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A Digital Framework for Flood Management: Integrating Machine Learning into Mobile Applications for Enhanced Emergency Coordination: A Case Study in Aceh, Indonesia

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Abstract

The escalating frequency and intensified magnitude of flood disasters, exemplified by the catastrophic events in Aceh, Indonesia, between 2023 and early 2026, have exposed critical vulnerabilities in traditional, reactive emergency management systems. Current frameworks often suffer from information blackouts, misaligned resource allocation, and a "one-size-fits-all" approach that neglects vulnerable populations. This study proposes SIAGA, an innovative mobile-based information system developed through a design science research (DSR) paradigm to optimize post-flood recovery. The methodological framework of this study is built upon a case study of Aceh, Indonesia. The system integrates a sophisticated multi-layered architecture: a machine learning (ML) engine adapted for automated disaster scale determination with explainable AI (XAI) for decision transparency, a hybrid multi-criteria decision making (MCDM) layer utilizing a tripartite weight synthesis and technique for order preference by similarity to the ideal solution (TOPSIS) logic for optimized logistics, and a resilient mesh network protocol for decentralized communication in infrastructure-constrained environments. Requirement engineering, conducted via a survey with 31 flood-affected respondents, validated the critical need for automated status determination and optimized supply chains. Results demonstrate that the SIAGA artifact successfully bridges the gap between complex predictive intelligence and tactical field response. By manifesting a high-fidelity interactive prototype, this research provides a scalable, socio-technical solution that enhances community resilience and ensures mathematically optimized resource distribution during humanitarian crises.

Keywords: Design Science Research, Disaster Informatics, Flood Management, Machine Learning, Multi-Criteria Decision-Making

INTRODUCTION

Floods are some of the worst natural disasters characterized by the ability to cause massive socio-economic disruption and mortality rates in the world (Gilga et al., 2025; Yazdani et al., 2026). The major risks associated with these catastrophes are due to their sudden nature and the destructive potential energy of water, which could damage structural foundations and inundate large regions in a short period (Kim & Choi, 2013; Singh et al., 2023). The growing frequency and intensity of floods have therefore posed a major threat to decision-makers across the globe (Dujardin et al., 2025; Wang et al., 2025). The recent figures provided by the Centre for Research on the Epidemiology of Disasters (CRED) illustrate an alarming increase in the lethality of floods with over 7700 casualties reported around the world in 2023 (CRED, 2023). In addition to the human lives lost, the financial losses have been staggering, surpassing the $20.4 billion mark in 2023 (Thakur et al., 2026; W. Zhu et al., 2026).

In accordance with this trend, the increase in hydrological instability has been observed in Indonesia, according to the official statistics of the Badan Nasional Penanggulangan Bencana (BNPB). Thus, 1255 cases of flooding occurred in 2023 despite the predominance of the El Niño climate phenomenon, displacing hundreds of thousands of people in Java, Sumatra, and Kalimantan. This trend became even more pronounced in 2024, where more than 1420 instances of floods have occurred. It peaked in 2025 when 1652 cases of flooding were registered, resulting in 1189 deaths, as well as displacing over one million residents due to flash flood features. As of January 2026, the province of Aceh turned out to be the most affected region within the archipelago. There have already been more than 500 fatalities in Aceh, and almost 92000 citizens remain in emergency shelters. The socio-economic implications of flooding in this region are significant as more than 75000 houses have been destroyed in North Aceh, while 89582 hectares of agricultural fields have been flooded. This is why the necessary budget for rehabilitation may go up to Rp33 trillion. Such facts clearly demonstrate the necessity for a high-tech flood management system in the region (Gong et al., 2025; K. Zhu et al., 2024).

Currently, although modern emergency management systems continue to improve, there still exist many operational issues in practice. The first one is the extreme uncertainty of the emergency events that occur suddenly and unexpectedly and have a certain degree of variability (Aktas Potur et al., 2025; Leta et al., 2026). The second problem is that the coordination and scheduling of various kinds of resources, such as rescue workers, relief supplies, and logistics of transportation, are still a constant bottleneck. This issue can be further complicated by such aspects as fragmented information flow, cognitive biases of decision-making process, and social mobilization barriers (Liu et al., 2025a). In this regard, decision-making in emergencies encounters four key challenges (uncertainty, heterogeneity, dynamicity, and complex interactions among stakeholders) (Li et al., 2025a). Therefore, it has become necessary to develop a decision-making mechanism under time constraints in an ever-changing environment in contemporary disaster science (Al-Juaidi et al., 2025; Mohajane et al., 2026).

The limitations of such structural framework can be addressed through the use of AI technology which will provide a paradigm shift towards proactive disaster governance from reactive disaster governance (Liu et al., 2025; C. Y. Liu et al., 2025). AI-powered modeling will have the computing capability required to examine extensive data sets in order to determine hidden patterns in the hydrological and topographical factors which cannot be easily discerned by human analysts (Al-Juaidi et al., 2025). AI technology allows the shift from "broad brush" planning towards more precise localized risk assessment. However, the full benefits of using AI technology can only be gained once it is combined with effective decision-making support systems which can address the multi-criteria aspect of resource allocation.

To address the above multifaceted issues, this research presents SIAGA, a new generation, comprehensive information system tailored to the needs of the disaster-prone environment in Aceh. In contrast to the generic “one-size-fits-all” approaches, this research highlights three major research contributions. Leveraging the ML techniques, SIAGA offers automated disaster classification (regional or national) using the explainable AI approach to help stakeholders comprehend the causes of such risks. This research applies hybrid TOPSIS logic in the implementation of subjective and objective weights to provide vital resources to at-risk populations without bias. To solve the problem of poor communication, SIAGA employs a mesh network protocol which creates an autonomous communication infrastructure that is independent of cellular infrastructure..

In adopting the research method of design science, the research does not only offer a mere theoretical framework but creates a tangible digital object. This is because the process guarantees that there is no difficulty transitioning from complicated AI-MCDM (multi-criteria decision making) computations to a simple mobile interface for post-flood recovery in vulnerable areas.

METHOD

The DSR approach was applied in this research in order to design a socio-technical solution in the shape of a mobile-based information system for flooding management (Zeng et al., 2025). In light of the need to counter recent catastrophically destructive floods, the research provides a case study of Aceh in Indonesia. The DSR approach can be conducted within a combined framework comprising user requirements identification, proposal of the predictive architecture based on AI algorithms, and creation of decision-making logic involving multiple criteria (Gregor & Zwikael, 2024; Pan & Zhang, 2023).

Requirement Engineering and User-Centric Design

In response to the current disaster of flooding in Aceh, Indonesia, this study applies an elaborate multi-step analysis approach that connects real world user needs and advanced prediction modeling. The first step entails gathering of primary data from a survey of user needs and requirements using a questionnaire (Google Form) aimed at determining the functional requirements for developing the flood management mobile application (Chatzistratis et al., 2025). This particular survey aims at identifying the user needs and requirements of three major components; the first is the measurement of the extent of disaster, second, logistics optimization and third, the use of mesh networks for offline communications in case conventional network structure fails (Seva et al., 2025a). This user-driven approach ensures that the next development process of the mobile application would be both technologically sound and practical to the field requirements of victims and emergency personnel.

Sample Inventory and Authoritative Geospatial Data Acquisition

The flood inventory in this study was generated using official disaster databases combined with high-resolution satellite imagery to attain maximum data integrity in building the predictive model. The historical data about the location of the flood affected areas was obtained using (BNPB) database. To cross-check these coordinates, high-resolution satellite imagery through Google Earth Pro was used to undertake spatial cross-validation (Guo et al., 2026; Kafi et al., 2025) to establish topographical and hydrological characteristics of the flood affected coordinates. For the purpose of eliminating spatial bias and facilitate binary categorization in the machine learning models, equal numbers of safe zone without any historical data on floods and stable topography were randomly picked through Google Earth Pro. This two-sourced data collection is meant to generate a highly accurate dataset which will act as the categorical dependent variable for the AI engine (Kangana et al., 2025). Figure 1 below shows the methodological framework that combines Google Earth Pro and BNPB database with machine learning and explainable AI to predict and model the flooding in Aceh.

Predictive Modelling and Risk Assessment

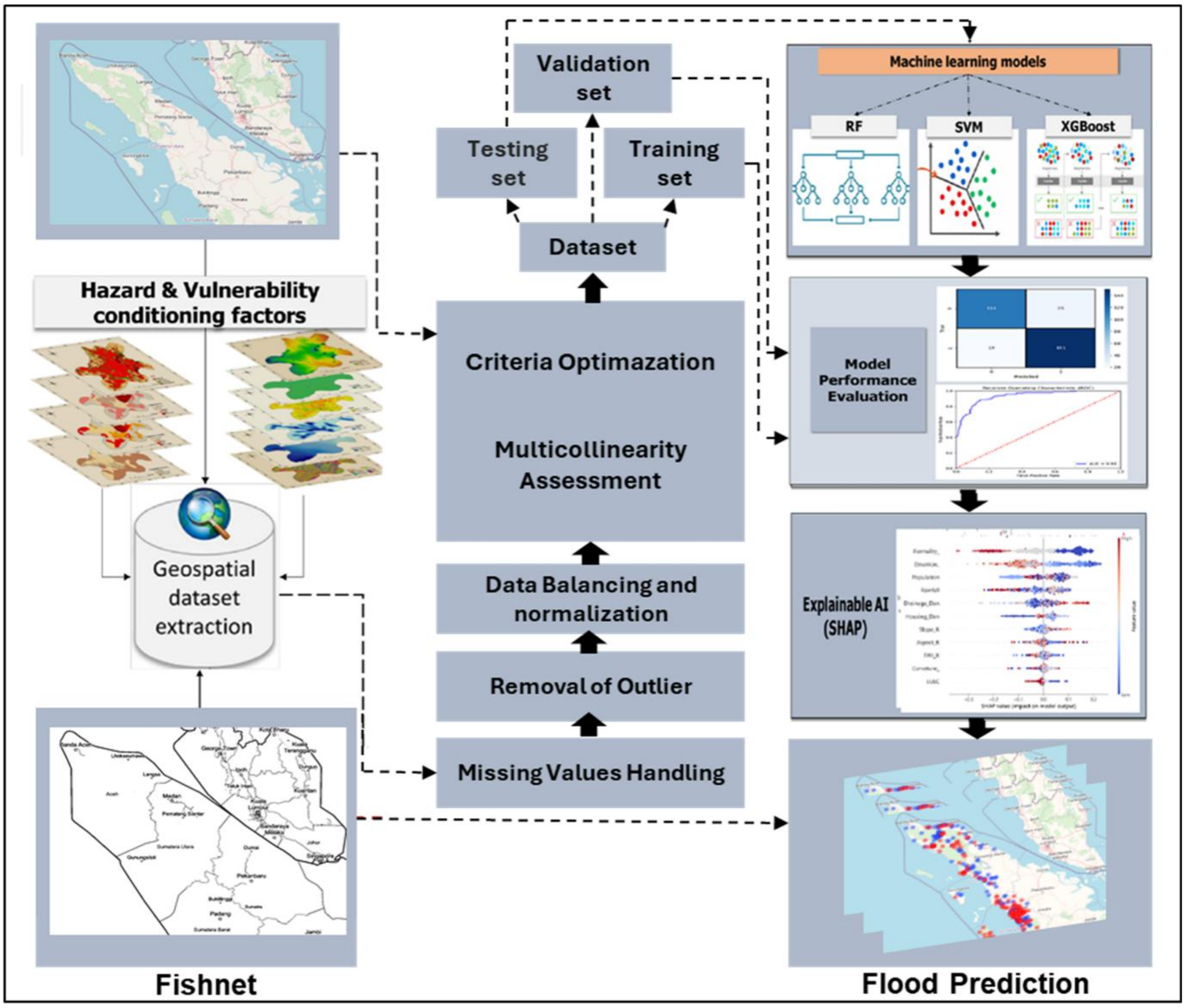

Figure 1. Methodological workflow for flood prediction and modelling, integrating Google Earth Pro and BNPB datasets with machine learning algorithms and explainable AI techniques

Table 1. Hazard conditioning factors

Major Factor	Conditioning Factors	Hazard	Vulnerability
Geological	Impervious Surface	√	
	Elevation	√	
	Slope	√	
Hydrological	Rainfall	√	
	Drainage Density	√	
Socio-physical	Housing Density		√
	Settlement Formality		√
	Hospital		√
	Shop		√
Social	Population Density		√

Modeling of flood risk for the current study is conducted using the comprehensive comparative study of the three most advanced machine learning (ML) models: RF, XGBoost and SVM. The methodology is based on the framework described by Kafi et al. (2025) (see Figure 1). This modeling technique is aimed at capturing non-linear dependencies between environmental predictors and flood events. The experiment design is based on the carefully selected dataset which is divided into 60% used for training and 40% for testing of the models in order to avoid overfitting. Using specialized libraries of Python programming language such as scikit-learn and XGBoost the models take into account five hazard predictors and five vulnerability indicators (see Table 1) through equation 1.

$$\text{Risk} = \text{hazard} \times \text{vulnerability} \tag{1}$$

For verifying the quality of the spatial products obtained, the predictive performance of each algorithm is analyzed based on certain statistical measures, namely, accuracy, kappa statistic, and area under receiver operating characteristic curve (ROC-AUC). While accuracy offers a basic evaluation measure, the kappa statistic compensates for the effect of randomness, an important aspect because of the possible discrepancy in the number of samples falling into two classes – the affected and unaffected areas. The ROC-AUC becomes a key measure for assessing the discriminative ability of the model in differentiating risk zones in the Aceh area.

Recognizing the 'black-box' limitation often associated with ensemble and kernel-based models, this study incorporates Explainable AI (XAI) using SHAP (shapley addictive explanations) algorithms (Kafi et al., 2025; Wang et al., 2025) . SHAP values, rooted in coalitional game theory, are employed to deconstruct the models' decision-making logic by assigning an importance value to each conditioning factor. This interpretability layer is crucial for emergency management in Aceh, as it allows stakeholders to understand the specific weight of variables such as elevation, slope, and rainfall in driving flood risk (Deroliya et al., 2022). By identifying these key hazards and insights, ensuring that the mobile application's recommendations are both transparent and justifiable to end-users and policy makers (Nazemi et al., 2024).

Multi-Criteria Site Selection Decision Scheme

Multi-criteria decision making refers to an advanced analysis approach that aims at assisting complex evaluation process of multiple alternatives through varying sets of indicators (Li et al., 2025). This approach is widely used in different fields of activity, such as emergency management, corporate strategy development and engineering designs, where the main purpose of the approach is to choose among alternatives or identify the best solution due to analysis of contradicting criteria (Aktas Potur et al., 2025). In the field of emergency management, decision makers should take into consideration various complex issues such as type of disaster, its geographical distribution, resources available and efficiency of response

(Liu et al., 2025a). In our research, we are dealing specifically with flood disasters, and the ten chosen indicators are divided into two major objectives, first – estimation of disaster scale status that is associated with environmental and hydrological criteria such as population, elevation, slope, rainfall and drainage density, and second – smart logistics optimization using urban infrastructure criteria such as impervious surface, housing density, settlement regularity, hospitals and shops.

As shown in Figure 2. The structure of the proposed decision-making framework includes a hierarchical four-layer architecture of indicator, methodology, weighting, and decision layers. The methodological framework introduced by Liu et al. (2025b) which was altered. First of all, the 10 indicators are converted to the maximization type and normalized in order to avoid dimensional incompatibilities. In the methodological layer, the subjective, objective, and correlation weights of every indicator are calculated using the following techniques. The subjective weight is calculated using Analytic Hierarchy Process (AHP) technique based on the expert judgment (Horbiński & Lorek, 2022), objective weight – Entropy Weight Method (EWM) based on the information entropy, and correlation weight – Pearson Correlation Coefficient (PCC). The obtained parameters are further merged with the arithmetic operations to form modified weights that form the basis of TOPSIS. With the help of the TOPSIS technique, the closeness of alternatives to the ideal and non-ideal solutions is assessed. The proposed hybrid approach allows taking full advantage of the original data and considering all the differences between the evaluation criteria due to the mathematical rigor of the model.

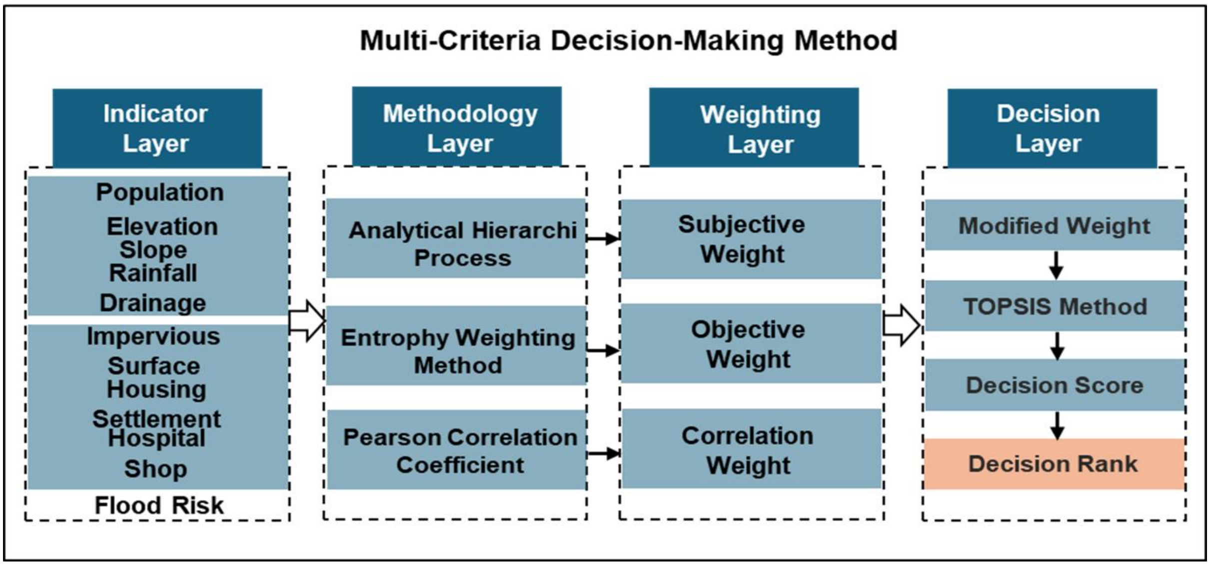

Figure 2. The site selection decision-making scheme. On the basis of 10 types of decision indicators, three different algorithms are combined to obtain the modified weights, and finally, the ranking scoring is accomplished by TOPSIS.

Mobile Application Architecture

Implementation of the SIAGA application from a technical perspective will involve a well-defined architecture that ensures efficient processing of information and user interaction. Based on the development process provided by Thakur et al., (2026), which can be adapted (as illustrated in Figure 3), the first layer in the architecture involves data ingestion in the form of raw geospatial data as well as ML risk outputs, transforming these data into a Standard Data Interchange Format, such as JSON or GeoJSON format (Horbiński & Lorek, 2022).

The heart of this architecture is the incorporation of strategic integration in the Django Framework, which plays the role of an advanced middleware between predictive intelligence and tactical decision making (Nazemi et al., 2024; Seva et al., 2025a). Under such circumstances, the Django backend acts as the execution component of the Machine Learning algorithms adopted from (Kafi et al., 2025), using real-time environmental parameters to calculate precise coefficients for floods. The predictive results are used not just in a visualization form, but are programmatically fed into the decision engine of the TOPSIS method as dynamic criteria. The framework generates the decision matrix automatically through a combination of the ML generated risk coefficients with the three weights, AHP subjectively, EWM objectively and PCC based (Liu et al., 2025b).

Through the asynchronous process handling provided by Django, the system will compute in real-time the geometric distance of every choice from the ideal solution and then push the sorted outcomes through the standardized data stream into the Front-End. The Front-End, constructed using a contemporary web stack of HTML, CSS, and JavaScript technologies, will render an easily understandable and interactive dashboard displaying the high-priority flood areas and optimal response routes (Horbiński & Lorek, 2022). This automated workflow will ensure that the complicated mathematical process of going from 'prediction of risk' to 'ranking the response choices' will be processed solely at the server side while the mobile application remains light and interactive for field workers even under the use of mesh networking (Thakur et al., 2026).

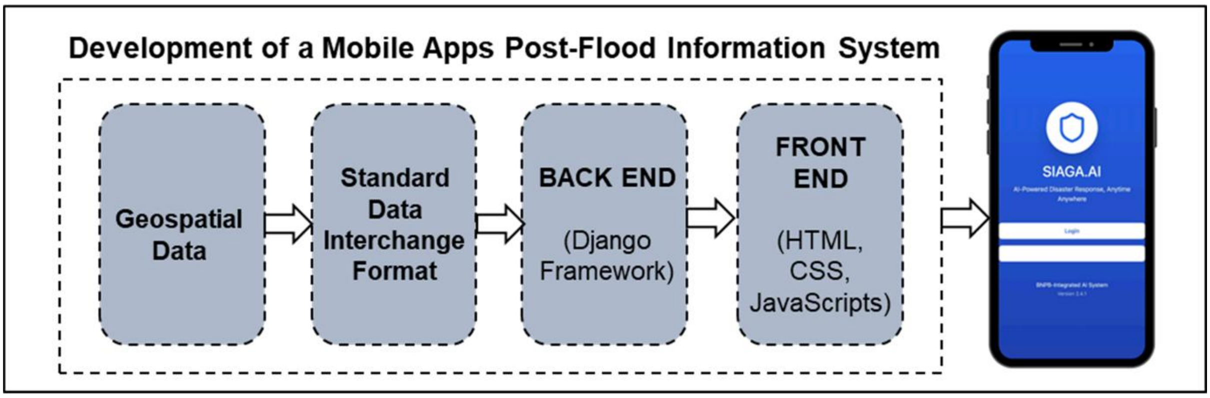

Figure 3. Proposed methodology for SIAGA mobile application development.

RESULTS AND DISCUSSION

Requirement Analysis and User Profiling

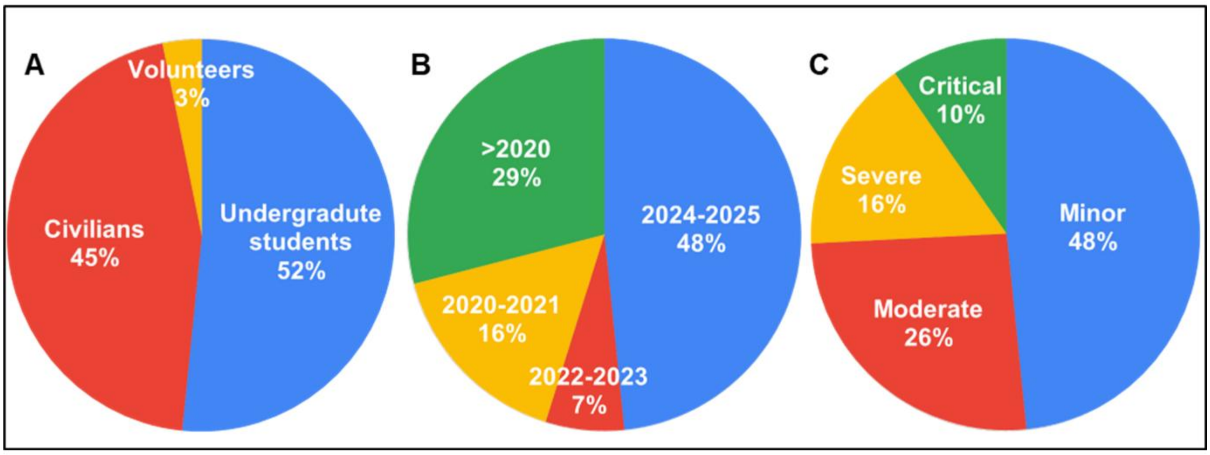

Figure 4. Survey-based evaluation result

The first stage in the design process cycle entailed conducting a rigorous user requirement analysis in order to make sure that the SIAGA mobile app still addresses the socio-technical requirements of the disaster-prone area in Indonesia. In all, there were 31 participants in the survey using the Google Forms questionnaire. As can be seen from Figure 4, the participant group consisted of a diverse demographic mix which is necessary for disaster management across multiple sectors. Specifically, the participant group included 52% undergraduate students, 45% civilians, and 3% volunteers.

In order to maintain the validity of the data collected, the study filtered the respondents who were personally impacted with the flooding disaster. From the timeline of the floods, a large number of cases have been observed recently (2024-2025, 45%) (Figure 4). It clearly shows that there is an urgent need for a modernized management system for coping with the climate-induced disasters occurring in the area. Besides, the level of impact that the respondents have faced from the floods has shown significant variations (see Figure 4): 48% have faced minor impact, 26% moderate, 16% severe and 10% critical impacts. Such levels of impact require that the SIAGA app provides a disaster assessment tool at different levels for prioritizing the areas of 'critical' and 'severe'.

Based on the demographics, an in-depth analysis was performed in order to understand the specific needs of users post-flood. It is important to highlight the high need for real-time information concerning the disaster scale and logistics. Users expressed the importance of having a system that would be able to identify the disaster situation without depending on cellular networks, which were often unstable at that moment. These results are directly used in designing the SIAGA artifact. Firstly, the high percentage of moderate and critical floods experienced by the users explains the use of the machine learning layer to give early warnings using XAI. Second, the demand for optimal logistics is taken into account using the TOPSIS layer that assesses smart logistics, including hospital, shops, and supply wharves (Gong et al., 2025).

A key finding from the requirements analysis is the challenge encountered by victims accessing authoritative disaster status information in times of floods. In Figure 5, a total of 62% of the respondents indicated that it was either "Moderately Difficult" (39%) or "Extremely Difficult" (23%) for them to determine the disaster status. The inability to access this information is worsened by the disjointed nature of the current sources of information. As illustrated in Figure 5, most of the respondents get their information from informal sources such as WhatsApp Groups (37%) and social media (29%), with only a few getting information from the official government/BNPB sources (12%). In addition, 14% of the victims indicated that there was no way they could access information at all in the height of the disaster (Xiao et al., 2025).

With regard to the recovery from flood events, the questionnaire helped identify the basic physical and utility needs that the system is supposed to assist in managing. As illustrated by Figure 5, "Food and Drinking Water" was the most important need, followed by "Clean Water" and "Essential Medicine." The high level of importance attached to "Power and Communication Utilities," and "Healthcare Access," highlights the importance of the mesh network features suggested, because survivors give priority to communication and healthcare in the wake of flooding disasters (Gong et al., 2025; Goyal et al., 2021).

Evaluation of Information Accessibility and Emergency Resources

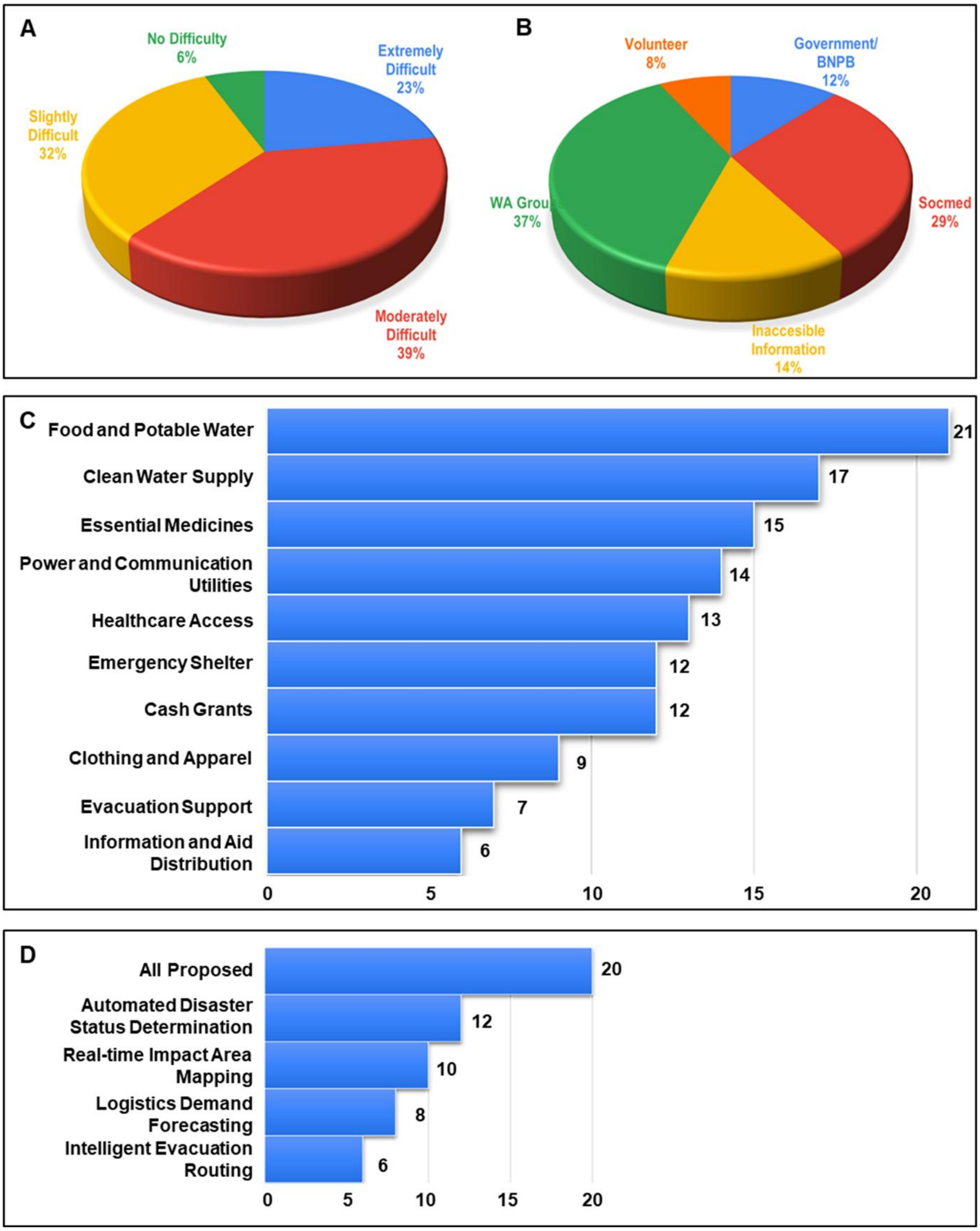

Figure 5. Survey-based evaluation results: (a) perceived difficulty in accessing flood status information during emergencies; (b) primary communication channels during flood events; (c) urgent post-disaster needs of flood victims; and (d) user preferences for AI-enabled features in disaster management applications.

The final aspect of the requirement analysis is directly related to the feature set of the SIAGA mobile application. Respondents were asked to prioritize the proposed features (refer to Figure 5). The majority of respondents (20 people) demanded the provision of "All Proposed" features, meaning that there is a need for an all-round multifunctional management tool. From individual features, the greatest demand was for "Automated Disaster Status Determination," then came "Real-time Impact Area Mapping" and "Logistics Demand Forecasting". These results form a solid basis for the technical components described above. The demand for automated disaster status determination is satisfied by the machine learning engine. It is used to analyze hazard and vulnerability data to instantly classify disasters. At the same time, the demand for logistics forecasting and mapping is addressed by the MCDM-TOPSIS decision layer. This module ranks and prioritizes the delivery of water, food, and medicine depending on their urgency and proximity to the affected area. This connection between the demands of the users and the components of the technical solution is what makes the SIAGA system architecture highly impactful for post-flood management (Goyal et al., 2021; Wang et al., 2025).

The process of moving from user requirements to a functional prototype is achieved via three main strategic components. They have been chosen to fill the gaps identified by the survey, mainly focusing on the availability of information and resource management in a constrained networked environment (refer to Figure 6).

The SIAGA software is the high fidelity digital artifact that is intended to fill the gap between complicated analysis modeling and emergency response operations in real time. The core of the user interface is the automated disaster scale determination module that gives the final status of the emergency situation using the synthesis of real-time hydrological data via the AI engine. As can be seen from the “Emergency Status” dashboard, the system analyzes real-time indicators (water level (240 cm), rainfall intensity) to give the status of the situation in terms of standardized levels of alerts, starting from regional to national ones. The advanced feature of “AI Recommendation” uses the foresight technology to predict the probability of escalation (for example, 88% probability of flash flood within two hours).

The “AI Data Breakdown” interface acts as the explainability module of the system’s predictive suggestions. With the decomposition of the aggregated risk score into three major environmental parameters including flash flood risk (88%), soil saturation (76%) and the effect of upstream rainfall (92%), the system explains the underlying rationale behind its escalation alerts. The significant contribution of the upstream rainfall effect implies that the model favors the hydrological information from higher altitudes and thus detects the surge of the floods well ahead of time. The level of granularity provided by this visualization enables the emergency response team to go beyond just binary alerts and understand the exact environmental factors influencing the current level of risk (Amérigo et al., 2024; Seva et al., 2025b).

Core Functional Features of the SIAGA Artifact

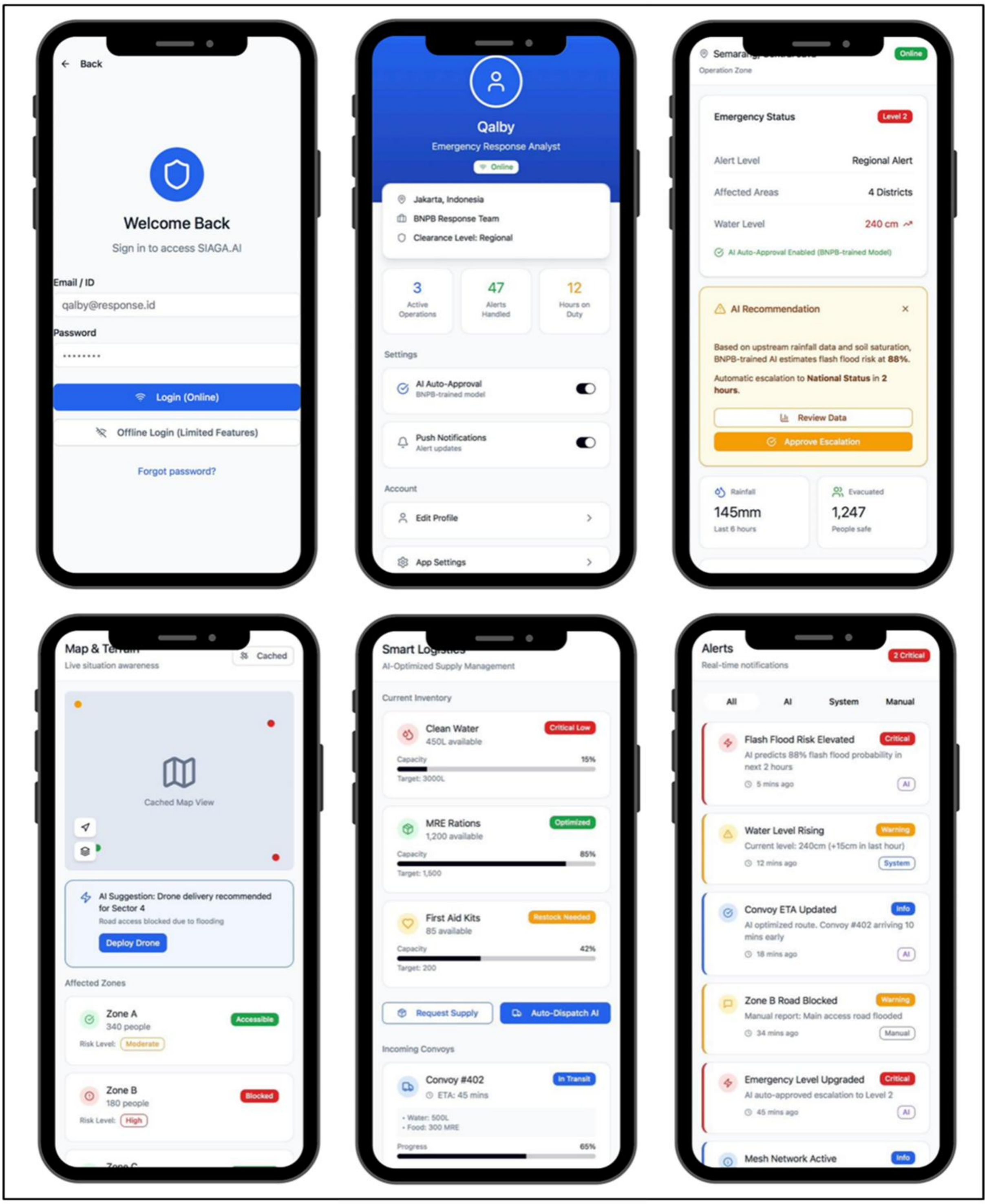

Figure 6. User interface mockups of the SIAGA mobile application

The scientific validity of the above-mentioned forecasts is ensured due to the BNPB disaster prediction model that has been comprehensively trained on a large database of previous disaster cases within the recent years. The use of the deep historical background allows this model to make a distinction between normal seasonal changes and real pre-disaster signs with great accuracy. According to the report, the confidence rate reaches 94.2%, which refers to the statistical reliability of the current forecast. Such high reliability rate, based on the database of the national authority (BNPB), creates a solid scientific basis for the implementation of proactive escalation without the usual period of manual verification.

From a functional perspective, the interface serves as the “ground truth” through which the situational awareness of all stakeholders can be coordinated. By converting multi-modal sensor input to numerical probabilities, the interface reduces any risks that may arise due to informal and biased information flow during high-pressure situations. In the event of an 88% chance of a flash flood, decision-making is not left to subjective interpretation but rather becomes an objective requirement driven by numbers. Through this, the AI-generated foresight makes it possible to move away from reactive geohazard mitigation to predictive governance (Besseling et al., 2026; Khandokar et al., 2026).

The second pillar of the artifact relates to the smart logistics and the AI-optimized supply management system that implements the critical needs discovered through requirement engineering. With this functionality, the application offers real-time visual representation of the key inventory items such as clean water, MRE rations, and first-aid kits through dynamic capacity bars and statuses such as "Critical Low" or "Optimized." Due to the implementation of the MCDM-TOPSIS logic into the system, it does not limit itself by only indicating stock volumes but also gives strategic suggestions. For example, the functionality of "Auto-Dispatch AI" and the recommendations of drone delivery for the inaccessible "Blocked Zones" (such as the Zone B on the Map and Terrain screen) ensure that the aid is dispatched according to the highest risk coefficients.

The “Map & Terrain” Interface – Shown in Figure 6. It offers real-time situational awareness screen that brings to life the discussed smart logistics and predictive capabilities. At the heart of this screen lies the ‘AI suggestion’ component, which detects important accessibility challenges (in particular, for sector 4) because conventional land route accessibility has been determined to be blocked owing to floods. Through generating a clear “Deploy Drone” recommendation, the system transforms intricate environmental data into actionable steps. This feature is especially crucial in overcoming isolation of risk sectors (Chang et al., 2021).

The additional analysis of the “Affected Zones” table shows how the artifact classifies geographical areas according to dynamic risk levels and population density. For example, zone B is clearly described as being ‘Blocked’ with a ‘High’ risk level and having 180 people within its boundaries, whereas zone D was classified as having ‘Limited’ access even when the risk coefficient was high. Through combining all these factors, SIAGA framework helps commanders to classify areas that need typical ground logistic operations and areas that need special air force assistance. Such a detailed approach backed up by the cached offline data provides an opportunity to deliver humanitarian aid precisely in places that have the highest risks (Paauw et al., 2026).

Moreover, the SIAGA app takes into account the challenge of the failure of communication infrastructure with the help of its resilient mesh network and situation awareness feature. Knowing the fact that 14% of the disaster victims experience total network blackout, the application has an “Offline Login” option along with the special mesh networking protocol that will make the mobile devices act as communication nodes. As a result, the functionality of the “Alerts” and “Map & Terrain” features will not be hindered by the absence of cellular connectivity and will allow peer-to-peer synchronization of important data like road blockage, water level rise, and convoy ETA. There is also a “Mesh Network Active” indication on the user’s interface that shows that he or she is part of the resilient local network, providing him or her with uninterrupted information exchange and “Cached Map Views.”

The working process of the communication resilience system is illustrated through the Alerts interface represented in Figure 6, which demonstrates real-time updates regardless of any infrastructure strain. One of the key aspects of this interface is "Mesh Network Actives," which shows the successful connection of the device to five nearby peer nodes. In this way, the functionality of the underlying decentralized protocol is assured and the critical data packets like 'Flash Flood Risk Elevated' alerts with their 88% probability forecasts continue to travel through the network regardless of the possible lack of any centralized cellular towers. The implementation of this local network allows maintaining the flow of the information at a high level and covering the 14% gap of victims left unconnected due to the complete blackout of networks.

In addition to connectivity status, the interface is a complete synchronization point where different data sources can be combined, from automatic predictions made by AI to manually confirmed reports. Alerts page organizes the data received in a systematic way, for example, “Zone B Road Blocked” report confirmed manually, and “Convoy ETA Updated,” automatically optimized by the AI. The combination of different types of data allows all parties, whether responders or victims, to have a single picture of operations. “System” generated alerts, for example, “Water Level Rising” at 240 cm, represent one of the ways how this app analyzes environmental telemetry, offering an important mathematical “ground truth” for quick decision-making about evacuation (Hamzaoui & Taillandier, 2026; Qi et al., 2021).

Additionally, the profile screen shown in Figure 6 reinforces this flexibility in the operation by controlling the human and machine authority that drives the process. The screen shows the user’s position in the system as an analyst and the regional authorization level they possess that determines their capacity for decision making in the system. In particular, the “AI Auto-Approval” switch, when activated, gives the BNPB-trained AI the capacity to make the pro-active escalations seen in alerts like the “Emergency Level Upgraded.” The combination of personal accountability and automation in the SIAGA model ensures that the SIAGA system not only sustains communication during emergencies but also expedites responses using authorized data-driven interventions (Kangana et al., 2025; Liu et al., 2025b; Salvati et al., 2021).

In order to validate and demonstrate the capabilities of the system's functionalities, a complete interactive prototype of the SIAGA system has been built. The interactive prototype provides a working design model that depicts the smooth flow of the data from the backend of the application which is Django-based to the frontend, which is HTML/CSS/JavaScript-based (Thakur et al., 2026). It also provides a platform for the demonstration of the system's "AI-Powered Disaster Response" process flow, from sign-in through to the deployment of logistical command operations. For further peer review and academic evaluation, an interactive artifact with the multi-layered dashboard system and the mesh network simulation environment is available in the following Figma repository: https://bit.ly/3Nr2g4E. This interactive prototype forms the last phase of the design science research cycle, confirming that the theoretical models for AI and MCDM are indeed able to manifest into a working mobile disaster management system.

CONCLUSION

In this study, a successful creation of an integrated digital artifact referred to as SIAGA has been created to help maximize post-disaster management in Aceh, Indonesia through the use of design science research (DSR). Through the integration of the empirical needs of the users along with the state-of-the-art computational frameworks, the study is able to fill in the existing information transparency and logistical gap in disasters. In the requirement engineering stage, the high level of dependency on informal channels of communication along with the lack of knowledge on official disaster status is noted.

Combining machine learning and XAI acts as the system's prediction mechanism for achieving accurate assessment of the scale of the disaster. This is supplemented with a combination of multi-criteria decision-making method (MCDM) and TOPSIS algorithm decision-making process that uses mathematical calculations to prioritize the delivery of basic necessities such as food, water, and medicine based on urgency and accessibility. The technology component of this study is based on the use of Django Framework and latest web stack so that these calculations can be accessed via an easy-to-use interface. Another innovative feature of this study is the usage of a robust mesh network protocol.

In sum, the SIAGA proof-of-concept system, developed using a highly immersive environment, serves as evidence that the combination of AI-powered insight analysis and strategic decision-making is achievable in the mobile realm. Although this paper offers a solid framework for the future studies in theory and structure, it leaves room for practical implementation of the testing phase and the inclusion of IoT sensor network systems to improve the accuracy of the predictive engine. This research provides a major methodological breakthrough in the field of disaster informatics.

SUGGESTIONS

With regard to the present state of development of the SIAGA artifact, the following recommendations can be made in order to increase its influence and level of technological advancement based on the analysis of its requirements. Although at the moment the artifact operates on the basis of historical and authoritative data provided by BNPB, in future versions it may be advisable to use real-time IoT sensors that can detect the water levels and rainfalls. Thus, the backend will be able to shift from the update mechanism to a streaming data flow, which will decrease the delay in the flash flood alert. For better performance of machine learning models in case of poor network access, edge AI technology may be used.

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