

Community Fault Reporting Model for the Proactive Disaster Management of Environmental Risks

Fathin Nabilla Md Leza¹, M. Asyraf N. Zahid¹, Nurul Izrin Md Saleh¹, Omar Mukhtar Hambaran², Nur Atikah Arbain¹

¹ Fakulti Teknologi Maklumat dan Komunikasi

¹Universiti Teknikal Malaysia Melaka, Malaysia

²Faculty of Science, Management & Computing

²Universiti Teknologi Petronas

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ABSTRACT

Environmental risks, such as infrastructure damage and environmental issues like potholes, overgrown trees, clogged drains, and broken streetlights, pose significant threats to public safety. This paper proposes the Community Fault Reporting Conceptual Model, named Urban Alert!, to improve environmental risk management through community engagement and data analytics in Malaysia. The model integrates geo-tagged, multi-platform community reporting with a data pipeline, followed by Business Intelligence (BI) and Machine Learning (ML) analytics to support the identification of recurring and risk-prone areas, enabling risk prioritization and early intervention by responsible authorities to implement proactive measures. The software prototype architecture and user interaction model are also presented in this paper. This study concentrates on the evaluation of architectural validation, prototype implementation, and preliminary analytic capabilities rather than extensive empirical deployment. It also improves the community fault reporting model by improving community data reporting, location tracking, data processing and cleansing, integrated with predictive analysis for proactive disaster management. This study contributes to SDG 11, Sustainable Cities and Communities that aims to make cities and human settlements inclusive, safe, resilient and sustainable by improving fault reporting in proactive disaster management.

Keywords: Fault Reporting, Business Intelligence, Proactive Disaster, Data Model, Environment risk

INTRODUCTION

Urban areas in Malaysia face numerous environmental and infrastructure challenges that have a substantial impact on public safety and quality of life. Common issues such as potholes, overgrown trees, clogged drains, broken streetlights and soil erosion are most often ignored until they lead to accidents or other hazards. Conventional reporting methods for such issues are often inefficient, leading to delays in addressing the problems and increasing the risk of natural disasters and accidents. Fault issues are typically first reported by community members, who are often the initial observers of these problems as they navigate their daily routes. Even seemingly insignificant, problems such as potholes, overgrown trees, or clogged drains can seriously threaten public safety. If these faults are not promptly maintained and repaired, they can escalate into serious hazards, leading to natural disasters or accidents such as flash floods or landslides, which may result in severe injuries or fatalities.

Current community-based fault reporting systems, such as “*Sisten Pengurusan Aduan Awam*” (SISPAA) [1] or Public Complaint Management System, allow the public to submit reports to government agencies. These systems require users to enter their personal details (e.g., NRIC, phone, email) and provide detailed descriptions and attachments (e.g., images or documents) of their reports. Users usually must wait for the update depending on the priority of the report and no transparency progress have been provided. Further proactive measures cannot

be identified due to lack of analysis and inefficient reporting management. However, reliance on manual reporting channels results in significant delays in information processing, often leads to inconsistent and inaccurate reporting of data. These time-consuming procedures impede responsible authorities from taking timely action, aggravating the delays in addressing issues and complicating effective proactive disaster management. Inaccurate location data and reports further contribute to misleading information, which makes further dissemination difficult.

Another prominent concern is the lack of public awareness regarding the status of their complaints, often stemming from a lack of transparency within the complaint handling process. This lack of information can lead to misunderstandings, delays in resolution and erosion of public trust [2]. Consequently, numerous environmental risks are disregarded, which cause severe natural disasters. For example, clogged drainage filled with trash contributed to major flood incidents in Taman Sri Muda Shah Alam Selangor, Malaysia, in 2021 [3]. The respected authorities did not perform regular drainage maintenance, which resulted in worse incidents during heavy rainfall. Another incident occurred in Cameron Highlands Pahang, Malaysia, where numerous landslides were reported [4]. Improper and irregular drainage maintenance, along with construction and development affecting land structure, exacerbated the situation, making it one of the worst recorded incidents [4]. There have also been many incidents reported due to unmaintained potholes [5], clogged drainage [6] and fallen trees [7]. Due to climate change, these issues may escalate, leading to more victims and worse disasters. These examples highlight the lack of accuracy and awareness in identifying and proactively preventing environmental and infrastructure risks that can cause disasters to occur. Even when a report is submitted, the intransparency of the process to completion due to inefficient management often leads to misleading and delayed information.

Therefore, in this paper, we propose a Community Fault Reporting Model that represents a departure from the current manual and tedious reporting process. This paper does not evaluate user adoption or public engagement behavior, but it demonstrates how community-based fault reports data can be transformed into actionable insights for identifying risk-prone locations through a conceptual and prototype system called Urban Alert! By leveraging Business Intelligence (BI) and Machine Learning (ML) analysis, this model aims to identify risk-prone areas to improve proactive disaster management while increasing the effectiveness and accuracy of current fault reporting and management. Combining BI and ML analytics allows the proposed model to provide data visualization and predictive analytics capabilities.

These tool analysis result contribute to effective proactive disaster management by improving transparency, public engagement, and the decision-making process for authorities. Before we can design and evaluate the model prototype called "Urban Alert!", we must first understand the state-of-the-art of current fault reporting methods for proactive measures available. This will help us identify the key requirements and features that the Urban Alert! model should address. Therefore, in Section 2, related works related to fault reporting in several domains will be presented, followed by the methodology of the research project in Section 3. Following is the structure of this paper: A literature review is presented in Section 2 to provide context for the research topic. Section 3 describes the methodology used in the study. Section 4 details the result and Section 5 discuss the contribution. Finally, Section 6 discusses the limitation and future work.

Related Work

In this section, related work of community fault reporting system in different existing applications are presented. Followed by related work data management and analysis approaches of fault reporting and research gaps in the subsequent sub-sections.

Community Fault Reporting Systems

SeeClickFix, launched in 2008 in the United States, is a community reporting platform for non-emergency urban issues such as potholes, broken streetlights, and vandalism. Reports are geo-tagged and routed to the correct municipal departments, with real-time tracking, feedbacks loop, and two-way communication that promotes transparency and public engagement [8], [9]. Recent study by [9] on SeeClickFix using large datasets demonstrates that collective citizen input has a substantial impact on government responsiveness particularly marked in public safety categories (e.g., traffic and street repairs), where collaborative reporting validates issue

severity and attracts higher public scrutiny. The platform also integrates with legacy systems such as 311, enabling municipalities to prioritize and manage incoming requests.

Nonetheless, according to Belarbi & Toufik (2020) and Schiff (2025), participation tends to favour digitally literate citizens, potentially excluding underrepresented groups such as the elderly, low-income populations, or those with limited internet access leading to inequities in fault resolution. This will lead to delay of fault resolutions perpetuating participation and service inequities especially high-risk fault but lack of active community engagement [9], [10]. Moreover, SeeClickFix addresses responsiveness of the fault resolution, it does not directly address mitigation for preventive maintenance especially for high density fault areas, making recurrence of certain faults likely. Concerns have also been raised over user privacy due to the visibility of reports containing personal information, indicating a need for stronger data protection.

In Asia, applications such as Citizen's Eye are used for decentralized community reporting in Nepal and Japan. The core features provided allow community to submit fault reporting of infrastructure, environmental, safety or public health directly to relevant authorities with geo-location tagging, media files upload (image and audio recording) and real-time notification. The application also features grid-based localization to allow high precision in capturing and encoding addresses. Citizen's Eye encourage community participation, hence improving accountability and reducing burden on resource monitoring. Similarly, My City Report is an open-source mobile application used across Tokyo developed by [11] in collaboration with the Tokyo Metropolitan Government and widely used since 2022 [8], [12]. It is used in some cities in Japan primarily focusing on road damage and infrastructure issues report directly to the authorities.

Moreover, [8], [12] highlighted the features that it covers wide areas including remote islands in Japan with transparent feedback loop allowing fast response times within few days of resolution [8], [12]. My City Report enables authorities to manage reports and real-time status tracking that works similarly with Customer Relationship Management (CRM) to resolve the complexity of dividing multi-coordination authorities using real-time analytic dashboard for damage detection and informed maintenance planning. Despite My City Report notable success in promoting community engagement, manual data processing is still used for classifying and reviewing reports, which limiting scalability and slows response during disasters or high-volume reporting scenarios.

Although machine learning is employed for road damage detection, there is lack of discussion and study on predictive analytics that integrate business intelligence and machine learning analysis for proactive disaster risk analysis, prioritization, and outcome forecasting. Additionally, cross- collaboration is inconsistent due to operational fragmentation. This is due to many authorities operating My City Report as an isolated system, limiting data sharing and meaningful insights. The application also lacks hazard monitoring and risk prediction tools which could provide early detection and mitigation, as the resolutions are reactive rather than proactive.

Other than My City Report, Chiba-Repo application is also used in Japan especially in Chiba City. The application emphasize multi-channel community engagement and integration of legacy authorities processes such as patrol, telephone, counter contact into a centralized CRM application[11]. Other than similar functionalities with MyCityReport, the application covers wide areas including remote wards and support data-driven planning with spatial analysis of report trends to focus clusters of faults. Nonetheless, Chiba-Repo application has high reliance on staff manual screening and processing from these analog channels which are tedious and time consuming, especially during high-volume reporting periods, affecting both reports validation and resolution.

While spatial and text mining are used in data analysis, it lacks discussion on integrating predictive analytics for proactive risk mapping, anomaly detection or automate prioritization. This is further impacted by silos, operational fragmentation in Chiba Repo as different city departments have different coordination hence slowing the response and fault resolution. Although validated reports can be accurate, the authorities may face delays in fault resolution and may lack the resources to respond to immediate high-risk reports particularly in the event of emergencies disasters.

Another open-source application named FixMyStreet is used in United Kingdom since 2007[13]. The application enable communities to report street-level issues such as potholes, streetlights and fly-tipping directly to the respected authorities[13]. FixMyStreets has evolved from a public reporting website into an integrated professional municipality tool, supporting both civic engagement and back-end automation. Recent studies by several researchers emphasized its evolving role as data source and operational model for urban infrastructure management and civic engagements platforms[14]–[16]. Data from FixMyStreet application have been widely used for research in geospatial analysis,[14] AI-powered text analytics[15], and multimodal urban analysis[16].

However, FixMyStreet remains reactive measures instead of preemptive solution. It closes the reporting loop for current faults but were not designed for real-time detection of emerging risks clusters or spatial risk visualization using any predictive analysis tools for proactive hazard mapping, trend prediction or risk forecasting. As a result, recurring faults may persist and affect public safety. risk clusters.

In Malaysia *Sistem Pengurusan Aduan Awam* (SISPAA) is a centralized public complaint management system, implemented for all local authorities and government agencies. The platform is used to transform conventional paper-based and fragmented reports into improved fault submissions, tracking and resolution including environmental hazards [1]. Similarly, MyJalan mobile application by Ministry of Works is specifically address infrastructure, road, street lighting, and public facility issues [17].

Both platforms have played a significant role in transitioning in improving public feedback mechanisms. Nevertheless, they still rely heavily on manual data processing, which causes further delay fault resolutions and creates administrative bottlenecks, especially during periods of high reporting volume. Both lack data cleansing measures to ensure the quality of the report submitted, as most reports submitted by users are in a free-text format. It also lacks data-driven risk mapping and predictive analysis for emerging geographical fault clusters, which causes recurrence of fault incidents, hinders proactive decision making, reduces the reliability of digital platforms and undermines public trust in fault resolution.

Table 1 below presents the comparison key features and limitations between existing community fault reporting applications

Table 1. Comparison of Existing Community Reporting Applications

| Feature/ Aspect | SeeClickFix (US) | Chiba-Repo, MyCity Report Citizen's Eye (Nepal, Japan) | FixMy Street (UK) | SISPAA/ MyJalan (Malaysia) |
|-------------------------|--|--|--|---|
| Platform | Web, mobile, social media | Multi-channel (app, email, phone, patrol, counter), Mobile and Web-based | Web, mobile | Web (SISPAA), mobile (MyJalan) |
| Geo-location | Map-based, automatic | Multiple options Map/photo-based, High-precision grid-map | Map-based | Basic location info (free text or map pin) |
| Reporting Range | Broad (incl. social), civic focus | Infrastructure issues, multi-channel, Broad (including environment /safety) and multi-domain | City/local defects | City-wide public complaints |
| Security | Moderate privacy, public visibility | Validated by manual screening, staff-only data, Standard data protection, no public exposure | Open reporting, privacy concerns exist | Mandatory complaint submission, limited privacy |
| Feedback/ Status | User votes, comment, transparent communication | Manual validation, slower updates, Fast real-time status tracking, CRM integration | User votes, comments | Limited feedback |

| | | | | |
|----------------------------|--|--|---|--|
| Public Engagement | High user engagement, transparency, collaboration | Multi-channel outreach, limited digital engagement Community reporting with strong authority interface, but active engagement | High user engagement, civic focus | Low engagement, mostly formal complaints |
| Data Analytics | Descriptive analytics, limited predictive modeling | Spatial and text mining, no predictive analytics, Basic ML for damage detection, lacks integrated predictive analytics | Descriptive data source, lacks predictive analytics | Minimal analytics |
| Integration | Integrations with legacy systems (e.g., 311), local authorities | Integrated CRM, multi-channel data collection with local government integration | Integrated with local councils | Local government siloed processing |
| Proactive Analytics | Reactive with emerging community validation, no predictive analytics | No proactive predictive analytics, Limited ML, no integrated predictive risk models | Reactive only, no predictive analytics | Reactive, no prediction |

Data Management and Analytic Approaches in Fault Reporting

Recent studies found that using Internet of Things (IoT) and Artificial Intelligence (AI) to manage urban disaster management. According to Zeng et al., (2023) focuses on the utilization of sensors in IoT systems for urban catastrophe management [18] while Samsurijan et al., (2023) reviews many AI elements in urban development and service delivery, highlighting the role of technology-based innovation systems in improving the efficiency of local authorities' delivery systems [19].

Some works also described the need of GIS support tools by Rezvani et al., (2023) discussed the importance of asset and disaster risk management in enhancing urban resilience [20]. They emphasized the operationalization of resilience components for local jurisdictions and the need for coordinated governance to mitigate long-term hazards in urban regions. Another study by [21] highlights the integration of AI and cloud technologies as well as time-series method and text data by [22] to create fault reporting in ICT systems for proactive disaster management. By implementing in in heterogeneous environment, helps in improving recovery actions [22]. Nevertheless, these studies often lack detail on practical data processing methods for effective analysis and preventive management.

A significant area of information technology, business intelligence, or BI for short, is concerned with how users interact with business domains and has a direct bearing on business operations [23]. It also consist of collection of software, technologies, and methods to discover valuable laws and patterns from data, transform data into knowledge, and support enterprises' decision making, marketing, and services [24]. For its benefits in business decision-making, it later has applied in several other domains as well in order to gain insights from their data. BI plays crucial roles in various sectors including urban parking management and sustainability projects Using BI solutions for parking management can significantly improve decision-making by offering advanced analytics such as parking occupancy, identification, and non-compliance detection [25]. It enhances parking management effectiveness by focusing on analytics, trends, and patterns for efficient parking operations.

Additionally the development of sustainable balanced scorecards that integrate governance, social, environmental, and ethical aspects demonstrates the importance of BI tools in integrating sustainability [26]. BI approaches also enhance support for corporate sustainability initiatives through multi-dimensional modeling

[27]. BI plays a significant role in analyzing traffic accidents to provide comprehensive data visualization dashboards for informed decision-making. By using BI platforms like Microsoft Power BI, businesses can utilize data analytics, visualization, and mining to turn raw data into actionable insights, aiding well-informed decisions [28].

The integration of BI and big data offers a competitive edge by focusing on customer-centric strategies and operational excellence, such as brand loyalty, customer trust, and outcomes. BI applications are also applied in sustainable actions such as addressing climate change. [29] discusses using business analytics and data-driven methods as decision-support tools to tackle climate change challenges. By integrating various platforms, BI tools enable organizations to transform raw data into actionable insights, supporting strategic decisions across multiple domains and enhancing overall operational effectiveness. These case studies demonstrate the value of business intelligence (BI) applications in advancing sustainability initiatives, strategic planning, and operational efficiency in different domains.

[30] describe that Failure Modes and Effects Analysis (FMEA) is underutilized in environmental risk assessment but can help identify potential product failures. They found that traditional statistical methods remain the most popular approach for fault detection and predictive maintenance compared to machine learning (ML) techniques. However, another study by [31][32], highlighted that machine learning predictive analytics can better allocate resources for disasters by forecasting impacted areas and displaced persons than current models. Their hybrid approach yields optimal forecasts by combining clustering from multiple data sources and fuzzy logic. Using machine learning techniques (e.g., SVM, Random Forest, Neural Network), they can forecast disasters like earthquakes, floods, hurricanes, and landslides, enhancing forecast accuracy by identifying intricate patterns in data.

[33] discussed that different data analytics techniques to enhance risk assessments in the US. Geology sector, including machine learning, big data and Geographical Information Systems (GIS). They highlighted the significant advancement of integrating these tools together for improved accuracy, efficiency and comprehensiveness risk assessments. Another study by [34] integrates environmental data using both statistical and machine learning approaches. By analyzing factors such as temperature, humidity, and air quality, predictive analytics can be leveraged to identify regions prone to epidemics, enabling early warnings and targeted interventions. Regardless of the methods used to leverage data for predictive analysis, there is still a lack of discussion on how the collected data are processed for analysis purposes, leading to potential bias and errors in analysis results that may affect forecasting ML models.

Data are collected from various sources (IoT sensors, crowdsourcing, social media, etc.) for environmental sustainability and disaster management [35], [36], [37]. These data are further analysed to identify risky and vulnerable areas and improve proactive disaster mitigation strategies. [36] emphasized the importance of integrating data from multiple sources for disaster risk management. Nonetheless, heterogeneous data sources often face data quality issues, which are a prominent concern when integrating these data. Careful and meticulous data cleansing measures are required for data fusion and consolidation to maximize data quality. [38] implements monitoring equipment's through data fusion and predictive selection using genetic algorithm analysis. [38] also highlighted data fusion stages that involve data collection, alignment, integration and analysis. By using this approach, potential faults can be identified early, allowing proactive maintenance and risk mitigation. However, there are lack of discussion on how to improve data consistency and accuracy during the data fusion.

While existing studies highlight the significance of community fault reporting in environmental risk management, they often overlook essential aspects of data processing and accessibility. Although the methods and applications aim to enhance reporting and decision-making, there is insufficient emphasis on ensuring transparency and accuracy in public resolutions. The works described thus far unfortunately lack detailed discussion on integrating data processing and cleansing measures to ensure high-quality, actionable insights. Therefore, an in-depth investigation is needed to bridge these gaps in current methodologies and technologies to improve the effectiveness of predictive analytics in disaster management.

Research Gaps

According to the literature, the efficiency of current fault reporting systems which include My City Report, Chiba-Repo, and Citizen's Eye from Japan; international models like FixMyStreet and SeeClickFix; and Malaysian platforms like SISPAA, MyJalan and data management approaches revealed several critical gaps in supporting proactive disaster management.

First, existing community systems are mostly reactive in nature rather than in proactive, which focus on receiving and managing citizen complaints rather than providing timely, helpful information for proactive measures. While some systems provide spatial visualization and clustering, they do not provide real-time insight for recurring and potential emerging risks. The proactive insights are mostly limited to some cases such as damage detection. As a result, early intervention and preventive maintenance are limited because fault reports are handled as isolated incidents rather than signals within a larger spatial-temporal risk framework.

Second, there is still lack of related works that focus on community-based reporting into actionable analysis. Most platforms prefer manual or semi-automated procedures, which lead to slow data processing and delayed responses, especially in emergency situations. Some studies highlighted the potential of forecasting using BI and ML approaches, however, there is still lack of discussion on how community-based data are systematically organized, cleansed to transform into actionable useful insights. This underscores the reliability of predictive analysis and the practical constraints for analytic-driven decision support for the authorities.

Third, there is fragmented operational cooperation across different stakeholders or authorities. Due to siloes operational management, this further complicates data sharing and leads to inconsistent data across platforms, and reducing collaborative management asses to manage fault, risk severity and prioritization. Moreover, there is a lack of a unified dashboard to transform the community-based data into proactive awareness and to identify new risks and allocate resources promptly. Fourth, there is inconsistent implementation of feedback mechanisms and transparency to status tracking. Most platforms lack feedback loops and often delayed, which further limits trust and accountability of public engagement. Because of this, communities are still unsure about how their reports will affect more than just individual case resolution.

Finally, there are limited proactive management and risk prioritization. In most platforms, they do not capable to rank faults according to temporal trends, spatial concentration, recurrence, or severity. Authorities and stakeholders are unable to systematically identify high-risk zones, forecast risk recurrence based on community recurrence reports or resource allocations for proactive maintenance. The existing platforms and analytics approaches lack real-time community-based data for analytic-driven preventive measures.

To address these research gaps, we proposed Urban Alert! data model to connect community reporting, data management and analytics to improve proactive disaster management in environmental risks. Urban Alert! also addresses these gaps by encouraging public engagement in reporting system for proactive disaster management. In the following section, we will present our proposed Community Fault Report Conceptual Model, named Urban Alert! that motivates these research gaps.

METHODOLOGY

In this research, we have divided the research methodology into several phases. The research project applies to both quantitative and qualitative methods. The quantitative methods are implemented during data collection through the evaluation phase. The initial step involves conducting a comprehensive review to identify research gaps in the existing literature on fault reporting systems and methodologies in several domains. Based on the identified gaps, it will motivate us to come up a user survey to identify further factors that influence the public engagement towards community-based reporting with random respondents and analyzing the collected data using BI approach.

The analysis is validated by identifying the research gaps from the insights collected from the literature and survey analysis. This analysis is used further to improve the proposed data model. The conceptual model is first designed, named Urban Alert! This phase also defines the architecture, user interfaces, and functional

requirements of the prototype model for implementation. The design process focuses on ensuring that the system is seamlessly accessible across different devices (i.e. mobile, desktop, and web) and is capable of accurately capturing location data and user-submitted fault details.

After the design of the model is completed, it is implemented as a system prototype. The prototype is being tested in selected areas nearby for data collection. This data includes geo-location coordinates, frequency of reports and types of issues reported. Additionally, we will use social media platforms to identify the occurrences of fault issues in nearby areas. Although this phase does not actively collect data from the public, the system's ability to accurately collect and store data is tested. The collected data is cleaned through a data cleansing pipeline process to improve data integrity. We analyze using Business Intelligence (BI) and Machine Learning (ML) tools. The analysis focuses on creating dashboard reports, map analysis and predictive models to visualize the distribution and frequency of reported faults, all based on quantitative data. These visualizations help identify patterns and trends and provide insights into areas that require immediate attention.

Both quantitative and qualitative metrics are used to measure the efficiency of the prototype model, such as the number of reports submitted, accuracy of geo-location data, response times, resolution rates, BI and ML analysis rather than long-term operational performance. Additionally, predictive analysis are carried out based on the data collected to identify potential problem areas and forecast future occurrences. This analysis will demonstrate the ability of the prototype to support proactive measures for disaster management. Finally, the evaluation and validation take place in which we evaluate the results of the analysis carried out by Urban Alert! After the evaluation and validation phase, the analysis results are documented and published. In the following section, we shall elaborate the Urban Alert! data model, encompassing the conceptual model, architecture and user interaction model.

Table 2 describes the research design steps taken in this research project.

Table 2. Methodology Steps

| No. of step | Research Method | Description |
|-------------|--------------------------------|--|
| Step 1 | Focus database search | <ul style="list-style-type: none"> - Literature review on community fault reporting systems and data management analytics in fault reporting - Identified gaps in trust, usability, transparency, and proactive measures |
| Step 2 | Survey design & implementation | <ul style="list-style-type: none"> - Developed structured questionnaire (25 items) - Collected 120 responses across urban, suburban, and rural areas |
| Step 3 | Survey analysis & validation | <ul style="list-style-type: none"> - BI dashboard analysis using Power BI - Spearman's correlation applied for statistical validation |
| Step 4 | Analysis Findings | <ul style="list-style-type: none"> - Mapped survey and literature findings to determine actionable insights, highlight critical gaps, and synthesize requirements for the new data model |
| Step 5 | Design data model | <ul style="list-style-type: none"> - Formulated the Urban Alert! conceptual model and system architecture, integrating validated factors from previous steps (trust, motivation, usability) as core design requirements |
| Step 6 | Implementation | <ul style="list-style-type: none"> - Deployed the Urban Alert! prototype, collected real-world geo-tagged reports, cleaned and analyzed data, and evaluated system performance (BI/ML analytics, spatial clustering) |

RESULTS

Factors of Public Engagement in Fault Reporting

A survey that has been conducted incorporates the findings of the conceptual model highlights the factors of public engagement in community reporting [39]. The results confirm that trust, intrinsic motivation, and ease of use are the strongest contributors to willingness to report, while awareness and perceived barriers exerted limited or non-significant factors.

These validated factors directly strengthen the conceptual model by emphasizing the central role of trust as a prominent factor for engagement, supported by usability and motivational elements. The survey findings suggested that the model should emphasis on privacy, transparency in reporting feedback, and trust-building mechanisms as foundational design requirements to improve community engagement. However, rather than replacing the main motivators for engagement, strategies addressing awareness campaigns and barrier reduction should be balanced [39].

To further validate these conclusions, the statistical analysis conducted with 120 respondents was used to validate survey results. Spearman's correlation results (as shown in Table 3) [39] demonstrated a highly significant relationship between trust and willingness to report ($\rho = 0.634$, $p < .001$), confirming trust as the most influential predictor of engagement. Motivation ($\rho = 0.204$, $p = .025$) and ease of use ($\rho = 0.182$, $p = .047$) also showed significant, though weaker, positive correlations. In contrast, awareness ($\rho = 0.157$, $p = .087$) and perceived barriers ($\rho = 0.110$, $p = .233$) were not statistically significant.

These results converge with survey results that highlighted trust, motivation, and usability as the key factors influencing engagement, while concerns such as privacy or lack of awareness had less explanatory power [39]. The high degree of convergence of statistical findings from the survey reinforces confidence in these conclusions and highlights the practical importance of building trust, clear system design, and clear privacy protections to encourage community engagement. Hence, the findings concluded that trust as the significant factor for willingness of public engagement.

Meanwhile, the reason both awareness and barriers (e.g. user-friendly interfaces, and user guidance) are non-significant, suggest that the high overall awareness among respondents who lives in urban areas and digitally literate, may have contribute to ceiling effects, reducing variance and obscured its impact. Without a corresponding belief in effectiveness, awareness alone might not result in action, suggesting that knowledge is required but not enough for engagement. When trust and motivation are taken into consideration, privacy and procedural concerns did not predict engagement behavior, indicating that strong motivators is necessary may be able to overcome perceived barriers [39].

Table 3. Spearman's rho Correlation Analysis Result [39]

| <i>Spearman's Correlations</i> | | | | | |
|---|-----|----------------|--------|--------------------------|----------------|
| Variables | n | Spearman's rho | p | Effect size (Fisher's z) | SE Effect size |
| 1.Willingness - Awareness | 120 | 0.157 | 0.087 | 0.158 | 0.093 |
| 2.Willingness - Motivations | 120 | 0.204 * | 0.025 | 0.207 | 0.094 |
| 3.Willingness - Trust | 120 | 0.634 *** | < .001 | 0.748 | 0.097 |
| 4.Willingness – Ease of use | 120 | 0.182 * | 0.047 | 0.184 | 0.093 |
| 5.Willingness - Barriers | 120 | 0.110 | 0.233 | 0.110 | 0.093 |
| * $p < .05$, ** $p < .01$, *** $p < .001$ | | | | | |

As a conclusion, the statistical findings and the literature reviews provide a foundation for the design of Urban Alert! conceptual model. The significant factors addressed are trust, personal motivations and ease-of-use, including less significant factors are awareness and barriers which directly affect the model design and structure of features. This result reinforces that engagement is not merely dependent on knowledge of reporting systems, but requires confidence in system transparency, internal motivation to act, and intuitive usability to reduce friction in reporting.

Drawing from these results, the conceptual model positions trust as the central construct, supported by motivation and ease of use as complementary enablers of engagement. In contrast, awareness and barriers are retained in the model as contextual elements, but play secondary roles compared to the dominant predictors. This alignment ensures that the conceptual model is both data-driven and behaviourally grounded, offering direct implications for design strategies such as building transparent data practices and feedback loops to strengthen trust, designing user-friendly reporting interfaces to reduce effort and encourage ease of use and cultivating internal motivations.

Incorporating these validated factors ensures that the conceptual model directly addresses the gaps identified in prior systems, which often emphasized awareness campaigns or reporting coverage but lacked mechanisms to foster trust and usability. The model thus serves as the theoretical and practical basis for the subsequent system architecture of Urban Alert!, ensuring that its design is not only technologically robust but also aligned with the behavioural drivers of public participation. Drawing from patterns in the survey (e.g., strong desire for community improvement, concern for public safety), the conceptual model links each system function—report submission, feedback delivery, authority assignment to validate drivers of engagement in the next sub-section.

Conceptual Model

The Urban Alert! system is designed to address the challenges of reporting environmental and infrastructure issues in Malaysia. By providing a platform that utilizes geo-location technology, ensuring accurate fault location capture, it allows users to submit images, providing additional context and evidence to support their reports. Following submission, the report is assigned to the responsible authorities (i.e. Municipal Council, Public Works Department, Department of Irrigation and Drainage, National Energy Limited (TNB) etc.).

The users can monitor the progress of the submitted report's issue resolution, which enhances accountability and transparency. Urban Alert! encourages community involvement and responsibility in maintaining public safety and infrastructure by including the public in the reporting process. Using the UML case diagram, the conceptual model for Urban Alert! is shown in Fig 1. The implementation of this model as a prototype is referred to as Urban Alert! System. Urban Alert! prototype involves four actors interacting with it. Within this system, four distinct actors engage with the Urban Alert! prototype. A breakdown of these interactions is provided below:

- **Communities:** Primary users from the public who alert and report various issues and receive notification about the reports
- **Authorities:** Group of users who are responsible for managing and addressing (i.e. Municipal council, Public Works) the issues reported by the communities
- **Administrators:** A group of authorizers to administrate the system and generate analysis of fault reports received
- **UAD:** a database that stores fault reporting records

We described the activities of the conceptual model in two distinct environments. The initial environment encompassed the action initiated by the actors (i.e. all users) to engage with Urban Alert! System. There are three activities involved in this environment:

- **Report Issue and Notification:** The system begins when a public user from the community reports any fault issues happening in real-time. The user submits a fault report (accessed via their device) to the

Urban Alert! System, which then triggers notifications about the status of their reports received and submitted for further processing.

- **Report Progress Management:** This activity begins once reports are received. Authorities and administrator users can view the status of each report and make necessary changes to it.
- **Generate Reports and Analysis:** An admin-initiated activity to manage reports and generate analysis reports using BI and ML tools.

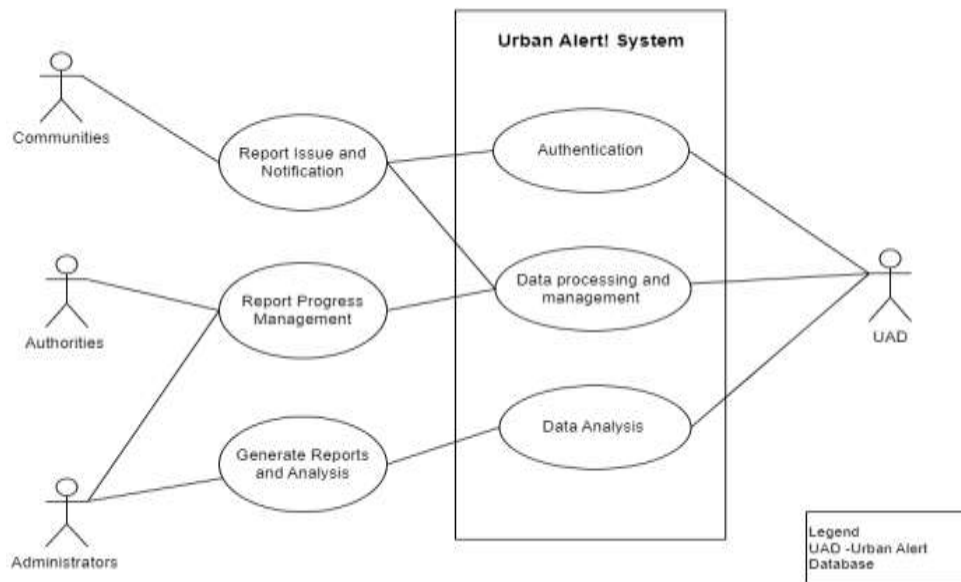


Fig. 1 Urban Alert! Conceptual Model

The second environment is encompassed within the Urban Alert! System. The process in Urban Alert's system components begins with authenticating users (authorities and administrators) before granting them access to the system. For public users, no authentication is needed, allowing for quick and easy reporting. However, some details and information under "Data Processing and Management" must be entered by the community user (e.g., name, phone number, email address, issue report) in order to be able to monitor the status of their report in Urban Alert! directly.

All reports are reviewed by the authorities, who then take appropriate action based on the severity of the risks. This activity manages the reports' status in addition to processing the details of reported fault issues. The "Data Analysis" activity performs analysis using BI and ML tools to analyze the data stored in the database (UAD). This component generates insights and reports that help authorities and administrators make informed decisions regarding proactive measures for urban management.

Urban Alert! Architecture Design

In practice, the Urban Alert! architecture is designed to facilitate efficient reporting of issues through a structured data flow across multiple layers. Each layer plays a crucial role in ensuring the system's functionality, security, and data integrity, as shown in Fig.2 Urban Alert! will be implemented as a web application with responsive features, enabling multiple users to access it seamlessly from their own devices (i.e. mobile, desktop, web browsers) in the access layer. All users will first be verified in the internet layer. However, authentication will only be required for administrators and authorities in order to confirm their identities and grant access to the corresponding processes.

The fundamental functions of the Urban Alert! are managed by the application layer. It includes location capture to pinpoint the exact location of reported issues and data processing to process the input data. This allows community users to submit data via real-time reports from their devices. The data submitted by users is collected and processed by this layer so that it can be stored in the database (UAD) and prepared in the next storage layer. A data cleaning pipeline is included for preparation and cleansing to ensure data accuracy and readiness for

further analysis. This pipeline is the prominent component in Urban Alert! as it will determine the data accuracy and integrity through data cleaning processes, which are divided into detail stages.

In the next data analysis layer, the data stored in the database is analyzed by using Business Intelligence (BI) and Machine Learning (ML). Power BI is adopted for data visualization, generating insights, visual map reports, and dashboards. Predictive analysis and insights are generated using machine learning (ML). Both BI and ML analysis are used to identify high-risk and risk-prone areas for proactive measures. Finally, the system's output components provide a variety of reports that are derived from the analysis.

In the current proposed model, machine learning is applied at an exploratory level using unsupervised learning techniques to support spatial risk pattern identification and fault clustering. Clustering methods are considered suitable due to the absence of fully labeled historical fault data and the need to discover latent patterns in community-generated reports. Spatial and temporal attributes such as fault type, report frequency, geo-location coordinates, and recurrence over time are used as input features to group fault reports into meaningful clusters representing potential risk-prone areas.

These comprise analysis reports for detailed insights, map reports to show visualization and identify geographic distribution issues, and raw reports for use in additional manual analysis. Additionally, raw reports can also be exported from the database, managed by Data Exporter as a middleware application to facilitate data exports. These outputs help authorities and administrators make informed decisions regarding proactive measures for urban management. In the next section, we will present the design of Urban Alert! interface web application.

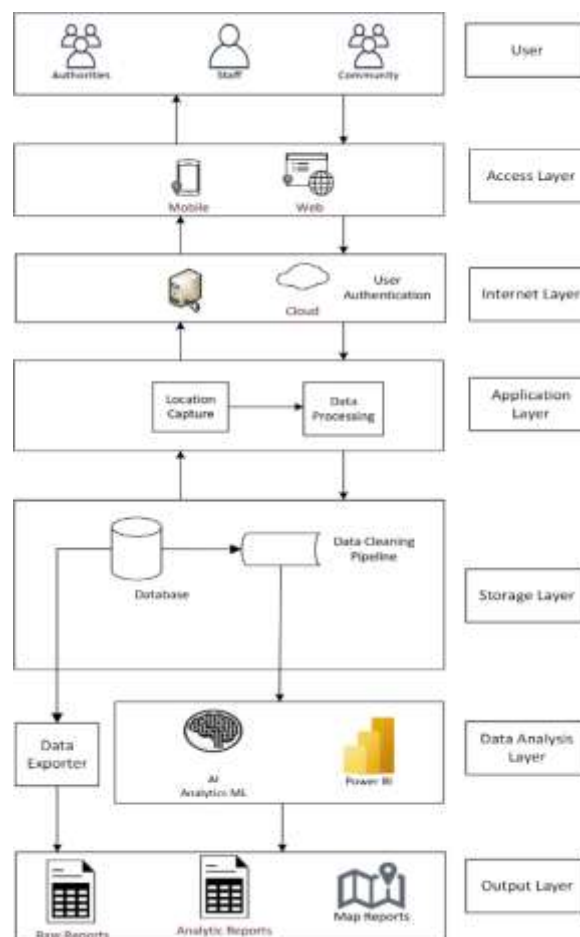
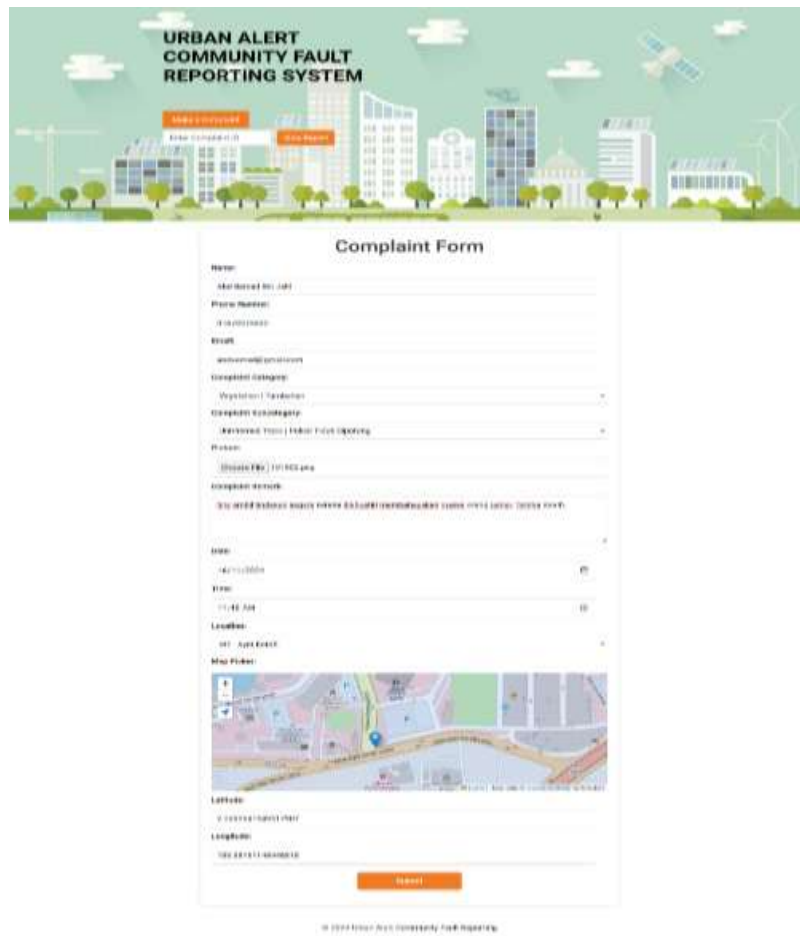


Fig. 2: Urban Alert! Architecture

User Interaction Model

In this paper, the user interfaces of Urban Alert! web application will be introduced. The user interface (UI) for the web application is developed using PHP language with the latest HTML bootstrap to ensure responsive compatibility with multiple platforms (web, mobile, and desktop version). This is intended to improve user

access to the platform from their own devices whenever they need to report a fault issue nearby. Figure 3 until Figure 5 shows the design of the user interaction model for the Urban Alert! web application.

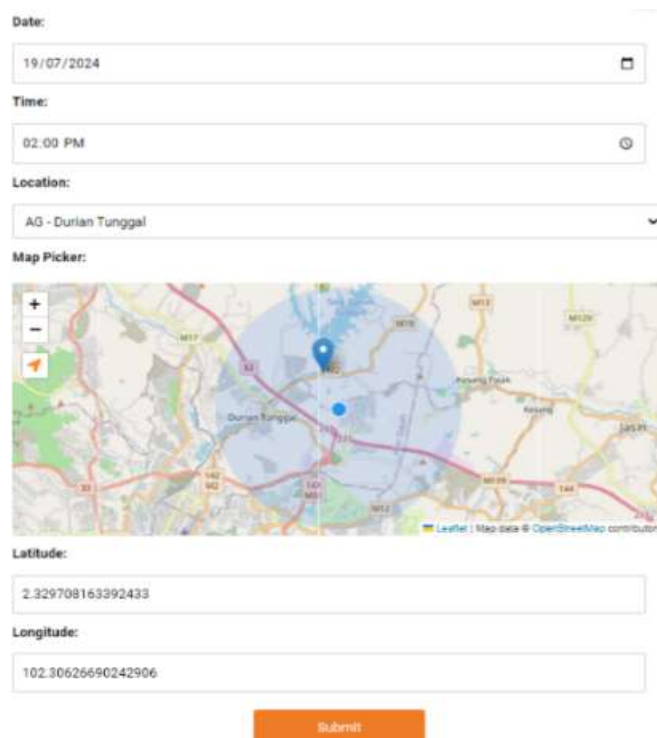


The image shows the main page design of the Urban Alert! web application. At the top, there is a header with the title "URBAN ALERT! COMMUNITY FAULT REPORTING SYSTEM" and a background illustration of a city skyline with a satellite in the sky. Below the header, there is a "Complaint Form" with the following fields:

- Name:
- Phone Number:
- Address:
- Complaint Category:
- Complaint Subcategory:
- Complaint Description:
- Complaint Status:
- Complaint Date:
- Complaint Time:
- Location:
- Map Picker:
- Latitude:
- Longitude:

At the bottom of the form, there is a "Submit" button. Below the form, there is a footer with the text "© 2024 Urban Alert! Community Fault Reporting System".

Fig. 3: Urban Alert! Main Page Design



The image shows the "Capturing Location Design" section of the Urban Alert! web application. It includes the following fields:

- Date:
- Time:
- Location:
- Map Picker:
- Latitude:
- Longitude:

At the bottom of the form, there is a "Submit" button. The map picker shows a map of Durian Tunggal with a blue pin indicating the location.

Fig. 4: Capturing Location Design



Fig. 5: BI Dashboard Design

DISCUSSION

Based on the reviews of existing community fault reporting systems, such as SeeClickFix, Citizen's Eye, MyCityReport, FixMyStreet, SISPA, and MyJalan, these applications consistently highlighted several key limitations: reliance on manual processing, fragmented user operation and engagements, absence of predictive analytics, and reactive actions rather than proactive management of reported faults. The literature also emphasized the challenges of data inconsistency, lack of integrated business intelligence (BI) tools, and minimal use of advanced analytics for proactive risk identification and resource prioritization for recurring faults.

These findings are further supported by the quantitative validation carried out by [39], confirming that existing systems, in particular those with limited feedback transparency and low user engagement are directly correlated with a decrease in trust, motivation and usability, as confirmed by the strong positive correlation results of Spearman's rho Correlation Analysis [39]. By mapping critical reviews to our survey and statistical findings, we verify that the weaknesses identified in the legacy systems are not only subjective but also systematically reflected in user perceptions and engagement data. The literature also highlighted the need for transparency in the status tracking, geospatial reporting and integrated analytics approaches of the proposed Urban Alert model.

Although the existing systems claimed to encourage community involvement, their lack of predictive mapping and automated data cleansing leads to ongoing service delays and poor use of the reporting data. Furthermore, most platforms is revealed that they do not use spatial clustering or multi-source data integration for proactive risk management. The survey findings in [39] also show that raising platform accessibility or system awareness is insufficient to increase community engagement thus, this consistently mapped with the literature findings of public outreach strategies. By integrating strong BI tools and dynamic user feedback systems, Urban Alert can address both analytical and operational gaps found in the literature to improve proactive disaster management strategies.

We discovered that the literature and survey findings support a set of priorities for future system implementation to incorporate integrated spatial analytics, pipelines for automated data processing, and status tracking as key components to improve user engagement in community reporting. This may increase engagement and feedback of users based on the established relationship between trust and motivation. The improved interaction model in Urban Alert is simplified and should be adapted to improve usability and motivation, especially to users from varied age groups. Through Urban Alert, it could lead to a full response to the opportunities and weaknesses described in recent literature and confirmed by the user survey analysis.

In order to address ethical and governance issues pertaining to extensive community data collection, Urban Alert! integrates privacy-aware design principles. To diminish the exposure of sensitive information, personal identifiers are minimized and report visibility is limited to authorized stakeholders. Rather than being made public, geolocation data is only utilized for risk analysis and decision support. To improve trust and governance,

future deployments will further enforce adherence to national data protection laws and role-based access control systems. Maintaining public participation and guaranteeing responsible use of citizen-generated data depend on addressing these factors.

Limitation and Future Work

Although the architecture and conceptual model of Urban Alert! show potential to improve for community-based fault reporting, several limitations are noted. The current work mainly focuses on proposed model design and preliminary user survey analysis, to determine the factors influencing public engagement. The evidence of operational effectiveness is still limited because empirical validation through large-scale deployment and real-world data analysis has not yet been carried out. In future work, we will extend this work to address practical issues identified during the implementation and evaluation of the prototype to improve these limitations.

The limited scale of real-world deployment also limits empirical performance evaluation, such as classification accuracy, confusion matrix, and predictive reliability, although the prototype shows that integrating community reporting with BI and ML analytics is feasible. Therefore, these performance metrics are positioned as part of future work that will be assessed through long-term data collection and widespread municipal deployment.

In order to gather operational fault data for an empirical assessment of proactive and recurring risk management, a full-scale prototype deployment will be carried out throughout local municipalities. During the deployment phase, the architecture of the system will be thoroughly tested in real-world environments, providing data to validate the BI analytic pipeline and ensuring seamless operational management of fully functional Urban Alert! prototype. These extensions will transform the current conceptual model into a ready platform for proactive disaster risk management. Future extensions also may integrate IoT-based sensor data (e.g., flood level, rainfall, or infrastructure monitoring) with community reports to enhance predictive accuracy and early warning capabilities.

CONCLUSION

In conclusion, we presented the motivation for this work and identified gaps pertaining to existing fault reporting systems and analysis studies of data management in analytics in reporting applications. We also introduced the Community Fault Reporting Model as Urban Alert! System prototype. The results of this research project will contribute to Sustainable Development Goal 11 (SDG 11), which focuses on Sustainable Cities and Communities. This project aims to make cities and human settlements inclusive, safe, resilient and sustainable by improving fault reporting in proactive disaster management.

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