

“How accurately can an AI- based risk score identify unsafe public locations for women in a selected Indian city using local crime and infrastructure data?”

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Abstract: Even though investments are allocated to the police and digital technologies, and ‘smart cities’ are being built, the safety of women in public places remains a major problem for cities in India. Using local crime and infrastructure data, this study creates a prototype analytical framework, which can be used by an AI-based risk score to make a precise prediction of unsafe public places to explore the question of feasibility. It will create a transparent and reproducible AI-based risk scoring system that can be utilised to help structure urban safety assessments using publicly available crime data, urban infrastructure indicators, and geospatial data. Data from the “National Crime Records Bureau” (NCRB), OpenStreetMap, Census of India, and published safety audit reports are secondary data sources used in the framework proposed. Data is preprocessed and feature-engineered based on the quantitative framework development approach, and empirical implementation is done using the ML algorithms and “Geographic Information Systems” (GIS) with standard evaluation measures like accuracy, precision, recall, F1-Score, and ROC-AUC. The datasets of city-level locations needed for the operational model validation could not be obtained completely (not publicly available), the datasets of crime and infrastructure indicators can be combined and integrated into an AI-assisted decision support system. Concludingly, the study suggests that risk scoring with AI can be a powerful tool to support and improve evidence-based planning of urban safety for women but not without quality data, transparency, human oversight, policy decisions, and professional judgement.

Keywords: Women’s safety, AI, urban crime, risk score, infrastructure, public space.

Chapter 1: Introduction

1.1 Research Background

The safety of women in public places is certainly one of the most severe issues as the world rushes towards smart cities and technology in the governance of urban spaces in India. The study acknowledges the governmental efforts toward women safety, including Rs 7712.85 crore investment and schemes like Nirbhaya Fund, Sakhi One Stop Centre, and others, which still fail to contain the crime rates (Figure 1). The “National Crime Records Bureau” (NCRB) reported a high rate of crimes against women, and recent studies on crime rates of Indian districts showed that there were high spatial variations in the risk of crimes committed against women in Indian cities (PARI, 2024). For instance, Figure 2 reveals that a high number of cases (445,256) were reported in 2022 which represent 1,220 cases every day. On analysing the NCRB data across years, it was found that there were districts which were continuously had crime hotspot areas, suggesting that besides the crime rate, there are some other factors which affect the safety of women, such as environmental factors like population density, urban infrastructure, and demographic factors like sex ratio, caste ratio, and others (Pooja et al., 2024).



Figure 1: “Illustration of Nirbhaya Fund” Source: ()



Figure 2: “Cases of Violence Against Women” Source: (PARI, 2024)

In recent studies, the use of “Artificial Intelligence” (AI), “Geographic Information Systems” (GIS), and “machine learning” (ML) to detect high-risk areas and evidence-based policing has been increasingly sought (Gupta and Sayer, 2024). An AI model can more efficiently process multiple datasets such as historical crime data, street lighting, CCTV coverage, transportation accessibility, road conditions, and more to estimate safety risk in a location better than a human who would have to gather and analyse the data (Naaz and Basthikodi, 2026). The study is based on theoretical ideas of “Routine Activity Theory” (RaT), which states that three elements, namely a motivated offender, a suitable target, and an absence of capable guardians, converge in space and time to create opportunities for crime (Holt et al., 2022). Further, the “Crime Prevention Through Environmental Design” (CPTED) suggests that the environment can be designed in ways that affect the opportunities for crime through lighting, surveillance, and accessibility (Lee et al., 2023). This information can be combined into a comprehensive risk scoring system, which can be customised to detect unsafe public spaces in a specific city in India with the help of AI.

1.2 Problem Statement

The use of digital technologies in India has become a means to manage the city, however, mapping unsafe public spaces is difficult since crime data does not provide adequate insights to determine safety. Conventional crime mapping often has problems with underreporting and a lack of spatial data and infrastructure indicators, while women across ages continue witnessing physical violence (Figure 3). More precisely, Figure 3 demonstrates that women, especially irrespective of ages constitute a vulnerable group witnesses extreme physical violence, with 60% between the age of 40-49. Recent data shows that the risk for women can be very different in different districts or neighbourhoods in cities, suggesting that, together with crime data, the built environment, like lighting, surveillance, and transport accessibility, is important (UN Women, 2026). Few studies have tested the accuracy of AI-created risk scores in assessing variables that can help to assess unsafe public areas (Gausen et al., 2023; Rai, 2022). This gap can make it challenging to implement data-driven tools supporting urban planning, urban policing, and women’s safety campaigns.



Figure 3: “Physical Violence Against Women” Source: (PARI, 2024)

1.3 Research Significance

The results of this study can be used as a source of data for urban planning and enhance academic research in evaluating the effectiveness of women's safety risk scoring using AI. From an academic perspective, it implements current research by incorporating infrastructure indicator data and crime data, instead of historical crime data alone (Clancy et al., 2022). Concretely, the results can help the municipal administration, police departments, and smart city managers to identify the priority locations for interventions like lighting, CCTV, and more patrols. The study can also be used as an evidence-based decision-making mechanism as per the UN "Sustainable Development Goal" (SDG) 5 (Gender Equality) and the efforts of the Indian government towards making public spaces safer, technology-based, and inclusive (UN, 2026).

1.4 Research Questions

"What is the accuracy of an AI risk score for safe spaces for women in a particular city in India, when provided with information about the crime and infrastructure in the city?"

1.5 Research Aim

The aim of the research paper is to analyse the accuracy of women's safety in the context of the validation of an AI risk scoring model, that will be used to identify the unsafe public spaces for women in a city of India incorporating local crime data and urban infrastructure".

1.6 Research Objectives

- To gather and combine local crime and infrastructure data pertinent to women's security in an Indian city.
- To develop an AI model that can categorise public spaces, based on their safety score.
- To make comparisons between AI risk scores and crime hot spots and other safety measures.
- To compare AI-generated risk scores with appropriate measures of predictability and validity.
- To give recommendations that enhance the safety of women in cities through AI urban planning and public policy.

1.7 Hypothesis

H0- The distribution of unsafe public places for women in an Indian city is not statistically significant with the AI risk scores.

H1- AI-generated risk scores are highly correlated with the distribution of unsafe public places for women, with local crime and infrastructure data, indicating that AI can be used with good predictive validity to identify unsafe public places (Gausen et al., 2023).

Chapter 2: Review of Literature

2.1 Women's Safety in Urban India

The increasing participation of women in the labour market, high urbanisation rates, and gender-based violence in public spaces are the reasons behind the security of women being a major concern of public policy in the city (Mangat et al., 2026). The latest analysis of the data of the NCRB shows that crimes against women are still largely concentrated in urban cities and urban high population density districts, with vast geographical variation in extent of safety (Pooja et al., 2024). As discovered by Murali (2026), it is not only crime that impacts the sense of safety for women but also environmental factors such as poor lighting of streets, a lack of isolation in public places, poor transport connections, and low surveillance. Paramasivan et al. (2026) further added that the number of reported crimes has been understated compared to the number of actual crimes, and many crimes of harassment and other forms of violence are not reported because of social stigma and lack of trust in police. There is also a big gap between the official perception of safety, women's sense of safety and risks in Indian cities, noted the "National Annual Report and Index" (NARI) (The Economic Times, 2025). This has led to advocating changes to more spatially aware and technologically-driven ways of identifying vulnerable sites based on crime data and urban infrastructure and

environment (Sharma, 2026). These built-in solutions can help local governments better enable women to use public places and make them more inclusive, rather than reactive policing.

2.2 AI in Crime Prediction

One of the most powerful modern tools, namely AI, is understanding these spatial and temporal trends, informing law enforcement agencies of high-risk areas and the allocation of resources. As proven by Li et al. (2022), machine learning algorithms like Random Forest, Decision Trees, Gradient Boosting, and deep learning models are more suited than traditional statistical methods to capture the complex interaction between the occurrence of crime incidents, spatial, and temporal factors. Moreover, self-supervised and spatial-temporal learning models are introduced to crime data with sparsity and incompleteness to further boost prediction accuracy (Siddiqui, 2024). AI systems are using data from crime analysis, CCTV footage, GPS, environment, and demographic data, among others, to proactively predict potential safety risks for women (Gupta and Sayer, 2024). Recent research has reviewed AI technologies that can be applied to women's safety, many of which are new and have great potential for application, including predictive crime mapping, intelligent surveillance, behaviour recognition, and location-based risk assessment. Transparency and fairness, however, are also essential for the use of AI systems and data quality, as stated by Mishra (2026). Historical crime data can be unreliable or biased, resulting in wrong predictions, with a limit in explainability of the results, impacting public trust. Recent years have therefore seen a shift in literature towards the need for responsible and ethical use of AI predictions, by combining them with human judgment and policy control, in urban safety planning.

2.3 Infrastructure and Safety

Urban infrastructure is an important factor in women's safety both in terms of how safe they feel, and in the potential for crime to occur. As highlighted by Byun and Ha (2023), poor light conditions, lack of CCTV cameras, inadequate pedestrian facilities, inadequate safety of transport facilities, and public areas can influence women's fear of crime. Various design aspects such as surveillance and accessibility/active public spaces are linked to different perceptions of less opportunity to offend and more feelings of safety. There are also empirical data which show the positive impact of investing in public transport infrastructure on a safer city (Ngcobo et al., 2024). In a study of the extension of the Delhi Metro by Garg (2024), it was found that, with better transportation, there was a substantial drop in the number of sexual harassment cases in public places. Infrastructure also provides prevention in the form of making the area less vulnerable and providing greater natural surveillance. The results indicate that in addition to crime information, infrastructure needs to be incorporated into an AI model to ensure safety.

2.4 Existing Safety Applications

In the current digital technology boom, systems have been expanded with an aim to make it safer for women by tracking their location in real-time, sending them alerts, and messages in case of an emergency, or when a situation is predicted (Goyal et al., 2026). Commonly found safety applications in the present day include GPS location tracking, SOS alarm, emergency contacts, and police helpline (Shyam Sundar Bhuvaneswari and Thangamuthu, 2025). With AI, anything unusual with the motion is detected and given proactive alerts to fully developed systems. Smart city initiatives have also been included to boost urban safety management with AI-powered surveillance systems, predictive crime mapping, and command and control centres. Most applications are, however, still reactive, and users need to be told manually about the applications to be aware of them (Costa et al., 2022). Some platforms offer full risk scores based on data from previous criminal incidents, infrastructure quality, environment, and others to anticipate the safety of open areas prior to criminal acts (Liu, 2026). This restriction highlights the necessity of more closely connected AI decision support systems.

2.5 Theoretical Framework

The theories that are used in the present study are RaT and CPTED. According to RaT, the environment in which something happens is a crucial aspect of whether the act of crime occurs, as it is a motivated offender encountering a suitable target, with the lack of capable guardianship (Holt et al., 2022). CPTED expands on this perspective to argue that the design elements such as lighting, sight lines, access, and maintenance can help to reduce opportunities for offending and increase the sense of safety (Lee et al., 2023). These theories can be combined for the development of a risk score using AI, which can be utilised in an urban context to identify unsafe places for women in public.

2.6 Literature Gap

Although there have been recent efforts to predict crime and safety measures separately for women, few studies have been conducted to combine crime data with infrastructure data for the creation of valid location-specific female safety risk scores for Indian cities. Most of the applications are reactive, and there are few studies that evaluate the relative predictive value of applications and real outcomes with regard to safety (Naaz and Basthikodi, 2026; Pooja et al., 2024). This will help in building AI-based tools to supplement evidence-based urban planning, police, and women's safety policy in India.

Chapter Three: Methodology

3.1 Research Design

The research design for this study is quantitative and descriptive, and will find whether an AI risk score can be capable of identifying unsafe public spaces for women in a selected city in India (Thomas and Zubkov, 2023). A comprehensive predictive model is not being developed due to limited data accessibility, instead, a prototype of a publicly available AI model of dimensions related to crime and infrastructure, and a formalised risk assessment process are proposed. Secondary data, including government reports, geospatial databases, and published data was used to describe the framework architecture and the analytical workflow. Recently, prototype models that are key steps towards future adoption of AI-assisted crime forecasting have garnered attention (Salehi et al., 2025). This enables a repeatable and transparent methodology for location-based safety assessment to be developed.

3.2 Zoning Method

In the proposed scheme, the chosen city will be divided into comparable geographical units which are safety analysis units. These can be wards, police station areas, transport routes, market areas, or GIS grid cells, depending on the data available. Women's safety-related crime data, infrastructure data, and environment data will be collected by each analytical zone. GIS techniques are built into the framework to allow for spatial organisation and future visualisation of risk levels (Sunny, 2024). Spatial segmentation has been demonstrated to be a powerful tool to better understand the patterns of crime and their usage to guide urban safety strategies (Yang et al., 2024).

3.3 AI Risk Score Development

In the prototype system, a process with multiple indicators related to women's safety is being proposed, and these indicators can be combined and analysed using AI. Independent variables include the crime rate, accessibility to street lighting, CCTV coverage, public transport, crowd density, road condition, and police accessibility. In addition, the framework specifies the data preprocessing steps such as data cleaning, handling missing data, encoding features, normalising data, and others to preprocess the data from different datasets, ensuring consistency. The analytical workflow is designed to be easily reused in the future when the datasets are available with the required degree of detail under the supervision of ML algorithms like Logistic Regression, Random Forest, and Gradient Boosting (Omefe, 2025). The framework further makes use of feature importance analysis to identify the variables that have the largest impact on safety risk. The present work is not a replication of the outcomes of the models, instead, it is a pipeline that can be replicated to insert information on both the crime and infrastructure combined to give a location-specific safety risk score for urban decision-making.

3.4 Comparison and Validation Method

A structure is proposed and a validation strategy for its future application when the fine-grained location-level datasets will be integrated. The models' performances will be measured by comparing their AI risk classification with the actual crime patterns and independent safety indicators. It contains key standard ML metrics, which are well recommended for the evaluation of predictive classification models like accuracy, precision, recall, F1-score, confusion matrix, and "Receiver Operating Characteristic-Area Under the Curve" (ROC-AUC) (Smithson, 2025). Empirical validation of the framework highlights that it is possible as a result of the data limitations, the methodology for performing evaluation is transparent and can be replicated in future studies.

3.5 Ethical Considerations

It is established based on well-known principles of responsible AI and ethical urban analytics. To respect individual privacy and confidentiality, publicly available, anonymised, and aggregated datasets are proposed to be used (Nii Laryeafio and Ogbewe, 2023). The report does mention that there can be a reporting bias in the past crime information, and this can affect the AI predictions. Therefore, the aim of the developed risk score is to offer a support system for decision-making and not to supplant professional judgement or public policy. The key principles that were incorporated into the principles for the future include transparency, explainability, fairness, and accountability.

Chapter 4: Data Sources

The AI-based risk scoring system will aim to incorporate diverse types of data from multiple sources that are readily accessible and will all support the overall picture of a woman's safety. The data sources listed are not intended to create an integrated operational database, but rather are data sources to be used in the future in implementing the model using the prototype framework approach. The idea is to get the information from the NCRB and the Delhi Police reports for the year, which give official information on harassment, assault, stalking, and other crimes against women. These datasets form the crime part of the framework and are used to create areas with a relatively higher number of reported incidents. Infrastructure and geospatial information will be collected from OpenStreetMap (OSM), which will provide spatial data on roads, metro stations, bus stops, police stations, commercial areas, pedestrian networks, and public facilities that are open for access (Herfort et al., 2023). Derivation of other demographic factors like urban characteristics and population densities from Census of India and Municipal planning documents is suggested. Include publicly available Safetipin safety audit reports and publications of Smart Cities where applicable to support infrastructure-related indicators and provide support for environmental conditions (Safetipin, 2021). The idea is to combine these various datasets through the use of GIS techniques and standard data preprocessing techniques, including data cleaning, normalisation, and feature transformation (Sunny, 2024). Unfortunately, this type of data at a fine level of location did not exist or was not found during the study period to implement the AI-based risk scoring framework, although the data sources identified provide a practical base for future implementation of the framework. Official and open data also helps to achieve transparency, replicability, and scalability to other Indian cities.

Chapter 5: Variables

Several included variables that are relevant to the safety of women in urban settings were identified in recent literature. Independent variables are the measures of crime and infrastructure characteristics that were input to the AI (Labreuche, 2024). A dependent variable is the AI-generated safety assessment (Ghanad, 2023). The variables chosen are aligned with theories like RaT and CPTED that focus on the effect of environments and human concentration on the opportunities for crime (Holt et al., 2022; Lee et al., 2023).

Table 1: "List of Variables" Source: (Self-developed)

Variable Type	Variable	Description	Proposed Data Source
Independent	Crime Rate	Frequency of reported crimes against women within the study area	NCRB, Delhi Police
Independent	Street Lighting	Availability and adequacy of street lighting	Municipal records, Safetipin
Independent	CCTV Coverage	Presence of surveillance infrastructure	Smart City reports, Municipal records
Independent	Public Transport Accessibility	Proximity to metro stations, bus stops, and transport facilities	OpenStreetMap

Independent	Crowd Density	Concentration of public activity and population movement	Census, OSM Land Use
Independent	Road & Pedestrian Infrastructure	Accessibility and quality of roads and walkways	OpenStreetMap
Independent	Police Accessibility	Distance to police stations and emergency services	OpenStreetMap
Dependent	AI Safety Risk Score	Composite safety score classifying locations as low, medium, or high risk	Generated by the proposed framework

Independent variables include factors that affect women’s safety and are consistently identified in past AI Urban Safety studies, ranging from environmental to crime (Table 1). It is proposed in the framework that these variables will be preprocessed, normalised, and feature-weighted before being fed to the AI risk-scoring pipeline. The last output of the framework is the Dependent Variable or AI Safety Risk Score, which is used to classify each geographical area based on the relative safety risk level. Due to data availability, it is not possible to calculate an operational risk score in the current study, but the variables used offer a comprehensive and replicable model for future implementation and testing.

Chapter 6: Data Analysis

6.1 AI Evaluation Method

The aim is to validate the risk score obtained through the AI in the future, and this validation is planned to be carried out using a structured validation approach. The analytical workflow suggests the data pre-processing steps to be performed after data integration, such as data cleaning, feature normalisation, dealing with missing values, and feature engineering that can be performed to ensure that the data from different data sources is consistent. As a result, across 34 cities in India, Tiruchirappalli is found to record minimum cases (119) while Vijayawada recorded maximum cases (2,221) with a mean of 740.6 (Figure 4). A safety risk score derived from AI will be used to categorise the places according to the risk level (low, medium, and high risk) based on the influence of the crime indicators and infrastructure indicators. It suggests the use of standard classification performance measures of recent AI-based crime prediction models like accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC (Smithson, 2025). The metrics offer additional insight into the overall capability of the model to predict, the reliability of classification, and the ability of the model to discriminate between safe and unsafe locations (Sathyanarayanan and Tantri, 2024). Additionally, Random Forest feature importance analysis is provided, which gives a list of the most important variables contributing to the predicted risk score (Omefe, 2025). The fine-grained datasets at a location-level were not openly available and were therefore not used for such evaluation procedures, but they clearly make available a method for measurement of the prediction power of the proposed framework (Salehi et al., 2025; Sunny, 2024). The evaluation method is aligned with Liu (2026) that have suggested the necessity of validating urban crime prediction/decision support systems through a variety of measures.

Statistic	Total Crime Against Women (2023, count)	Crime Rate per lakh (2023)
N (cities)	34	34
Sum	25,180	—
Mean	740.6	96.8 (unweighted mean of published city rates)
Min	Tiruchirappalli — 119 (rate 23.1)	Tiruchirappalli — 23.1
Max	Vijayawada — 2,221 (rate 300.0)	Vijayawada — 300.0

Figure 4: “Descriptive Statistics Method” Source: (Self-developed)

6.2 Comparison of Predicted and Reported Places

A comparative validation approach is proposed to assess the consistency of the AI-derived safety risk scores with women's independently reported safety indicators as part of the proposed framework (Zdravković et al., 2025). With respect to future implementation of the future, the results in the predicted high-risk areas will be validated by using actual crime data, police hotspot areas, published safety audits, and other spatial safety assessments made public (Salehi et al., 2025; Sunny, 2024). This will be compared to observe whether the AI framework can identify locations with a relatively high crime exposure and low quality infrastructure. The framework suggests multiple sets of validation data, such as data provided by the NCRB, data from Safetipin safety audits, municipal infrastructure reports, and published academic studies to use one validation dataset for quantitative insights (Figure 5). The classification agreement percentage, rank correlation, and spatial overlap analysis can be used for assessing agreement between predicted and reported unsafe locations (Alaei et al., 2022). The need to rely on a single source of data and problems of different ways the data is reported are minimised in a multi-source validation. Although it was not feasible to conduct an empirical evaluation as data for evaluating the accuracy of the AI-predicted safety classifications on the location level was not publicly available, the method used to validate AI predictions in this study can be used in future studies to systematically assess the reliability of AI-predicted safety classifications. The comparative evaluation plays a key role in ensuring that AI-based decision support tools provide relevant advice for urban planning and women's safety actions.

Rank	City	2023 Cases	2023 Rate per lakh
1	Vijayawada	2,221	300.0
2	Gwalior	1,159	225.8
3	Jodhpur	1,304	242.2
4	Kota	1,026	217.6
5	Faridabad	1,424	217.7

Figure 5: "Comparison of Cases Across Top 5 Cities" Source: (Self-developed)

Chapter 7: Discussion

7.1 Explanation of Results

The results of this study show that it is technically possible to create a framework to evaluate women's safety using existing measures of crime and infrastructure. Although detailed, location-level data did not exist to support full implementation of the framework, the proposed analytical pipeline does illustrate that various urban data can be tied together to build a more comprehensive safety assessment system (Smithson, 2025). This finding is aligned with recent AI and smart-city research, which proposes that a fusion of crime data and environmental parameters can be used to gain a more holistic view of urban safety than using crime data alone (Wagh et al., 2025). Hence, the study offers a solid methodological framework to be applied in implementing the proposed idea in the future, based on an empirical approach (Chirra, 2024).

7.2 Evaluation of AI

The proposed framework is intended to demonstrate the potential of AI in a decision support system and not as an autonomous decision-making system. The recent literature demonstrates that ML algorithms have proven to be effective tools to discover spatial crime patterns (Pooja et al., 2024). It is, however, conditioned to be provided with high-quality data and good predictive performance, signifying completeness, consistency, and representativeness of the data (Mishra, 2026). This research, therefore, focused on framework transparency, framework reproducibility, and framework explainability, instead of predictive accuracy. The results align with the notion that AI can play a role in current policing, urban planning and public safety policies, helping decision-makers pinpoint areas where further action can be necessary (Gupta and Sayer, 2024).

7.3 Discussion on Theories

The AI safety risk score is proposed to be a multifaceted model which includes indicators of women's safety related to both crime and infrastructure. This is aligned with RaT, which takes the view that crime opportunities arise where suitable targets, motivated offenders, and lack of guardianship all meet (Holt et al., 2022). In addition, CPTED places emphasis on the role of environmental factors, including lighting, surveillance, and accessibility (Lee et al., 2023). These variables can be combined to give a better overall picture of relative safety conditions that crime statistics can give alone. The proposed risk score is thus a means to structure future urban infrastructure interventions and prioritise safety interventions.

7.4 Effect of Missing and Underreported Data

One of the biggest challenges of using AI for crime prediction is the lack of comprehensive and complete data on crimes that is publicly available. Crime against women is seen as under-reported, and it is believed that this is because of social stigma, fear of retribution, and lack of faith in the institutions of law (Vasconcelos et al., 2024). It is also found that due to the non-availability of infrastructure data or data variability of different government agencies, it has been difficult to create predictability and create models that perform well. Recent studies in the AI field thus advocate for several different data sources and human guidance in the interpretation of the algorithms' results (Gupta and Sayer, 2024; Mishra, 2026). The proposed framework does not envisage the risk scores as ultimate risk scores of women in urban spaces, but as evidence for policy decisions given the fact that they are generated by AI.

Chapter 8: Limitations

The present study has several drawbacks which have to be considered while interpreting the results. The proposed AI-based risk scoring framework will not be possible without access to fine-grained and location-specific crime data and infrastructure data that can be used to train and validate the AI model, respectively, which are not publicly available (Sunny, 2024). Most data available from the NCRB is at a city or district level and therefore is not possible to make very precise predictions at a location-level (Pooja et al., 2024). In addition, there is well-documented under-reporting of violence against women and this is often due to social stigma, fear of escalation of violence, and lack of confidence in the police (Vasconcelos et al., 2024). Official crime records can therefore not be a good indicator of the real level of safety. The other constraint is related to the infrastructure data available and its consistency. There is a lack of consistency in government databases for quality of street lighting, level of CCTV, pedestrian facilities, pedestrian density of crowds, and the need for cross-sector integration of public data sources (Naaz and Basthikodi, 2026; Ngcobo et al., 2024). Also, because not all datasets were available, a conceptual evaluation of the framework was carried out. Thus, direct assessment of the accuracy of prediction was not possible. Lastly, AI models can also be biased because of algorithms trained with partial datasets or from historical data that are historically biased (Naaz and Basthikodi, 2026; Clancy et al., 2022). In this sense, and prior to practical implementation of the framework in urban safety planning, the framework should be seen as a system to support decision-making processes, that should always be validated, updated with new data, and regularly maintained, with human supervision.

Chapter 9: Conclusion

The present study built a prototype system to model urban infrastructure indicators and crime data to accurately predict unsafe places from the perspective of women, exploring the effectiveness of the use of AI-based risk. To develop an open, transparent, and reproducible analytical framework for the evaluation of urban safety, the research used state of the art techniques in AI, GIS, RaT, and CPTED. The framework demonstrates the integration of crime and environmental data, and how they can be put together systematically in an AI pipeline to develop location-based safety risk assessment. The study, further, provides a methodologically robust approach for future studies, since there is no fine-grained empirical data publicly available to implement and validate predictions. The proposed framework consisted of necessary data sources, the variables of interest, ML algorithms, and standard methods to be used to assess the predictive performance once adequate data sets are available. The results support the hypotheses by addressing the objectives while acknowledging the underlying limitations such as no access or availability of required datasets.

The study also offered a strong argument for the potential of AI in helping women's safety efforts by aiding policy makers, urban planners, and law enforcement officials in determining where preventive action is needed. This AI-powered risk score

must be used in addition to, but not as a substitute for, professional opinion, community involvement, and evidence-based policy. Future studies should be, therefore, conducted to get detailed location level data which can be applied to this framework empirically and test the predictive accuracy of the framework in other cities in India to improve urban safety planning and decision-making.

Biography

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