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An Incident Management System for the Police Force

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Abstract

In our modern era, where advancement in healthcare and technology have greatly contributed to the increase in the world population, the resilience of police Incident Management Systems, especially traditional ones, is being questioned. This is especially relevant as incident rates rise as a direct consequence of population growth. In this context, factors such as prioritization, response time and optimum use of already scarce resources at disposal of police forces become critical. While some of these aspects are already being addressed to some extent, this paper leverages technologies such as Robotic Process Automation (RPA), Geographic Information Systems (GIS) as well as Business Intelligence (BI) for visualization and Artificial Intelligence (AI) for prioritization to assist in Incident Management and Response. The aim of this paper is to critically analyze several existing incident management systems and propose a system prototype that uses a centralized database to cater everything from incident reporting from the citizen's perspective to its resolution across several actors. The system was evaluated through a survey targeted at Mauritian citizens. The paper concludes by presenting feedback on the system prototype and pave the way for future works. The feedback gathered highlights the public's enthusiasm for the implementation of such intelligent technologies, with many believing it would significantly enhance their incident reporting experience.

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I. INTRODUCTION

It is undeniable that the police forces play an utmost important role in the societies worldwide. Their responsibilities encompass maintaining public safety, preventing and investigating crimes as well as maintaining public order through law enforcement [1]. One of their major duties is responding to calls and assisting people in need, whether through direct solicitation or emergency hotlines. However, the ever increasing demands on these hotlines pose a significant risk of overwhelming the services due to the growing population.

One notable instance occurred in 2020 in the UK, where inconsistencies in emergency hotlines caused a major surge in the main 999 emergency hotline, leading to a high volume of dropped calls [2]. This incident highlights the need for more robust systems to enable police forces to respond more effectively to calls, investigate crimes and extend their help to vulnerable members of society. The advent of new technologies has significantly transformed police operations, with digital data opening avenues for enhanced analytics and better strategic resource deployment [3].

Moreover, there is a critical need for improved methods of dispatching resources beyond the traditional approach used in the UK, which involves a dispatcher handling calls indiscriminately [4]. This method often results in delays, particularly when addressing high-priority requests from the public. Efforts to implement more intelligent policing systems are underway globally. A notable example is the Emergency Policing and Incident Command (EPIC) system implemented in Cape Town, which has increased public safety through a unified control platform, an interactive map, and real-time tracking of vehicle and resources [5].

This paper proposes a prototype for an incident management solution for the police force that leverages several technologies such as Geographic Information System (GIS), Robotic Process Automation (RPA), Artificial Intelligence (AI) and Business Intelligence (BI). A Systematic Literature Review (SLR) has been conducted to gather insights on existing incident management processes and systems alongside the use of AI. The prototype has been developed using agile methodology and evaluated with members of the public through semi-structured surveys.

Section II of the paper discusses the findings of the literature review. Sections III and IV elaborates the proposed prototype, while Section V evaluates the solution's effectiveness. Finally, Section VI concludes the paper.

II. LITERATURE REVIEW

This section presents the findings of the SLR related to Incident Management aspects, existing systems, and the application of Artificial Intelligence in the police operations.

A. Main Components of an Incident Management System

Several incident management systems have been identified in the reviewed literature. Some papers focused on countryspecific scenarios, while others discussed commercial solutions provided by companies. The following section highlights the main aspects of these systems.

The first case study discusses the incident management system of the Finland Police. The three main components most relevant to the Incident Management Process are the VIVRE Network, the POKE Field Command System and a Helpdesk. The VIVRE Network is used by several emergency services in Finland, including fire rescue and emergency units. Its main objective is to facilitate a smooth cooperation among various stakeholders in the operation teams. It serves as the foundation for the POKE Field Command System, which promotes real-time data retrieval and communication through text and status messages. Additionally, the Helpdesk reinforces the system by providing a single point of contact for resource dispatch [6].

Another system is the Emergency Policing and Incident Command (EPIC) system used in South Africa. EPIC incorporates SAP-CRM, SAP Investigative Case Management, EOH CAD, and GIS to create a centralized emergency platform for efficient information sharing during disasters. The system also provides a comprehensive analysis of lessons learned from each incident [7].

The Japanese Disaster Information Management System (DIMS) leverages AI to manage incident response, mostly during natural disasters. Its components include a GIS module, utility status indications, asset management and L-Alert Common Public Information designed for public safety and security. These components are used across different prefectures of Japan as needed [8].

In Mauritius, the police force employs a GIS-based system for mapping and dispatching. This system provides GPS tracking functionalities to optimize dispatching, resource monitoring, area measurement, and surveillance. It is operational in Port-Louis, the capital city, and in Grand Baie village [9].

Several commercial software solutions have also been identified, including Veoci [10], DH4 [11], Dlan [12], Adashi [13] and ArcGIS [14]. Common components found in these systems include GIS mapping, real-time visualization, analytics, resource management, notifications, and database integration. Additionally, Computer Aided Dispatch (CAD) and process automation were frequently observed in at least three or more of these solutions.

It is also essential to allocate the optimal resources to respond to incidents, a task that becomes challenging with manual systems. Automated systems can significantly enhance decision-making by providing more informed and efficient resource allocation [4].

B. Use of AI in Incident Management and Emergency Response with a focus on Police Force

This section elaborates the application of AI in incident management.

Most of related works in this field focus on the applications of computational intelligence (CI). For example, decision trees are employed for task classification, and Artificial Neural Networks (ANN) have been identified as potential tools for managing complex incident responses. Genetic algorithms also play a role resources optimization and emergency management [15]. Additionally, Case-Based Reasoning (CBR) systems have been explored for managing resources, assessing risks and making informed decisions [16].

When it comes to the use of AI in policing for incident management, research is relatively limited. Most AI applications in this area are concentrated on predictive policing or crime anticipation systems, utilizing machine learning (ML) [17]. Classification methods applied to police records, with a focus on determining incident priority, are also a key area of interest. The performance of algorithms like Naïve Bayes, Support Vector Machine (SVM), XGBoost and Random Forest has been evaluated in various studies [18]. In the Netherlands, the police utilize a triage system and specialist agents to assign incidents, logged through text, to the appropriate response teams[19].

C. Challenges in using AI in the Police Force

The use of AI in the incident management process presents both technical and ethical challenges. One major concern is the potential for racial and ethnic biases in crime anticipation systems, often stemming from biased datasets [20]. Another challenge is the public's trust in AI. A survey conducted in the United Kingdom revealed that participants trusted the decisions made by police officers more than those made by algorithms, especially concerning fairness and the allocation of resources [21].

D. Conclusion

The findings of the SLR reveal several important aspects of incident management systems worldwide. Many studies emphasize the use of GIS mapping, CAD, notifications, and resource optimization. Some countries have already implemented these technologies to enhance their incident management processes. However, research on the application of AI in policing remains sparse., with most studies focusing on expert prediction and anticipation. Although several theoretical application of AI have been proposed, practical implementations are still rare. Process automation is also emerging as key feature in commercial solutions, but comparative studies on intelligent incident management systems are still lacking. This scarcity may be attributed to the novelty of these technologies in the context of incident management and policing. Nevertheless, classification methods for prioritization and triage show promise and could significantly enhance the incident management process in the future.

III. PROPOSED SYSTEM

This section describes the prototype system, which consists of three main actors (user groups) and different functionalities. The actors are as follows:

- Reporting User

This actor represents the general population, who report incidents through the system for police attention.

- Controlling Officer

A designated officer oversees the system, monitoring the status of incidents and taking appropriate actions when necessary.

- Police officer

Police officers are dispatched along with necessary resources, such as vehicles, to respond to incidents reported by users.

The architectural of the proposed system is illustrated in Figure 1.

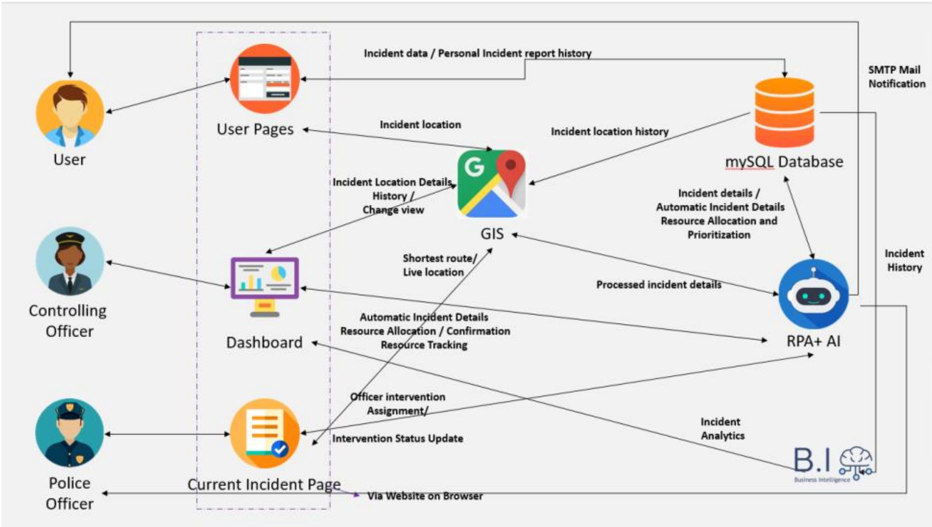

Figure 1. Architecture Diagram for Proposed System

The functionalities of the proposed system are:

- Website
  The website allows reporting users to enter details locations of incidents.
- Dashboard

The dashboard is tailored for the Controlling Officer and provides four main functionalities:

1. Visualization of ongoing incidents, with the ability to manually manage incidents by adjusting priority levels and resources assigned.
2. Real-time visualization of dispatched resources, including their exact locations.

.

- GIS Module

The GIS Module is used to handle location details; while reporting incident from user perspective, displaying of incident and resource locations on the dashboard and route suggestion for attending the incident.

- RPA and AI

To promote a more streamlined approach, the incident management process is carried out by RPA. The incident reported is classified according to its priority level using a joint AI module in the RPA workflow. The system tracks which officers are on duty at any specific time. The first aim of the RPA module is updating the availability of officers according to their shifts and availability. It also classifies incidents based on the jurisdiction of the nearest police post using the Haversine Formula, which calculates distances using coordinates. The AI module estimates the number of officers needed for each incident, and resources are dispatched accordingly. Finally, the RPA module is responsible for sending email notifications, such as when a

3. Recording incidents reported via emergency hotlines for users who prefer phone communication.
4. Analytics and filtering of past incidents for improved insights.

- Police Officer Page

The Police Officer page offers a unique view for each officer assigned to respond to an incident. This page includes details of incident, information about other officers and resources (e.g., vehicles) assigned to the same incident and a suggested route to the incident location. Officers can also update the incident status, which in turn notifies both the Controlling Officer and the Reporting Officer.

police officer is assigned to an incident or when the Reporting User opts for status update.

- BI

BI tools are used to analyze history incident data, providing graphical visualizations and filtering options for stakeholders to gain more insights.

- Centralized MySQL database

The MySQL database serves as the central repository for all data related to incidents, users, and officers, supporting the overall incident management process.

IV. DEVELOPMENT OF PROPOSED SOLUTION

This section summarizes the different steps undertaken during the development of the proposed solution.

A. Analysis and Design

The Swimlane diagram in Figure 2 illustrates the key aspects of the proposed solution, highlighting the interactions between the actors and the process of incident prioritization.

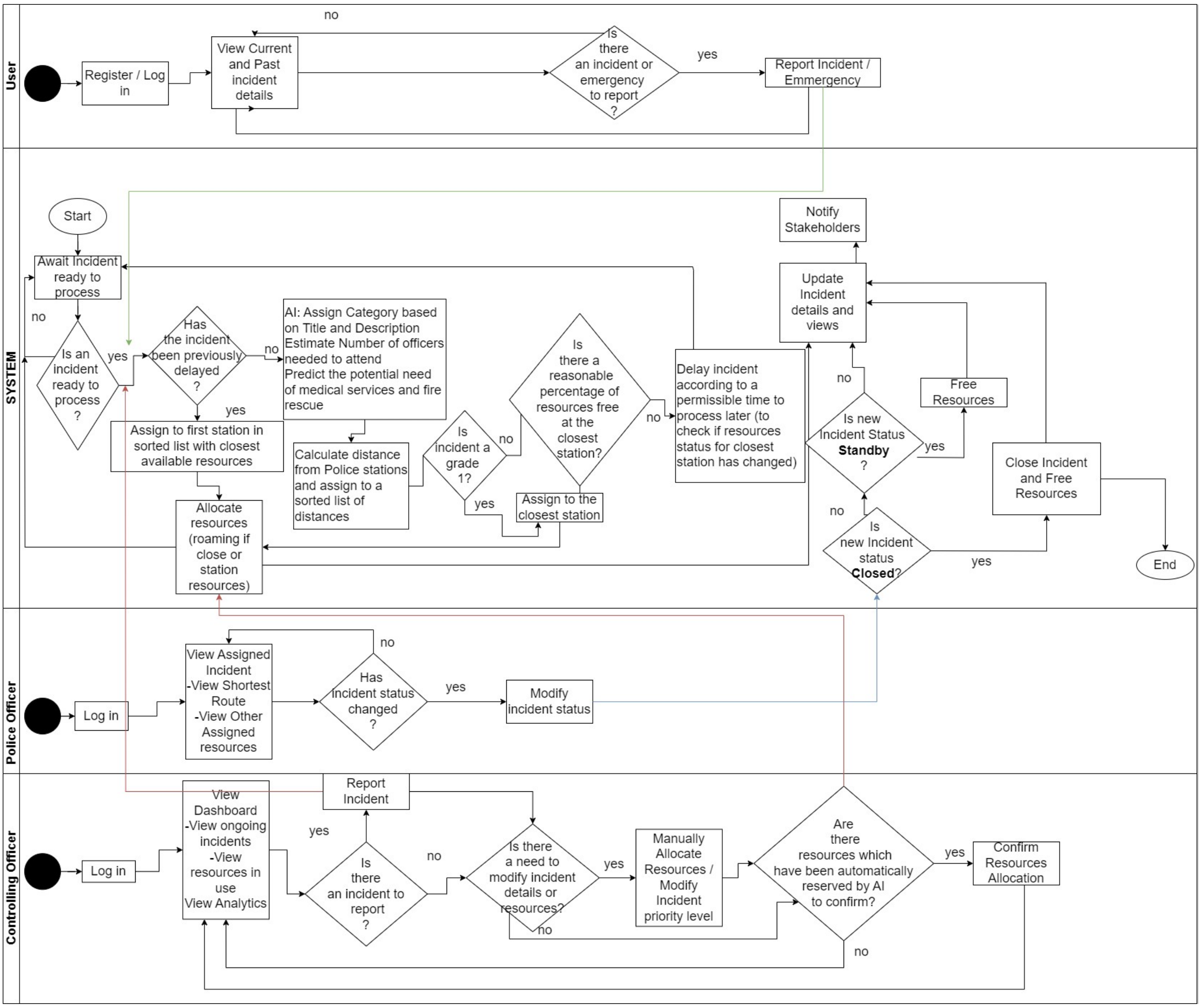

Figure 2. Swimlane Diagram for the Overall Incident Management System

To prioritize incidents, four classes for priority levels were identified: Grade 1, Grade 2, Grade 3 and Grade 4. Grade 1 represents the highest priority, requiring immediate action, while Grade 4 indicates the lowest priority. The AI classifier is responsible for predicting the priority level of each incident, and the system responds according to the estimated priority. A summary of these priority levels is provided in Table 1.

Additionally, the AI is designed to automatically allocate resources and predict the need for medical and/or fire rescue services based on the description of the incident, as shown in Figure 2.

B. Implementation

The following tools were used for implementing the prototype:

-Visual Studio was used for coding of the web pages and implementing the associated logic.

-MySQL Workbench served as the centralized database, storing information about incidents, users, officers and police stations, ensuring the smooth running of the system.

-UI Path Studio [22] was used to streamline processes via RPA. It was responsible for sending email notifications to the concerned users and setting up a basic shift system for police officers, allowing the system to account for their availability.

Table 1
Grade Descriptions of Incidents for Prioritization

Priority	Type of Response	Characteristics
Grade 1	Immediate	-For life threatening situations -Emergency assistance -Offenders still in close perimeter of crime scene -Larceny
Grade 2	Prompt	-When resources not immediately available -Immediate response not required
Grade 3	Delayed	-For non-top priority cases
Grade 4	Recording	Complaints only for recording purposes

-Google Maps was integrated to handle the GIS aspects, such as location management and maps visualization.

-Tableau was used for the BI analytics and visualization, connected via Google Sheets to streamline data flow.

Agile Development Methodology was adopted, using an iterative and incremental approach to feature development and prioritization.

C. Synthetic Data Generation

Given the lack of existing data and the confidential nature of the problem domain, synthetic data was generated for training the AI models. This process was carried out using simple prompts [23], via Davinci-003 text engine. The data generated through Davinci-003 was manually validation and later fed into Gretel AI to produce a larger dataset.

The following prompt was used for Davinci-003:

Given {categories_description}, {type} generate fictional 999 report, number of officers needed and fire rescue or medical services required given {services_description}

The categories description refers to the list of incident priorities and their description; type refers to potential incident types, such as riot, larceny, murder. Services_description outlines the case scenario for medical and fire rescue services.The generated data was stored in CSV format with the following fields: ‘incident description’, ‘category’, ‘type’, ‘number of officers’, ‘fire rescue yes or no’, ‘medical services yes or no’.

Due to limitations on the OpenAI API key, the initial data set generated through Davinci-003 was validated and further expanded using Gretel AI. As a result, a total of 7,264 data records were obtained.

D. Training of AI Models

AI models were trained using Naïve Bayes to prioritize the incidents, estimate the number of officers required for incident response and whether medical and/or fire rescue services will be needed throughout the intervention, providing additional insights for decision-support.

Before training the classifier models, basic text processing steps, including stop words removal, lemmatization and use of TF-IDF were applied [18].

Figure 3 illustrates the overall model training steps involved in training the AI models.

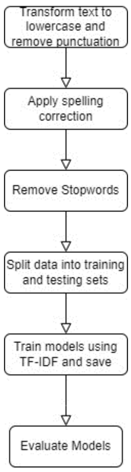

Figure 3. AI Models Training Steps

In the training process, 70% of the data was used for model training, while 30% was used for testing. The records were randomly assigned to either the training or testing datasets.

E. Evaluation of AI Models

Several metrics were used to evaluate the AI models. However, since these models were trained using synthetic data, the performance metrics should not be considered fully representative of real-life scenarios. The evaluation metrics and confusion matrices for each model are shown below:

-Grade Classifier
Precision: 0.8229
Recall: 0.8234
F1-Score: 0.819219

Table 2 illustrates the confusion matrix for the Grade Classifier, comparing the model’s predicted grade with the actual grade. Diagonal values represent the correct Grade prediction count for each category.

Table 2
Grade Model Confusion Matrix

		Actual Grade of the Incident			
		Grade 1	**Grade 2**	**Grade 3**	**Grade 4**
Model Prediction	Grade1	**560**	56	59	13
	Grade2	52	**660**	59	2
	Grade3	16	56	**532**	2
	Grade4	11	26	32	**38**

-Number of Officers
Precision: 0.8070
Recall: 0.8197
F1-Score: 0.8061

Table 3 illustrates the confusion matrix for the Number of Officers classifier. The numbers of officers allocated to the incidents, as per the synthetic data, would be 2,4,6 and 8. The correct Number of Officers prediction v/s the Model’s prediction is mapped. Diagonal values represent correct Number of Officers prediction count for each category.

Table 3
Number of Officers Model Confusion Matrix

		Correct Number of Officers			
		2	**4**	**6**	**8**
Model Prediction	**2**	**1483**	45	16	1
	4	130	**160**	46	4
	6	25	42	**110**	6
	8	33	20	24	**29**

-Fire Rescue Classifier
Precision: 0.9497
Recall: 0.9499
F1-Score: 0.9498

Table 4 illustrates the confusion matrix for the Fire Rescue binary classifier The correct Fire Rescue Services Need prediction v/s the Model’s prediction is mapped. Diagonal values represent correct need prediction count for each category, namely correct ‘yesses’ predicted as ‘yes’ and correct ‘nos’ predicted as ‘no’.

Table 5 illustrates the confusion matrix for the Medical Services binary classifier. The correct Medical Services Need prediction v/s the Model’s prediction is mapped. Diagonal values represent correct need prediction count for each category, namely correct ‘yesses’ predicted as ‘yes’ and correct ‘nos’ predicted as ‘no’.

Table 4
Fire Rescue Model Confusion Matrix

		Correct Need	
		yes	**no**
Model Prediction	yes	1541	52
	no	57	524

-Medical Services Classifier
Precision: 0.9239
Recall: 0.9241
F1-Score: 0.9238

Table 5
Medical Services Model Confusion Matrix

		Correct Need	
		yes	**no**
Model Prediction	yes	1268	68
	no	97	741

-Spam Classifier
For this the dataset[24] was used alongside sample of generated incidents for ham.
Precision: 0.9978
Recall: 0.9978
F1-Score: 0.9978

Table 6 below illustrates the confusion matrix for the spam binary classifier. The correct spam prediction v/s the Model's prediction is mapped. Diagonal values represent correct spam prediction count for each category.

Table 6
Spam Model Confusion Matrix

		Correct Spam Prediction	
		spam	ham
Model Prediction	spam	660	0
	ham	2	236

The spam classifier was used in order to increase the admission of legitimate requests and filter out malicious ones. However, the spam incidents are displayed to the controlling officer whereby he can still remove them from spam if ever misclassified and assign resources accordingly.

F. Summary of Evaluation of Models

The evaluation results indicate that binary classifiers for spam, fire rescue and medical services displayed high precision, all exceeding 90%. However, the models were less precise when predicting the grade of incidence and the number of officers needed, although they still achieved reasonable accuracy with scores above 80%. It must be acknowledged that use of synthetic data for such sensitive cases may have impacted the model's performance in terms of metric analysis. Additionally, some classes were underrepresented in the synthetic data generation process, which carried over into the testing splits.

Further tests were conducted by feeding sample incident descriptions into the models. In most cases, the models accurately predicted the grades and number of officers, with occasional deviations where the predicted grade was within 1 level of the correct grade or number of officers was within 2 of the actual estimate. Given that the system allows manual modification of predicted fields as a safeguard, the models were retained.

G. User Interfaces

This section showcases some of the user interfaces for the user, controlling officer, and police officer, with the main features are highlighted.

- User

Figure 4 illustrates the sign-up interface on a mobile view for the user.

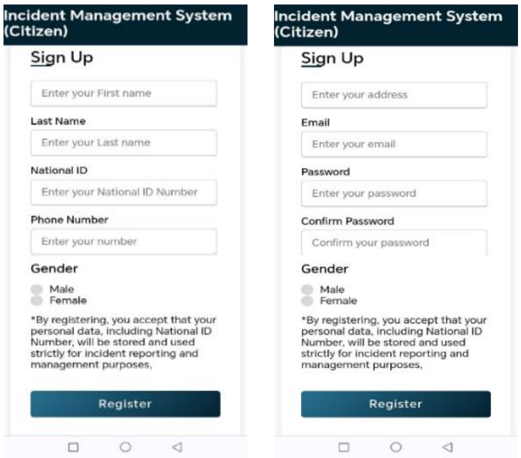

Figure 4. Sign Up Screen for Citizen

A logged-in user can access on-going and past reported incidents, as illustrated in Figure 5.

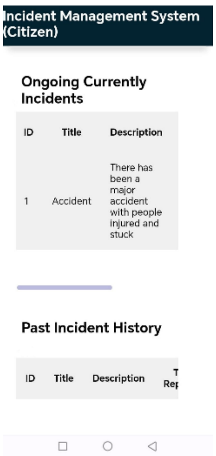

Figure 5. Ongoing and Past Incidents Report for Citizen

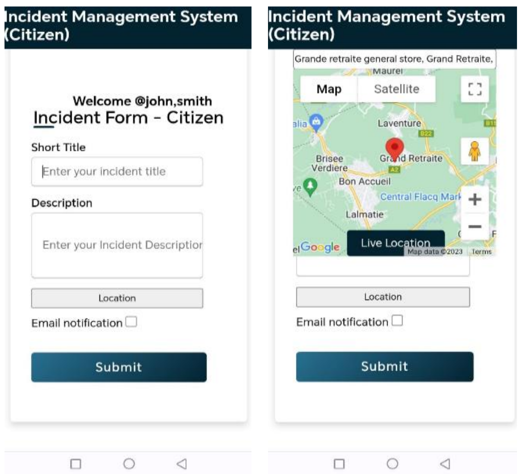

Figure 6. Ongoing and Past Incidents Report for Citizen

The user can select the incident location in three ways:
- Pinpoint the location on the interactive map.
- Opt for live location with the live location button
- Search a location using the search bar.

This is illustrated in Figure 6.

On this page, the user can also request to reopen a past incident, providing a justification, as illustrated in Figure 7. If the user does not have an account but wishes to report an incident, they can bypassing the sign-up and login process via an emergency form, as illustrated in Figure 8.

- Controlling officer

The controlling officer has four main pages in the dashboard: The on-going incidents illustrates details about current incidents, spam incidents, and request to re-open incidents, as illustrated in Figure 9. Clicking on an incident opens a modal window where incident details can be updated, automatic resources targeted by system validated or manual resources can be allocated, as illustrated in Figure 10. This functionality also applies to re-opened incidents and misclassified spam incidents. Additionally, the resources page allows live tracking of police officers and vehicles, displaying their information as illustrated in Figure 11.

Figure 7. Re-Opening Request of Closed Incident from Citizen

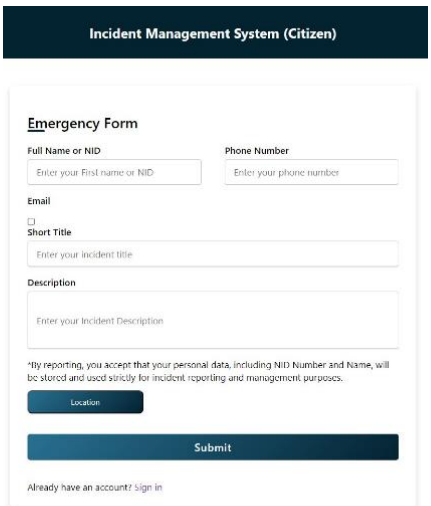

Figure 8. Emergency Report Form to By-pass Sign Up and Log In for Citizen

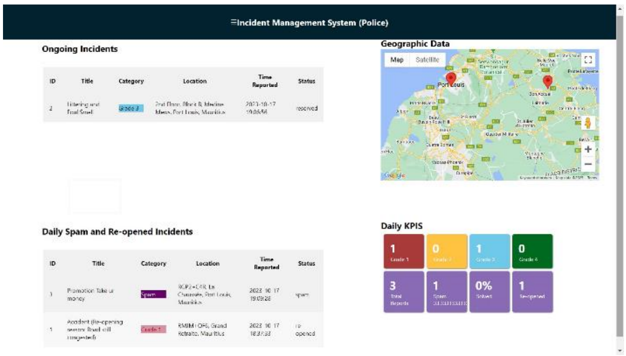

Figure 9. Ongoing incidents, Spam and Re-Open requests for Controlling Officer

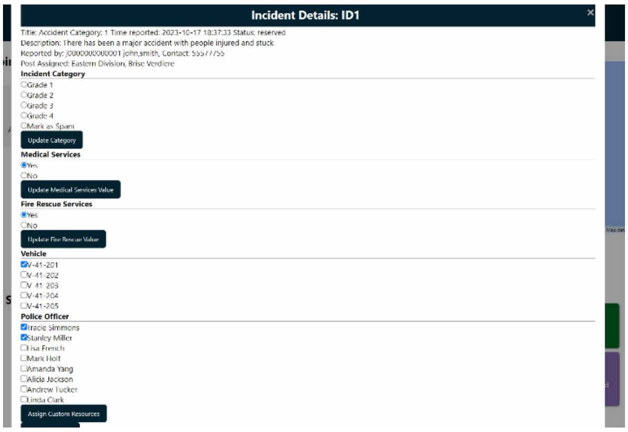

Figure 10. Modal to Display Additional Incident Details and Further Actions

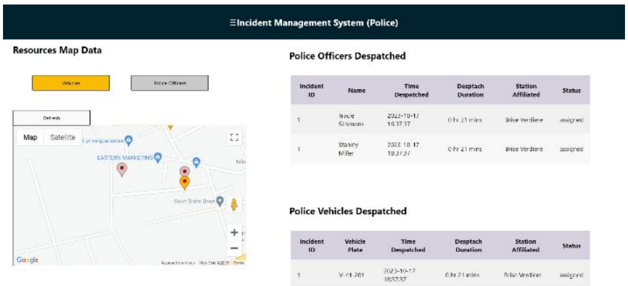

Figure 11. Resources Page to track Dispatched Resources Locations

The incident report page allows the controlling officer to manually input details for incidents reported via phone calls, as in Figure 12.

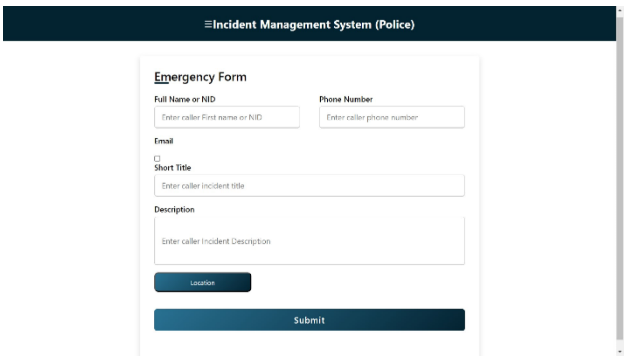

Figure 12. Emergency Form for Controlling Officer to key in call details from hotlines

The analytics page displays past incidents history using an embedded Tableau dashboard with filtering options, as shown in Figure 13.

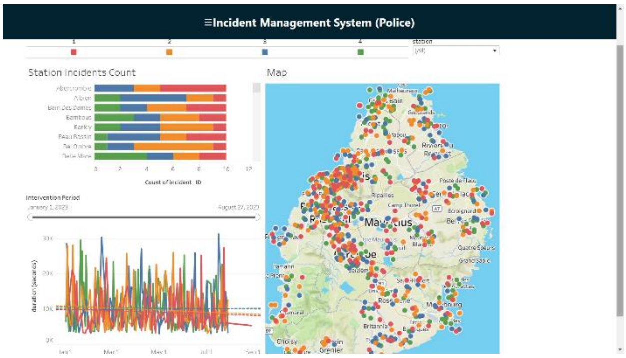

Figure 13. Analytics and Filtering abilities using Tableau BI for Incident History

- Police Officer

After logging in, the police officer can view incidents assigned to him, as illustrated in Figure 14.

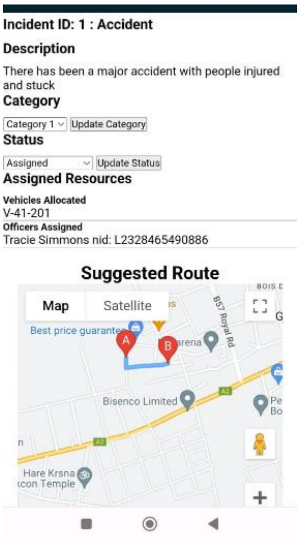

Figure 14. Police Officer Page to attend to Incident

The police officer can see and update incident details and status, view other resources assigned to the same incident, and access a suggested route to the incident location.

H. Testing

Three testing methodologies were initially carried out during the development process, namely unit testing during implementation of sprints, integration testing across modules and system testing to validate all features and ensure proper functionality.

V. EVALUATION

A survey was conducted targeting the general public of the Republic of Mauritius, during which the features of the system their interfaces were demonstrated. Participants were asked for their opinions on various aspects of the system. The survey was administered using Google Forms and shared through social networks. Hence, no specific demographic was chosen. This section presents the findings of the survey.

A. Survey results of the general public on the system

A total of 69 responses were collected from the participants of varying age groups, as displayed in Figure 15.

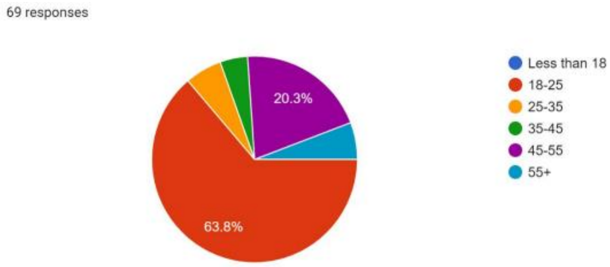

Figure 15. Age details of surveyed persons

Participants were asked about four main aspects of the system, in addition to demographic information:

- Use of the web interface to report incidents
- Reporting and other user actions in the system
- The Incident Management Process of the system
- Their overall experience and perception of the system

Figure 16 illustrates participants' comfort level with reporting incidents via a website form.

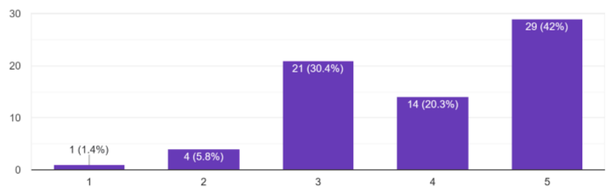

Figure 16. Readiness to report incident by web form

Several questions were asked to gain the perception of the public on incident reporting and other user actions within the system. These questions are summarized in Table 7, with an associated code for reference. Figure 17 illustrates the results. Participants were also asked about their views on the system's incident management process. The main questions are summarized in Table 8, with corresponding codes for ease of reference. Their overall experience and perception of the system were recorded as outlined in Table 9.

Table 7
Questions on Reporting of Incidents and User Actions

Question details	Code
Ease of filling up sign up and log in forms	R01
Ease of filling incident details forms	R02
Ease of selecting incident location	R03
Satisfaction on seeing their current incidents and status	R04
Satisfaction on seeing their past incidents history and being able to re-open an incident	R05
Satisfaction with email notifications	R06

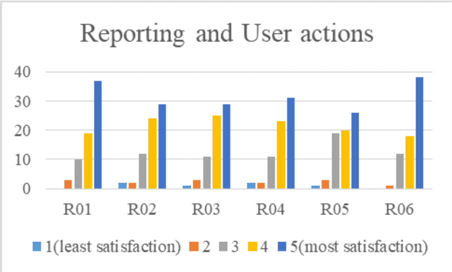

Figure 17. Results of Questions on Reporting of Incidents and User Actions

Table 8
Views on the Incident Management Process of the System Questions

Question details	Code
Views on automatic post assignment, automatic resource allocation, and AI use for prioritization	P01
Use of AI to predict need for medical and fire rescue services	P02

Figure 18 illustrates the results. The results for the first three questions are shown in Figure 19 and Figure 20 shows the results for question E04.

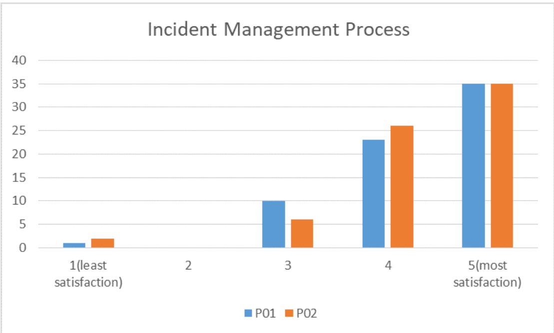

Figure 18. Results of Incident Management Process of the System Questions

Table 9
Questions on overall experience and perception of System

Question details	Code
Agreeing to share some personal information for proper incident management	E01
Including AI in incident management process	E02
Overall satisfaction with developed features	E03
Features of the system that most caught their attention	E04

A. Summary of findings for General Public survey

A survey results indicate that the system was well-received by the general public across different age groups, particularly in terms of the user interface and system processes.

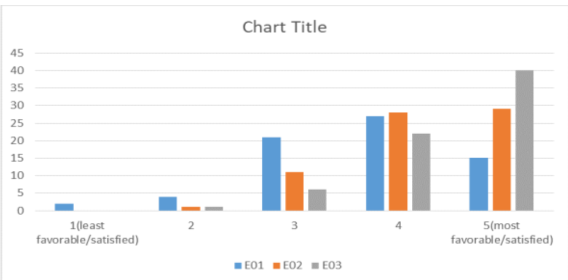

Figure 19. Overall experience and perception results part 1

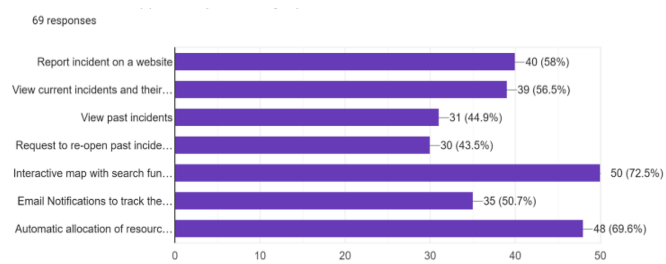

Figure 20. Overall experience and perception part 2

A vast majority of participants were comfortable with the inclusion of their personal data in the system for smoother incident management. They also showed minimal resistance to the application of AI in the overall process. The most attractive features to the participants were the interactive map for selecting the incident location and the system's automatic resource allocation capabilities.

VI. CONCLUSION

The paper demonstrates the application of several innovative technologies in the field of incident management in policing through a prototype system. As evidenced by the surveys conducted among citizens, the system was positively received, with participants acknowledging the importance and potential benefits of implementing such intelligent systems. The paper highlights a smooth and symbiotic implementation of RPA, AI, GIS and BI technologies in incident management, which could address several challenges currently faced in the incident management process.

There is a noticeable lack of studies pertaining to the implementation of these technologies in policing-related incident management. Most of the available literature tends to cover predictive policing. Furthermore, training AI models for this system requires access to descriptive incident reports, which were not readily available due to the confidential and sensitive nature of such data. As a result, synthetic data the path for synthetic data was used for training, but this data may not fully represent real-world situations, limiting its precision.

As future work, the system could greatly benefit from a more advanced user interface designed for a broader audience, including senior citizens, individuals with special needs and non-literate users. For example, AI could be used to allow direct voice capture of incident reports. The system could also expanded to support for multiple languages. Moreover, it would be valuable to gather feedback from policing bodies to validate the viability of such a system. While the AI models have been designed to prioritize incidents through categorization, optimizing resources in high-volume situations, the lack of real-world data limited testing to smaller incident samples. Access to real incident would significantly improve the system's AI models, helping to better evaluate its performance. Real data on incident frequencies, categories and corresponding resource availability, in collaboration with policing bodies, would facilitate more accurate stress and strain testing through simulations.

Additionally, the implementation of a centralization incident management system could be extended to include other stakeholders such as fire rescue and medical aid services. This would allow a central point for information exchange, improving the pace at which information is retrieved and processed. Such a system could contribute to more efficient incident management and faster response times for all involved stakeholders.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of the paper.

AUTHOR CONTRIBUTION

The authors confirm contribution to the paper as follows: study conception and design: Fabien Seevatheean and Zarine Cadersaib; data collection: Fabien Seevatheean; analysis and interpretation of findings: Fabien Seevatheean; draft manuscript preparation: Fabien Seevatheean and Zarine Cadersaib. All authors had reviewed the findings and approved the final manuscript.

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