distance D_e , representing the distance to the nearest police station or hospital.

To ensure comparability across features, each attribute is normalized to the range $[0,1]$ using min-max normalization:

$$\hat{i}_e = \frac{i_e - \min(I)}{\max(I) - \min(I)} \quad (17)$$

where I denotes the set of values for a given feature across all edges.

For features where higher values indicate better safety conditions (eg., L_e, P_e, V_e), the normalized value $\hat{i}_e$ is used directly. For features where higher values indicate increased risk (e.g., $\hat{C}_e, D_e$), an inverse transformation is applied:

$$\text{invert: } \hat{i}_e^{(inv)} = 1 - \hat{i}_e \quad (18)$$

Proximity/access score (continuous): To model accessibility to emergency services, the distance D_e is transformed into a bounded accessibility score using an exponential decay function:

$$A_e = \exp\left(-\frac{D_e}{\lambda}\right) \quad (19)$$

where λ controls the rate at which accessibility decreases with distance. The resulting score A_e is normalized to the range $[0,1]$, where higher values indicate better accessibility.

Weighted Safety Score (per edge): The normalized features are combined to compute a unified safety score S_e for each road segment, where higher values indicate safer conditions. The safety score is defined as:

$$S_e = w_C \cdot (1 - \hat{C}_e) + w_L \cdot \hat{L}_e + w_P \cdot \hat{P}_e + w_V \cdot \hat{V}_e + w_A \cdot \hat{A}_e \quad (20)$$

where w_C, w_L, w_P, w_V, w_A are weighting coefficients satisfying $\sum w_x = 1$. The term $(1 - \hat{C}_e)$ converts crime intensity into a safety contribution.

Automatic weight estimation: To determine feature importance in a data-driven manner, entropy-based weighting is employed. Let i_{xy} denote the normalized value of the feature y for the edge x . The probability distribution is computed as:

$$p_{xy} = \frac{i_{xy}}{\sum_x i_{xy}} \quad (21)$$

The entropy of a feature y is given by:

$$e_y = -k \sum_x p_{xy} \ln(p_{xy}) \quad (22)$$

Where $k = \frac{1}{\ln(n)}$ ensures normalization. The degree of divergence is computed as:

$$d_y = 1 - e_y \quad (23)$$

Finally, the weight of each feature is obtained as:

$$w_y = \frac{d_y}{\sum_y d_y} \quad (24)$$

These weights are subsequently used in Eq. (20) to compute the overall safety score.

Edge cost formulation for graph search: The computed safety score was transformed into a routing cost function to enable integration within the optimization framework. Let rc_e be the routing cost on edge e (to be minimized):

$$rc_e = \alpha \cdot \frac{d_e}{d_{max}} + \beta \cdot (1 - S_e) + \gamma \cdot \frac{t_e}{t_{max}} \quad (25)$$

Where: d_e represents the length, d_{max} is the maximum edge length used for normalization, S_e is the safety score in the range $[0,1]$, t_e denotes the expected travel time. The parameters α, β, γ are weighting coefficients that reflect user preferences or learned importance. The term $(1 - S_e)$ represents the residual safety risk associated with the edge.

Multi-objective problem (formal): For Pareto-based multi-objective optimization, an objective vector was defined to simultaneously minimize travel distance, safety risk exposure, and travel time:

$$\min_{\pi \in \Pi} F(\pi) = [Distance(\pi), RiskExposure(\pi), Time(\pi)] \quad (26)$$

$$\text{Where for route } \pi \text{ (sequence of edges): } Distance(\pi) = \sum_{e \in \pi} d_e \quad (27)$$

$$RiskExposure(\pi) = \sum_{e \in \pi} (1 - S_e) d_e \quad (28)$$

$$Time(\pi) = \sum_{e \in \pi} t_e \quad (29)$$

A multi-objective optimization strategy based on the Slender Loris Optimization Algorithm (SLOA) was employed to search for Pareto-optimal routes that balance efficiency and safety.

Post-processing: ranking & user preference: During post-processing, k candidate routes $\{\pi_1, \dots, \pi_k\}$ obtained from the optimizer were evaluated and ranked based on user preferences. Let the preference vector be defined as:

$$u = [u_1, u_2, u_3], \sum u_x = 1$$

A composite score for each route is computed as:

$$Score(\pi) = u_1 \cdot \frac{Distance(\pi)}{\max_x Distance(\pi_x)} + u_2 \cdot \frac{RiskExposure(\pi)}{\max_x RiskExposure(\pi_x)} + u_3 \cdot \frac{Time(\pi)}{\max_x Time(\pi_x)} \quad (30)$$

The normalization ensures comparability across objectives, and routes are ranked based on the computed score, where lower values indicate more preferable routes.

Uncertainty & Bayesian fusion (optional): If multiple sensors estimate the same feature (e.g., pedestrian density from camera and mobile counts), the estimates were fused with variances σ_1^2, σ_2^2 via precision-weighted average:

$$\hat{i} = \frac{i_1/\sigma_1^2 + i_2/\sigma_2^2}{1/\sigma_1^2 + 1/\sigma_2^2} \quad (31)$$

$$Var(i) = \frac{1}{1/\sigma_1^2 + 1/\sigma_2^2} \quad (32)$$

3.3 Multi-objective route planning algorithm

In this work, safe route navigation is formulated as a multi-objective optimization problem (MOOP). The routing decision considers both travel efficiency and safety. Instead of optimizing only the shortest path, the proposed framework evaluates routes based on a weighted combination of multiple criteria.

The weighted sum method is adopted to manage trade-offs between conflicting objectives. Each objective function is assigned a user-defined weight, and the weighted objectives are aggregated into a unified optimization function. This formulation enables the identification of routes that balance travel distance and safety risk. Although the shortest route may not always be the safest,

the weighted framework allows prioritization of safer routes while keeping travel distance within acceptable limits.

For solving the optimization problem, the Slender Loris Optimization Algorithm (SLOA) [20] is employed to discover optimal safety-aware routes efficiently.

Slender Loris Optimization Algorithm

The Slender Loris Optimization Algorithm (SLOA) is a nature-inspired metaheuristic based on the adaptive and cautious behavior of slender lorises during foraging and predator avoidance. The algorithm models two primary behavioral phases: The exploration phase, which represents movement between trees and avoidance of predators, enabling global search across the solution space. Exploitation phase: Represents focused food-gathering behavior, allowing local refinement of promising solutions. A key mechanism in SLOA is the Route Penalization Factor (RPF), which discourages revisiting previously explored sub-optimal regions. This improves convergence efficiency and prevents premature stagnation. The complete biological modeling and mathematical derivations of SLOA are detailed in Vijaya Lakshmi et al. (2024). In this study, the algorithm is adapted specifically for safety-aware path planning over an urban road network. Continuous position updates in the original SLOA are reformulated as discrete node transitions and segment substitutions suitable for graph-based routing.

Slender Loris Optimization Algorithm (SLOA) for safety-aware path planning

In the context of urban safety-aware routing, each candidate solution represents a feasible route:

$R_x = \{v_1, v_2, \dots, v_n\}$, $v_k \in V$, where V denotes the set of road network vertices.

The objective function is defined as a weighted combination of distance and safety-related risk components: $f(R_x) = w_1 \cdot D(R_x) + w_2 \cdot C(R_x) + w_3 \cdot E(R_x)$ (33)

Where: $D(R_x)$ = total travel distance of route R_x ; $C(R_x)$ = normalized crime risk along R_x ; $E(R_x)$ = environmental risk score (lighting, pedestrian density, POIs) along R_x ; w_1, w_2, w_3 = user-defined weights for balancing objectives.

This formulation allows users to adjust preferences between travel efficiency and safety exposure. SLOA iteratively updates candidate routes based on the safety-risk landscape of the urban environment, ensuring effective exploration and convergence toward safer and efficient solutions.

Problem representation

- Let the city road network be represented as a graph $G = (V, E)$ where V is the set of intersections and E is the set of road segments.
- Each candidate route R_x is represented as a sequence of nodes.

Algorithm steps

Input: Road network graph $G(V, E)$, population size m , max iterations Max_{itr}

Output: Optimized safe route R_{best}

1. Initialization: Generate a population of candidate routes: $\{R_1, R_2, \dots, R_m\}$ randomly across the network.
2. Evaluate Fitness: For each candidate route R_x ,
 - a. Compute the multi-objective function $f(R_x)$ based on distance, crime risk, environmental risk, and safety indices from eq (33)
3. Repeat until convergence or max iterations:
 - a. Route Update (Exploration & Exploitation)
 - // Exploitation: refine promising routes

$$R_x^{t+1} = R_x^t \oplus \alpha \cdot S_f(R_x^t) \cdot (R_{best}^t - R_x^t) \quad (34)$$

Where:

R_{best}^t = best route in population at iteration t

α = adaptive learning rate

S_f = safety factor derived from crime and environmental scores

The operator $\oplus$ represents a discrete route modification operator, which performs segment replacement while preserving path connectivity within the graph $G(V,E)$.

// Exploration: search for new paths

$$R_x^{t+1} = R_{best}^t + \epsilon y \cdot (R_r^t - R_x^t) \cdot rand(0,1) \cdot Penalty(R_x) \quad (35)$$

Where:

R_r^t = randomly selected route

ϵy = safety-visibility factor

$Penalty(R_x)$ = penalization factor discouraging revisits to risky areas

- b. Safety-Constrained Selection: If R_x violates safety constraints (e.g., high crime zones above threshold):

$$f(R_x) \leftarrow f(R_x) + \lambda \cdot Penalty(R_x) \quad (36)$$

where λ is a large penalty coefficient

4. Termination: Identify R_{best} with the lowest combined safety-cost score
5. Output: Return optimized route R_{best}

The above algorithm provides the optimization mechanism for updating candidate routes. The evaluation of each route is governed by the safety-aware objective function described in Eq. (37) and Eq. (38), where segment-level safety indices are aggregated to compute the overall route risk. Thus, SLOA operates as the search engine, while the safety-index formulation defines the decision criteria for route selection.

Multi-objective-based safe route optimization

The path $SR = \{e_1, e_2, e_3, e_4, \dots, e_N\}$ is the sequence of road segments that connect the source and destination. Equation 37 builds on the segment-level safety indices defined earlier (Equation 20) by aggregating the safety scores of all segments in a candidate route, while also incorporating user-preference weights and distance considerations. This formulation allows the optimization algorithm to evaluate entire routes based on combined safety, distance, and availability criteria.

Objective function:

$$SR = \arg \min_{R \in \Pi} \left[w_1 D(R) + w_2 \left(\frac{1}{SI_{CA}} + \frac{1}{SI_{POI}} + \frac{1}{SI_{FPR}} + \frac{1}{SI_{HM}} + \frac{1}{SI_{PRS}} + \frac{1}{R_A} \right) \right] \quad (37)$$

Where, $D(R)$ denotes distance; w_1, w_2 denote user preference weight-age of two objective distance and safety; SI_{CA} denotes safety index score based on historical crime and accident events; SI_{POI} denotes safety index score based on POI accumulation; SI_{FPR} denotes safety index score based on frequency of preferred routes in general; SI_{HM} denotes safety index score based on human mobility; SI_{PRS} denotes safety index score based on Peer recommendation score; R_A denotes route availability score predicted using LSTM-AM.

The fitness of each candidate route is evaluated based on the objective function designed. The intensity of RPF can be used to prevent repetitive visits to sub-optimal routes. As the routes are explored and determined to be less favorable, whether it be due to decreased safety or increased distance, the RPF intensities associated with the roads can be augmented. This alteration serves to dissuade the algorithm from choosing these roads in subsequent iterations, effectively evading solutions that have already been visited. After the completion of the optimization process, the optimal safe and short route through the road network is returned as the best route found.

Equation (38) represents the final optimization function used within SLOA, derived by integrating the aggregated safety indices defined in Eq. (37).

For a given candidate route $R = \{e_1, e_2, \dots, e_n\}$ the problem is framed as minimizing:

$$\min F(R) = [w_1 \cdot D(R) + w_2 \cdot T(R) + w_3 \cdot S_{risk}(R)] \quad (38)$$

Where: $D(R)$ – Total travel distance; $T(R)$ – Estimated travel time; $S_{risk}(R)$ - Aggregated safety risk score for route; w_1, w_2, w_3 – Weight coefficients derived from user preference and women-safety priorities.

Women-aware safety risk score

The proposed WOMEN SLOA is a nature-inspired metaheuristic technique designed to solve multi-objective route optimization problems in urban networks. The algorithm itself is data-agnostic, meaning its optimization process does not rely on gender or time-specific factors by default. Safety characteristics significant to women's mobility, such as CAW function and safety index values derived from the dataset. While the optimization strategy remains generic, the routing becomes women-safety-aware through the data-driven safety objectives shown in Table 4.

Table 4. Component and women link

Component	Meaning	Women Link
cip_e	Crime incident probability	General safety
crp_e	Collision risk probability	General traffic safety
CAW_e	Crime Against Women severity score	Women-specific
NTS_e	Night-Time Safety Index	Women-specific
LSP_e	Lighting & Surveillance Presence	Women-specific
$\alpha, \beta, \gamma, \delta, \eta$	Tuneable weights	Higher for women's safety

Thus, women-specific outcomes are produced by data-driven weighting, not by the algorithmic structure itself.

4 Implementation

In the present study, open-source data from OpenStreetMap were used. To build the navigation application, digital map data had to be obtained, as it would serve as the foundation for creating the edges and vertices that depict road networks. To extract geospatial data from the digital OpenStreetMap dataset, the OSMnx Python Package was used. Considered the Washington DC city map for our implementation. Total vertices (nodes): 10030 Total edges: 26912. The topology network abstract of the map is depicted in Figure 4.

A crime dataset from Washington, D.C., obtained from Kaggle (Mraz, 2024), was used in this study. The dataset covers a wide range of criminal incidents across the city. To analyze temporal trends, the data was divided into three-hour intervals, enabling a detailed examination of crime occurrences throughout the day. In addition, a publicly available accident dataset from the District of Columbia Open Data platform (District of Columbia Government, n.d.) was utilized. The dataset contains a total of 306,383 recorded incidents. Accident rates and temporal patterns were analyzed alongside the crime data.

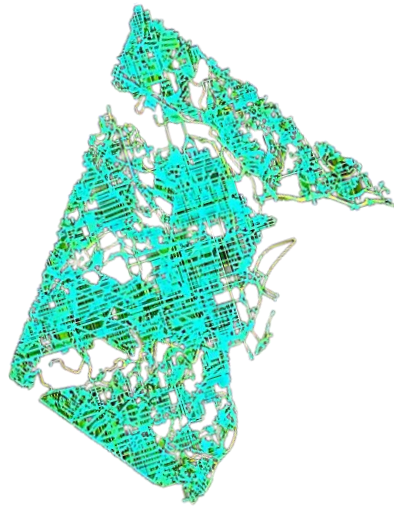


Figure 4. Abstraction of the Washington DC topology network map

The corresponding heat maps of crime and accident distributions are presented in Figures 5 and 6.

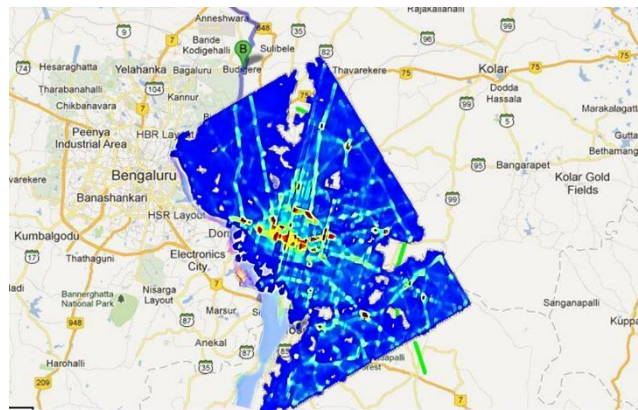


Figure 5. Heat map of crime incident

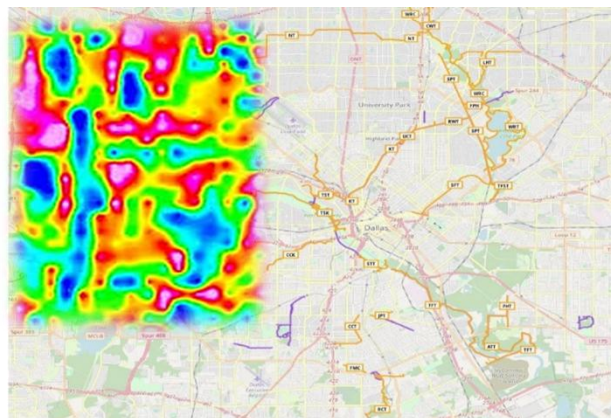


Figure 6. Temporal trends with the crime dataset

In the domain of human mobility analysis, significant interest lies in examining the spatial distribution of cafés and restaurants within the Washington, D.C. area. By utilizing the Overpass API, OpenStreetMap data can be accessed to compile an extensive inventory of these establishments. This collected information serves as the foundation for constructing the POI map. An openly accessible POI dataset from the District of Columbia Open Data Platform is incorporated to conduct a comprehensive risk analysis. By analyzing the concentration and dispersion of POIs,

a risk scoring system is formulated to identify regions with potential concern within Washington, D.C. The POIs are first geocoded and subsequently map-matched to their actual geographic locations using latitude and longitude coordinates. The map-matched POIs are illustrated in Figure 7.

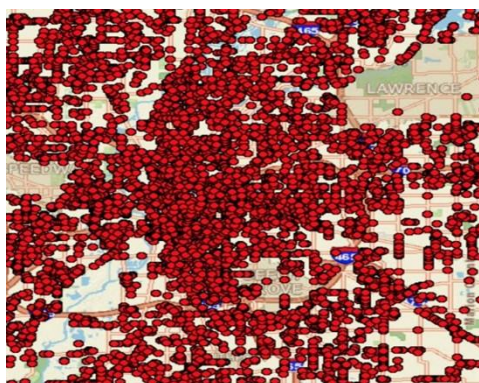


Figure 7. Geocoded POI Distribution Map



Figure 8. Footmark graph from taxi trip data

The primary objective of the Frequent Preferred Route (FPR) approach is to capture historical routing preferences of travellers, which is beneficial in practical navigation scenarios. In this study, a taxi trajectory dataset from Washington, D.C. (2017) is utilized to construct a footmark graph (District of Columbia Government, 2017). The dataset includes detailed trip records such as origin, destination, timestamps, distance, and fare, enabling the analysis of urban mobility patterns. The observed taxi footmarks are illustrated in Figure 8. Based on trajectory analysis, frequently used routes and high-traffic streets are identified. Busier routes are considered relatively safer due to higher activity levels. Late-night (post-10 PM) trips are analysed to identify active streets, as summarized in Table 5.

Table 5. TRIP analysis of busy streets

Busiest Streets	Trips
Origin Streets (Pick-ups)	
UNIT BLOCK COLUMBUS CIRCLE NE	390
100 BLOCK GALLOWAY STREET NE	208
3100 BLOCK 14TH STREET NW	95
100 BLOCK IRVING STREET NW	91
5900 BLOCK GEORGIA AVENUE NW	84
UNIT BLOCK H STREET NW	63
3000 BLOCK 14TH STREET NW	47
900 BLOCK 23RD STREET NW	44
2200 BLOCK C STREET NW	42
1400 BLOCK P STREET NW	41

Busiest Streets	Trips
Destination Streets (Drop-offs)	
3100 BLOCK 14TH STREET NW	40
2300 BLOCK GOOD HOPE ROAD SE	33
1500 BLOCK ALABAMA AVENUE SE	28
UNIT BLOCK H STREET NW	28
1700 BLOCK COLUMBIA ROAD NW	23
1200 BLOCK 16TH STREET NW	20
100 BLOCK IRVING STREET NW	19
2300 BLOCK 24TH STREET SE	18
5800 BLOCK GEORGIA AVENUE NW	18
1500 BLOCK BENNING ROAD NE	17

When requesting a route, users may specify whether they are novice or experienced drivers. Based on this classification, the prototype-level Peer Recommendation Score (PRS) provides experience-aware route suggestions using feedback from users within the same category. Novice users are guided toward simpler routes, while experienced users may receive routes suited to more complex conditions. A Route Evaluation Function (REF) updates the PRS using user feedback collected after route completion. Although currently implemented at the prototype stage, this mechanism demonstrates the potential for incorporating community-based safety perception in future systems.

WOMEN-SLOA: Way Optimized Multi-Objective Enriched Navigation using
 Slender Lori's Optimization Algorithm

Name:

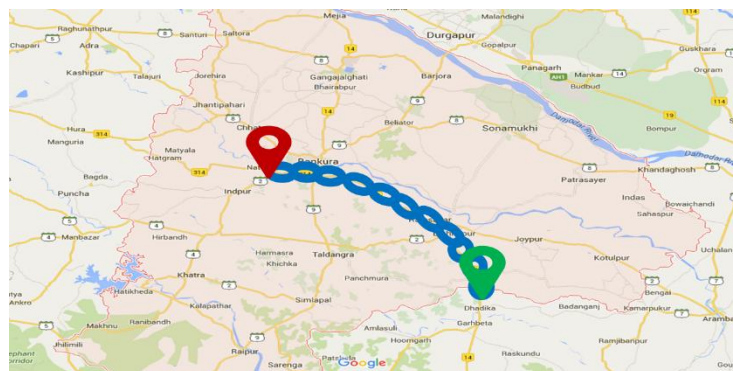
Email:

Gender:

Age:

Driving
☒ Novice Driver
 ☐ Experienced Driver

(a) User driver experience clustering



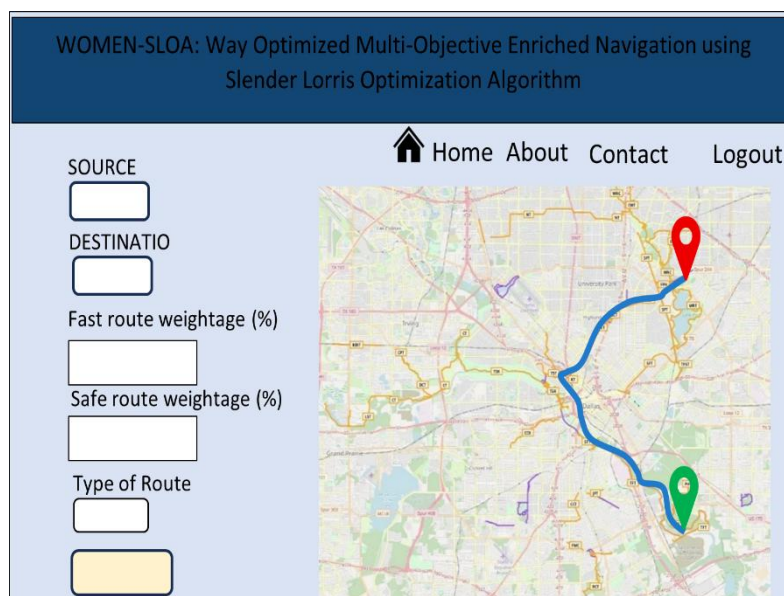
(b) Route trajectories for Feedback



(c) Event Reporting Feedback



(d) User Preference for safe and fast route



(e) Multi-objective optimized route

Figure 9. WOMEN_SLOA Prototype

5 Result comparison and discussion

This section presents the performance evaluation of the proposed WOMEN_SLOA framework. Figure 9 (a-e) illustrates the user interface, including the trajectory visualization, event reporting window, and the implementation of a web-based template for the proposed WOMEN_SLOA system. The blue route denotes a multi-objective path, recommended based on user-defined weight preferences for both speed and safety.

The proposed WOMEN_SLOA system is evaluated against four widely recognized optimization algorithms in terms of response time. Particle Swarm Optimization (PSO) (Bonyadi & Michalewicz, 2017) is a well-established technique with proven efficiency and adaptability. The Whale Optimization Algorithm (WOA) (Mirjalili & Lewis, 2016), inspired by the cooperative hunting strategies of humpback whales, offers an effective balance between exploration and exploitation. Likewise, the Rhinoceros Search Algorithm (RSA) (Tian et al., 2017) and Elephant Herding Optimization (EHO) (Li et al., 2020) are included as baseline models to provide a broader comparative analysis of social behaviour-based optimization strategies. Seven independent routing scenarios were evaluated to compare the response-time performance of the proposed WOMEN_SLOA framework against four baseline optimization algorithms. The experimental setup employs a population size of 30 ($n = 30$) and a maximum of 50 iterations ($\text{max_itr} = 50$).

Across all test cases, it has been consistently observed that SLOA delivers the most efficient route in terms of average system response time. Tables 6 and 7, along with Figure 10, illustrate the comparative performance analysis of the WOMEN_SLOA model against the four baseline optimization models. Busy pathways are generally perceived as safer due to continuous pedestrian and vehicular movement, which can discourage potential threats and provide a sense of security for commuters, particularly during late hours or in unfamiliar areas. The proposed methodology effectively addresses a key research gap in existing literature: minimizing fear and perceived danger among late-night travelers. By prioritizing both perceptual and actual safety, the WOMEN_SLOA framework adopts a more comprehensive and user-centric approach to safe route navigation. A primary limitation of this work lies in the dependency on the quality and completeness of the datasets used. Any gaps, inaccuracies, or inconsistencies within the underlying data can influence the effectiveness and reliability of the generated safety recommendations.

Table 6. Comparison of Mean Response Time Across Routing Scenarios

Scenario	PSO	RSA	WOA	EHO	SLOA
1	2.2345	1.9878	2.7689	2.6543	1.8564
2	3.2316	3.4567	4.2145	4.3456	2.8756
3	3.1072	4.2134	4.5234	4.1297	3.0121
4	2.4536	2.1256	3.1843	2.7439	2.2180
5	4.3289	4.7345	4.9324	3.9076	3.8754
6	2.4115	3.3457	2.5643	2.9548	2.4325
7	1.8965	2.1521	2.5738	2.0262	1.5463

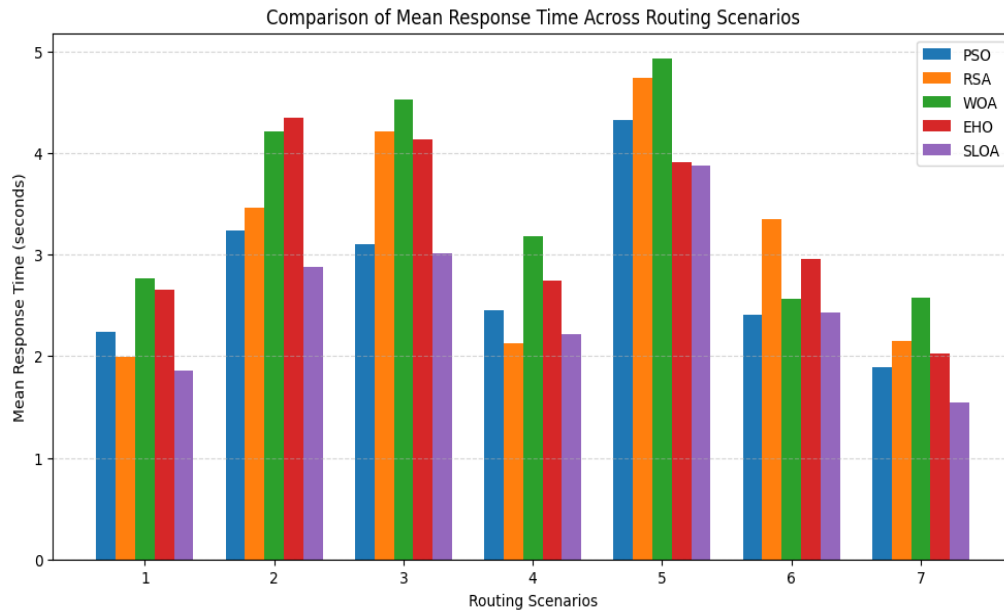


Figure 10. Comparison of Mean Response time

Table 7. Performance of LSTM-AM based WOMEN_SLOA safe route system.

TERMS	PSO-LSTM-AM	RSA-LSTM-AM	WOA-LSTM-AM	EHO-LSTM-AM	SLOA-LSTM-AM
Accuracy	0.87515	0.91045	0.9159	0.92732	0.93283
Precision	0.88642	0.89742	0.90632	0.92842	0.93007
Sensitivity	0.91421	0.92753	0.92742	0.93824	0.93326
NPV	0.88217	0.89134	0.90267	0.92123	0.93002
FPR	0.11172	0.10021	0.092213	0.0821	0.061725
FNR	0.088754	0.07275	0.072754	0.06276	0.061124
F1-Score	0.89275	0.91292	0.917522	0.92752	0.938523
FDR	0.19652	0.10082	0.099622	0.07252	0.068642
MCC	0.79822	0.82002	0.830721	0.85962	0.868622
Specificity	0.88215	0.89852	0.90762	0.92282	0.932612

* NNPV – Negative Predictive Value; FPR – False Positive Rate; FNR – False Negative Rate; FDR – False Discovery Rate; MCC – Matthews Correlation Coefficient.

In addition to objective safety indicators, the framework also considers the possible influence of human safety perception on routing decisions. Since large-scale participatory travel-experience data is not publicly available, the perception component is modeled as a probabilistic variation of the computed safety index to emulate subjective user judgment. Unlike approaches that infer safety experience by associating user visits with incident occurrence, this representation captures perceptual variability while preserving the real spatial patterns of crime and accident data.

To examine how routing strategies respond to perception-oriented safety variation, the spatial exploration behavior of different optimization algorithms is summarized in Table 8.

Table 8. Route exploration behavior under perception-oriented safety variation

Model	Route Exploration Pattern	Spatial Distribution Coverage
PSO-LSTM-AM-PRS	Early convergence	Major roads and commercial zones
RSA-LSTM-AM-PRS	Moderate exploration	City-center and transit corridors
WOA-LSTM-AM-PRS	Balanced exploration	Dense urban residential clusters
EHO-LSTM-AM-PRS	Wide exploration	Extended urban zones including suburban links
SLOA-LSTM-AM-PRS	Adaptive exploration	Comprehensive city-wide coverage including night-time hotspots

Table 9. Comparison of performance measures

Model	Avg. Crime Exposure Reduction (%)	Avg. Accident Risk Reduction (%)	Night-time High-Risk Zone Avoidance (%)	Overall Safety Score Improvement (%)
PSO-LSTM-AM	18.6%	15.2%	21.7%	19.3%
RSA-LSTM-AM	21.4%	17.5%	25.1%	22.6%
WOA-LSTM-AM	24.9%	19.8%	28.4%	25.7%
EHO-LSTM-AM	27.3%	21.6%	31.5%	28.8%
SLOA-LSTM-AM	33.8%	26.4%	39.1%	36.2%

As a result, the comparison emphasizes how effectively each routing model avoids hazardous areas shown in Table 9. The findings clearly demonstrate that, across all evaluated safety metrics, the proposed SLOA-LSTM-AM model consistently outperforms existing optimization-based routing techniques. It effectively avoids high-risk night-time zones, minimizes travel through accident-prone intersections, and achieves the greatest reduction in exposure to crime-dense regions. These outcomes highlight the strength of Slender Loris Optimization in enabling more cautious and adaptive path planning, directly supporting the core objective of ensuring safer mobility. Furthermore, performance indicators were evaluated to confirm that the safety improvements are achieved without compromising route feasibility or travel practicality.

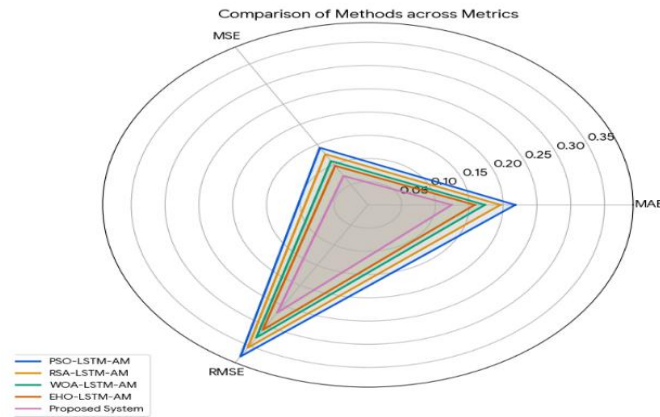


Figure 11. Comparison of performance measures (MAE, MSE, and RMSE)

The comparison of error metrics demonstrates the effectiveness of the proposed system over existing hybrid models. Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) are used to evaluate prediction accuracy and stability, as shown in Figure 11. The PSO-LSTM-AM and RSA-LSTM-AM models exhibit higher error values, indicating larger deviations between predicted and actual outputs. WOA-LSTM-AM and EHO-LSTM-AM show moderate improvement due to enhanced optimization capability, reducing both absolute and squared errors. However, the proposed system achieves the lowest MAE, MSE, and RMSE values, reflecting superior learning efficiency, minimized variance, and improved generalization performance. These reductions confirm that the proposed approach enhances prediction precision and robustness by effectively optimizing parameter tuning and temporal feature extraction compared to conventional optimization-assisted LSTM models.

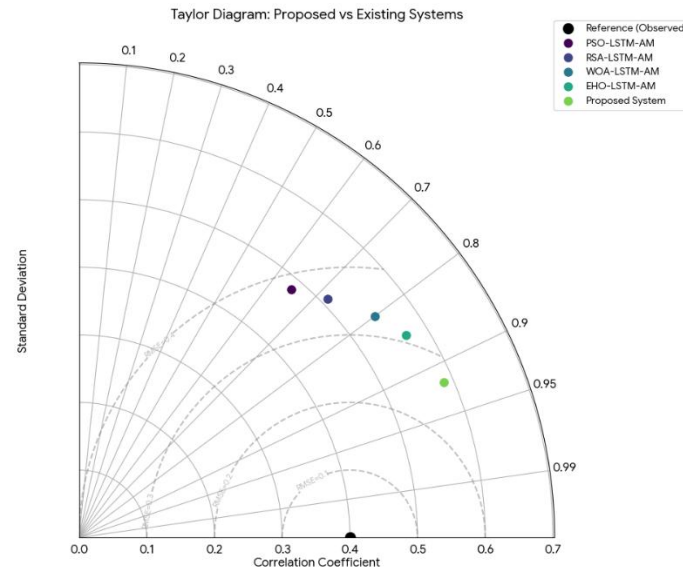


Figure 12. Comparison of Taylor plot of the proposed and existing systems

The Taylor diagram illustrates the comparative performance of the proposed system against PSO-LSTM-AM, RSA-LSTM-AM, WOA-LSTM-AM, and EHO-LSTM-AM using correlation coefficient and standard deviation with respect to the actual observed (ground truth) data from the dataset, as shown in Figure 12. Models positioned closer to the reference point indicate better agreement with actual data. The proposed system lies nearest to the reference arc, showing the highest correlation and a standard deviation closely matching observed variability, which reflects improved predictive consistency. In contrast, PSO-LSTM-AM and RSA-LSTM-AM are farther away, indicating weaker correlation and larger deviation, while WOA-LSTM-AM and EHO-LSTM-AM demonstrate moderate alignment. Overall, the diagram confirms that the proposed approach achieves superior statistical similarity and stability, highlighting its effectiveness in capturing underlying data patterns compared with existing optimization-assisted LSTM models.

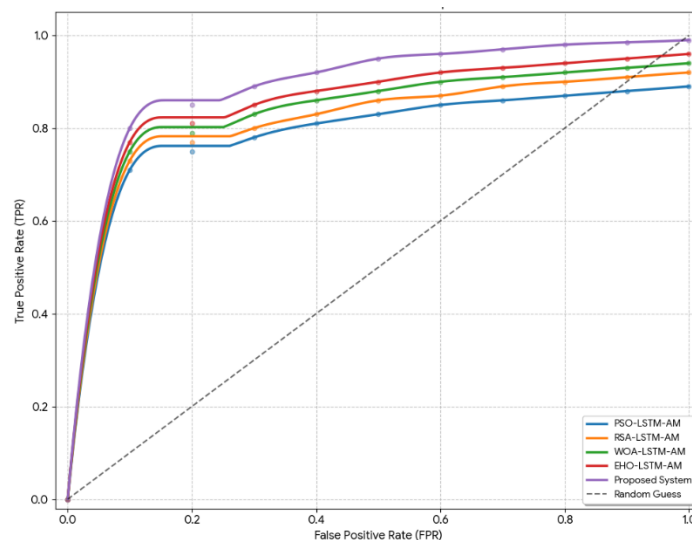


Figure 13. Comparison of the AUC-RoC curve of the proposed and existing systems

The AUC-ROC comparison across training epochs demonstrates the progressive improvement in classification capability for all models, while highlighting the superior convergence behavior of the proposed system shown in Figure 13. At early epochs, existing methods such as PSO-LSTM-AM, RSA-LSTM-AM, WOA-LSTM-AM, and EHO-LSTM-AM show moderate discrimination ability, reflected by lower AUC values. As training progresses, their performance gradually increases,

indicating better separation between positive and negative classes. However, the proposed model consistently achieves higher AUC scores at each epoch, revealing faster learning and stronger generalization. By the final epochs, it approaches near-optimal AUC values, suggesting highly accurate decision boundaries and reduced misclassification. Overall, the results confirm that the proposed approach enhances predictive reliability and robustness compared to the existing optimization-assisted LSTM models.

6 Conclusion

By addressing the safety challenges associated with night-time navigation, this work presents a data-driven framework for identifying and recommending safer travel routes. The proposed WOMEN_SLOA model evaluates the safety of each road segment using historical crime and accident records, together with contextual indicators such as points of interest, preferred routes, and human mobility patterns. Based on the computed safety index, the Slender Loris Optimization Algorithm (SLOA) is employed to discover routes that balance safety, travel distance, and travel time. To further study the influence of human judgment on navigation decisions, a perception component is incorporated as an extension of the framework, enabling analysis of how experiential awareness may affect route selection. The proposed approach overcomes the limitations of static safety-aware routing by enabling adaptive and context-sensitive route selection. Comparative analysis with established meta-heuristic algorithms demonstrates the effectiveness of the SLOA-based strategy in identifying safer paths while maintaining practical travel efficiency. The results also indicate that limited safety observations may affect recommendation quality. Future work will therefore investigate advanced learning strategies, such as transfer learning, to enhance robustness and predictive capability in data-sparse urban environments.

Data Access Statement

The datasets used in this study are publicly available and all data sources are cited and included in the reference list. No new dataset was generated during this study.

Author and Contributor Statement

Vijaya Lakshmi: Conceptualization, Writing - Original Draft, Methodology, Software, Visualisation;
Suresh Joseph: Supervision, Writing - Review & Editing, Validation

Use of AI

During the preparation of this work, the authors used ChatGPT for language refinement and Grammarly for grammar checking and improving readability. After using these tools, the authors reviewed, edited, and validated the content as needed, and take full responsibility for the content of the publication.

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Conflict Of Interest (COI)

There is no conflict of interest.

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