Towards Safer Journeys: Integrating Crime Awareness and Emergency Features in a Navigation System for Bangladesh

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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Approval

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Abstract

Public concern about personal safety during everyday travel in Bangladesh has intensified, particularly in dense urban corridors where incidents such as theft, harassment, and assault shape route choice and mobility confidence. Existing navigation tools optimize for speed and distance but rarely incorporate risk awareness, leaving commuters without actionable, location-specific safety cues. In the prior academic literature, researchers have mapped crime, proposed safety scoring, and explored risk-aware routing; however, most systems remain prototype-level, lack deployment in the Bangladeshi context, and seldom integrate human-centred evaluation or application-grade interfaces. This gap at the application layer motivates new exploration that marries usable design with credible data and transparent methods. In this study, we design and implement a crime-aware mobile navigation application that combines a city-scale crime map, a community "report crime" flow, and a safety-weighted routing module. Our methodology blends HCI and analytics, where a user study (survey and interviews) to surface needs and expectations, a curated Dhaka incident dataset with engineered severity levels, and statistical analyses, for instance, χ^2 for association; ANOVA/Kruskal–Wallis for group differences to validate design assumptions about how risk varies across categories. Results indicate a significant association between crime type and gender and coherent separation of engineered severity across crime categories, supporting the product's hotspot visualization and safety-aware routing choices. We present a working, cross-platform mobile application built with React Native (Expo), FastAPI, and Supabase with crime map, reporting, and safer-route features; an HCI-grounded evaluation of feature usefulness and acceptability; and a statistical analysis that informs design defaults where there are filters, labels, and routing weights. Together, these contributions demonstrate a feasible, user-centred "safety layer" for everyday navigation that can be piloted at a ward scale and extended through community participation.

Keywords: Safe route optimization, Crime hotspot, Travel security in Bangladesh, User experience in safety navigation, Geospatial crime mapping

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Chapter 1

Introduction

1.1 Background

An alarming concern in Bangladesh, travel safety, has been affecting millions of commuters daily, where unsafe road environments and security issues are prevalent. To elaborate, this concern has become multidimensional over the past few years, starting from unregulated traffic systems and poorly maintained infrastructure to crime-prone areas, which makes the public not only uncomfortable but also vulnerable [2]. Particularly in poorly lit regions, crowded streets, public transportation hubs, remote locations from police stations, and even extremely packed streets, incidents like theft, harassment, and traffic accidents are remarkably frequent [31]. Moreover, public places have developed as crime hotspots where the majority of the affected population are women and vulnerable groups [31]. Commuters are left vulnerable to pickpocketing and even physical assault in public modes of transportation, as these spaces are often overcrowded [25].

Aside from all these, the overall situation has been aggravated by recent events, such as the July uprising in 2024. As multiple police stations and other administrative infrastructures were damaged, the security of the general public has become more susceptible to more frequent crimes as the effectiveness of the law remains compromised, with the police struggling to return to full operation [48], [42]. Consequently, due to the apparent inadequate presence of the police and their negligible response to increasing crime rates, criminal activities have risen to an extent where commuters get openly mugged in broad daylight [48], [51]. All these factors combined have left daily commuters feeling unsafe, diminishing their confidence [1].

1.2 Rational of the Study or Motivation

In recent years, Bangladesh has witnessed a significant increase in crime rates in urban areas, and it is intensified public concerns regarding personal travel safety. Majority of the current navigation systems, like Google Maps, only give the most efficient route. It does not consider the safety aspects which can potentially expose travelers to safety threatThe motivation behind this study is to design a navigation system that incorporates crime awareness and emergency response system components focusing on Bangladesh. The purpose of this system is to help people make safer decisions while travelling. The system includes live data about crimes, user and police complaints, and weighted safety to routes in order to improve public safety and increase confidence among users while ensuring efficient and safe navigation.

Moreover, when an emergency occurs, a safety navigation system allows travelers to connect to emergency services, which adds to the overall reliability of travel [54]. Data-driven crime preventive tools have proven effective for preventing crime and safety [46]. Nevertheless, such measures in Bangladesh remain limited. Crime data is available from the police, social media, and news, but it is interpreted differently and not consistently kept. This study aims to create a user-friendly navigation system for Bangladesh which organizes these resources and fulfills local travelers' safety requirements and specifications.

1.3 Problem Statement

Commuters remain vulnerable to potential risks while traveling since they are often unaware of information regarding crime-prone areas [8]. Even though existing navigation systems are widely used, these systems lack features concerning safety of those on the go, such as, crime hotspot alerts, safe route recommendations, and emergency services vital for reducing travel risks [55]. In addition, current systems, which recommend routes on the basis of modes of transportation, remain unsuccessful in adapting to a dynamic set of safety features, for instance, these are unable to develop models based on safety in order to suggest routes based on consistently updating data curated from commuter feedback and prior road incidents [32].

This pressing issue is further aggravated due to lackings of integrated news articles, social media posts, and community alerts [30]. The prominent socio-geographic challenges of Bangladesh, such as overly populated urban areas and inadequate measures of emergency, are not addressed or prioritized for the sake of user safety by existing systems. Consequently, commuters feel added uncertainty and anxiety when moving across unfamiliar routes and areas, impacting on their confidence and freedom to travel [5]. Therefore, all of these combined call for the requirement of using a navigation system that incorporates crime data, user specified features, and emergency response features to further ensure more secure journeys [17]. This research intends to develop a navigation system concerning travelers' safety tailored to their specific needs in order to resolve the mentioned issues and promote trust, security, and confidence in travelling.

1.4 Research Questions

We have curated the following research questions to direct the study and ensure that it remains closely aligned with its social impact and practical implementation.

- **RQ1:** What safety challenges do travelers in the urban context face, and how do these challenges have an impact on the usability of existing navigation systems?
- **RQ2:** How can a smartphone-based, community-reported, crime-aware navigation app facilitate safer travel decisions for the users?

- **RQ3:** How can an app assistant for reporting and route guidance measurably improve access to safer routes and users' willingness to travel?

Answering these questions will clarify the nature of everyday safety barriers, assess whether a privacy-preserving, community-informed smartphone approach can address them, and test if such support changes route options and travel willingness. Collectively, the results will indicate whether safety-aware navigation is both necessary and workable in Dhaka-like, data-constrained settings and will point to practical priorities for responsible rollout.

1.5 Objective

This research aims to design and evaluate a crime-aware navigation system to improve public safety in both urban and rural regions of Bangladesh. The key objectives are:

- **Developing a safety-focused navigation system:** Designing a navigation system that maps and plans routes which focus on safety by analyzing crime data and incidents reported by users and adapts to both urban and rural settings starting from densely populated cities to less monitored rural areas.

- **Analyzing user experiences and safety perceptions:** Identifying safety concerns and perceptions of the general public by conducting structured surveys, in-depth interviews, and focus group discussions which include a diverse group of users starting from students to professionals, tourists, and other people who commute on a regular basis and understanding the gravity of existing limitations such as lack of knowledge about crime hotspots, navigation of high-risk areas with limited knowledge and emergency assistance features.

- **Integrating crime data sources for reliability:** Gathering crime-related information from official sources such as police records, verified social media reports, and neighborhood alerts, and developing a mechanism for validating the reliability of user-generated crime reports and filtering out misinformation in order to ensure accurate and updated safety assessments and maintain data integrity.

- **Improving route planning with protective features:** Implementing user-oriented features such as crime-prone area alerts, emergency protection options, and alternative safe route recommendations based on verified crime data.

- **Bridging the gap in travel safety for Bangladesh:** Addressing the lack of crime-sensitive travel technology in Bangladesh, where many users rely on generic navigation apps that do not factor in safety risks, and validating the diverse safety concerns of travelers in Bangladesh by proposing a system that can alert users while commuting in potentially unsafe areas.

By addressing these objectives, this research offers an extensive guideline for developing a reliable, user-safe navigation system that helps users make conscious decisions while traveling and makes them less vulnerable to potential safety threats.

1.6 Methodology in Brief

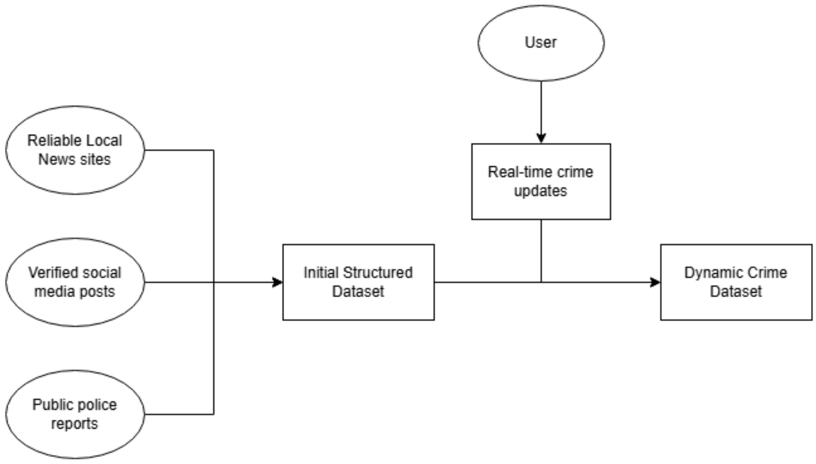


Figure 1.1: Dynamic dataset creation workflow

As illustrated by Figure 1.1, the primary objective of this research paper is to introduce a convenient and user-oriented system that will enable users to prioritize their safety when navigating to their desired destination. The proposed methodology consists of 5 modules that are described as follows.

A. Dataset Collection and Creation: Due to the lack of detailed publicly available crime datasets in Bangladesh, we plan to create a structured dataset by scraping data from reliable local news sites, verified social media posts, public police reports, and other sources. The dataset will have important features such as crime type, date, time, location, severity, description, and images. Furthermore, to make the dataset dynamic and polished over time, we plan to integrate real-time user crime updates which will be verified to ensure accuracy. Over time, the old data entries will be removed automatically to warrant relevance for our analysis.

B. Crime Analysis: We want to use a machine learning model to analyze crime patterns, which will be used to mark locations and predict safe routes. We plan to use the LightGBM model for its high precision, accuracy, and F1 score according to prior research done on crime prediction [20]. Through key features of our dataset like crime type, severity, and date, the LightGBM model will give safety scores to specific geographic locations. Weighting will be done on the severity of the crime to classify areas properly.

C. Integration with Map: To predict safe routes, we need to integrate and map our processed safety scores of locations to their respective geographic coordinates. We will use Google Maps API or OpenStreetMap (OSM) to incorporate our processed safety scores into map data, resulting in the routing parameter being safe instead of time and distance. We can generate safe, moderate, and unsafe routes by adding the cumulative safety score along the waypoints of a route. Moreover, highlighting previous crime incidents in the location points of the recommended routes will help with visualization for the users.

D. User-Centered Design: We want our app to address people's existing travel concerns, and provide features based on their needs. Thus, to ensure that, we will conduct surveys and in-person interviews. Based on that, we will plan the user interface of our system. Some features we have in mind are crime alerts, emergency contact, and real-time feedback.

E. App Development (Prototype Implementation): We have built a production-lean prototype that implements the pipeline end-to-end. The React Native client exposes: (i) a crime map with incident details, (ii) crime map statistics summarizing spatial/temporal patterns, (iii) "recent incidents near me" with community up-vote/down-vote signals for veracity, and (iv) anonymous reporting for user-submitted events. A FastAPI backend computes segment-level risk and routing, and Supabase provides authentication, storage, and real-time updates. OSM-based routes are enriched with crime-aware context derived from safety scores, enabling risk-aware decisions without prescriptive labels.

F. System Evaluation (Feature Perception & UI Assessment): After development, we have run a structured survey on users' perceptions of the interface and the usefulness of each feature. Participants rated the clarity of the crime map and statistics, the perceived reliability of the vote-based "recent incidents near me," the ease and willingness to use anonymous reporting, and overall intent to adopt the app. Open-ended feedback guided revisions, such as configurable proximity-based safety alerts, and at the same time, raised concerns for a robust verification of reported incidents.

1.7 Scopes and Challenges

This study develops and evaluates a mobile, safety-aware navigation prototype for Dhaka using a pragmatic, application-layer stack. The scope centers on three core features: a crime map that visualizes incident hotspots and recent reports, a report crime flow that collects structured, anonymous submissions, and a safer route recommender that penalizes paths near recently reported incidents within a tunable radius and time window. Human–computer interaction (HCI) principles guide the interface (clear affordances, privacy-aware defaults, low friction), and evaluation combines a user survey with targeted statistical analyses on a curated set of incidents. Analytically, we favor interpretable, lightweight methods: a 1–5 engineered severity scale inspired by crime-harm weighting in policing [7], Pearson's χ^2 to test the association between crime type and gender [3], one-way ANOVA for mean differences and the distribution-free Kruskal–Wallis test for rank-based differences across categories, and DBSCAN to identify spatial hotspots without prespecifying the number of clusters. These results are used to inform design and routing choices rather than as ends in themselves. These findings inform design and routing choices rather than serve as ends in themselves. Real-time inputs during the study come from user reports and curated public sources; fully automated social-media ingestion is reserved for future work once moderation pipelines are resourced. City-scale integration with external navigation stacks is treated as a downstream pathway via a simple “safety-weights” API; the thesis itself targets prototype deployment and a ward-level pilot model.

In order to get an idea of the general public’s perception, many different techniques, including surveys and interviews, are implemented so that the vulnerabilities and risks factors people are subject to can be figured out and evaluation of a safer route system can be performed properly. Integrating data inputs from users is to be implemented with a goal to develop the safe route system as accurately as possible. To address these requirements, core features accommodate safer paths, visualization of crime endangered zones and safety measure associated functionalities. Infrastructure concerns like hardware and software concerns along with quality and connectivity of data are to be evaluated on grounds of technical feasibility of the system. Additionally, crime trends can be identified with the help of predictive analysis. Historical crime data, when incorporated with clustered algorithms, can assist authorities in initiating proactive measures when emergencies do occur. Finally, the study aims to assess the system’s ability to raise safety and confidence among commuters while the development of widespread crime prevention policies and strategies are to be directed through the academic findings.

Developing this study comes with several challenges. One of the biggest barriers is obtaining accurate and reliable data on crime-prone areas in Bangladesh due to the inadequacy of resources from existing law enforcement agencies and inconsistent reporting mechanisms [14]. In addition, a substantial number of incidents such as theft, robbery, and even fatalities go unreported, making it harder to assess the dynamic situation of travel safety concerns [53]. Moreover, engaging diverse user groups, especially women and other vulnerable populations, in order to gather inclusive and unbiased feedback adds another layer of complexity. There are both logistical and ethical considerations in ensuring that participants feel safe and comfortable sharing their experiences. Location precision and map matching are variable on lower-end Android devices; the app mitigates this via reverse-geocoded confirmation, draggable pins, and graph snapping before routing. Authenticity and moderation require process and tooling (community voting, optional evidence placeholders, rate limits, reviewer queues) that add operational cost even in pilots. Ethical guardrails avoid stigmatization and surveillance risk by using restrained visuals, an option to fuzz coordinates when appropriate, and minimizing long-term traceability of submissions. Finally, the existing conditions, such as inconsistent internet connectivity, limited access to smartphones, and inadequate knowledge of smartphone expertise, especially among vulnerable groups and rural areas, has made it difficult to implement and test safety-focused features effectively [13], [21], [28]. All these challenges combined call for approaches that match the socio-economic and technological standards, ensuring all-user inclusivity.

1.8 Contributions

This thesis advances safety-aware urban navigation for data-constrained contexts through a combination of methodological, algorithmic, and systems contributions. Concretely, we contribute:

- **Empirical understanding of user needs:** Characterized risk perceptions, reporting preferences, and adoption barriers among Dhaka commuters in order to establish human-centred requirements for a safety-aware routing system is achieved from our mixed-methods (surveys and semi-structured interviews) study approach.

- **Credibility-aware, spatio-temporal routing formulation:** We formalize route selection as shortest path on a road graph with edge costs augmented by a safety penalty that varies with incident severity, recency, time-of-day/locality, and community credibility signals. The resulting formulation is explainable and tunable for real-world deployment.

- **Deployable mobile system for low-data settings:** We implement an end-to-end application with features like Crime Map, Report Crime, Crimes Near Me, and Safer Route on an open, low-cost stack (React Native/Expo, FastAPI, Supabase, OSM), demonstrating practical feasibility without proprietary map services or privileged police feeds.

- **HCI-informed interface patterns:** Through iterative prototyping and a UI walk-through study, we contribute design patterns that balance situational awareness with low cognitive load (calm map markers, chip-based filters, inline explanations, anonymity-first reporting) and document their acceptability to target users.

- **Privacy-by-design and governance template:** We specify and implement a data-minimizing operational model, e.g., anonymous intake, no public reporter identity, row-level access control, clear disclaimers on advisory use, offering a replicable blueprint for ethically constrained deployments.

Together, these contributions deliver an empirically supported problem definition, a credibility-aware routing method, and a privacy-preserving, deployable mobile system, providing a logical framework for safe, user-trusted navigation in Dhaka and similar low-open-data cities.

1.9 Thesis Organization

The remainder of this thesis is organized as follows:

- Chapter 1 introduces the problem context, motivation, objectives, and a brief methodology outline.

- Chapter 2 reviews related work on crime mapping, risk-aware routing, and crowdsourcing, positioning the study within Dhaka's data constraints.

- Chapter 3 states the problem and design requirements, describes data sources and ethics, and outlines the system scope.

- Chapter 4 details the methodology and design process—survey/interview protocols, dataset creation, preprocessing/feature engineering, modeling, routing, and the mobile implementation.

- Chapter 5 presents empirical results and evaluation—statistical analyses, comparative positioning, and user-driven design adjustments.
- Chapter 6 discusses interpretations, practical implications, limitations, and recommendations for pilot deployment.

Chapter 2

Literature Review

This review depicts the shift from basic time-optimal navigation to safety-aware routing, and it outlines the core technologies currently present, such as crime mapping, real-time alerts, that enable it. We summarize evidence on datasets, prediction models, routing, mapping platforms, and differential designs to point to shortcomings in their real-world validation. Bangladesh's urban features add to the issues caused by limited data, bad impact, and heavy traffic, which is given particular attention.

2.1 Preliminaries

Developed initially for efficient routing and traffic updates, navigation systems are currently being reassessed for their potential to improve safety by including emergency features and crime awareness. An outline of the fundamental ideas, theories, and technical developments that underpin the creation of a crime-aware navigation system is provided in this section. To help users get to their destinations quickly, modern navigation systems use a combination of GPS, Geographic Information Systems (GIS), and data processing. These systems, which primarily focus on route optimization and traffic management, is now being used in integrating safety-related features, for instance, crime mapping and emergency response mechanisms, gaining popularity and traction in recent years. Research highlights that crime-aware navigation systems can significantly improve user confidence as it basically provides information about high-risk areas and offers safer route alternatives [17]. In addition, crime mapping and real-time data analysis play a crucial role in identifying crime-prone areas and alerting users, and help keep them informed [22]. For the creation of crime-aware navigation systems, various data sources, including news reports, social media updates, law enforcement databases, and community alerts, can be used.

On the other hand, SOS alerts and direct communication with emergency services are critical components of safety-oriented navigation systems [26]. These features enable users to seek immediate assistance in case of distress. Empirical studies indicate that when navigation systems incorporate real-time emergency reporting, users experience measurable gains in safety, driven by faster awareness of nearby incidents, clearer guidance on avoidance options, and increased willingness to take precautionary detours [45]. Most importantly, Bangladesh faces unique challenges that concern travel safety due to its diverse geographic landscape, rapid urbanization, and socioeconomic factors. Urban areas which are characterized by high population density and complex traffic conditions, often experience crimes for example, theft, harassment, violence, etc. It is important to understand that these difficulties are essential for designing a navigation system that effectively addresses the safety concerns of all travelers.

2.2 Review of Existing Research

A. Dataset Utilization and Creation:
There are Studies regarding safety-focused navigation which have implemented both historical datasets and crowdsourced datasets, and the effectiveness of the system can vary based on it. Be-safe travel, a web-based application [10], incorporates a local crime dataset from Surabaya City to assess its system. Similarly, SafeNav [35] uses a historical dataset from L.A. and population density data from Google Places API to estimate unsafe zones. On the other hand, SPaFE [33] and CrowdSPaFE [41] use crowdsourced crime data in addition to using historical crime datasets for generating safe routes. SPaFE uses real-time user feedback, law enforcement updates to dynamically improve its dataset. Although real time datasets promote dynamic crime evaluations, they can cause inconsistencies as some user-generated data might be fake, biased, or delayed. Moreover, some crime reports may go unreported, making the dataset unreliable. On the other hand, historical datasets fail to take into account complex real-world situations such as pandemics, economic downfall, riots, etc, leading to inaccuracies in crime prediction. Furthermore, research on crime trends in Bangladesh [49] talks about the lack of structured, granular crime data or police reports. Overall, hybrid datasets incorporating both historic datasets and crowdsourced feedback seem to be a promising approach.

B. Crime Prediction Using Machine Learning:
Several Machine language models have been used by the papers reviewed for crime prediction and route optimization. Integrated Women's Security System [43] has used Logistic Regression and Decision Tree model to classify crime-prone areas. Safe Route system [18] utilizes deep reinforcement learning (DRL) to optimize route finding. One paper was successful in achieving 91% accuracy after hypertuning using the Random Forest algorithm. All three of these papers have used historical data to work on so the challenges of real-time data are not acknowledged in these solutions. If the quality of the data changes, some models might have a shift in their efficiency. Moreover, aside from the quality of data, varying crime densities might also change a model's accuracy. In Crime Analysis and Prediction [19], it is highlighted that generalizing a model is very difficult across various regions as external factors like population density, functioning traffic systems, and changing crime trends play a role in it.

C. Safe Route Optimization Algorithms:
A significant number of the reviewed papers have leveraged existing algorithms for route optimization, which include Safe Route Recommendation [37] incorporating the Djikstra algorithm, SafeNav [35] implementing the K-Nearest Neighbors (KNN) algorithm, and SafeRoute [38], using the K-means clustering algorithm. In contrast, some papers chose to introduce novel optimization algorithms to develop

safety-based navigation systems. For instance, SPaFE [33] integrates multi-attribute decision-making (TOPSIS) to enhance the ant colony optimization (ACO) method and develop the SPaFE algorithm, which is used to dynamically assess numerous safety factors. CrowdSPaFE [41], which is a continuation of [33], enhances the SPaFE algorithm and develops the CrowdSPaFE algorithm, which is a population-based algorithm able to adapt to dynamic crime reports and incorporate real-time user feedback, making the route optimization process more attuned to emerging threats. Moreover, Avoiding crime routing navigation [50] puts forward a customized model that gives different weights to crime types which adjusts route safety preferences dynamically. Furthermore, Privacy-Enhanced Safe Route Planner [23] proposes pSS, a personalized safety score model travel experiences of users' travel experiences while also maintaining privacy. However, systems relying on existing models face limitations like struggling to blend real-time updates, limiting their dynamic response effectively. On the other hand, crowdsourced and dynamic optimization models depend significantly on user involvement causing potential bias, and crime-weighted co-optimization models face computational complexity challenges, especially in densely populated cities, resulting in prolonged processing time for real-time routing. Additionally, personalized navigation systems give rise to privacy issues, where user location details must be obscured to mitigate security risks.

D. Mapping Technologies:
Mapping technologies are important in the navigation systems targeted at improving safety as many studies use available APIs and other platforms for visualizing crime data and safety information. For instance, Be-Safe Travel [10] uses the Google Maps API to let users see interactive crime data and routing suggestions while SPaFE [33] implements OpenStreetMap to enable sophisticated routing algorithms for safer pathfinding. The same applies to Safe Route [44], which uses Google Maps to advise routes for those most at risk: people with sight impairment While these mapping tools are easy to use and provide interfaces that rely on current data, one of the problems they face is the absence of integration with real-time updates and this could be problematic for dealing with immediate dangers such as crime activity or road incidents. These mapping systems that we have suggested are also stagnant by nature, which sometimes limits the degree of flexibility and adaptation of these applications to user demands, or to the local environment.

E. Technological approaches for real-time and context-aware systems:
The technological illustration for integrating crime awareness and safety into navigation is seen in the papers *Be-Safe Travel* [10], *A Context-Aware Mobile-Based System for Crime Prevention* [26], and *Smart Navigation with Crime Clustering and SOS Alert* [52]. In *Be-Safe Travel* [10], users are made aware of the risk levels while commuting as the routes are categorized into three levels which are blue being the safest, green being moderately risky, and red being highly risky based on the pre-existing crime data. Moreover, the paper [52], along with dynamic mapping of crime-prone areas by combining both pre-existing and real-time data, provides users with an in-built SOS alert to notify emergency contacts or appropriate authorities in case of any unfavorable situation. Furthermore, with the help of geo-fencing and real-time data processing, users are notified with automatic alerts including nearby police stations, hospitals, and emergency contacts whenever they enter a

high-risk zone ensuring users remain updated with their commute [26]. However, these systems still face challenges like high dependency on available crime data, high implementation costs, and privacy issues due to location tracking. In addition, real-time updates come with substantial computational costs and resources which may have an impact on system stability and performance. Nevertheless, all these drawbacks can be solved if the data accuracy, development cost scale, and privacy concerns can be upgraded.

F. Privacy-Enhanced and Decentralized Systems:
The study [23] addresses the growing concerns regarding data privacy and user security in a safety-centric navigation system by introducing the concept of computing safety scores using decentralized data storage and one-way mapping techniques, simultaneously making sure that the sensitive data of users remains secure. This is because centralized databases share user's data in a central entity, threatening the privacy and security of users whereas decentralized databases reduce data exposure as users can personalize their data and safety scores [23]. To illustrate, the app prototype introduced in [23] generates personalized safety scores from crowdsourced data while maintaining anonymity, which ultimately ensures a user-driven and private approach. On the contrary, such systems carry a decent chance of the data being sparse in quantity and user contributions being uneven, and ultimately threaten the reliability of the recommendations and updates. In addition, ensuring the accuracy of the data becomes difficult in the absence of a centralized database system. Despite these drawbacks, privacy-enhancing-based systems are crucial for gaining user trust and safe navigation.

G. Systems with Limited Implementation and Testing:
A decent number of the reviewed papers have one thing in common, and that is the absence of real-world implementation of the proposed systems. Since these systems were never practically implemented and remain limited to theoretical models, simulations, or small-scale testing, they remain invalidated to date. *SPaFe* [33], *SafeRoute* [18], and *Crime-Avoiding Routing Navigation* [50] proposed systems that are assuring in design but have not been examined on the basis of their efficiency in dynamic real-world environments due to the absence of large-scale deployment. These systems were tested based on simulations and historical crime data, which brings their reliability in high-risk scenarios into question. In *Be-Safe Travel* system [10], the proposed system is only applied in Surabaya, Indonesia, limiting its use to a larger scale. In addition, the *Be-Safe Travel* system [10] and *Crime Analysis and Prediction* [19] also rely on pre-existing crime data, which remains unreliable for dynamic and emerging crime rates and patterns and leads to inaccurate recommendations and results, breaking user trust. While these drawbacks impact the reliability of such systems, these systems carry a strong potential for ensuring safety of the commuters, particularly in densely populated and high-risk cities like Dhaka. Real-world deployment and validation can substantially improve the reliability of these systems.

2.3 Summary of Key Findings

Several studies propose the development of crime-aware navigation aids that predict and suggest safer routes for travelers using machine learning, crowdsourced crime data, and AI-driven crime clustering algorithms. These systems work on the modification of existing algorithms to make use of historical crime data and current situational data. For example, clustering algorithms such as K-Means or Ant Colony Optimization can be used, which are then risk-weighted and optimized along with Google Places' API and police crime databases. There are major limitations, such as a lack of widespread data, dependence on an active internet connection, absence of real-time crime reporting, scaling problems within crowded cities, heavy reliance on users for information, and the high amount of processing needed. Many models are still at the conceptual stage needing practical optimization work. Some of these issues can be resolved by optimizing data availability with law enforcement, creating capabilities to patch without the internet, community reporting algorithms, and patching the algorithm's complexity. In Bangladesh, especially in risk-heavy cities like Dhaka, this could be of great use due to the high rates of urban crime and erratic expansion of cities. Avoiding crime, tourists, night-shifters, or even the most vulnerable can receive real-time notifications which could provide them with safer means of transportation. Although this approach is advantageous, crime-aware navigation can only be useful after effective development, as it poses some challenges, such as the availability of data, improving real-world integration, and the ability to scale it for practical use in cities.

Chapter 3

Requirements, Impacts and Constraints

3.1 Final Specifications and Requirements

Before constructing the system, it is essential to define clear technical and methodological requirements that respond to the limitations identified in existing works and the local data environment of Bangladesh. This section describes the basic needs, resources, and assumptions that drive the design of a proposed crime-aware navigation framework for improving personal safety while travelling.

3.1.1 Methodological Requirements

The research approach combines quantitative and qualitative methods to grasp safety perception and convert this information into measurable parameters of the system. The design is informed by two complementary data streams, visualized in figure Figure 3.1. First, user studies (surveys and interviews) inform user-centred requirements. Second, verified crime records, subsequently enhanced with crowd-sourced reports, support modelling and validation.

A. User-oriented data collection:
Structured surveys and short interviews are required to gather perceptions of safety, commuting habits, and user expectations for safety-based navigation tools. These inputs ensure that the design will be informed by real commuter needs rather than abstract assumptions.

B. Contextual crime data:
Due to the unavailability of official datasets of Dhaka, a manually curated and verified record of incidents serves as the primary data source. In order to allow mapping of spatial and temporal patterns, each incident report must include at the very least type of crime, approximate location and time incident.

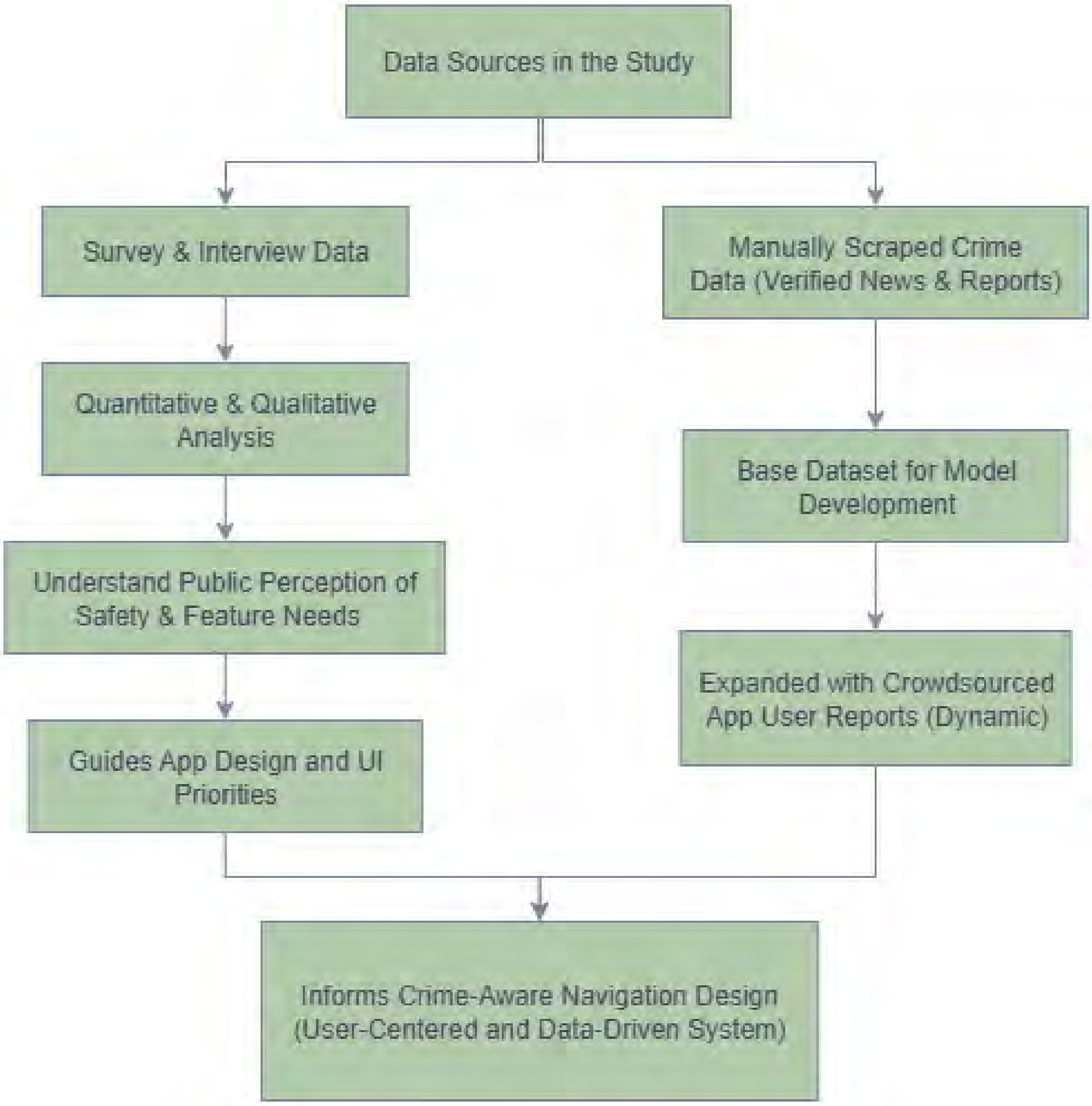


Figure 3.1: Data sources and their utilisation in the study

C. Data Sources and Utilization:
Two distinct forms of data are employed in this study, each serving a separate purpose within the overall framework. Survey and interview data are used for quantitative and qualitative analysis to examine public perceptions of safety, commuting behavior, and expectations for safety-oriented navigation systems. The findings from this analysis directly inform the design priorities and functional layout of the proposed application. In parallel, the crime data comprises verified historical incidents gathered from credible online and print sources. Over time, this dataset improves with crowd-sourced incident reports submitted through the app, allowing it to evolve and reflect changing urban safety patterns.

3.1.2 Technical and Resource Requirements

The proposed safety navigation system uses open-source, cross-platform, and affordable technologies, which are suitable for academic research and can be easily scaled for deployment.

Table 3.1: Preliminary technical and resource requirements

Resource Category	**Preliminary Requirement**	**Rationale**
Frontend Framework	React Native Expo	Enables rapid cross-platform development for Android and iOS, supporting integration of maps, geolocation, and safety features through a single unified interface.
Backend Framework	FastAPI (Python)	Provides a lightweight and efficient backend for data communication, safety score retrieval, and integration with analytical models.
Database and Cloud Platform	Supabase (PostgreSQL-based)	Offers an open-source cloud database with built-in authentication and row-level security, making it suitable for storing verified incidents and user-reported data.
Mapping Framework	OpenStreetMap (OSM) or Google Maps API	Provides reliable geolocation data and visualization for route generation and crime hotspot mapping.
Software Tools	Python and Google Sheets	Used for preprocessing, analysis, and spatial validation of the dataset.
Hardware	Standard workstation with $\geq$ 8 GB RAM and a stable internet connection	Sufficient for dataset preparation, backend deployment, and prototype testing.
Storage and Backup	Cloud drive or Supabase storage with access control	Ensures data integrity and secure backup of verified crime records.

The stack in Table 3.1 is deliberately low-cost and open-source to ease the path from prototype to deployment where React Native Expo enables a single iOS/Android codebase; FastAPI supplies a lightweight service layer for model-driven safety scores; Supabase (PostgreSQL) provides authentication and row-level security for verified and crowdsourced reports; OSM/Google Maps power mapping and routing; and Python/Google Sheets handle preprocessing and spatial validation, all runnable on modest hardware with simple cloud backups.

3.1.3 Functional Specifications

Based on early observations and the problem definition, we first identified the key functions that would scope the proposed system and guide user validation of which features mattered most. Building on that groundwork, this section now states the final functional requirements as externally observable behaviours the system is required to provide, defined in a form suitable for evaluation in the prototype and a ward-level pilot.

- **Incident validity:** A submission is required to be rejected if its time is in the future.

- **Required fields:** A report is required to include type, location, and time; description/media are optional.

- **Location entry and fallback:** Users are required to set a location by search or a draggable pin; if reverse geocoding fails, raw coordinates are required to be accepted and shown. Timestamp capture. Date and time pickers are required to produce an ISO-8601 timestamp.

- **Privacy notice:** The client is required to state that the reporter's identity is not displayed and only incident details (type, time, location) are stored for analysis.

- **Crimes-near-me feed:** The system is required to surface a feed of nearby incidents filtered by distance and recency (defaults: 5 km, 7 days), with configurable parameters.

- **Hotspot awareness:** The map is required to visualise recent incidents with basic category filters and a compact legend.

- **Safer-route computation:** The routing service is required to compute a route whose edge costs combine length/time with a safety penalty derived from recent incidents, and to return route geometry and duration.

- **Mode toggles:** The client is required to allow users to select a transport mode (e.g., walk, bike, car) before route calculation.

- **Submission gating:** The submit action is required to remain disabled until required fields are valid, with specific inline error messages.

- **Community validation:** Reports are required to support upvote/downvote and flagging; the backend is required to derive a lightweight credibility signal that influences prominence.

3.1.4 Data Availability and Expected Constraints

The research detects several problems regarding the availability of verified data, its quality, and scope. Since all records are authenticated manually and derived from credible news and internet reports, the data might not be comprehensive. This renders it more credible but less statistically profound and scalable.

Previous research indicates that poor maintenance of records and a lack of open data have, for a long time, limited Bangladesh crime studies on the basis of data [56]. Similarly, GIS crime mapping in developing settings normally complains of incomplete datasets and disparate spatial standards [59]. They suggest integrating diverse resources such as verified reports and crowdsourced crime statistics to mitigate the shortcomings. Internal consistency is also difficult to achieve, as variations in the area names, coordinate accuracy, and missing values must be normalized before joining. These limitations individually influence the design of the system and the preprocessing and modeling of data.

3.2 Societal Impact

Coming from an initiative to improve commutation safety of the general public, the safer route navigation system is clearly based on shaping user behavior, perceptions, and adapting spatial usage to current crime trends. The following subsections assess its societal effects concerning safety, mobility, legal, health, and cultural aspects in the urban Dhaka context.

3.2.1 Impact on Society

Urban mobility in Dhaka has aggravated over the years due to congestion, inadequate infrastructure, and perceptions of insecurity [34], [9]. Commute time period, duration, and modal split across areas vary significantly as found in a neighborhood sustainability evaluation [34]. In addition, travel mode and route choice are strongly influenced by perceptions of transportation among different groups. To illustrate, people with mobility issues consider travel discomfort and calculated risks when selecting modes of transportation [47].

The system recommends routes based on safety scores of each location, which enables users to choose routes that may be technically longer yet safer, instead of suggesting the shortest rout,e which conventional navigation systems do. This, in turn, reduces the spatial and user group mobility variations by allowing users, who previously had the mobility-avoidant behavior arising from paranoia of crime, especially among vulnerable user groups such as women, the elderly, the disabled, and students, to commute with a sense of added confidence and security.

However, widespread usage of safe and optimized routes could result in redirecting the congestion to previously low-traffic zones and exposing other areas to new crime hotspots. Therefore, cautious monitoring is required to make sure that the system does not involuntarily create new congested or crime hotspot areas.

3.2.2 Safety Impact

Given that the system's primary objective is to rank routes based on computed safety scores, the most immediate and measurable impact area lies within the domain of improving personal safety.

Crime-Aware and Risk-Weighted Routing: Since the system evaluates each possible road segment in the route based on safety scores, based on both crime density and severity, the users are able to receive more detailed and evidence based suggestions rather than just "safe" vs "unsafe" classifications. The incorporation of spatial weightings, which is derived from reported incidents, provides a more realistic visualization of safety across neighborhoods, rather than just generalized assumptions that warrant a sense of safety among users.

Temporal and Spatial Sensitivity of Scoring: Crime patterns in Dhaka vary significantly depending on temporal and spatial factors, like different hours of the day, days of the week, and across neighborhoods [6]. To add, improper infrastructure like low lighting, confined streets, and lack of access to law enforcement agencies have actively contributed to the surge of road crime occurrences in Dhaka [36]. Moreover, studies based on Savar, Ashulia, and Dhamrai have identified certain streets being considered as high-risk zones [4]. Incorporating these findings, the proposed system takes into account temporal and spatial factors, further refining the circumstantial recommendations of safer routes. This brings a consistent sense of security across Dhaka neighborhoods and the current time of crime trends.

Reduction in Aggregate Risk Exposure: By reducing the frequency of users travelling in crime hotspot areas (based on crime density or severity), the proposed system can decrease users' exposure to potential safety hazards while commuting. Even though there is a lack of direct empirical validation for Bangladesh, SafeRoute illustrates that about 17 of user proximity has been reduced to identify crime locations while maintaining reasonable travel duration [18]. Implementing this principle in the urban context of Dhaka could potentially bring similar results for commuters in Dhaka, further improving the sense of security and safety among them.

3.2.3 Health Impact

Health is not directly influenced by this navigation system; however, some secondary health benefits can be acquired in the context of Dhaka.

Reduced Psychological Stress: People who travel often feel anxious while travelling through the environments classified as unsafe during low-light hours and isolated urban areas [57]. A study on pedestrian safety conducted in Dhaka shows that household choices of mode of transport are influenced by risk perception [29]. The suggested scheme can protect individuals from anxiety and psychological stress subsequent to commutation. The routing actions will lead individuals towards less crime-prone or safer routes to reduce the chances of incidents or contact with criminal and anti-social elements.
Encouragement of Active Mobility: By improving the perceived safety of walking and cycling areas can enable users to use these active modes of mobility more frequently, which in turn contributes to improving overall cardiovascular health and reducing health risks associated with sedentary commuting. A study conducted in Global South has proved that feelings of insecurity during travel can substantially reduce active mobility participation [58]. Therefore, by diminishing the exposure to high crime risk zones, the system promotes healthier and more sustainable commuting tendencies.

Reduction of Injury and Victimization Risk: Since the proposed system potentially diverts the users from areas prone to crime (based on severity or density), the probability of users being exposed to theft, assault, robbery or related incidents decreases, which consequently contributes to reduced medical and societal expenditures affiliated with injury and trauma as a result of such incidents.

3.2.4 Legal Impact

The concerns related to legal framework branches primarily from the collection of sensitive spatial information, public crime entries, and user-reported incident data. Since the system is implemented in a region where data protection policies are still being developed, it is expected to come across some potential challenges concerning legal responsibility, privacy, and agreement to maintain lawful operation.

Data protection and privacy compliance: Bangladesh, at present, has a lacking of comprehensive data protection law equivalent to the EU's General Data Protection Regulation (GDPR), however, drafts such as the Personal Data Protection Act (PDPA) imply an emerging legal framework for data protection and governance [40]. The proposed system ensures full compliance with international best practices concerning data as it collects no personally identifiable data. All reported incidents are stored anonymously, only storing the essential spatial and categorical information needed to update the database. Moreover, Supabase's cloud level authentication and row-level security protects the stored data from unauthorized access which lines up with fair data handling principles of necessity and proportionality.

Data Source Legitimacy and Intellectual Property: Technologies involved to build this system, namely React Native, FastAPI, and Supabase, are all regulated complying with intellectual and non commercial research usage under permissive open source licenses (MIT or Apache 2.0) [12], [11], [39]. In addition, verified media sources are being utilized within legal boundaries for academic purposes. These measures altogether develop a compliant framework that safeguards user privacy, diminishes liability, and aligns with intellectual property rights.

3.3 Environmental Impact

This section measures the sustainability and environmental impact of the proposed system, and since our project mainly incorporates software and digital infrastructure, it leads to a minimal environmental footprint. However, the sustainability and environmental impact still need to be considered in terms of resource use and efficiency.

A. Sustainability:
The system supports sustainability as it decreases the need for paper records and physical reports by digitizing the input and storage of incident data. Thus, it reduces material waste and promotes long-term accessibility. Using open-source, cloud-based solutions like Supabase and React Native warrants efficient use of shared computational resources, which in turn avoids unnecessary hardware demand.

B. Environmental Impact:
Because the project uses cloud computing and online storage, it may lead to higher indirect energy use from data center operations. However, this is reduced by the project's small-scale academic deployment and the use of optimized code and lightweight frameworks. These factors lower server load and data transfer.

In summary, the proposed system supports sustainable digital practices through resource efficiency and reduced material dependency while maintaining a low ecological footprint.

3.4 Ethical Issues

The whole procedure of building the crime aware navigation system raises several ethical considerations along with corresponding professional responsibilities. As the system deals with spatial data related to crime incidents and allows users to report such incidents as well, ethical conduct is unavoidable to user trust and preserve the social purpose of the research. This section shapes the main ethical issues affiliated with data privacy, transparency, and responsible use of open source resources.

3.4.1 Ethical Issue 1: User Privacy and Data Confidentiality

As mentioned before, since the system accepts submissions from users including sensitive information about spatial and temporal markers, it is designed to keep track of no personally identifiable data. All user generated reports are anonymous and only essential information such as location and the type of crime along with time of occurrence is stored. This guarantees that neither user identities nor personal devices can be traced through stored data.

Professional Responsibility: Strong anonymization and security standards are implemented throughout the data lifecycle. The system only allows authorized users to view or modify stored information which is ensured by secure authentication, encryption, and row-level access control. These practices also align with the draft *Personal Data Protection Act 2023 of Bangladesh*, which highlights consent based data use and purpose limitation [40].

3.4.2 Ethical Issue 2: Data Accuracy and Fair Representation

The proposed model incorporates verified and crowd-sourced data, so ethical considerations extend to the accuracy and fairness of the information. Hence, inaccurate or biased reported incidents could wrongly contribute to certain neighborhoods being more unsafe than they might be in reality, further strengthening spatial inequality.

Professional Responsibility: At present, the system enables users to upvote submitted incidents they believe to be valid or downvote those suspected to be fraudulent. This community enforcing procedure offers a preliminary layer of reliability control for crowdsourced data. Nevertheless, a formal validation and verification procedure such as cross-checking incidents with credible media or community sources has not yet been implemented. Future works of the framework aim to introduce these checks to ensure only the verified and validated user entries get included in the main dataset upon which the safety scores are calculated and safer routes are suggested based on that. Enacting such mechanisms is essential to maintain data accuracy and fairness, ensuring that no community or individual is unintentionally harmed through spread of misinformation [15].

3.4.3 Ethical Issue 3: Transparency and User Autonomy

Transparency regarding system functionality and user rights is a core principle of the ethical considerations of the proposed system. Even though the system computes safety scores based on crime dataset incorporating both severity and frequency, the users must understand that these results are predictive estimations of historical data, so it does not guarantee real time safety. The system can only infer relative risk from past incidents and spatial patterns, meaning that sudden or unreported crimes remain beyond its predictive scope.

Professional Responsibility: Users are to be informed using appropriate disclaimers within the application interface and accompanying documentation that routes recommended by the system are advisory, that is relative to existing crime database, so it does not guarantee the optimum real time security. Currently, the system does not enable users to override the safe route suggestions in case they want to use faster or alternative paths, however, future updates aim to incorporate this flexibility to maintain user autonomy and informed decision making. Hence, such measures concerning transparency alights with responsible AI and data-ethics principles emphasizing informed consent and realistic expectations [16].

3.4.4 Participants privacy - Surveys and Interviews

Collecting perceptions about safety through surveys and interviews introduces risks to participant privacy and autonomy, including inadvertent disclosure of sensitive location–time contexts and potential distress when discussing incidents. Ethical conduct requires data minimization, clear consent, and the right to skip/withdraw.

Professional Responsibility: The study proceeds under Institutional Review Board (IRB), and informed consent is obtained before any personal data are gathered. Only purpose-limited variables are recorded, so direct identifiers are not stored. Data integrity [27], confidentiality, and privacy are protected via access controls and anonymous online survey tooling where necessary. Participants may withdraw at any time, and data retention/destruction follows IRB guidance.

3.5 Project Management Plan

This section outlines the management framework adopted during the development of the *Safer Route Navigation System*, detailing the schedule, budget structure, and resource allocation. The project spanned twelve months and was divided into three four-month phases, each with specific objectives and milestones to ensure steady progress from conceptualization to implementation.

3.5.1 Schedule

The development of the software was divided into three phases. The first stage for the first four months consisted of a thorough literature review of crime-aware navigation systems and mechanisms, and methods to identify gaps in spatial safety modelling techniques in the Bangladeshi urban context. User surveys and stakeholder interviews were conducted to measure public views and confirm the system's relevance. Based on the findings, the group outlined data needs, tech specs, and a designed workflow that leads to the next steps.

During the second stage, from 5th to the 8th month, work focused on the development of the various system models as well as the design of the complete system. It involves the creation of a safety score model that combines the severity of incidents and frequency to quantify spatial risk. Multiple machine learning configurations were evaluated, and the optimal model is integrated into a custom Dijkstra-based routing algorithm to balance route length and safety. Concurrently, a mobile app prototype was developed to visualize comparative safety routes and intuitive interaction.

The last stage in months 9 to 12 is application development and appraisal, where we fully developed and integrated the system using React Native frontend, routing services FastAPI, and Supabase Database and Authentication. Then the prototype was tested through a user survey for functionality and usability that evaluated the interface and navigation logic. The concluding period was dedicated to debugging, optimization, and the compilation of the project documentation.

3.5.2 Budget and Cost Framework

The financial plan was designed to maintain sustainability across prototype (laboratory) scale utilizing open-source technologies and free-tier services to minimize expenditure.

Prototype (laboratory scale): Implemented using free or low-cost tools such as the Expo client, Supabase's free plan, and OpenStreetMap (OSM) under fair-use conditions. Estimated cost: US\$0–45/month ($\approx$ BDT 0– BDT 5,000).

Resource Management
Project resources were allocated based on expertise and task specialization across the three development phases:

Phase 1: Two members conducted literature review and survey preparation; two members handled data structuring and documentation.

Phase 2: One member developed the safety-score model and risk estimator, while others implemented the routing logic and designed the interface prototypes.

Phase 3: The full team collaborated on system integration, testing, and final reporting.

Project oversight was maintained through weekly progress meetings and version control via GitHub, ensuring traceable deliverables and collaborative synchronization. This iterative management structure supported adaptability in addressing unforeseen data inconsistencies and design refinements.

3.6 Risk Management

Every system carries risks that can affect performance, security, and user trust. In this project, the main risks involve sensitive location data, errors in crowd-sourced reports, and reliance on third-party cloud services, so this section outlines the key risks encountered during development and deployment and the measures taken to reduce them.

Table 3.2: Summary of key project risks and mitigation strategies

Risk	Impact	Mitigation Strategy
Data Breach	High	Use Supabase's managed encryption, TLS, and Row-Level Security (RLS) to secure user data during storage and transmission.
Data Inaccuracy	Medium	Apply manual verification, preprocessing, and moderation of crowdsourced data to maintain dataset quality and reliability.
System Downtime	Medium	Implement regular backups, API modularization, and comprehensive error logging to ensure system recovery and stability.
Model Limitations	Medium	Use interpretable models such as LightGBM and retrain them periodically with new data to maintain predictive accuracy.
Ethical Misuse	High	Incorporate verification and user flagging mechanisms to prevent false or misleading reports and ensure responsible app use.

The following sections describe each risk category, which is mentioned in Table 3.2 in a detailed manner, and also note the specific strategies applied to mitigate them.

A. Data Breach and Security Risks
Unauthorized access to stored data is a significant concern, which is why Supabase's built-in encryption at rest and TLS in transit is used to ensure secure data handling. Row-Level Security (RLS) policies limit visibility based on user authentication. No personally identifiable information is collected in the user reports table, which reduces exposure in case of a system breach.

B. Data Inaccuracy
Because the dataset starts with manual curation and later incorporates community reports, inconsistencies can emerge. To reduce noise, submissions undergo preprocessing checks and a moderation step before they are admitted to the live dataset.

C. System Reliability
Disruptions in APIs or backend services could interrupt route generation and hotspot visualization. The backend is built with FastAPI and modular endpoints, and it leverages Supabase's cloud redundancy to avoid single points of failure. Scheduled backups and structured error logging support swift diagnosis and recovery.

D. Model Performance Risks
A limited training set can weaken generalization. LightGBM was selected for its efficiency and tolerance of class imbalance, and incremental retraining will sustain accuracy as new data accumulate.

E. Ethical Misuse and User Trust
Malicious or misleading reports jeopardize both operations and credibility. The application provides a flag-and-review workflow and requires authentication for suspicious activity. Clear disclosures about data sources and privacy practices further

reinforce user confidence.

The identified risks mainly deal with data reliability, ethical use, and technical continuity. The suggested mitigation strategies use Supabase's current security setup and FastAPI's modular design and prioritize transparency and user trust. In conclusion, continuous monitoring, user feedback, and regular audits will strengthen risk resilience during the project lifecycle.

3.7 Economic Analysis

This subsection evaluates whether a safety-aware navigation system like ours is financially realistic in Bangladesh. The analysis is grounded in the actual stack we built—React Native (Expo) for the client, a FastAPI service for routing, Supabase for database/realtime/auth, and OpenStreetMap (OSM) for maps—and considers two deployment levels: the thesis prototype and a small ward-level pilot in Dhaka.

The prototype was intentionally designed to run on free or very low-cost tiers: the Expo client, Supabase's free plan for light usage, and OSM tiles under fair-use. Moving beyond the lab introduces modest, predictable costs: a one-time Google Play developer account fee of US$25 (≈ BDT 3,000), an optional domain/SSL at US$10–15/year, and hosting for the routing/API service. A single small VPS (1–2 vCPU, 2–4 GB RAM) is adequate for our FastAPI workload and costs roughly US$15–40/month. Supabase can remain on the free tier for small evaluation cohorts; for a ward-level pilot, a paid tier in the US$25–100/month range is typical to lift connection limits, enable backups, and add monitoring. Because we use OpenStreetMap, there are no metered map or directions API fees; switching to commercial map stacks would immediately dominate the budget and is not required for a pilot. Push notifications (Expo/FCM) and email authentication remain near-zero at this scale, aside from negligible background compute to schedule/send messages. To reflect real operations, we include a small moderation/operations stipend (review of flagged reports, simple data QA) of US$100–200/month. Summing these items, a ward-level pilot operates at approximately US$150–355/month (≈ BDT 17,000–BDT 40,000), while the lab prototype remains US$0–45/month.

Even before accounting for broader social benefits, the system yields direct efficiency gains. Automating hotspot collation, proximity alerts, and report intake can reasonably offset 8–16 hours of staff effort per month, which at typical local rates equates to US$80–320 (≈ BDT 8,000– BDT 32,000). A second recurring benefit is the creation of a cleaned, geocoded incident dataset for Dhaka. Because credible, structured safety data are scarce, reusing this dataset across semesters or partner agencies avoids repeated scraping and cleaning—fairly valued at US$100–300/month (≈ BDT 10,000–BDT 30,000) in analyst time. These conservative benefits already match or exceed expected pilot costs; any reduction in exposure for vulnerable commuters (e.g., fewer incidents along known hotspots) adds unpriced social value.

At prototype scale, the system is essentially free to run. At ward scale, recurring costs are small enough to fit a university grant, NGO pilot, or municipal CSR budget. The architecture also supports integration as a "safety layer": our backend produces segment-level safety weights that can be exposed via a simple API and consumed by third-party routers or displayed as an overlay heatmap. This avoids heavy infrastructure duplication and concentrates costs on maintaining a lightweight API and database—roughly the same ranges noted above. If revenue is pursued, a fixed integration fee or a small monthly license to partner organizations is feasible without changing the technical design.

Because the application is built on open-source tools and cost-controlled services, it is economically viable beyond the thesis. A six-month ward pilot at roughly US$200–300/month is realistic and near break-even using only conservative time-savings estimates; when the social value of safer routing is considered, the case strengthens further. The clearest financial strategy is to keep OSM tiles, run lean hosting, and present the system as a reusable safety layer that partners can adopt without large infrastructure changes.

Chapter 4

Proposed Methodology

4.1 Design Process or Methodology Overview

The main goal of this study is to design and execute a navigation system that helps keep track of crime alerts and offers emergency services. Traveling within Dhaka city can put your personal security at risk. The methodology involves a multi phased process which will first identify the problem through a literature review and user studies, followed by data collection and analysis, model development, and system design. Both quantitative and qualitative research methods are used to understand user concerns and design an appropriate solution. The proposed system will integrate machine learning techniques to predict safety scores and implement a routing algorithm that prioritizes safer journeys based on these predictions. The overall sequence is summarized in Figure 4.1.

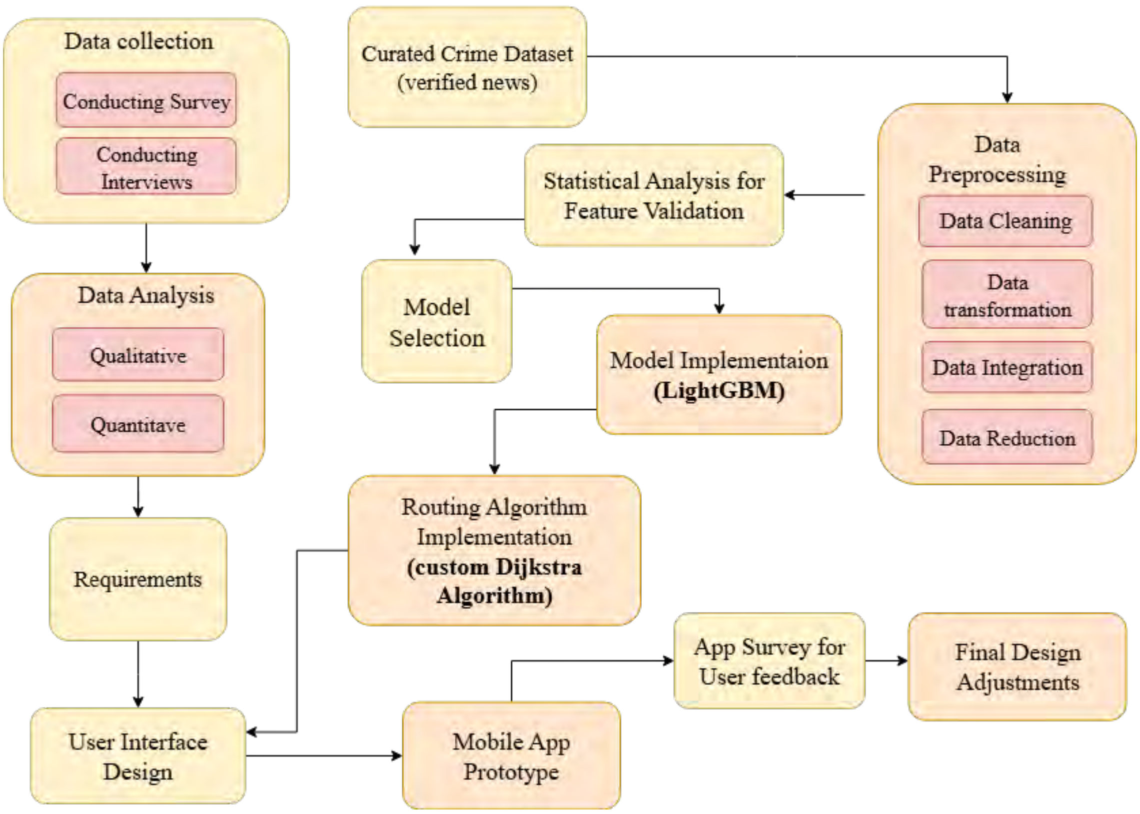


Figure 4.1: System workflow

A. User research:

A citywide survey of 155 respondents captures commuting patterns, perceived risk, and willingness to use safety-aware routing, producing the descriptive baselines needed for feature prioritization and model inputs. To complement this, 15 in-person interviews elicit context and nuance around everyday safety. We conduct open coding on interview transcripts, then iteratively compare and cluster codes to derive themes (e.g., gendered vigilance, time-of-day effects, trust in information, community response, and structural barriers). These themes directly inform the information architecture and the explanation elements in the UI.

B. Incident dataset creation:

Because comprehensive public crime datasets are not available for Dhaka, the study compiles a manually verified dataset (2022–present) from official police communications where accessible and verified national news sources such as The Dhaka Tribune, The Daily Star, and Prothom Alo. Each record includes type, time, textual area location, and geocoordinates. A severity weight (1–5) is assigned by crime type to support risk scoring. Data preparation standardizes labels, removes duplicates, geocodes locations, and engineers features (e.g., hour-of-day with cyclic encoding; neighborhood zones via KMeans). Area-level risk is normalized to a 0–100 safety score with Min-Max scaling.

C. Modeling and validation:

Multiple learners are tested to estimate safety scores at the location/edge level. Classifiers (e.g., KNN, LightGBM-Classifier) are explored but set aside due to class imbalance. Regressors like LightGBM, Gradient Boosting, and Random Forest are then evaluated with R^2 and MAE; RandomizedSearchCV tunes hyperparameters. LightGBM is selected for its accuracy and efficiency on sparse, imbalanced, non-linear patterns. Statistical tests support design choices: a chi-square test of independence examines crime type vs gender patterns; ANOVA and Kruskal–Wallis check consistency of the engineered severity scale across types; and DBSCAN inspects spatial clustering to corroborate hotspot-centric visualization and routing penalties.

D. Routing algorithm:

The routing component augments Dijkstra's algorithm by adding a safety penalty derived from predicted risk, prioritizing safer alternatives when distance differences are small. This safety-weighted routing favors paths that avoid high-risk segments while preserving reasonable travel efficiency and enabling safer travel choices for users.

E. Interface and implementation:

Low-fidelity user flows and screens are first drafted in Figma, then implemented as a mobile prototype in React Native (Expo) with a FastAPI backend and Supabase data layer. The application applies designs over OpenStreetMap tiles and provides hotspot pins and area score, enables incident reporting, offers alternative routes, and displays clear safety explanations derived from model outputs and themes from the qualitative analysis

These steps create a transparent, logical methodology that connects users' needs via curated data, trusted models, explainable routing, and usable UI, under the constraints of Dhaka's data landscape.

4.2 Preliminary Design or Design (Model) Specification

The proposed system for crime-aware navigation has a preliminary design that depends on the foundation of data driven crime prediction, route planning suggestions, that is to be incorporated into a mobile application interface. Each modular component of the system's design plays an important role in enhancing user experience, safety, and future scalability.

4.2.1 System Level Design Overview

The proposed system architecture comprises the following four interconnected components:

A. Dataset Collection: Given the unavailability of open crime datasets or centralized APIS in Bangladesh, manual scraping of data from online news articles is implemented. All the crime-relevant information is extracted and categorized in a tabular dataset with location (Detailed Location, Longitude, Latitude, and Area), gender of the victim, and time of the incident. It acts as a foundation for the predictive models.

B. Safety Score Prediction: This module implements Machine Learning models to predict the safety score(0-100; 0 means most safe and 100 means most unsafe) of a specific location. To test the accuracy of the safety, several models were implemented, including both classifier and regressor models. However, the manually scraped dataset is highly imbalanced since the moderately safer zones outnumber the high crime zones, so the results achieved from classifier models are not up to par. Moreover, a clustering algorithm model like DBSCAN did not give a satisfactory result, again owing to the imbalanced dataset containing isolated crime zones. On the other hand, regressor models like LightGBM regressor, Gradient Boosting Regressor, Random Forest Regressor, and XGBoost produced better accuracy and generalization in predicting safety scores of each location, which further acts as the weights of the edges in implementing routing algorithms. Among all the models, LightGBM Regressor has been chosen as the final model for having the highest R2 score and Mean Absolute Error (MAE) score.

C. Routing Engine: A modified Dijkstra algorithm, specifically integrated with the LightGBM model, is implemented to generate routes by considering the safety scores of individual locations along with the distance, unlike conventional navigation algorithms. Each edge is weighted based on length and predicted safety score, where low safety risk locations are penalized in the cost function. This enables the system to suggest safer routes even if those are slightly longer in distance, prioritizing safety over short distances.

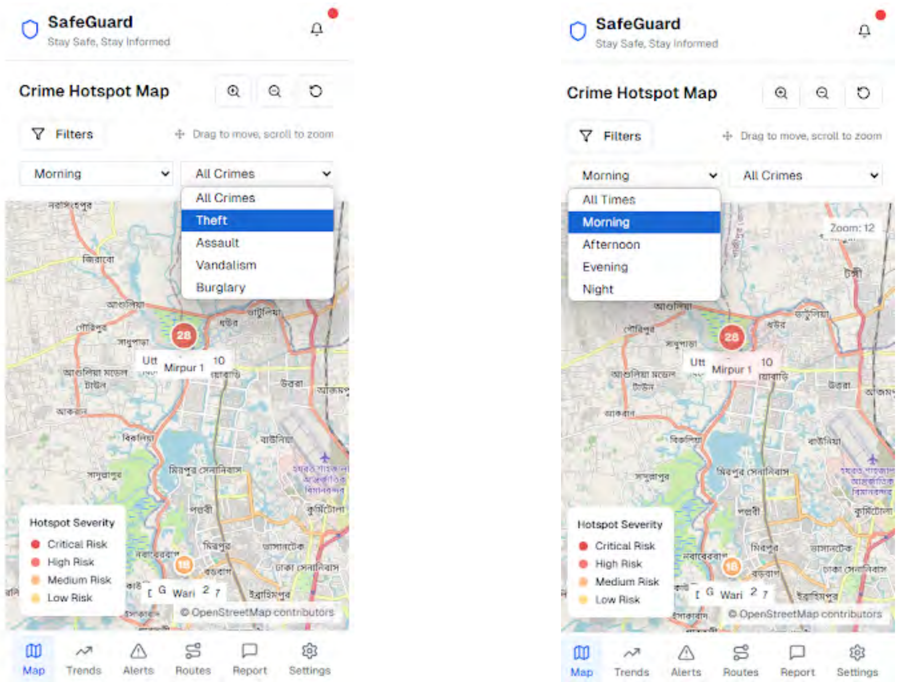
D. User Interface: The UI currently is of a front-end mobile prototype, developed with Figma, enacting user interaction with the navigation system. It displays a crime hotspot map based on different timings of the day(Morning, Afternoon, Evening, and Night) with different risk levels (Critical Risk, High Risk, Medium Risk, and Low Risk) based on areas, and provides recent incidents alerts. The interface suggests route planning, which has multiple options like Safest, Fastest, and Balanced, each with its individual risk level. Although the backend integration has not been implemented yet, all the modules combined offer the blueprint for real-time interactivity in future work.

4.2.2 Feature Specifications

The core functionalities of this system have been enacted in the UI. The front-end is modular, allowing user interactivity and future integration of the backend and additional functionalities.

Core Features displayed in the UI

- Time-Based Crime Hotspot Map with area-specific risk levels breakdown (Critical Risk, High Risk, Medium Risk, and Low Risk) and types of crimes (Theft, Vandalism, Assault, Burglarism, etc.) as shown in Figure 4.2

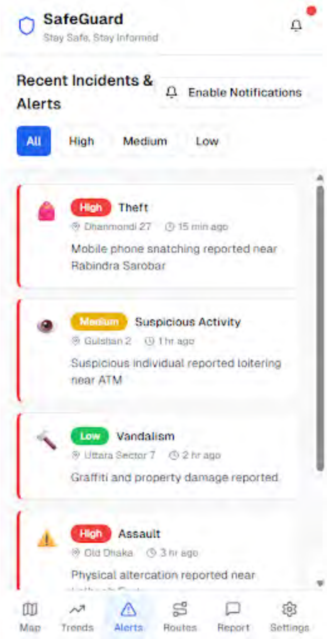


(a) (b)

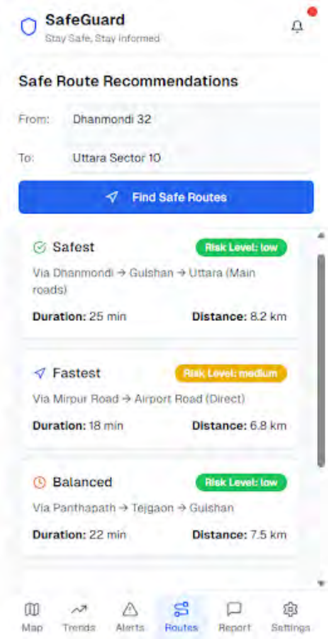
Figure 4.2: Crime hotspot map with respect to time and crime types

- Recent incident alerts to increase situational awareness as shown in Figure 4.3 (a)

- Safe Route Suggestions with three route options, which are Safest, Fastest, and Balanced, with specific risk levels for convenient comparison as shown in Figure 4.3 (b)



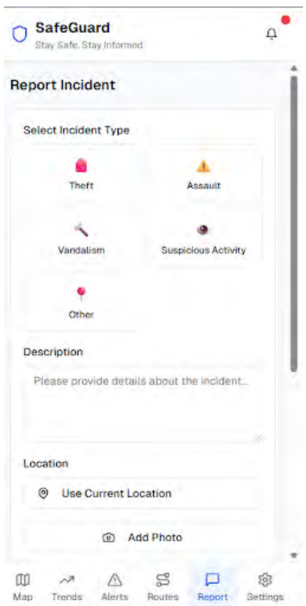
(a) Recent incident alerts



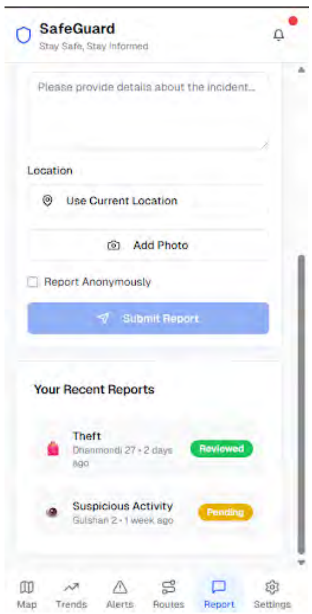
(b) Route suggestions

Figure 4.3: System alerts and routes

- User-Reported Incidents to enrich local crime data as shown in Figure 4.4



(a)



(b)

Figure 4.4: Report incidents

Other Planned System Features

- Emergency SOS Button for immediate distress alerts
- Live Crime Feed Integration from third-party or official sources
- Profile-Based Routing Preferences (e.g., avoid dark paths at night)

4.2.3 Design Constraints and Assumptions

While designing the system, some constraints and assumptions have surfaced, which are duly noted for future enhancements.

A. Data Availability and Quality: The current working model only relies on the manually scraped data from news articles due to lack of official dataset or APIs in Bangladesh. As a result, the data accuracy, consistency, and timeliness are affected.

B. Lack of Real-Time Crime Reporting: The absence of live integration from police or government feed disables the system to implement real time crime reporting.

C. Bias in Data Sources: An unbalanced perception of rural or underrepresented areas may result from news reports that overreport crimes in prominent or urban areas.

D. Limited Geographic Scope: The system initially covers only certain areas in Dhaka, leaving other areas unsupported until more data is gathered.

E. User Trust and Perception: Users may find the system skeptical or dismiss the suggestions given by the route, especially in case the system does not suggest their usual routes.

F. Privacy and Ethical Concerns: If user movement or location data are stored,future analysis of data may raise concerns with regards to its privacy and ethics among users.

These constraints and assumptions are carefully considered and contribute to the overall system development.

4.3 Data Collection

This section summarizes the empirical foundation of the study. We first describe the quantitative survey used to characterize everyday mobility and perceived risk, then outline the interview protocol and thematic coding that surfaced context-specific safety constructs. Finally, we document the curated crime dataset assembled from verified Bangladeshi outlets (e.g., Dhaka Tribune, The Daily Star, Prothom Alo) and specify its fields and provenance. Together, these inputs ground the analyses that follow and align the evidence base with the study's safety-aware routing objectives.

4.3.1 Quantitative Analysis: Survey

A survey was conducted to explore the travel instincts and safety concerns of the general people in Bangladesh, which got a total of 155 responses, among which the distribution of participants between female (54.2%) and male gender(45.2%) is almost equal, the age range 18-25 being the most dominant (78.1%). Most participants are students (78.1%) and are mostly from Dhaka (90.3%) with smaller representations from other cities such as Rajshahi, Khulna, Feni, Chittagong, and Gazipur. When asked about perceptions of safety within own city, around half of the participants responded feeling "Very unsafe" and "Somewhat unsafe" as illustrated in Figure 4.5.

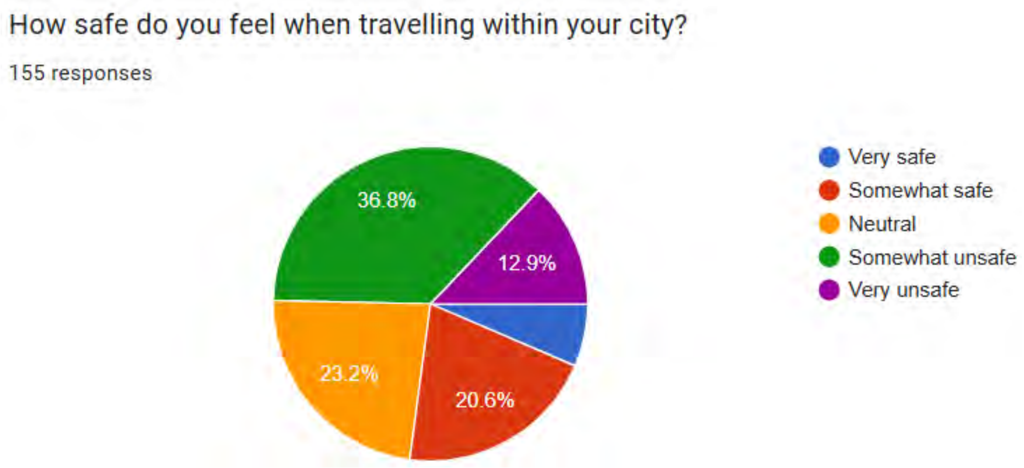


Figure 4.5: Perceived safety in respective city

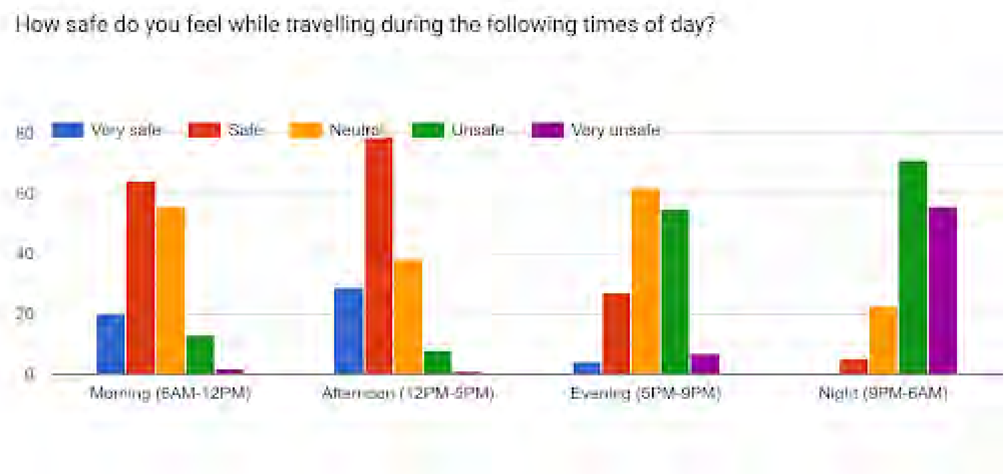


Figure 4.6: Perceived safety with respect to different times of the day

Almost two-thirds of the participants admitted traveling alone most of the time, and 63.2% acknowledged that they consciously avoid certain areas due to safety concerns. Additionally, Figure 4.6 illustrates over 70% of respondents feel extremely unsafe after 9 p.m., portraying a sharp decline in perceived safety. Many people rated walking and public transportation as risky or somewhat unsafe, while personal vehicles were considered the safest form of transportation.

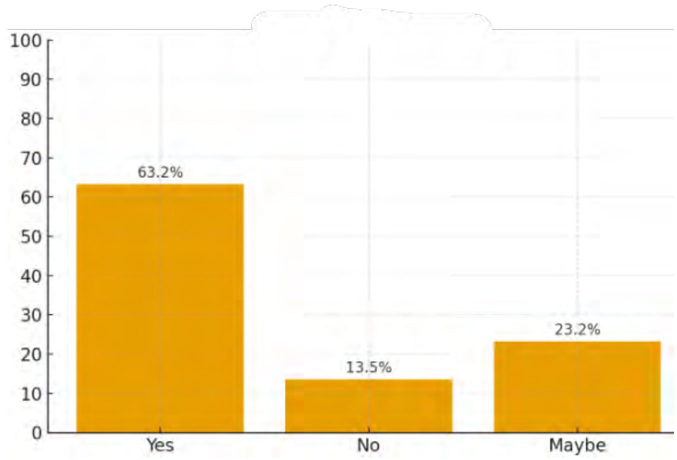


Figure 4.7: Safer Route Navigation Participant Demand

Almost all the participants use smartphones (96.8%), and 88.4% use navigation apps while commuting, mainly Google Maps (94.2%) although only 12.9% use it in every trip. Despite this, Figure 4.7 shows that 63.2% of the participants expressed a strong interest in using a crime-aware navigation app, and more than half expressed trust in a system that relies on crowdsourced data to suggest safe routes, which ultimately indicates a prominent concern for travel safety.

Moreover, a high user engagement in the system is noted as over 90% respondents showed willingness to report incidents, and 76.8% admitted that they would use an emergency alarm in unsafe situations. In such cases, the majority expressed willingness in informing close family (86.5%) and friends over authorities.

However, most of the participants showed their concern over data breach or data exploitation by third parties. This indicates a strong need for building a robust, data protective system integrated with transparency.

4.3.2 Qualitative Analysis: Interviews and Thematic Analysis

The interviews revealed that the perceptions of safety in Dhaka urban commuters are contextual and complex. It is shaped by social identity, environment, and technology. Safety was not understood as a stable condition rather perceived as something continuously negotiated, influenced by gender, time of day, familiarity with routes, and the availability of reliable transportation or information.

We analyzed the interviews we had recorded and later scrutinized by continuously comparing them to create high-order concepts. By using this grounded, inductive approach, five dominant themes emerged: Safety as a Gendered and Contextual Experience, Navigating Safety Through Mobility Choices, Trust and Skepticism Toward Technology, Community Contribution and Emergency Support, and Structural and Systemic Barriers to Safety. All these themes show how participants view, negotiate, and co-create safety within the urban issues of Dhaka.

1. Safety as a Gendered and Contextual Experience

Feeling safe is deeply linked to gender, place, and time. It is not an experience but a situation. Among the participants, women were always aware of risk and adopted precautions while travelling for everyday activities. A frequent topic of conversation was discomfort during close-contact rides, being stared at while walking, or travelling alone after dark. The physical environment itself was less important than the feeling of having or not having control and visibility. One student explained,

> "While in a rickshaw, when the road is silent, I begin to think of what I would do if anything goes wrong. I share my location or pretend to talk on the phone. I am not always in danger, but I always have to be on alert."

From such responses, we can deduce the mental load a woman has to carry to ensure she is safe when she travels, including the checklist of safety strategies. This is a form of emotional labour that men seldom face. Another female interviewee said that her family restricts her from going out after a certain hour. In this instance, security is evidently an issue that restricts mobility outside one's home. In contrast, male participants described feeling mainly safe but occasionally avoiding some areas at night (like Mohammadpur, Asad gate, and side lanes in Gulshan) due to dark and isolated surroundings. The responses of women reflect a continuous negotiation with safety in their everyday lives, whereas the responses of men indicate conditional or reactive engagement with it.

2. Navigating Safety Through Mobility Choices

The participants made their travel decisions using purposeful techniques, which assisted them in managing the perceived level of threat. Individuals choose their travel alternatives through ongoing decision-making that relies not only on basic convenience but also on a sense of control. The safety advantages of private cars and CNGs come from their ability to provide protected travel spaces which give user's privacy and shield them from unwanted social interference. Most of the respondents considered buses and walking as unsafe options because they felt threatened when traveling during night hours on deserted roads in either of these transport. A teacher described her approach,

> I never use empty roads for my travels. I choose to spend extra money on CNG or rickshaw services because I prefer being in the presence of others when I travel. I never think about bus travel after 9 p.m."

From her statement, it is evident how safety affects our ability to move, even if it comes at a higher cost or less convenience. The participants who frequently commuted mentioned using route planning strategies that involved selecting paths that had adequate lighting and were not secluded before taking any shortcuts. A male respondent mentioned avoiding Mirpur's back lanes after dark because he said, "they feel unsafe even if nothing actually happens." Such comments indicate that travel behavior in Dhaka relies on informal heuristics of familiarity, visibility, and human presence instead of formalized safety protocols. Therefore, mobility turns into a risk management strategy that is influenced by lived experience rather than infrastructure.

3. Trust and Skepticism Toward Technology

Through the study of user perception in the interview respondents, we can deduce that technology played an important role in shaping participants' sense of safety yet its implications are limited. The majority of the participants of the study reported using Google Maps daily but they failed to mention any link between the app and their personal security. The primary function of the system focused on delivering navigation and traffic updates instead of providing safety alerts about dangerous situations, but personal safety should be a key aspect when navigating. The interviewees showed great interest in technology which would supply authentic security updates about roadways and nearby incidents in real-time. A female medical student expressed her interest,

> "If the app tells me a crime happened near my route, it's useful but only if it's verified. Otherwise, people will just panic for no reason."

The concern that she had about misinformation about crime data was shared by several others, who mentioned that false alerts could create unnecessary fear and distrust rather than giving helpful insights. Some of the participants stated they would use a safety application only when it provides exact explanations about unsafe routes through documented incidents by providing their accurate locations and corresponding dates. One participant stated that "current navigation applications in Dhaka display traffic information, yet they do not provide safety features," which depicts a clear gap between user requirements and existing technological solutions. People who are prone to using digital safety solutions showed interest in safety-based navigation, but they require proof of transparency, as well as reliable and verifiable information about their specific location and nearby crimes.

4. Community Contribution and Emergency Support

The results of the interviews showed shared accountability and community involvement. As long as they stay anonymous, several individuals said that they would be reporting in order to improve public safety. One young woman explained,

> "I would definitely report if it helps others avoid danger. But I don't want my name or number to show; it should protect me first."

Others had similar views, emphasizing that anonymity would determine their level of trust in such systems. The necessity of immediate response systems was also highlighted by a number of interviewees. One Bashundhara user recommended an emergency button that would connect directly with family or nearby users, while another said she preferred an alert system that might notify people around me who can actually help. According to one participant, It's not always your family that can help you in critical moments, it's people who are nearby."

This subject reflects a broader awareness that safety is a group awareness rather than merely an individual quality. One respondent used the expression "helping others helps everyone," which summarizes this cooperative mentality that defines advancements in Dhaka's community based digital safety.

5. Structural and Systemic Barriers to Safety

Safety focused technologies grabbed the interest of the participants. They did, however, repeatedly claim that technology is unable to address the fundamental structural issues facing urban Dhaka. Many said that weak policing, inadequate street lighting, and a lack of accountability all compromise public safety. These problems were frequently viewed as the primary sources of anxiety and doubt, outweighing any potential benefits of technology. One guy commuter summed up the limitation quite well,

> "These apps are great ideas, but they can only work if the basics are right, such as if streets are lit, if people care, and if the police act. Without that, technology can only do so much."

Others expressed similar problems, pointing out that even the most effective safety system would find it difficult to operate well in communities with little public concern or no law enforcement. Another Badda member highlighted that "no app can make a dark street safe" in the absence of government obligation and maintenance. These observations show that users have an understanding that, although digital innovation can raise awareness, human accountability and institutional change are necessary for sustainable safety.

6. Overall Synthesis

The finding reveals that safety in Dhaka is very context-specific, gendered, and dynamic. Women perceive safety as continuous negotiations with respect to space, visibility, and control, while men view it as situational and manageable. Travel decisions like route, mode of transportation, and timing are conscious safety mechanisms based on the lived experiences of all participants.

Participants showed enthusiasm towards the reintroduced safety navigation system. However, they advised that its effectiveness would depend on verified and up-to-date information, respect fior privacy, and responsiveness in emergencies. They hoped that technology would not replace social responsibility, but rather strengthen it. In this way, technology would promote solidarity, trustworthy reporting, and guidance, and help people help one another.

In the end, safety in Dhaka is sustained because of not only the infrastructure or technology but, importantly, the relationship between reliable information, user participation, and community engagement. This information was directly incorporated into the system's design priorities. Priorities comprised verified data collection and anonymization. Additionally, they included features for individual security and participatory, community-driven safety.

4.3.3 Crime Dataset Creation

Due to the unavailability of comprehensive public crime datasets in the context of Dhaka, we decided to create our own dataset. We have scraped data manually from official reports and verified news sites such as Dhaka Tribune, The Daily Star, and Prothom Alo to ensure the quality of the dataset. Keeping user needs in mind from our quantitative and qualitative analysis, the following fields were chosen for our dataset, which are crime type, year the crime was committed, gender of the victim, name of the general area the crime happened, detailed information about the place of crime, latitude, longitude, and time of crime. Recent data were taken to maintain relevance, where the earliest data record is from 2022. To add credibility and transparency, we have added a link to the crime news in every record of the dataset.

	Crime_Type	Year_of_Crime	Gender	Area_Name	Detailed_Area	Latitude	Longitude	Location	Time	link
1	Theft	2024	Female	Bashundhara R/A	Bashundhara R/A D-Block	23.813764	90.433050	(23.813764, 90.433	Night	https://www.faceboo
2	Assault	2023	Female	Bashundhara R/A	Bashundhara Madani Aven	23.800218	90.446824	(23.800218, 90.446	Morning	https://www.dhakatrib
3	Murder	2025	Female	Purbachal	Gutiyabo, Purbachal	23.851302	90.486335	(23.851302, 90.486	Morning	https://www.dhakatrib
4	Murder	2024	Female	Purbachal	Bridge No 4 in Sector 2 of P	23.832019	90.506819	(23.832019, 90.506		https://www.dhakatrib
5	Murder	2024	Male	Purbachal	Kanchan Bridge on the wes	23.835319	90.544462	(23.835319, 90.544		https://www.dhakatrib
6	Murder	2024	Male	Purbachal	Purbachal's Agla area	23.88872405	90.56259337	(23.888724054830	Noon	https://www.dhakatrib
7	Robbery	2025	Male, Female	Purbachal	Kadirar Tek area of Purbach	23.83538008	90.4694994	(23.835380077046	Midnight	https://www.dhakatrib
8	Robbery	2025	Male	Purbachal	Stadium area of Purbachal's	23.83734282	90.48145132	(23.837342817560	Dawn	https://www.dhakatrib
9	Robbery	2024	Male	Purbachal	Purbachal's Jalshiri area	23.81233062	90.51257785	(23.812330617493	Dawn	https://www.dhakatrib
10	Robbery	2024		Purbachal	Sector 8 of Purbachal	23.84447781	90.52013272	(23.844477811708	Midnight	https://www.dhakatrib
11	Murder	2024		Purbachal	Bridge No 4 in Sector 2 of P	23.832019	90.506819	(23.832019, 90.506	Night	https://www.dhakatrib
12	Mugging	2025	Male, Female	Uttara	Road 9 of Uttara's Sector-7	23.87056328	90.39880335	(23.870563284157	Night	https://www.tbsnews.
13	Mugging	2025		Mohammadpur	Adabor	23.77254981	90.35336822	(23.772549805081	Night	https://www.dhakatrib
14	Mugging	2025		Bashundhara R/A	Kuril Biswa Road in Dhaka	23.81788905	90.42100073	(23.817889046684	Night	https://www.dhakatrib
15	Murder	2024		Narayanganj	DIT Road, near Ali Ahmad C	23.6144509	90.50160751	(23.614450898559	Morning	https://www.dhakatrib

Figure 4.8: Crime dataset for Dhaka

The dataset consists of 122 rows detailing incidents of various crime types, ranging from theft, vandalism, to murder and mugging. Each crime type is given a severity score based on a weighting scale (varying from 1-5) that depends on the seriousness of the crime. For example, murder, rape, and abduction are given the highest severity weight, which is 5, whereas the severity weight of vandalism is 1, and theft is 2.

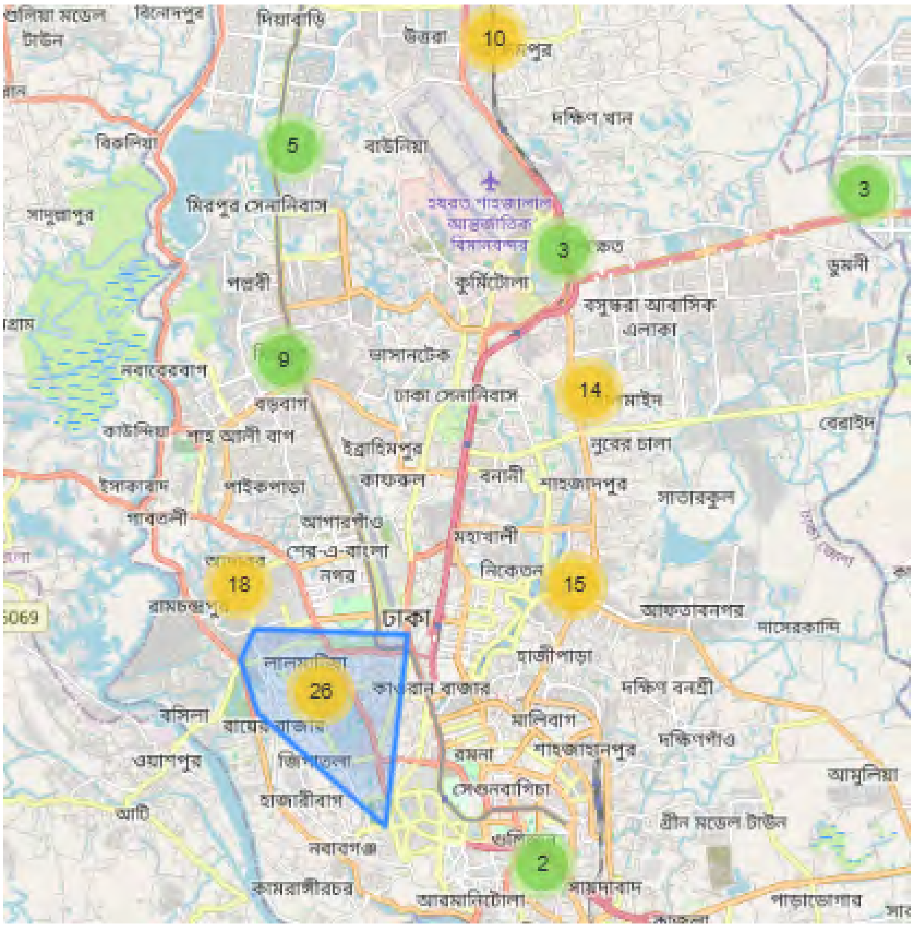


Figure 4.9: Crime incidents in Dhaka visualized by severity (clustered view)

The map of Dhaka displayed above is plotted to visualize crime incidents from our created dataset. The crime pins are colored red, orange, and green based on the severity of the crime. It helps to visually identify the crime hotspots of the city and evaluate crime patterns by their location and severity.

4.4 Data Processing and Feature Engineering

The dataset we created is cleaned, pre-processed, and engineered properly to accurately perform crime risk analysis. The dataset originally had some rows where the `Gender` field had missing values, and there were some problems with inconsistent casing creating noise in the data. Therefore, we performed standardization of categorical data. The missing values of the `Gender` field were filled as `unknown`, and all values were normalized to lowercase. Then the values for `Crime_Type` were also converted to lowercase, and any excess spacing was trimmed to avoid duplication. Lastly, `Area_Name` was title-cased as there were some inconsistencies observed while grouping without this adjustment. The resulting schema and engineered fields are summarized in Table 4.1

Table 4.1: Crime dataset features

Feature	**Type / Encoding**	**Role / Notes**
Raw fields		
Crime Type	Categorical (normalized)	Used to derive severity (1–5).
Year	Integer (2022–)	Recency/context.
Gender	Categorical	Descriptive stats; fairness cuts.
Area Name	Categorical	Spatial context / grouping.
Detailed Area	Free text	Human interpretability; not modeled.
Latitude, Longitude	Float	Mapping; basis for clustering.
Time of Crime	Categorical	Mapped to hour; then cyclic.
Source URL	String (link)	Provenance / audit.
Engineered fields		
Severity	Ordinal 1–5	Harm weighting from crime type.
Hour	Integer 0–23	From time mapping.
Hour_sin, Hour_cos	Float in [-1,1]	Cyclic time features for model.
Zone (KMeans)	Integer	Spatial cluster id.
Area Safety Score	0–100 (min–max)	Severity-weighted area risk.

Secondly, we assigned safety scores for each area depending on the frequency of crimes in that area and the severity of crimes that occurred. For this, we added severity weights (ranging from 1 to 5) to each crime depending on its seriousness. Then, we grouped the data by `Area_Name` and computed the total severity by summing the severity weights of all the crimes that happened there.

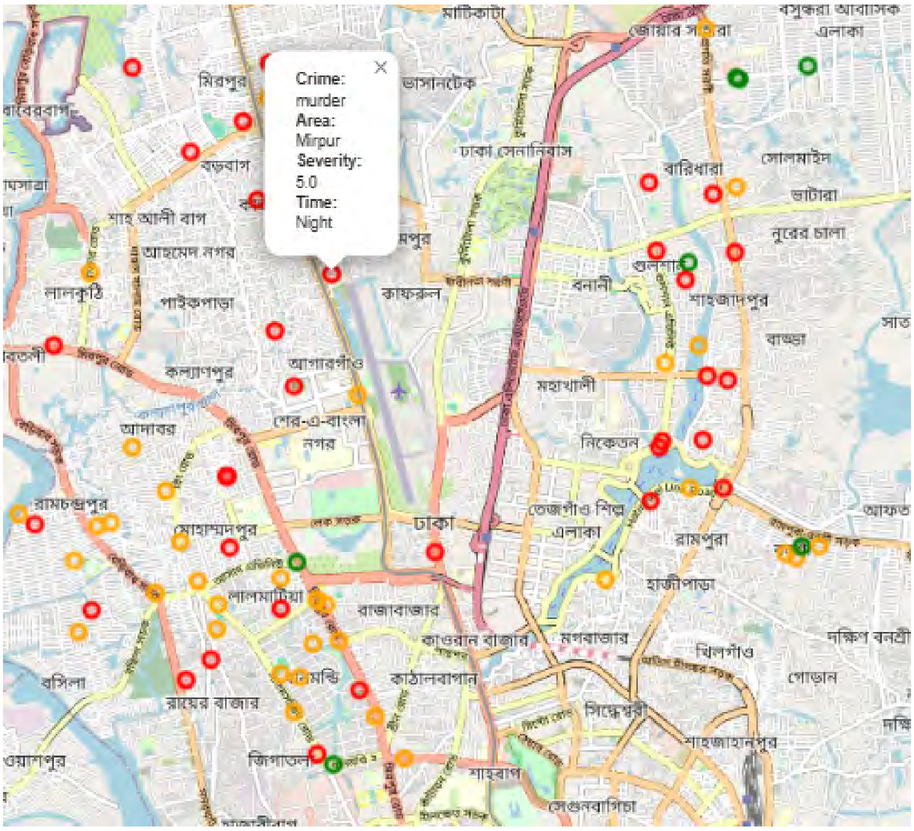


Figure 4.10: Crime incidents in Dhaka visualized by severity

$$\text{Total Severity} = \sum \text{Severity of all crimes in the area}$$

After that, we derived safety scores for each area by scaling the total severity of that area using Min-Max scaling and mapped the values between 0 and 100. The derived safety scores of the areas indicate the corresponding risk level of that area, where 0 indicates the safest and 100 indicates the most unsafe.

$$\text{Safety Score} = 100 \times \frac{\text{Total Severity} - \min(\text{Total Severity})}{\max(\text{Total Severity}) - \min(\text{Total Severity})}$$

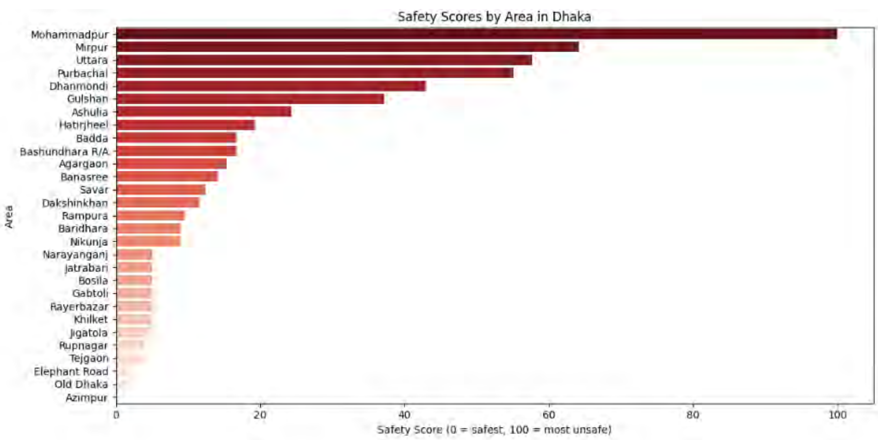


Figure 4.11: Safety scores generated for areas in Dhaka

Thirdly, we engineered `Time` feature from vague time forms like morning, noon, etc, to a representative hour format, such as morning is 9, night is 22, midnight is 0, etc. After that, these hours were parsed to a datetime format so that later on, our model can interpret them properly. After that, we performed cyclic encoding on our hour values as hours of a day work circularly and so that our model understands that hour 23, which is night, and hour 0, which is midnight, are close to each other Lastly, we encoded spatial crime patterns by using K-Means clustering to group geographical coordinates or latitude-longitude pairs into zones. This zone feature will be used later on for our model training and testing. The final training matrix consists of spatial coordinates, cyclic hour encodings, and a learned zone index, with a coordinate-level safety score as the target, as illustrated by Table 4.2.

Table 4.2: Model training and target features

Feature	**Type**	**Source / Derivation**	**Rationale**
latitude	float	scraped coordinate	spatial risk signal
longitude	float	scraped coordinate	spatial risk signal
hour_sin	float	$\sin(2\pi \cdot \text{hour}/24)$; hour mapped from time label	cyclic time-of-day encoding
hour_cos	float	$\cos(2\pi \cdot \text{hour}/24)$; hour mapped from time label	cyclic time-of-day encoding
zone	int	KMeans cluster id (k=30) from lat–lon	meso-scale spatial pattern
Target	float	location-level safety score $y(\text{lat}, \text{lon}) \in [0, 100]$; assigned from the area's min–max-scaled, severity-weighted incident total	supervision signal for regression

4.5 Model Selection

A number of predictive models were implemented to estimate the safety score of each reported location using the inputs in Table 4.2. Initially, some classifier models like KNN Classifier and Light Gradient Boosting Classifier Model were developed; however, due to highly imbalanced data where underreported areas are highly outnumbered by highly reported crime areas, the results came out to be poorly generalized and highly inaccurate for moderately safe zones. Additionally, a clustering algorithm model DBSCAN, was also enacted with hopes of efficient clustering of areas, but once again, due to a biased dataset, it dismissed isolated but critical incidents as noise.

To further validate the modeling direction, a small benchmark was conducted to compare several supervised and unsupervised approaches. The Multinomial Logistic Regression performed poorly under class imbalance (Accuracy $\approx$ 0.56; weighted F1 $\approx$ 0.53), while a Binary Logistic Regression model distinguishing between violent and non-violent incidents achieved stronger performance (Accuracy $\approx$ 0.72; violent F1 = 0.81). Unsupervised methods provided additional insights: hierarchical clustering produced four distinct groups, one of which was dominant, and DBSCAN successfully detected several micro-hotspot clusters containing 3–4 cases. Furthermore, Apriori association rule mining revealed interpretable high-confidence rules (e.g., “Night + Area = Other → Male”), offering useful contextual relationships between time, location, and victim attributes. These experiments guided the final framework, favoring LightGBM, GBM, and Random Forest for safety scoring, Binary Logistic Regression for violence flagging, and clustering with Apriori for hotspot discovery and feature refinement.

However, on the other side, regressor models like Light Gradient Boosting Regressor Model (LightGBM), Gradient Boosting Regressor Model (GBM), Random Forest Regressor, XGBoost, and CatBoost gave better results in predicting the safety scores of separate spots as they are more resilient to imbalanced datasets. Among these, Light Gradient Boosting Regressor Model (LightGBM), Gradient Boosting Regressor Model (GBM), and Random Forest Regressor performed comparatively better than the others owing to their algorithmic strengths.

LightGBM Regressor is chosen considering how it handles big, unbalanced datasets with remarkable speed and efficiency. It is powered by leaf-wise tree growths and histogram-based algorithms, which makes it a cut out for non-linear data patterns like ours. Moreover, it is highly tunable, making it ideal for further optimization. Likewise, KMeans clustering (optimal cluster size = 30) has been applied to capture regional patterns, and in order to finetune hyperparameters, RandomizedSearchCV has been implemented.

Gradient Boosting Regressor (GBR) sequentially eliminates prediction bias and connects complex feature relationships, which is suitable for subtle variations in safety indicators.

Random Forest Regressor (RFR) is resistant to overfitting, especially in the case of noisy or sparse data, and gives stable outputs as predictions from several trees are averaged.

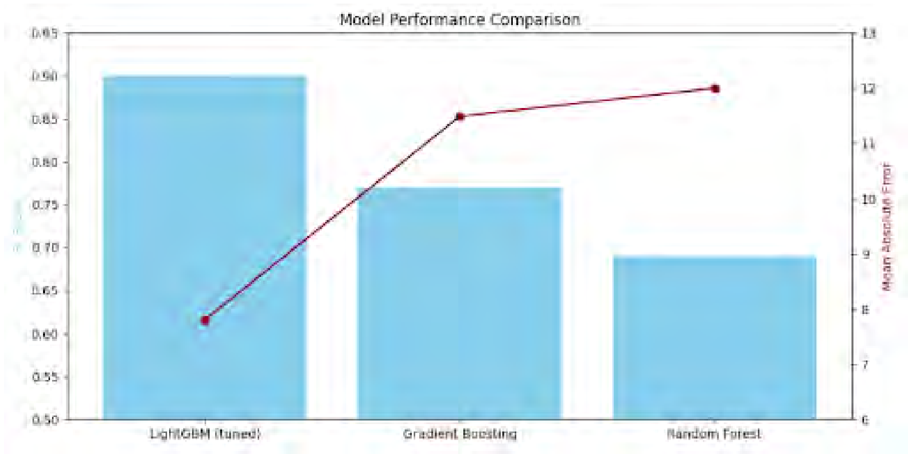


Figure 4.12: Comparison of regression model performance based on R^2 Score and Mean Absolute Error (MAE) across LightGBM (tuned), Gradient Boosting, and Random Forest.

Model	Type	R^2	MAE
LightGBM Regressor (tuned)	Gradient boosting	**0.90**	**7.81**
Gradient Boosting Regressor (GBR)	Gradient boosting	0.76	12.20
Random Forest Regressor (RFR)	Ensemble trees	0.73	12.43

Table 4.3: Regression models for safety score prediction

These three models have been evaluated on the basis of the R2 score and Mean Absolute Error (MAE) score. Among them, LightGBM turns out to be the best performer with an R^2 of 0.90 and MAE of 7.81, followed by GBR (R^2: 0.76, MAE: 12.20) and RFR (R^2: 0.73, MAE: 12.43). It is evident from the performance graph that LightGBM performs better than the other two in terms of accuracy and error. Based on these findings, LightGBM is chosen as the final model.

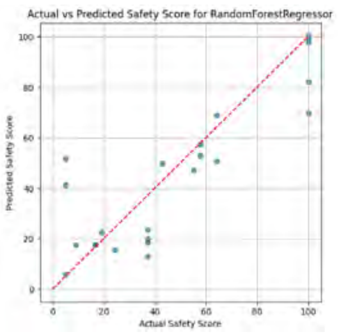


Figure 4.13: Random Forest Regressor

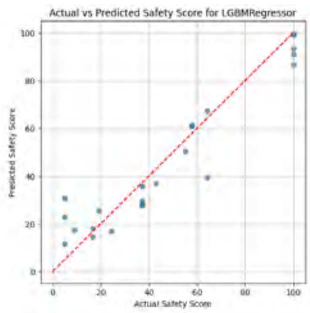


Figure 4.14: LightGBM Regressor (tuned)

Figure 4.15: Gradient Boosting Regressor

4.6 Statistical Test for Feature Relationship

This section summarizes the inferential tests used to examine key relationships in the dataset and reports the resulting evidence without extended interpretation (detailed analysis appears in Chapter 5). We begin with an omnibus test of association for two categorical variables—crime type and gender—using Pearson's Chi-Square. We then evaluate whether an engineered, ordinal severity score differs across multiple groups using both a parametric (one-way ANOVA) and a non-parametric (Kruskal–Wallis) omnibus test to ensure robustness under potential non-normality and unequal group sizes.

4.6.1 Pearson's Chi-Square Test of Independence (Categorical × Categorical)

We need to assess whether two categorical variables are statistically associated. Pearson's chi-square is the standard omnibus test for independence in an $r \times c$ contingency table when expected counts are generally adequate.
To examine whether the distribution of two categorical variables differs, we constructed an $r \times c$ contingency table whose cells contain the observed counts O_{ij} for

the first variable i and the second variable j. Let the row totals, column totals, and grand total be

$$R_i = \sum_j O_{ij}, \qquad C_j = \sum_i O_{ij}, \qquad N = \sum_i \sum_j O_{ij}. \tag{4.1}$$

Under the null hypothesis of independence, the expected frequency in each cell is

$$E_{ij} = \frac{R_i \, C_j}{N}. \tag{4.2}$$

Departures from independence were summarized with Pearson's Chi–square statistic

$$\chi^2 = \sum_{i=1}^{r} \sum_{j=1}^{c} \frac{(O_{ij} - E_{ij})^2}{E_{ij}}, \tag{4.3}$$

which, under H_0, follows a chi–square distribution with

$$\mathrm{df} = (r-1)(c-1) \tag{4.4}$$

degrees of freedom. The p–value is

$$p = \Pr\big(\chi^2_{\mathrm{df}} \geq \chi^2_{\mathrm{obs}}\big). \tag{4.5}$$

As Table 4.4 illustrates, significant associations ($p < 0.05$) were found between *Crime Type* and *Gender*, *Severity*, and *Area Name*, as well as between *Severity* and *Gender*. These relationships suggest that crime patterns in Dhaka exhibit notable gendered and contextual variations, while temporal factors show no significant influence on either crime type or severity.

Variable Pair	χ^2	**df**	p**-value**
Crime Type × Gender	206.77	72	< 0.001
Crime Type × Severity	610.00	90	3.11×10^{-78}
Crime Type × Area Name	649.67	504	1.17×10^{-5}
Severity × Gender	26.51	15	0.0330
Severity × Area Name	152.71	140	0.219

Table 4.4: Summary of chi-square test statistics across variable pairs

4.6.2 ANOVA & Kruskal–Wallis for k-Group Comparison

We engineered a severity score (1–5) from crime labels to enable consistent group comparisons. To test whether mean severity differs across crime types ($k > 2$), one-way ANOVA provides an efficient parametric omnibus test when variance is reasonably homogeneous and group sizes are moderate.

One–Way ANOVA (Parametric)

Let there be k crime–type groups; group i has size n_i and mean $\bar{x}_i$, and the grand mean is $\bar{x}$. With $N = \sum_{i=1}^{k} n_i$, the between- and within-group sums of squares are

$$SS_B = \sum_{i=1}^{k} n_i(\bar{x}_i - \bar{x})^2, \qquad SS_W = \sum_{i=1}^{k}\sum_{j=1}^{n_i}(x_{ij} - \bar{x}_i)^2. \tag{4.6}$$

Mean squares and the test statistic are

$$MS_B = \frac{SS_B}{k-1}, \qquad MS_W = \frac{SS_W}{N-k}, \qquad F = \frac{MS_B}{MS_W}. \tag{4.7}$$

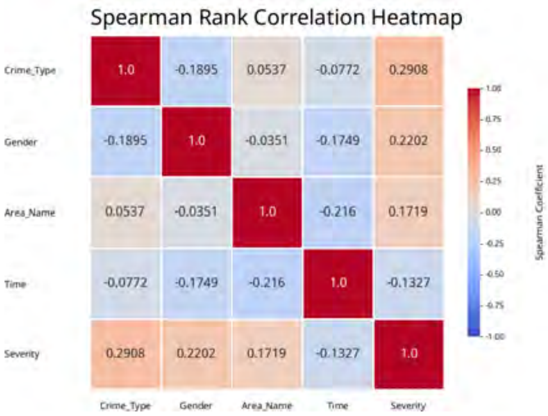
Under standard assumptions, $F \sim F_{k-1,\,N-k}$ and

$$p = \Pr\big(F_{k-1,\,N-k} \geq F_{\text{obs}}\big). \tag{4.8}$$

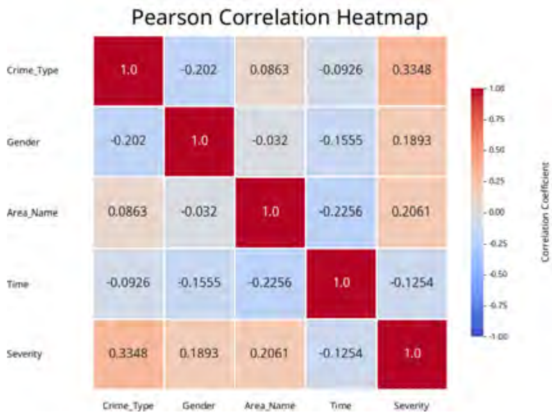
Correlation matrices provide an at-a-glance map of pairwise associations among numeric or ordinal variables. For linear relationships, Pearson's correlation coefficient is defined as:

$$r = \frac{\operatorname{cov}(X,Y)}{\sigma_X \sigma_Y},$$

where $\operatorname{cov}(X,Y)$ is the covariance between variables X and Y, and σ_X and σ_Y are their standard deviations. For monotonic trends, Spearman's rank correlation coefficient (ρ) applies the same formula on ranked values.
In this study, we treated *Severity* (1–5) as the outcome and *Crime Type* as the grouping factor for an ANOVA (parametric check). We also computed Pearson and Spearman correlation matrices over the encoded variables {*Crime Type (coded)*, *Gender (coded)*, *Area Name (coded)*, *Time (coded)*, *Severity*} to visualize broad association patterns (used descriptively, not for inference). The ANOVA result was significant ($p < 0.01$), indicating that mean severity differs across offense categories.



(a) Spearman rank correlations among encoded variables (*Crime Type*, *Gender*, *Area Name*, *Time*, and *Severity*). Positive associations appear in red, negative in blue. Moderate positive links exist between *Severity* and both *Crime Type* ($\rho = 0.29$) and *Gender* ($\rho = 0.22$).



(b) Pearson linear correlations among the same variables. Pearson's r captures linear dependence. A mild positive link was found between *Severity* and *Crime Type* ($r = 0.33$).

Figure 4.16: Contrast between Spearman (rank-based) and Pearson (linear) correlation matrices for key encoded variables. Both indicate weak-to-moderate associations, with *Severity* showing consistent positive relations to *Crime Type* and *Gender*, suggesting contextual rather than structural dependencies.

4.6.3 Distributional contrasts across groups (Kruskal–Wallis, Mann–Whitney U, Wilcoxon Signed–Rank)

Rank-based nonparametric tests were applied to examine group differences and associations without relying on normality or homogeneity of variance assumptions. These methods are robust alternatives to classical parametric tests and are suitable when data are ordinal or distributions deviate from Gaussian form.

Kruskal–Wallis Test ($k > 2$ groups). This test evaluates whether multiple independent groups originate from the same distribution. It extends the Mann–Whitney U test to more than two groups. The test statistic is defined as:

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1), \quad H \sim \chi^2_{k-1} \ (H_0),$$

where R_i is the sum of ranks in group i, n_i is its sample size, and N is the total sample size.

Mann–Whitney U Test (two independent groups) Used to compare two independent samples, this test ranks all observations and computes:

$$U = \min(U_1, U_2), \quad U_1 = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1,$$

where R_1 is the rank sum for group 1. The smaller U value is used for significance testing.

Wilcoxon Signed-Rank Test (paired samples) For paired or matched data, this test examines whether the median difference between pairs differs from zero. It ranks the absolute differences $|d_i|$ and computes:

$$W = \min(W^+, W^-),$$

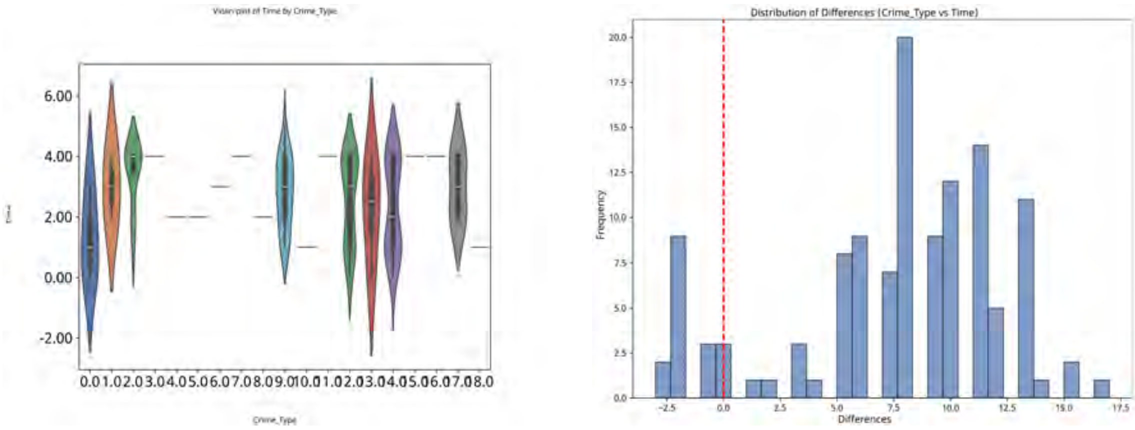
where W^+ and W^- are the sums of positive and negative signed ranks, respectively.

We prioritized these nonparametric methods when normality or equal variance assumptions were doubtful or when variables were ordinal/categorical. Kruskal–Wallis was applied for k-group contrasts, Mann–Whitney for two independent groups, and Wilcoxon Signed-Rank for paired specifications produced by the analysis workflow.

Test	Variable Pair	Statistic	p-value
	Crime Type × Severity	$H = 121.000$	$p = 0.000$
Kruskal–Wallis	Crime Type × Gender	$H = 44.6697$	$p = 0.0005$
	Area Name × Severity	$H = 43.2185$	$p = 0.0331$
	Gender × Severity	$U = 824.000$	$p = 0.000$
	Crime Type × Severity	$U = 12858.000$	$p = 0.000$
Mann–Whitney U	Area Name × Severity	$U = 13384.000$	$p = 0.000$
	Area Name × Time	$U = 1230.500$	$p = 0.000$
	Crime Type × Gender (add. run)	$U = 14281.500$	$p = 0.000$
	Time vs Severity	$W = 1688.000$	$p = 0.000$
Wilcoxon Signed-Rank	Area Name vs Severity	$W = 103.000$	$p = 0.000$
	Area Name vs Time	$W = 129.500$	$p = 0.000$
	Crime Type vs Gender	$W = 30.000$	$p = 0.000$

Table 4.5: Summary of nonparametric test statistics across variable pairs

Nonparametric analyses verified several statistically significant relationships, tabulated in Table 4.5. Distributions of *Severity* differed markedly across *Crime Type*, *Gender*, and *Area Name* ($p < 0.05$), while paired comparisons such as *Time vs. Severity* also yielded significant deviations. These results reinforce the context-specific and gendered nature of safety-related crime patterns in Dhaka.



(a) Violin plot of *Time* by *Crime Type*, showing group-level variation tested with the Mann–Whitney U statistic. Wider sections indicate higher observation density across crime categories.

(b) Distribution of paired differences between *Crime Type* and *Time* for the Wilcoxon Signed-Rank test, with the red line marking zero median difference.

Figure 4.17: Contrasting group-level and paired nonparametric results: the violin plot depicts temporal spread across crimes, while the histogram visualizes within-pair shifts driving the Wilcoxon analysis.

4.7 Routing Algorithm Design

To determine the safest route through Dhaka's pedestrian network, this study employs Dijkstra's algorithm. It computes the minimum cumulative cost between two nodes in a graph. Traditionally, Dijkstra's algorithm operates solely on physical distances to find the shortest route. In our initial approach, this conventional distance-based Dijkstra outputted the most direct route.

To enhance decision-making, we proposed an augmented version of Dijkstra's algorithm, where the edge weights are no longer just distances. Instead, they are adjusted based on safety predictions from a LightGBM regression model trained on crime data. The predicted safety score for each node is used to calculate a composite risk for every edge as the average of the two nodes it connects. These scores are then used to penalize paths that pass through potentially unsafe zones. It steers the algorithm toward safer alternatives, even if the total travel distance increases.

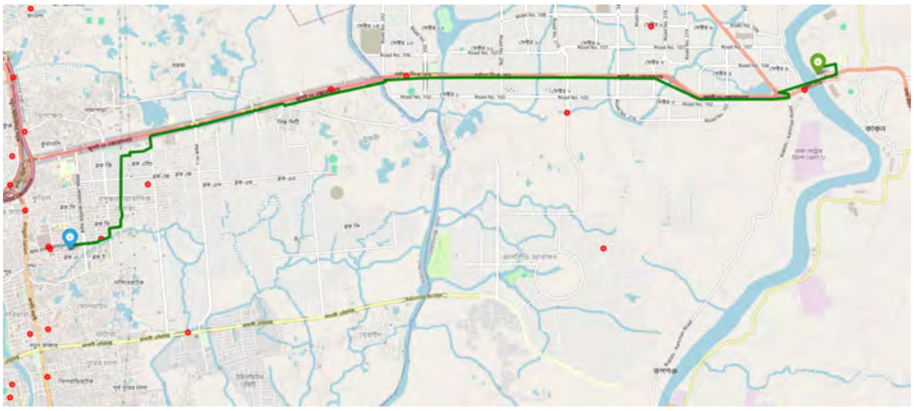


Figure 4.18: Route generated using standard Dijkstra's algorithm considering only physical distance

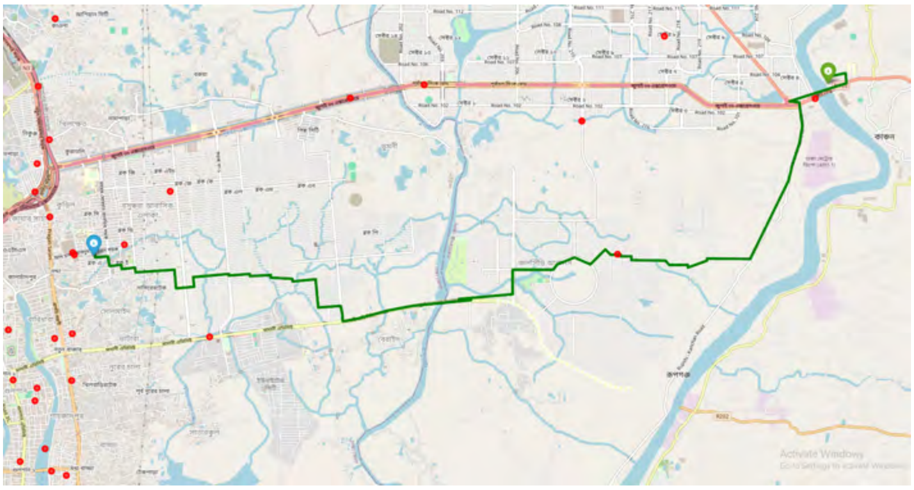


Figure 4.19: Route generated using Dijkstra's algorithm integrated with LightGBM-predicted safety scores

The improvement is visually evident when comparing the two resulting maps. The first map shows the shortest route calculated using only the traditional Dijkstra algorithm. In contrast, the second map integrates model-predicted safety risks into the routing process. The resulting path avoids high-crime areas. It offers a more secure travel experience. This comparison highlights the benefit of risk-aware routing, where user safety is prioritized over mere efficiency.

To compute the cumulative safety-aware cost for a path PPP, the following equation was used:

$$\text{Cumulative Path Cost} = \sum_{(u,v)\in P} \text{Length}_{(u,v)} \times \left(1 + \alpha \cdot \text{AvgPredictedSafety}_{u,v}\right)$$

Here, $\text{Length}_{(u,v)}$ is the physical length of edge (u, v), $\text{AvgPredictedSafety}_{u,v}$ is the average predicted safety score between nodes u and v, and α is a tunable parameter.

4.8 Mobile Application Implementation

This section documents the working mobile prototype namely its stack, architecture, feature modules, deployment, and operational characteristics. User-interface rationale and design iterations are analyzed separately in Chapter 5.

4.8.1 Technology stack

The client is built with React Native using Expo, targeting Android for field testing. The backend is a FastAPI service that exposes routing and incident-report endpoints. Supabase provides the data layer (PostgreSQL, authentication, and realtime subscriptions) for users, incidents, and telemetry. Maps are rendered with OpenStreetMap tiles and vector data under fair-use; the app maintains a small on-device cache to improve responsiveness in low-connectivity conditions.

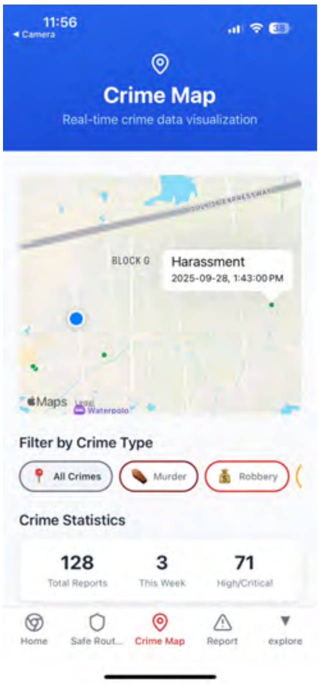
4.8.2 Architecture and data flow

At launch, the app requests location permission and initializes three subsystems: map rendering, a lightweight incident summary fetch, and the routing client. When the user selects an origin–destination pair (or drags pins on the map), the client sends a routing request to the API that contains origin/destination coordinates, mode, and a profile flag (e.g., safest/balanced/fastest). The API constructs candidate paths on the road graph, computes a composite cost that combines travel time with a safety penalty informed by recent incident density/severity, and returns a small set of labeled alternatives with metadata (approximate time, length, safety score, and an encoded geometry). The client then renders the alternatives on the map, lets the user switch profiles, and provides step-by-step directions for the selected route.

4.8.3 Feature Modules

The following features have been developed keeping the user needs deduced from qualitative and quantitative analysis in mind:

(A) Crime Map: Visualizing Safety Hotspots
The Crime Map functions as the application's ambient awareness layer. Its information architecture prioritizes rapid comprehension at a city scale while preserving precision when zoomed. The map canvas occupies the dominant portion of the screen to minimize cognitive switching between the list and the spatial view. Incidents appear as compact, color-coded markers that encode type and severity without overwhelming high-density neighborhoods. Tapping a marker opens a succinct callout with the incident label and timestamp; fuller details are accessible from the incident list below, preventing large overlays that would obstruct navigation. Filtering is implemented through horizontally scrollable chips, such as All Crimes, Murder, and Robbery, that allow immediate subsetting without leaving the view. The selected filter persists across sessions to reinforce continuity and reduce setup time. A compact analytics strip presents three carefully chosen metrics, which are total reports, this week's reports, and the count of high or critical incidents that help balance short-term change with overall context and risk perception.



(a) Crime Map home view with clustered markers and filter chips for scanning

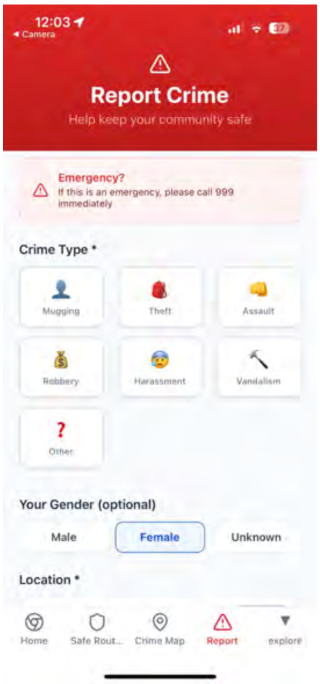
(b) Incident callout showing type and timestamp

Figure 4.20: App feature concerning crime map

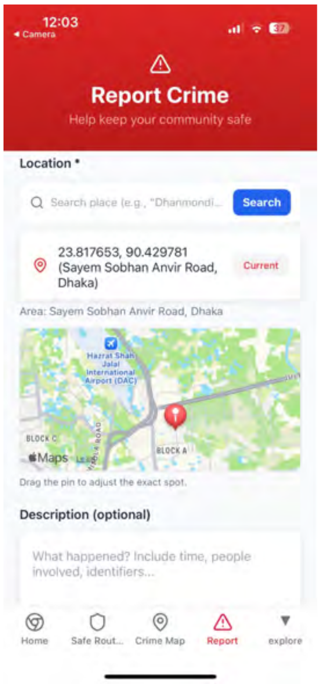
The lower section lists recent incidents in cards that repeat the same iconography as the map for cross reference. Each card shows the area name or coordinates, a relative or absolute time, and a small severity badge. If location permissions are disabled, the screen defaults to a city-level view with a non-blocking tip; if the network is slow, the map frame shows a contained loading state rather than a modal. Privacy is also preserved by never exposing reporter identity, and coordinates can be fuzzed to the nearest road segment when appropriate. The visual language avoids sensational elements that might distort perceived risk.

(B) Report Crime: Community-Driven Data Collection

The reporting flow is designed for precision with minimal friction. Crime type selection uses recognizable emoji-style icons paired with short labels to reduce reading load and support quick categorization. Selecting "Other" reveals a secondary list so the main surface remains uncluttered for common cases. Location capture follows a "trust but verify" pattern. Users can search a place name (OpenStreetMap geocoding), use 'My Location' to fetch coordinates, and fine-tune via a draggable pin on a mini map. The chosen coordinates and reverse geocoded label are displayed together so users can confirm that the map and text are synchronized.



(a) Crime Type Selection with recognizable icons



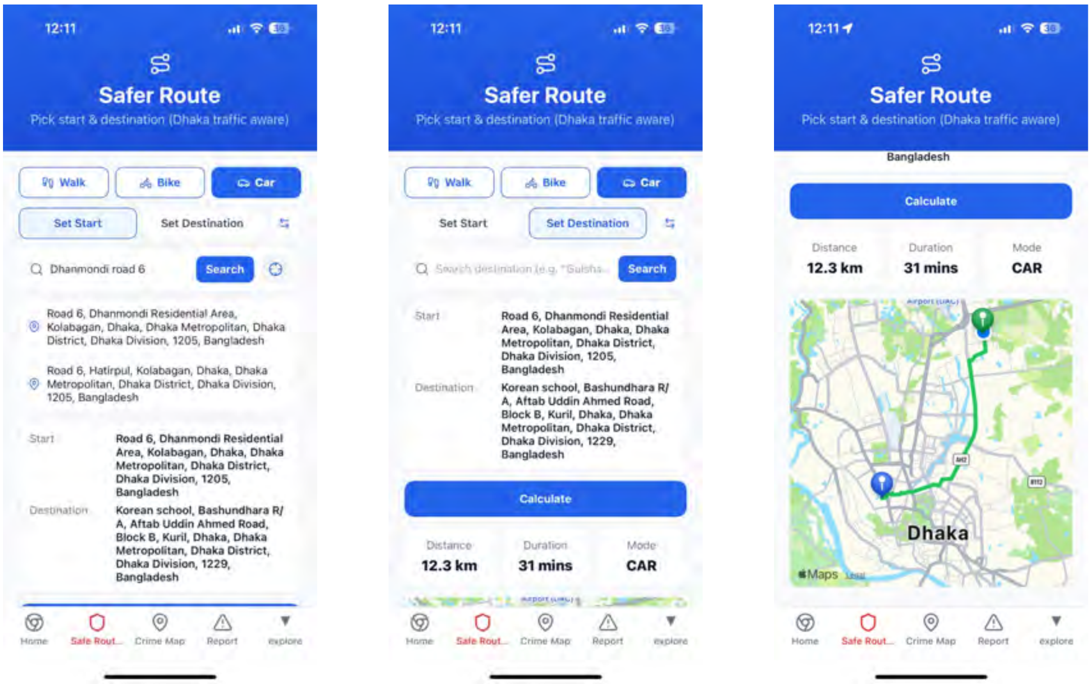
(b) Draggable pin confirming map-to-coordinate sync

Figure 4.21: App feature concerning crime reporting

If reverse geocoding fails, the coordinates are still accepted and clearly shown. Time is explicit and required through separate date and time pickers that yield an ISO timestamp for analysis. The description field is optional, multiline, and gently limited to dis courage pasting long social posts. A scaffolded evidence card communicates that photos or audio can be attached when enabled, setting expectations without blocking submission. Anonymity is explained in a persistent banner, and the app does not collect personal identifiers. When the user grants location, a one-time tip clarifies that only the incident location is stored. The submit button is disabled until type, location, and time are valid and errors are specific and inline.

(C) Safer Route: Toggle Modes of Transportation

The Safer Route module supports start and destination entry by search or map and offers clear mode toggles, for instance, walk, bike, and car. After calculation, a single, legible route polyline is rendered with mid-weight stroke and rounded turns to remain readable over dense road networks. A metric bar surfaces distance, duration, and mode. The safety aspect is communicated in plain language, for example, safer than average for this area/time, to avoid implying false precision. Edge costs combine conventional length or travel time with a safety penalty derived from recent incidents within a tunable radius and window.



(a) Start and Destination input via search

(b) Metric bar with distance and duration

(c) Computed route with polyline overlay

Figure 4.22: App feature concerning safer route

(D) Usability, Accessibility, and Visual Cohesion All modules share a consistent visual grammar that reduces learning cost. Bold, colored headers anchor context, and large primary actions clarify the next step. Compact metric cards reduce scanning effort. Typography meets mobile accessibility guidance, tap targets exceed 44×44 pt, and color is never the sole carrier of meaning icons and short labels co-encode state. Motion is limited to micro interactions, so the tone remains calm, appropriate for a safety application. All UI strings are isolated for localization; moreover, distance and time formatting follow the device locale.

4.8.4 Current limitations

Routing is server-side only (no fully offline computation). Incident density remains sparse in several wards, which can reduce the stability of safety scores. These limitations are documented here for completeness; design implications and planned improvements are discussed in Chapter 5.

Chapter 5

Result Analysis

5.1 Performance Evaluation

We assessed the system's three main modules through a user survey, namely Crime Map, Report Crime and Safer Route. The items were focused on usefulness, impact and trust. Responses were summed up as percentages of agreement from a rating scale (strongly agree to strongly disagree).

5.1.1 System Effectiveness

Crime Map (awareness): Most of the respondents said that they would feel more informed, and would be able to better determine which area to visit or avoid with a live map that adds type marker/time markers. The basic filters people want to drill down by crime type, together with lightweight stats (totals, this week, high/critical), can better inform people of local risk and trends. A lot of people said that before going to any place or planning a route they check the map.

Report Crime (confidence and quality): Respondents consistently say that pinning location and entering date/time lead to confidence that report reaches the right people. Many said the option to report anonymously would make them more likely to report. A smaller sub-group of people preferred reporting with identity. As most people believed, adding any extra detail improves the reliability.

Safer Route (decision impact): Most respondents found the Safer Route screen useful for daily journeys. Furthermore, many suggested that displaying the distance and duration of the potential safe route impacts their choice. Some people warned that "safe route" could sometimes depend on whether an urban area is dense. They felt that "safe" was not static, and if not communicated properly, could create anxiety.

Implication: Survey responses across modules indicate that the respondents value clear, recent, and precise information and visible credibility signals (e.g. community voting, flags, verification steps). This will help you make fewer and better choices.

5.1.2 System Efficiency

Decision speed and ease: Many open-ended comments asked for users to be able to "check quickly" and "see the safe way at a glance". Our system supports this by presenting a clear recommended route and maintain a filterable map with a simple key. This allows for quick scanning with minimal taps.

Smooth performance when it matters: Users indicated that they would use the app on their move and at times with weak signal. To achieve that, the workflow updates surrounding incidents in small chunks instead of full refreshing of map, and keeps the chosen route visible when fresh information is not available. If routing does not work for a bit, the app would rather have the user have a path on their screen than a session that just displays the message your session is no longer active.

Implication: The survey suggests we reduce choices and keep the UI straightforward and the system design supports this with a lightweight stack and lean interactions. As per the requirements, the client is implemented in React Native (Expo) and the server in FastAPI in order to keep requests small and responsive; routing returns just the geometry and the duration that is needed on the screen; the map uses simple category filters and simple key as opposed to heavy layers. The "Safer Route" requirement has all the distance/time information combined with a safety penalty in a single computation and no multiple alternative routes and no extra redraws. In the updates regarding the building , we also kept planned credibility features lightweight so that they do not hinder the speed of the interface. When put together, they correspond to what users wanted ("check quickly") and they make the app efficient in practice: there are fewer on-screen decisions, minimal map refresh, and a client–server path with latency that supports use on the go.

5.1.3 Reliability

Our system has reliable performance and we try to present it in a way that our users can perceive. Every report indicates what happened, where it happened (pin location), and when it was reported (in the detail). Reports gain trust through the following built-in checks: community upvotes/downvotes; flagging of suspicious items; basic GPS-time validation; similar reports in the same area and time window. Reporting is anonymous by default to protect contributors. We avoid blanket labels like "unsafe zone"; instead, each item shows nearby incident counts, and the interface points to practical help when relevant. In short, reliability comes from visible facts and clear checks.

5.1.4 User-Perceived Utility (Survey Findings)

The evaluation of users focused on whether it was helping in situational awareness and reporting confidence, and route choice. When asked whether seeing crime markers of type and time helps decide whether to visit or avoid an area, 75.4% of respondents said "Definitely yes" and 18.6% "Probably yes." This shows a strong perception of the value of the ambient risk layer. Using the type filter to find specific features, such as Murder, Robbery, etc., was rated Extremely useful (41.5%) or Very useful (39.8%), which helps to carry out risk exploration for those features. A clear communication system can increase confidence in community reports. When using a precise map-pin and explicit date/time, over 58.6% of the participants reported "Definitely yes"; and 30.2% said "Probably yes". Further, the anonymity was rated Essential (69.8%) or Important (19.0%). This is a large validation of the privacy-by-design intake flow. As many as 67.2% (Definitely yes) and 27.6% (Probably yes) would choose a different route when being shown distance, duration, and a safety-aware path. This shows the optimization objective and traveler choice match up.

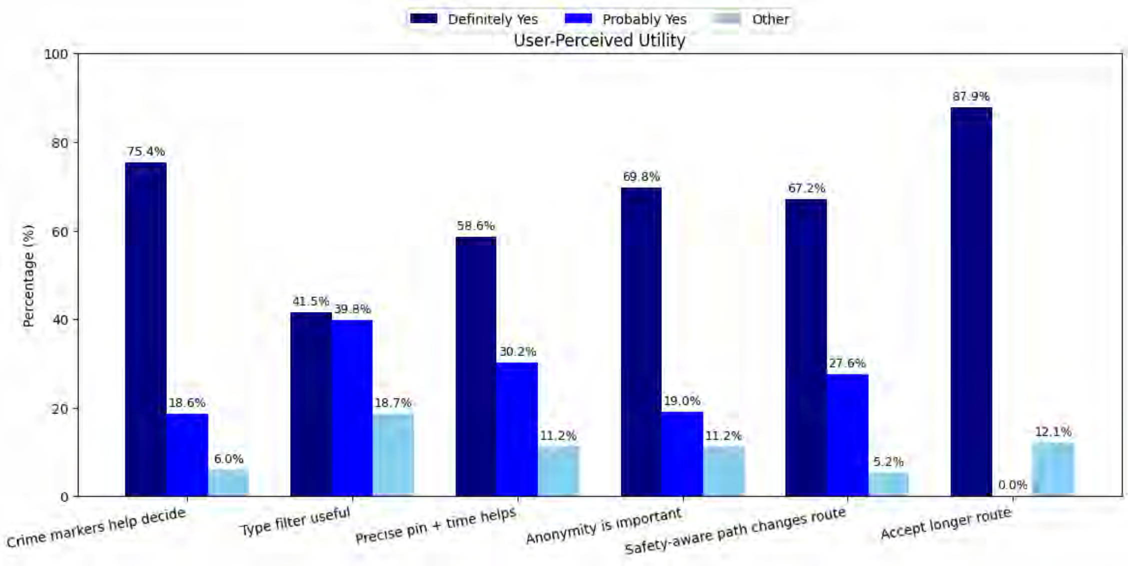


Figure 5.1: User responses indicating the perceived usefulness of key safety-oriented navigation features, showing strong preference for route safety and anonymity options.

The complete response table in the export of the survey confirms these tendencies. Repeatedly, participants recommend having mechanisms to upvote and flag things. Also, using photos to substantiate reports.

6. Summary of Findings

The system satisfies the evaluation expectations for a safety-aware navigator as it achieves a principled routing objective which reflects the observable hotspots, interactive performance in realistic use, effective defence in depth to ensure data integrity, and has received user acceptance focused on the awareness, reporting, and routing tasks. Based on the evidence, users are firstly likely to use the application and secondly comply with the application and use safer routes. This is the main objective.

5.2 Analysis of Design Solutions

This section evaluates the proposed safety-aware navigation system Crime Map, Report Crime, and Safer Route with emphasis on the modeling and routing choices that make the design workable in the field. The route engine combines a hypertuned LightGBM safety model with a Dijkstra search that minimizes a safety-weighted path cost instead of geometric distance alone.

5.2.1 Feasibility

The system is feasible to deploy and sustain because the architecture separates lightweight mobile UI from deterministic server logic and an inexpensive data layer. Technology stack and responsibilities handle where the client (React Native/Expo) works with map rendering, inputs (crime type, location pin, time), and result presentation (route polyline, distance, duration, safety label). The server (FastAPI) owns two bounded computations: (i) safety scoring and (ii) route search. The database (Supabase/Postgres) persists incident reports, cached scores, and minimal metadata. Maps/roads come from OpenStreetMap. Model feasibility. Following model selection in 4.5, LightGBM was chosen for its strong performance with small-to-medium tabular data and its interpretability. The final model was hyperparameter-tuned (e.g., number of leaves, minimum data in leaf, learning rate) using cross-validation to control variance in a data-limited setting. Features are deliberately compact and inexpensive to compute per node: geographic coordinates, time-of-day encodings (sin/cos), and a K-means zone index that coarsely captures neighborhood effects. This design allows batch scoring (e.g., per hour) and caching, so request-time work is limited to applying weights not re-training or heavy inference. The system degrades gracefully: if fresh safety scores are unavailable, the service uses cached scores; if neither is available, routing falls back to pure length/time. The data contract between client/server is stable (start/destination, mode, optional local time), simplifying maintenance and future extensions.

5.2.2 Strengths and Weaknesses

The system is explainable end-to-end, which is unusual for safety-aware navigation. On the modeling side, the hypertuned LightGBM classifier operates on a deliberately small, human-interpretable feature set of latitude/longitude, cyclical hour encodings (sin/cos), and a coarse K-means zone index. The model's feature importance and simple partial-dependence curves can be translated into plain language for example, "risk tends to rise around late night hours in zone X" because these features have clear semantics. This interpretability makes it easier to audit behavior, communicate trade-offs to non-technical stakeholders, and revise the model as more data arrive. LightGBM also gives strong bias–variance control in a data-limited, noisy setting. Hyperparameters such as number of leaves, minimum data in leaf, and learning rate were tuned via cross-validation to avoid overfitting while still capturing local structure. class imbalance and missingness is tolerated by the learner, better than many linear baselines. Its inference is CPU-fast so it enables to pre-compute hourly node scores and cache them and it keeps request-time work minimal and latency predictably low on modest servers an operational advantage for pilots.

This form has several strengths. Firstly, non-negativity and triangle consistency is preserved, hence Dijkstra remains optimal and fast. Secondly, it exposes clear knobs (α, β, time window, spatial radius) that product and policy stakeholders can set to reflect local tolerance for detours versus risk. Lastly, the router naturally skirts emerging hotspots without painting the map in alarmist colors as the penalty aggregates node scores and recent reports. The result is behavior that is predictable to users and routes remain geographically sensible while still capturing meaningful safety differences. The UI reinforces trust in these mechanics. Users see distance, duration and a safety rationale, which aligns with mental models formed by mainstream navigation apps. The interface reduces cognitive load and helps users form accurate expectations about why a slightly longer path might be preferable by avoiding per segment "danger" coloring and instead summarizing the overall trade off. The modular architecture cached model scores, stateless routing API and a thin mobile client further strengthens the design by making it maintainable, scalable and auditable. The quality of safety weighting depends on report coverage and recency. In low data neighborhoods the model's estimates regress toward priors and may miss micro-hotspots. The current penalty function is intentionally simple. It does not yet incorporate richer context for instance, lighting, business hours, crowd presence and calibration should be revisited as more labeled data accumulate.

5.2.3 Ethics, Privacy, and Responsible Scaling

The application minimizes sensitive data handling and designs for responsible growth. Reports are anonymous by default; where appropriate, incident coordinates are snapped/fuzzed to the nearest road segment to reduce pinpointing private residences. Visual language avoids alarmist color schemes or per-segment "danger" labels to prevent risk amplification. Community mechanisms (flagging, up/down voting) provide a lightweight credibility signal without exposing identities. From a scaling perspective, the model and router are modular and versioned. Safety scores can be regenerated on a schedule (e.g., hourly) or incrementally updated near new reports. The API is stateless, enabling horizontal scaling; the graph cache can be shared across workers. These practices allow the system to expand from a ward-level pilot to larger coverage while preserving privacy and operational clarity.

5.3 Final Design Adjustments

This section depicts the refinements introduced after analyzing survey responses. It sets a focus on strengthening authenticity, accountability and trust in user-submitted reports. Particularly, respondents prioritized two mechanisms for validating community data, which incorporate photographic evidence and enable community voting on report credibility. As illustrated by Figure 5.2 A large majority supported both approaches and that is with 70.9% endorsing the inclusion of photos for authentication and 65.8% favoring upvotes/downvotes as a lightweight credibility signal. The updates below describe the design rationale, user-flow changes, data model extensions, and safeguards added to operationalize these preferences.

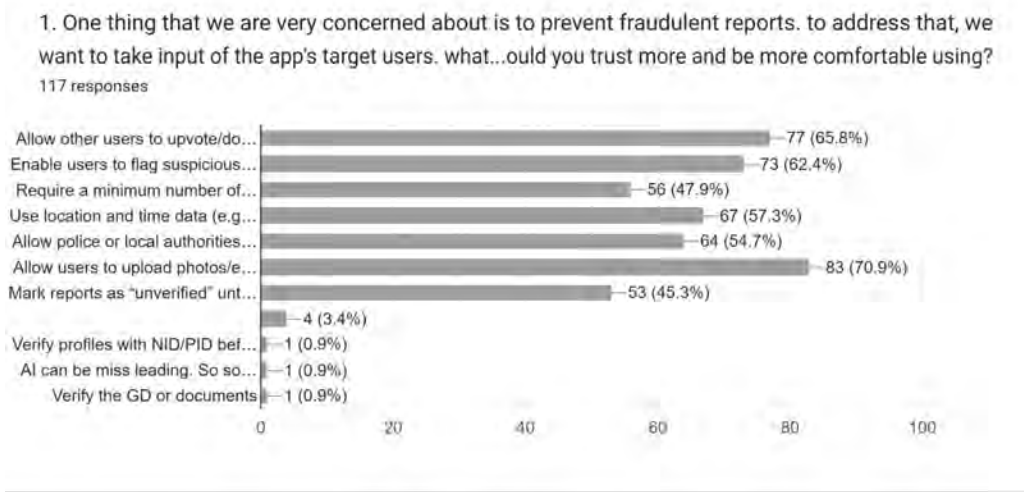


Figure 5.2: Survey opinion on fraudulent reports

5.3.1 Photo Evidence for Report Authentication

The Report Crime screen now includes a visible "Add Photo or Evidence" card to signal our intended direction on credibility. Users can tap to open the system picker, see a thumbnail preview, and remove the placeholder if they change their mind. A brief notice reminds users not to include faces or private details. At this stage, the feature is UI-only, where uploads are disabled, and there is an offline icon and "upload coming soon" hint. It is in our plan to upload images to the device, and the files are to be stored on our servers. If a user proceeds to submit a report, the app saves the report without an image for now and shows a non-blocking message that photo evidence will be supported in a future update. This staged approach lets us validate the placement and wording of the evidence control while we finalize the storage pipeline (planned: Supabase Storage with report, then photo links) and moderation flow. When uploads are enabled, the design will remain the same and small preview, removable selection, and optional use, while keeping privacy protections and lightweight performance in place.

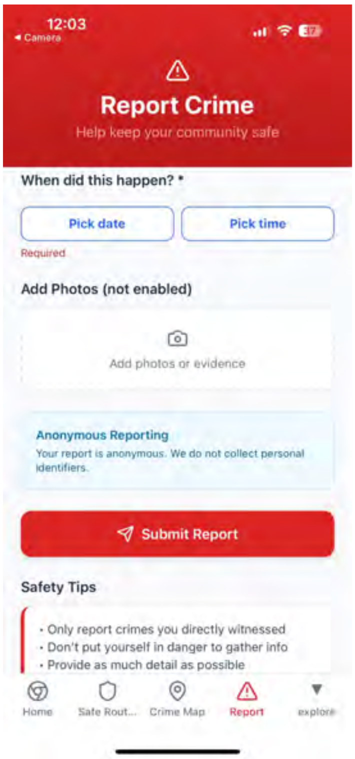


Figure 5.3: Photo evidence for reporting crime

5.3.2 Community Voting: Upvotes and Downvotes

To complement photo evidence with an ongoing reputation signal, each report now accepts community votes, which are an upvote that marks the report as helpful/-credible, while a downvote flags it as questionable or unhelpful. The voting interface appears as a compact control adjacent to the incident card and within the detail view. To prevent brigade effects, vote counts are shown in aggregate without revealing voter identities, and each device or account is limited to one reversible vote per report.

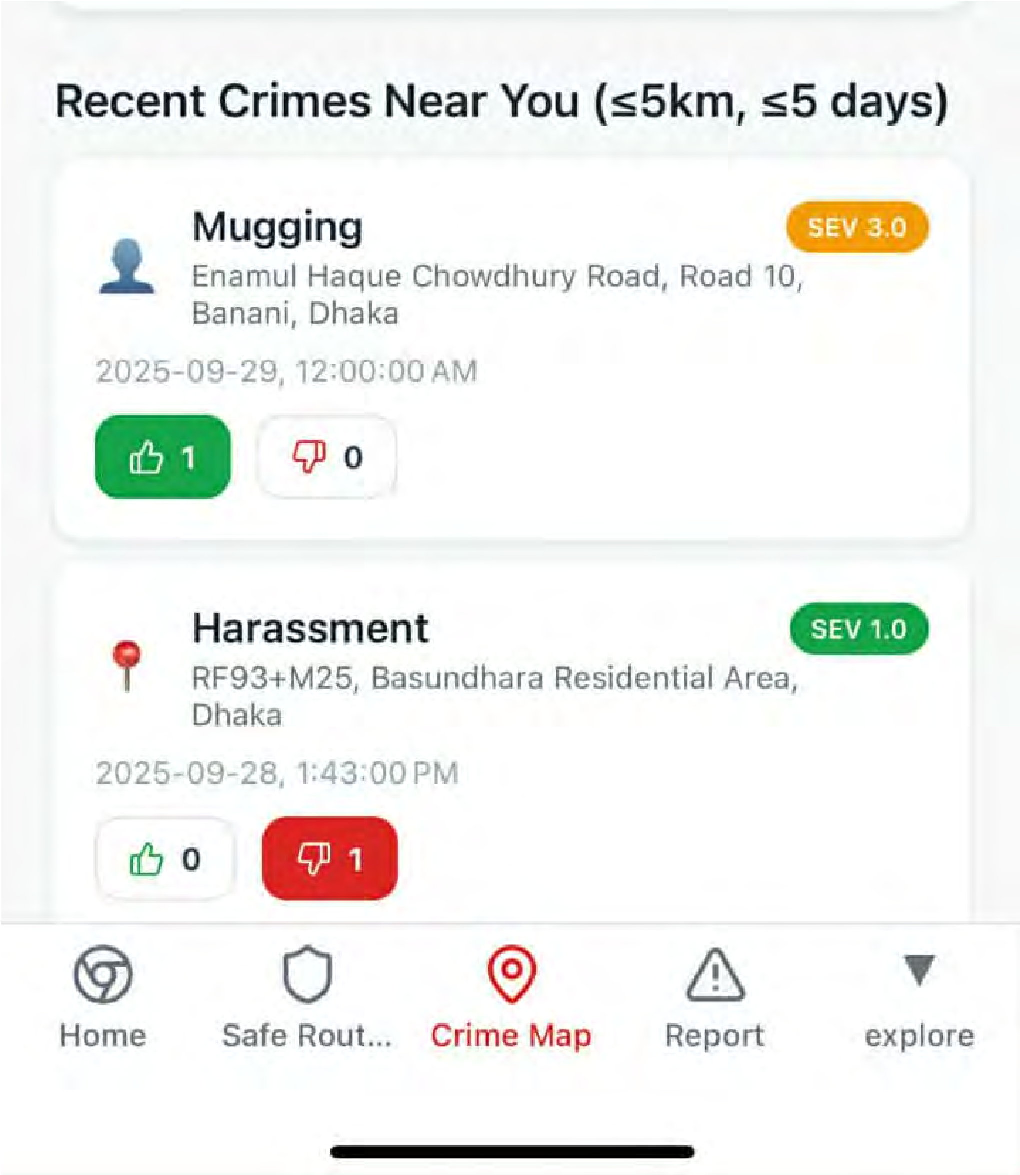


Figure 5.4: Recent crime display with up-vote and down-vote feature

Votes feed a credibility score that decays over time and is capped to limit outsized influence from a short burst of activity. In the navigation service, credibility modulates the incident-based penalty on surrounding edges: highly upvoted reports sustain a stronger short-term penalty, while heavily downvoted reports contribute a reduced or null penalty. This approach keeps the map responsive to community signals without allowing adversarial spikes to fully suppress safety adjustments.

From a data perspective, a separate $report_votes$ table stores a stable user or device hash, the report id, the vote (+1/–1), and timestamps. To deter duplicate participation, device fingerprints are salted and periodically rotated; when accounts are enabled, authenticated users supersede device hashes. Suspicious voting bursts are rate-limited server-side and queued for review.

5.3.3 Sign Up and Log In for Provenance

Given the sensitivity of safety reporting, identity remains a crucial factor; however, respondents' comments indicated a willingness among some users to create accounts if it improved trust. The application, therefore, introduces an opt-in account system. Anonymous reporting is preserved as the default path, while signing in (email or phone) unlocks conveniences such as saved places, personal report history, and the ability to revise one's own reports. When present, account provenance increases a report's initial credibility weight modestly, but does not override community signals or evidence. Personally identifying information is never displayed, and only a neutral icon appears on the incident detail. This design balances accountability and privacy, allowing users to contribute meaningfully without exposing their identity to the public.

5.3.4 Survey Driven Change Log

To make the design responses traceable to user needs, Table 5.1 synthesizes the most frequent issues raised in the survey and the specific changes we implemented. Four items were shipped in this iteration, which are credibility voting, privacy-preserving reporting, a proximity/recency "Crimes Near Me" feed, and decluttered map styling—while one item (push alerts/SOS/photo uploads) is planned for the next release, reflecting feasibility and moderation constraints.

Table 5.1: Survey-driven change log for final design adjustments

Identified issues from users	**Design response**	**Status**
"Who should I trust?"	Upvote/downvote credibility with time decay; anonymous aggregation.	Implemented
"I don't want my identity exposed."	Authentication required to report; no reporter details shown publicly.	Implemented
"I want to know what's happening around me."	*Crimes Near Me* feed filtered by recency and distance.	Implemented
"The map felt cluttered."	Neutral icons, clustering, and recency styling.	Implemented
"Send me alerts / add SOS / allow photo proof."	Push alerts, SOS, and photo attachments kept for the next iteration.	Planned

5.4 Statistical Analysis

This section examines whether the patterns observed in our 122 incident records are statistically credible and how they inform the app's design choices. After basic cleaning, such as text normalization and duplicate removal, we engineered a consistent severity score (1–5) from crime labels to enable group comparisons. We then tested three focused questions: (i) Are crime type and reported gender associated? To answer that, we did the Chi-Square Test of Independence (ii) Does the engineered severity differ across crime types in the expected way? Hence, we did One-Way ANOVA with a Kruskal-Wallis robustness check, and (iii) Do incidents exhibit spatial clustering? To answer that, we did DBSCAN hotspot detection on latitude or longitude. We used a two-sided $\alpha = 0.05$ threshold, checked basic assumptions such as cell counts for chi-square, normality, or variance for ANOVA, and preferred non-parametric or reduced tables when assumptions were weak. Only results that were statistically meaningful and decision-relevant are retained in the subsections that follow, and full code and ancillary diagnostics are provided in the appendix.

5.4.1 Overview and analytic stance

This section interprets the results reported in section 4.6, emphasizing the strongest signals and why they matter for understanding relationships among `Crime_Type`, `Severity`, `Gender`, `Time`, and `Area_Name`. Because most variables are categorical (or ordinal after recoding), we prioritize association tests (χ^2 with Cramér's V) and rank-based procedures (Kruskal–Wallis, Mann–Whitney, Wilcoxon), using parametric ANOVA as a concordance check where appropriate. Throughout, we highlight the best results (largest test statistics, smallest p-values, clearest visual separations) to ground each claim.

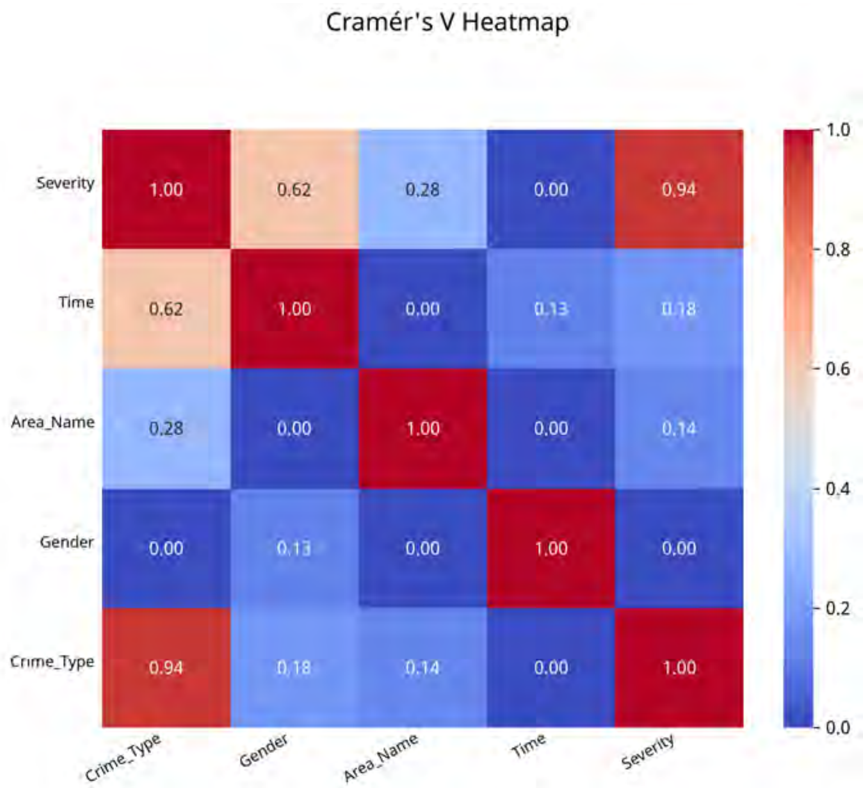


Figure 5.5: Cramér's V heatmap

5.4.2 Global association structure (categorical × categorical)

The overall association map is dominated by pairings that involve `Crime_Type`. The strongest evidence is the dependence between `Crime_Type` and `Severity`, with a very large chi-square and minuscule p-value $\left(\chi^2(90) = 610,\ p \approx 3.1 \times 10^{-78}\right)$. This indicates that the score we engineered from crime type to severity across offense categories is consistent with the constructed 1–5 scale. A second robust signal appears for `Crime_Type` × `Gender` $\left(\chi^2(72) = 206.77,\ p < .001\right)$, showing that the composition of crime types differs by gender groups.

On the Cramér's V heatmap, the `Crime_Type–Severity` and `Crime_Type–Gender` cells should appear among the warmest (largest V), while `Crime_Type–Time` and `Severity–Time` remain cool. The Pearson/Spearman heatmaps can be used to visually cross-check monotonic structure, but any high values there must be read cautiously because numeric encodings of categories can fabricate "linear" artifacts. Where both the V heatmap and rank/χ^2 tests align (e.g., `Crime_Type–Severity`), the finding is especially compelling.

5.4.3 Severity patterns by crime category (ANOVA & Kruskal-Wallis)

Both ANOVA (significant, $p < .01$) and Kruskal–Wallis ($H = 121.00, p < .001$) converge on the same conclusion: severity differs materially across `Crime_Type` groups. Given that Shapiro–Wilk flagged nonnormality in related settings (see Section 5.4.5 below), the Kruskal result is particularly persuasive because it does not rely on normality. Together, these tests establish that the offense category is a primary organizer of severity, not an incidental correlation.

From a reporting and policy perspective, these results justify crime-type–specific severity summaries, targeted prevention framework, and (if modeling) inclusion of `crime_type` as a key predictor for severity-related outcomes. They also imply that pooling between crime types when analyzing severity would mask important heterogeneity.

5.4.4 Gender differences (Mann–Whitney & Kruskal–Wallis)

The two strongest pieces of evidence for gender effects are

- **Mann–Whitney on Severity by Gender:** $U = 824.00,\ p < .001$, indicating a distributional shift in severity between gender groups.

- **Kruskal–Wallis on Gender across `Crime_Type`:** $H = 44.67,\ p = .0005$, showing the composition of crime categories differs by gender.

A further Mann–Whitney run (`Crime_Type` × `Gender`, $U = 14281.50,\ p < .001$) supports the same theme. Collectively, these results imply that gender is associated not only with the type of crimes recorded,ed, but also with the typical severity theseeese incidents.

Practically, this supports gender-stratified summaries and motivates testing `Crime_Type` × `Gender` interactions in any predictive or explanatory modeling. It also has communication value: stakeholders can quickly see that observed gender differences are statistically credible and not small-sample artifacts.

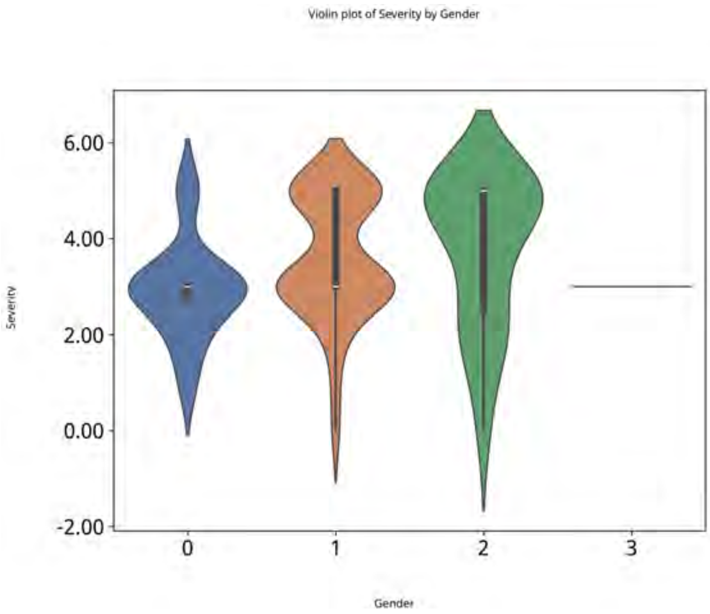


Figure 5.6: Gender–Severity violin plot

5.4.5 Spatial and Diagnostic Evidence

Spatial contrasts show a statistically credible and comparatively modest structure in the data. A Kruskal–Wallis test comparing *Severity* across *Area Name* is significant ($H = 43.22$, $p = .033$), indicates that some areas consistently exhibit higher or lower severity distributions than others. This pattern supports treating space as nonuniform rather than random with respect to severity. At the same time, it is noted that these spatial effects are weaker than the primary signals documented elsewhere. Therefore, it is best interpreted as contextual modifiers useful for local prioritization rather than as first order drivers of severity.

Distributional diagnostics further inform method choice. Shapiro–Wilk normality checks show non-normality for relevant settings (e.g., $W = 0.8380$, $p < .001$ for severity in a representative test), validating the emphasis on rank-based procedures such as Kruskal–Wallis, Mann–Whitney, and Wilcoxon over parametric alternatives when modeling severity and related outcomes. This diagnostic context also explains why agreement between ANOVA and Kruskal–Wallis in other sections increases confidence: key conclusions are robust to assumption violations and not artifacts of a single test family. For reporting, the analysis recommends showing a median-ordered dot/box plot of *Severity by Area Name* to visualize spatial shifts and including one Q–Q plot (or residual Q–Q from the ANOVA comparison) to document non-normality without clutter.

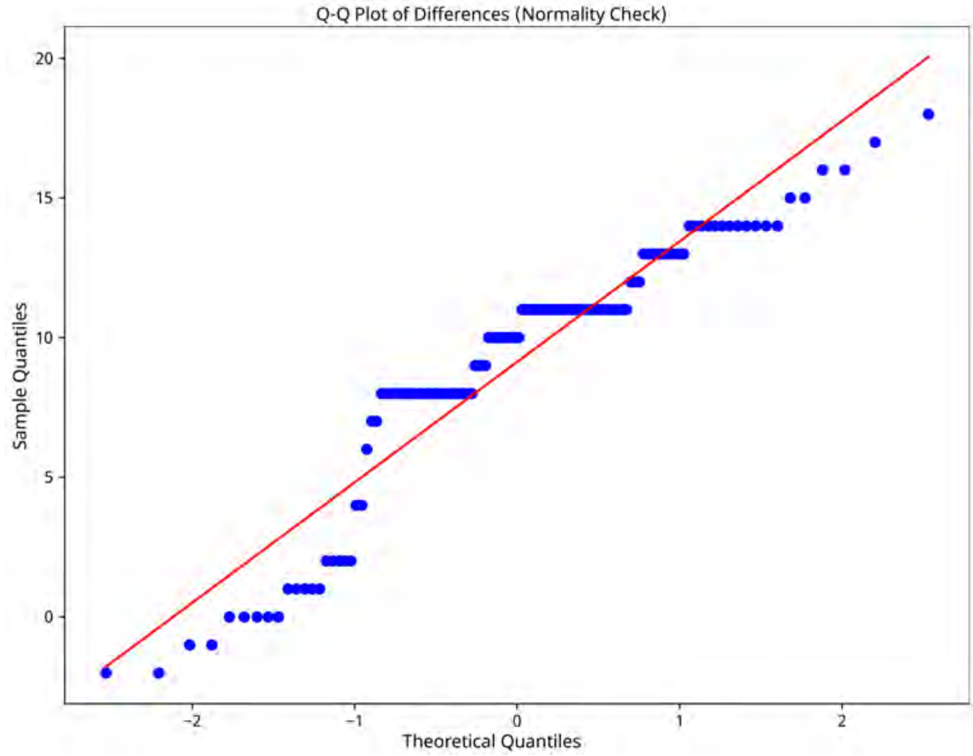


Figure 5.7: Representative Q–Q plot

5.4.6 Practical implications and prioritization for reporting

Prioritization is guided by findings that are statistically decisive, convergent across methods, and directly actionable for interface and policy. By these criteria, crime category remains the central organizer of severity: a very large chi-square ($\chi^2(90) = 610,\ p \approx 3.1 \times 10^{-78}$), together with a corroborating Kruskal–Wallis result ($H = 121.00,\ p < .001$), shows that severity is systematically structured by offense category, with robustness to non-normality. In parallel, gender evidence contributes substantial decision value: *Crime Type* × *Gender* exhibits strong compositional differences ($\chi^2(72) = 206.77,\ p < .001$; Kruskal $H = 44.67,\ p = .0005$), and *Severity by Gender* shows a clear distributional shift (Mann–Whitney $U = 824.00,\ p < .001$). Finally, *Area Name* × *Severity* yields a contextual but credible signal (Kruskal $H = 43.22,\ p = .033$), supporting spatial fine-tuning (e.g., local dashboards, hotspot emphasis) rather than driving the primary narrative. Together, these results are "best" because they combine extreme statistical strength, methodological robustness, and direct practical impact on how the app should tailor views by crime type first, then by gender, with area used as a contextual layer for prioritization.

5.5 Comparisons and Relationships

Table 5.2 contrasts prior safe-navigation systems with our Dhaka-focused prototype across focus, data dynamics, local adaptation, and community integration.

Table 5.2: Comparative overview of existing crime-aware navigation systems and the proposed Dhaka-based framework.

Aspect	SafeRoute (Deep RL) [18]	SPaFE / CrowdSPaFE (Crowdsourced Multimodal Recommenders) [33], [41]	Be-Safe Travel (GIS/Web App) [10]	Bangladesh / Dhaka Studies [24], [6]	Our Proposed System
Main Focus	Safe route optimization using reinforcement learning	Integrating historic + crowdsourced safety signals	Plotting safe routes using Google Maps APIs	Mapping local crime hotspots	Integrating algorithmic routing, crowdsourcing, and GIS data for Dhaka
Data Source	Police crime records (static)	Historic + real-time crowd reports (simulated)	Static or periodically refreshed GIS data	Limited official data	Real-time user reports + verified local data
Adaptation to Local Context	U.S. cities (Boston, NYC, SF)	Generic urban testbeds (simulated)	Generic web-based cities	Focused on Bangladesh	Specifically designed for Dhaka, Bangladesh
Community Involvement	None	Crowdsourced reports and feedback	Minimal / none	Not implemented	Anonymous reporting, upvotes/flags, credibility indicators
Dynamic Updates	No (static data)	Yes (simulated feedback loop)	Limited (time-staggered layers)	Rarely available	Real-time updates with community input
Explainability / Transparency	Focus on algorithmic efficiency	Algorithmic optimization	Simple map visualization	Analytical focus only	User-visible safety trade-offs and explanations
Crowdsourcing Features	No	Yes (simulated, structured reports)	No	Not applicable	Yes – real user input, evidence upload, moderation
Data Freshness	Static police data	Simulated dynamic data	Periodically refreshed	Limited or outdated	Live, community-updated incidents
Geographical Focus	USA	Global/urban (simulation)	Generic global use	Bangladesh	Dhaka (urban + community-based validation)
Main Limitation	Static data, no real users	No field validation	No community feedback	Lack of open data	Combines all strengths with local adaptation
Unique Contribution	RL-based safe routing	Population-based multimodal recommender	Web-based safe route finder	Empirical crime hotspot data	Locally adaptive mobile system with crowd credibility, transparency, and verified field results

5.5.1 Positioning our system in the literature

Crime-aware routing has been addressed on three general fronts: (i) safe routing algorithms that optimize distance vs. risk of crime exposure; (ii) crowd-sourced recommenders that take into account recent events and feedback; and (iii) GIS/web applications that plot historic crime and suggest ”safe” routes. Our solution integrates the three dynamic risk modeling, local adaptation in Dhaka, crowdsourced reporting with credibility indicators, and we piloted it with users through survey in the context of Dhaka.

5.5.2 Algorithmic safe routing vs. our proposal

SafeRoute frames safe navigation as a deep-RL path-finding challenge and reports up to 17% decrease in local average distance from crimes while keeping paths competitive in length in U.S. cities (Boston, NYC, SF) [18]. We re-weight the road graph in the same way with safety penalties, but in three ways different from U.S. downtowns: (1) we target Dhaka street-level hotspots and time-of-day behavior; (2) we present the trade-off to end-users in-app, as consistent with our survey finding that users accept moderate detours for safety; and (3) we incorporate live, crowd-submitted incidents rather than relying primarily on archival reporting. SafeRoute's RL formalization is effective but is only tested against static police data; our deployment and analysis are focused on freshness and explainability for traveler decision-making [18].

5.5.3 Crowdsourcing & multimodal recommenders

SPaFE is a population-based safe-path problem that incorporates both historic and crowdsourced signals [33]; CrowdSPaFE expands this with dynamic feedback and recent happenings and attains state-of-the-art gains in simulated tests [41]. Our approach conforms to that line, low-friction, anonymous complaint reporting, evidence attachments, and timed upvote/flag moderation and test in a Dhaka use-case with real end-users. In contrast to SPaFE/CrowdSPaFE's algorithmic focus, we offer design and field evidence of trust, data credibility, and adoption in a low-open-data setting.

5.5.4 GIS/web applications that surface "safe roads"

Be-Safe Travel demonstrates a web-safe-route finder using Google APIs, weighing security versus distance [10]. These systems highlight the practical requirement for safety-aware routes but normally depend on static or time-staggered refreshed layers and lack community feedback and emergency procedures. Our system advances this class by: (i) real-time consumption of user reports; (ii) local taxonomy/crime time-aware penalty for Dhaka.

5.5.5 Local empirical context: Bangladesh & Dhaka

Bangladesh-specific studies point out that crime mapping using GIS is in the nascent stage and that large cities (Dhaka, Chattogram) possess densely concentrated urban hotspots [24], [6]. These findings substantiate our hotspot-sensitive edge penalties as well as our emphasis on community reporting and freshness since official open data are limited. Our user study further shows high willingness to pay minutes for safer paths as well as need for anonymity + evidence + community moderation, which we enforce in-app.

5.5.6 Relative net contribution to current work

Collectively, current works confirm that (a) exposure can be minimized at the route level [18], (b) crowd information can alter routing to prevailing conditions [33], [41], and (c) GIS layers can make safety obvious to tourists [10]. Our contribution is to synthesize these threads into a combined locally adapted mobile system for Bangladesh with open trade-offs, community credibility signals, and to create user-validated utility in Dhaka

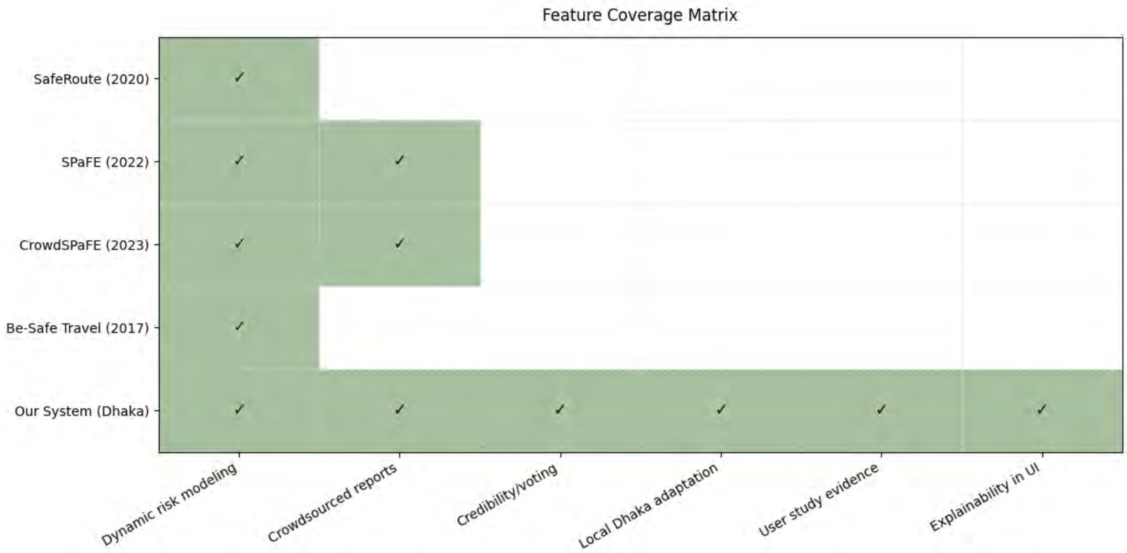


Figure 5.8: Comparative feature coverage of prior safe-navigation systems and our proposed application.

5.6 Discussions

Here, we synthesize what the study's analyses and prototyping collectively show about crime-aware navigation in Dhaka. The discussion interprets the empirical signals—from survey/interview themes, clustering of incidents, and model performance in light of the project's objectives to provide credible safety cues and explainable, safety-weighted routing. Then we consider the practical implications for data pipelines, interface design and ward-level deployment and we have emphasized how community reporting and lightweight credibility signals can inform routing without compromising privacy. Finally, we acknowledge key limitations in data coverage, external validity and verification capacity, and indicate near-term avenues to strengthen reliability and impact. This framing sets up the detailed interpretation, implications, and limitations that follow.

5.6.1 Interpretations

The results of system evaluation, data analysis and model performance illustrates us that the proposed crime-aware navigation framework can combine data driven safety insights with real-time route guidance.

The dataset, despite being collected manually had enough variation in both space and time to capture significant crime patterns within Dhaka. DBSCAN clustering results produced one major hotspot cluster and several other smaller clusters, conforming to the assumption of crime non-uniformity and location dependence. The routing module incorporated these hotspot zones to assign a high risk weight to roads that were near these hotspot zones.

The LightGBM model has a coefficient of determination (R^2) of 0.90 and a mean absolute error (MAE) of 7.81. LIGHTBGM was a bit smoother, faster, and more consistent with generalization compared to Logistic Regression and Random Forest. The most important variables are crime type, time, and area category. These conform to spatial–temporal patterns we observed, according to a feature importance analysis.

The application managed to convert these analytical outputs into a real-time mobile informer. The Crime Map showed the risk zones clearly. Report Crime allowed people to continuously upload information with a choice of anonymity and proof uploading. Safer Route allows for changing the route as per the model prediction and user reporting. All these features showed how this system can combine data analysis, machine learning, and user interaction in a single safe use case.

5.6.2 Implications

The research's conclusions could have a number of effects on theoretical progress or execution **A) For data and modeling:** Through the use of shared spaces with the right techniques, a crime scoring system can be implemented in places that are thought to have little data. By integrating crowdsourced incident reporting into our work system, we can ensure that it is constantly current and sustainable. The amazing amount of data will grow as more confirmed reports are recorded, resulting in ongoing progress. This makes it possible to continue safety monitoring for a long time.

B) For application design: Three different lightweight technologies were used in the system's design: a Supabase structure, fast API, and react native. Even complex information can be presented to nonprofessional users because to the successful combination of analytical results and an easy to use interface. The software becomes a useful safety companion for daily usage thanks to features like safety weighted routing, danger visualization, and SOS notifications.

C) Implications for Urban Safety Management: Prediction combined with data from a particular area can assist identify dangerous spots and then encourage safer travel through those places. City officials will benefit from this framework in the future since it will allow them to assign tools, motorcycles, and other equipment. For example, the approach could give scores for passenger safety. In summary, it has been proven that this method values trust, safety consciousness, and transparency.

5.6.3 Limitations

Future improvements must consider some limitations despite the promising results.

A. Data completeness: Since the dataset has been verified therefore it possesses a limited coverage. In addition, it includes publicly available news and user reports. The absence of access to official police records may lead to spatial representation gaps or insufficient reporting of specific crime types. Sometimes, officials can be partnered with, and consumers can report continuously to manage this.

B. Model generalization: The LightGBM model was trained on features related to Dhaka. While the outcomes for this environment were strong, it must be retrained before deploying in other regions or cities with different environmental and behavioural features.

C. App evaluation scope: The usability testing stage was executed with a small number of participants over a short period. Even though the feedback received was positive, it is still recommended to conduct pilot studies at the large scale to understand their real-world performance, long-term adoption, and the extent to which people change their travel safety habits.

D. Verification of user-generated data: Although a reporting and flagging mechanism is built into the app, verification is still partly manual. Adding trustworthy photo evidence checks, credibility scores for data contributors, and automated anomaly detection could reduce misinformation and improve the integrity of datasets.

In conclusion, the results show that the proposed crime-aware navigation system effectively combines reliable data processing, an accurate predictive model, and a practical mobile application. The performance of the Model, which was extensively evaluated with meaningful data and user validation, suggests that it can contribute to safer urban navigation in Bangladesh. But, for the tool to really work as it should, it needs more data, more testing, and checks. When these limitations are fixed, the system will become a scalable, real-time urban safety system that will be useful both for commuters and city officials.

Chapter 6

Conclusion

6.1 Summary of Findings

This section wraps up the story of our work—what problem we set out to solve, what we built, and what we learned from real people using it. We highlight the main takeaways on demand, feature performance, and feasibility, note the limits of the current prototype, and point to clear next steps. In short: where we are, what worked, and what comes next.

6.1.1 Human-centred demand and risk perceptions

Formative evidence shows pervasive anxiety around everyday mobility and strong willingness to use digital tools that reduce exposure to risk. Surveys indicate near-universal smartphone access, high familiarity with mainstream navigation, and intent to consult a safety-aware alternative for new or unfamiliar areas. Interviews highlight time-of-day asymmetries (evenings/nights), mode-specific vulnerability (walking, two-wheel), and the need for precise, micro-location cues. Privacy expectations are explicit: participants are willing to report to help others but prefer anonymous or pseudonymous contributions with clear consent boundaries. Overall, the problem is socio-technical and interactional—demanding not just data and algorithms, but interfaces that respect attention, privacy, and cognitive load.

The Crime Map's map-first view with compact, color-coded markers and chip filters—enabled fast situational awareness; lightweight callouts (type, time) and a small analytics strip (totals, this week, high/critical) were consistently rated "useful at a glance," and calm, legible markers were preferred over aggressive heat maps. The Report Crime flow—crime-type tiles, searchable location with a draggable pin, date/time pickers, and an optional description—felt both simple and precise; clear anonymity messaging increased willingness to report, no personal identifiers are collected, and inline validation/explanations reduced errors while encouraging concise, factual entries. For Safer Route, a single clear route polyline with distance/duration and plain-language safety cues was favored; participants accepted modest detours when the rationale was transparent (e.g., "avoids recent incidents near [landmark]"), validating safety as a cost factor rather than a visually dominant overlay.

6.1.2 Contributions to the Field

This work lays out a workable safety guideline for the public who can use to navigate to places in big cities. Qualitative and quantitative analyses have been done so that people understand better how frequent accidents happen and how to prevent them. It introduces a credibility based routing algorithm in which edge costs depend on safety weights alongside usual distance and time weights. It also provides a clear and quick access to making informed travel choices. The system is operationalized through an end-to-end mobile application built on open infrastructures such as React Native Expo, FastAPI, Supabase, and OSM. It does not rely on restricted police datasets to inform travellers on the road safety information they should be aware of. It uses this open and community-gathered data to give safety recommendations. The localized dataset compiled for Dhaka which is combined with verified severity weighting and hotspot analysis, offers a unique empirical basis for subsequent research on urban safety and mobility of individuals.

This research contributes to the human-computer interaction field by embedding privacy, transparency, and ethical safety in the implementation, beyond algorithmic design. Anonymized intake, clear consent mechanisms and community-based credibility scoring is being translated for abstract and ethical principles into actionable practice. The approach shows how participatory data collection, combined with interpretable modeling, can build user trust and situational awareness in environments where institutional data is scarce. Overall, the study establishes a sustainable human-centered pathway to develop contextually adaptive safety applications in emerging urban contexts.

6.1.3 Recommendations for Future Work

Future work should be extending this foundation by continuing data enrichment, stronger verification pipelines and scaled field deployment. Reliability will be enhanced by establishing a structured data pipeline that fuses community reports with verified institutional sources. Modular governance mechanisms for instance, community moderators and transparent labeling such as, "verified," "community-confirmed" can sustain trust at scale. Routing should incorporate temporal decay, uncertainty visualization, and adaptive safety radii, along with explicit user autonomy. Exposing multiobjective controls such as, time vs. safety and let travelers select among clearly explained alternatives rather than defaulting to a single 'safest' path. At the user-experience level, localization, accessibility, and inclusive design especially Bangla first interfaces—remain essential for equitable adoption. In parallel, implement an emergency SOS module: a privacy-preserving trigger that can alert pre-chosen contacts and optionally notify nearby verified users/responders about incidents, subject to rate-limits, opt-in visibility, and audit trails.

Ward-level pilot with civic or NGO partners under a transparent evaluation frameworkThe is a next step. Metrics such as participation rates, moderation accuracy, incorporating selection of alternate routes, SOS activation/response patterns, and perceived safety improvements can guide iterative refinement. Long-term sustainability lies in positioning the system as a reusable "safety layer" API, enabling external apps and institutions to consume validated safety data without duplicating infrastructure. Advancing along these lines can mature the prototype into a trustworthy public utility that strengthens both personal mobility and collective resilience in Dhaka.

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Appendix A: Survey Questionnaire

Purpose. Understand travel safety concerns to inform a safety-aware navigation system (Dhaka focus).
Anonymity. Responses are anonymous; no passwords or sensitive identifiers are collected.

Phase 1 — A little about yourself

Q1. What is your age? *(Single choice)*

- Under 18
- 18–25
- 26–35
- 36–45
- 46–60
- Over 60

Q2. What is your gender? *(Single choice)*

- Male
- Female
- Non-binary
- Prefer not to say

Q3. What is your current occupation? *(Multiple choice)*

- I am a student
- I am a full time employee
- I am a part time employee or private tutor
- I am retired

Q4. Which city are you living in?

____

Phase 2 — Your views on safety

Q5. How often do you travel alone? *(Single choice)*

- Always
- Often
- Sometimes
- Rarely
- Never

Q6. How safe do you feel when travelling within your city? *(Single choice)*

- Very safe
- Somewhat safe
- Neutral
- Somewhat unsafe
- Very unsafe

Q7. Do you actively avoid certain areas due to safety concerns? *(Single choice)*

- Yes
- Sometimes
- No

Q8. How safe do you feel at the following times of day? (Mark one per row)
Very safe / Safe / Neutral / Unsafe / Very unsafe

- Morning (6AM–12PM)
- Afternoon (12PM–5PM)
- Evening (5PM–9PM)
- Night (9PM–6AM)

Q9. How often do you feel there are enough safety measures on your daily routes? *(Single choice)*

- Always
- Often
- Sometimes
- Rarely
- Never

Q10. How often do you feel the need to call someone to feel safer while traveling? *(Single choice)*

- Always
- Often
- Sometimes
- Rarely
- Never

Q11. How safe do you feel in the following modes of transportation? (Mark one per row)
Very safe / Safe / Neutral / Unsafe / Very unsafe

- Public transport
- Ride apps

- Personal vehicle
- Walking

Q12. In the last 12 months, have you experienced or witnessed any of the following while traveling? *(Check all that apply)*

- Theft or pickpocketing
- Harassment or assault
- Vandalism or property damage
- Suspicious behaviour that made you feel unsafe
- None of the above
- Other: ______________

Phase 3 — Devices and navigation habits

Q13. What type of device do you primarily use while on the go? *(Single choice)*

- Smartphone
- Button phone
- Tablet
- Other: ______________

Q14. Do you use any apps for navigation while traveling? *(Single choice)*

- Yes
- No

Q15. If yes, which navigation apps do you use regularly? If no, choose "None". *(Multiple choice)*

- Google Maps
- Waze
- HereWeGo
- MapQuest
- None
- Other: ______________

Q16. How often do you use these navigation apps during your journeys? *(Single choice)*

- Every trip
- Most trips
- Occasionally
- Rarely

- Never

Q17. Would you use an app that provides the safest route based on recent crime data? *(Single choice)*

- Yes
- No
- Maybe

Q18. Would you trust a safe-route recommendation based on crowd-sourced data? *(Single choice)*

- Yes
- Neutral
- No

Q19. What privacy concerns, if any, do you have regarding sharing your location for safety purposes?

Q20. In an emergency, whom would you want the app to notify? *(Check all that apply)*

- Family
- Friends
- Police
- Nearby users
- Hospitals

Q21. If you were in a potentially unsafe situation, would you use an in-app alarm to alert nearby people? *(Single choice)*

- Yes
- No
- Maybe

Q22. Would you contribute by reporting incidents or marking unsafe areas? *(Single choice)*

- Yes
- No

Q23. How interested would you be in the following app features? (Rate 1–5)

- Real-time safe route navigation 1 2 3 4 5
- Crime alerts and notifications 1 2 3 4 5
- "Feeling Unsafe" emergency contact notification 1 2 3 4 5

- Crime hotspot map 1 2 3 4 5
- Community reporting of incidents 1 2 3 4 5

Phase 4 — Final input

Q24. Do you have any additional suggestions for features or improvements?

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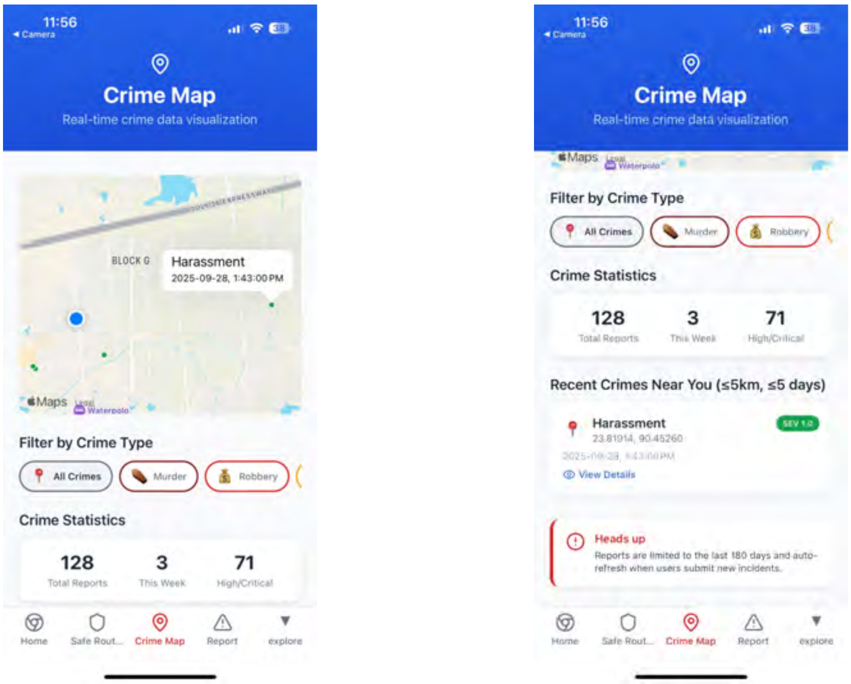
____

Appendix B: App Feature Evaluation Survey

Purpose. Evaluate perceived usefulness and impact of proposed app features (Crime Map, Report Crime, Safer Route).
Anonymity. Responses are anonymous and confidential.

Feature — Crime Map



(a) (b)

Figure 6.1: Crime Map feature from app

Q1. Do you think seeing crime locations on a live map would help you feel more aware of safety in your surroundings? *(Single choice)*

- Definitely yes
- Probably yes
- Not sure
- Probably no
- Definitely no

Q2. Would the crime markers and location details (e.g., type of crime, time) help you decide which areas to visit or avoid? *(Single choice)*

- Definitely yes
- Probably yes
- Not sure
- Probably no

- Definitely no

Q3. Is filtering by crime type (e.g., murder, robbery) useful for understanding specific risks in an area? *(Single choice)*

- Extremely useful
- Very useful
- Somewhat useful
- Slightly useful
- Not useful at all

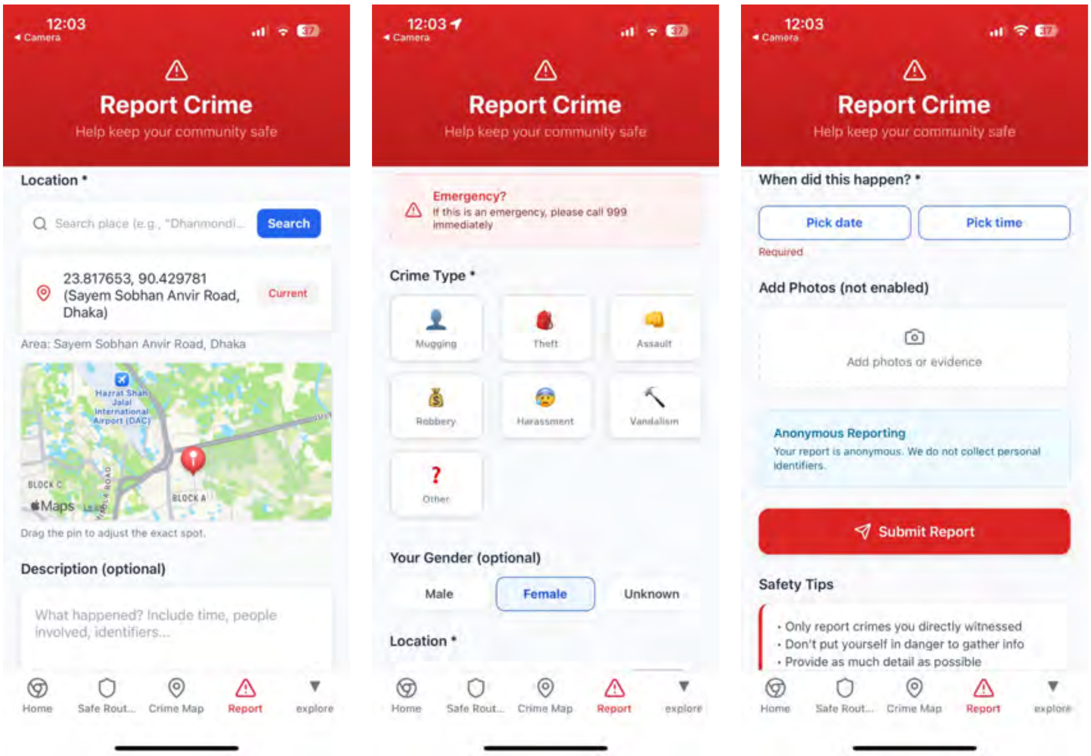
Q4. Would the crime statistics shown (total reports, crimes this week, high/critical incidents) make you feel more informed about safety trends? *(Single choice)*

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Q5. Based on what you see, how likely are you to check the Crime Map before visiting a new place or planning a route? *(Single choice)*

- Very likely
- Likely
- Not sure
- Unlikely
- Very unlikely

Feature — Report Crime



(a) (b) (c)

Figure 6.2: Report crime feature from app

Q6. Does the ability to mark the exact location on a map increase your confidence that your report will reach the correct authorities or community members? *(Single choice)*

- Yes, it significantly increases my confidence
- Yes, but only slightly
- Not sure / Neutral
- No, it doesn't make a difference

Q7. Would the option to report anonymously make you more likely to use this feature if you witnessed or experienced a crime? *(Single choice)*

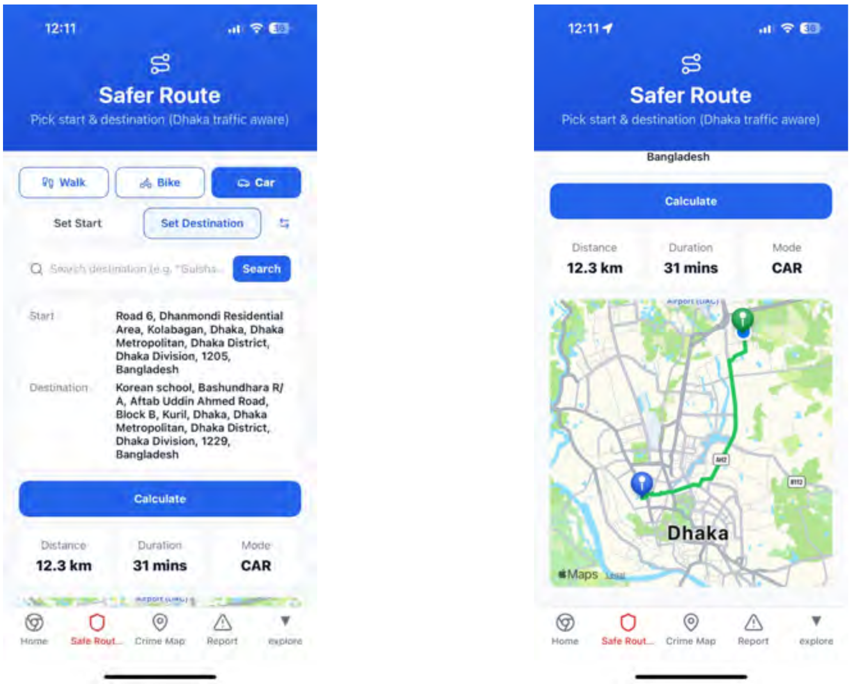
- Yes, I'd be much more likely to report
- Maybe, it makes me feel safer but not sure
- No, anonymity doesn't affect my decision
- No, I would prefer to report with my identity

Q8. How useful is the option to add extra details (e.g., description, photos, evidence) for improving the quality and reliability of reports? *(Single choice)*

- Extremely useful — it helps provide a clearer picture

- Useful — but not always necessary
- Slightly useful — I might not use it often
- Not useful — I prefer a simple form

Feature — Safer Route



(a) (b)

Figure 6.3: Crime Map feature from app

Q9. How helpful would the "Safer Route" feature be in planning your daily travel? *(Single choice)*

- Extremely helpful
- Very helpful
- Moderately helpful
- Slightly helpful
- Not helpful at all

Q10. Do you think having details like distance, duration, and safest path displayed will influence your route choice? *(Single choice)*

- Yes, definitely
- Yes, to some extent
- Not sure
- Probably not
- No, it won't affect my choice

Report Verification & Final Feedback

Q11. Which approaches would you trust to help prevent fraudulent or low-quality reports? *(Check all that apply)*

- Allow other users to upvote/downvote reports based on credibility
- Enable users to flag suspicious or false reports for review
- Require a minimum number of similar reports from different users before marking as "verified"
- Use location and time data (e.g., GPS + timestamp) to cross-check report validity
- Allow police or local authorities to review and verify reports
- Allow users to upload photos/evidence to support their report
- Mark reports as "unverified" until confirmed through user feedback or additional data
- Other: ________________

Q12. Do you have any suggestions or ideas to improve the app's features or make it more helpful for users like you?

____

____