ACTION-FIRST AI FOR FACILITIES MANAGEMENT: PRIORITISING POST-FLOOD ASSET REPAIRS TO RESTORE ACCESS TO ESSENTIAL SERVICES

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Abstract. Flood recovery in developing countries is often hindered by fragmented information and ad hoc repair prioritisation, delaying restoration of essential services. This study proposes an Action-First AI approach for post-flood facilities management that prioritises asset repairs based on service criticality, population impact, accessibility, and operational feasibility. Using a design science research approach, a conceptual framework was developed from the literature and evaluated through qualitative expert review involving disaster management, facilities management, and digital systems professionals. Expert insights were then used to derive a conceptual flow model and a prototype decision-support dashboard demonstrating how prioritisation logic could be integrated within existing FM systems. Rather than presenting a technical AI implementation, the study provides a conceptual blueprint for embedding AI-inspired decision support into FM workflows to enhance transparency, coordination, and effectiveness of post-flood recovery planning.

Keywords. *Action-First AI; Facilities Management; Post-Flood Recovery; Asset Repair Prioritisation; Decision-Support Systems*

1. Introduction

Flood disasters pose multifaceted challenges for infrastructure systems and the communities that depend on them, particularly in developing countries where critical assets are already vulnerable, and recovery resources are limited (Rathnasiri et al., 2023). In late 2025, Sri Lanka experienced devastating floods and landslides triggered by Cyclone Ditwah, affecting millions of people and causing widespread damage to roads, bridges, power networks, water systems, and healthcare facilities. These disruptions severely constrained access to essential services and livelihoods across the island nation. The disaster's direct economic impact, measured by physical damage, exceeded USD 4 billion, underscoring the urgent need for more effective and systematic approaches to post-flood infrastructure recovery and facilities management (Kodituwakku & Amaratunga, 2026). Rapid restoration of essential services is a central objective of post-disaster recovery and resilience planning (Ngulube et al., 2025). However, conventional post-disaster response practices in facilities management often rely on manual damage assessments, fragmented information, and heuristic prioritisation processes (Wickramaarachchi & Lakshani, 2026). These approaches frequently lack analytical rigour and transparency, particularly under conditions of uncertainty and resource scarcity (Amaratunga & Kodituwakku, 2026). As a result, critical repair decisions may be delayed, repair resources may be allocated inefficiently, and vulnerable populations may experience prolonged service disruptions and unequal recovery outcomes (Rathnasiri et

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al., 2025). These challenges are particularly pronounced in developing contexts, such as Sri Lanka, where institutional capacity constraints and socioeconomic vulnerabilities exacerbate the consequences of infrastructure failure.

Artificial intelligence (AI) has emerged as a promising tool for enhancing disaster risk management, with applications spanning early warning systems, damage assessment, resource allocation, and decision support (Delos Reyes et al., 2026). AI-driven approaches can integrate heterogeneous data sources and support faster, more informed decision-making in time-sensitive disaster environments (Sharma & Krishna, 2026). Nevertheless, much of the existing literature on AI in disaster management remains focused on predictive analytics and damage characterisation, whereas comparatively little attention has been paid to action-oriented decision frameworks that directly guide post-disaster repair prioritisation within facilities management systems (Bidwai & Van den Dool, 2025). In particular, there is a lack of research on how AI-inspired decision logic can be embedded into existing facilities management workflows to support practical, transparent, and socially responsive recovery decisions in resource-constrained settings (Rathnasiri et al., 2025; Mithrashree et al., 2026).

To address this gap, this study explores an Action-First AI perspective for post-flood facilities management. The focus is on supporting decisions that prioritise asset repairs according to service criticality, population impact, accessibility, and operational constraints, with the aim of restoring essential services more effectively. Rather than treating AI mainly as a predictive tool, the study positions it as a means of supporting actionable recovery decisions that are aligned with operational needs and public benefit (Aththanayake et al., 2026). This paper contributes to the growing discussion on AI-enabled disaster recovery by examining how action-oriented decision support can strengthen facilities management practice after floods. It offers a contextually relevant contribution for Sri Lanka and other developing countries, where post-disaster recovery often takes place under severe resource and coordination constraints (Hussainzada et al., 2026). In doing so, the study highlights the potential of AI-inspired prioritisation to support more transparent, timely, and equitable recovery planning.

In this study, AI is defined in a focused and practice-oriented sense. It does not refer to a fully autonomous machine learning system or a predictive analytics model trained on large-scale post-disaster datasets. Rather, AI refers to AI-inspired decision-support logic that uses structured post-flood information, facilities management knowledge, and transparent prioritisation rules to support repair sequencing decisions. The novelty of the proposed Action-First AI approach lies in its emphasis on immediate operational action rather than prediction alone. Unlike conventional decision-support systems that mainly organise information, or AI-assisted disaster frameworks that often concentrate on hazard prediction or damage detection, the proposed approach is designed to prioritise repair actions within facilities management workflows by combining service criticality, population impact, accessibility, interdependencies, and operational feasibility. The approach is therefore intended as a human-centred and explainable decision-support framework that strengthens professional judgement rather than replacing it. The scope of the research is limited to post-flood recovery-oriented facilities management rather than routine infrastructure maintenance or the full disaster management cycle. The focus is on repair prioritisation during the recovery stage, after damage has occurred, with the aim of restoring essential services under constrained conditions. Accordingly, the study does not address autonomous machine learning, computer vision, robotics, or hazard forecasting systems, but instead focuses on explainable ranking and prioritisation mechanisms for post-flood decision support.

2. Methodology

2.1. RESEARCH DESIGN AND APPROACH

This study adopts a qualitative Design Science Research (DSR) approach to develop and evaluate an Action-First AI framework for post-flood facilities management. DSR is appropriate because the aim of the study is not only to analyse an existing problem, but also to produce and justify a purposeful artefact in the form of a conceptual framework and associated design artefacts for practical use in a real-world context (De Sordi, 2021). In line with established DSR literature, the study is concerned with problem relevance, artefact design, rigorous grounding, and evaluation of utility and quality (Hevner et al., 2004; Peffers et al., 2007; Grover & Thareja, 2020). The study was structured with reference to Hevner’s three-cycle view of DSR. The relevance cycle is represented by the practical problem environment, namely the challenge of prioritising post-flood asset repairs in resource-constrained facilities management settings in Sri Lanka. The rigour cycle is represented by the structured review of literature on AI in disaster management, infrastructure recovery, facilities management decision-making, and decision-support systems, which provided the theoretical and methodological grounding for the study. The design cycle is represented by the iterative development of the conceptual framework, followed by its refinement through expert evaluation and the derivation of the conceptual flow model and prototype dashboard.

The study began with problem identification and motivation, followed by the definition of the objectives of a solution through the review of post-flood recovery and AI-related literature. This was followed by design and development of the Action-First AI framework, demonstration through its representation as a conceptual flow model and dashboard, and evaluation through qualitative expert review. Communication is represented by the presentation of the framework, its rationale, expert-informed refinement, and design implications in this paper. Because the study does not involve a full technical implementation, the evaluation was designed as a formative assessment of the conceptual artefact rather than a summative test of a deployed system (Grover & Thareja, 2020). Following design science evaluation principles, the expert review focused on the utility and quality of the proposed artefact through criteria including conceptual clarity, logical coherence, completeness, practical relevance, feasibility of integration with existing FM systems, transparency of prioritisation logic, and perceived usefulness for post-flood decision-making. These criteria informed the semi-structured expert review and the subsequent refinement of the framework and related design artefacts (Hevner et al., 2004; Venable et al., 2016).

The research, therefore, treats the initial framework, conceptual flow model, and prototype dashboard as interrelated DSR artefacts developed through iterative engagement between the problem environment, the knowledge base, and expert evaluation. Rather than relying on large-scale datasets or quantitative simulation, the study uses literature grounding and practitioner-informed evaluation to ensure that the resulting artefacts are both contextually relevant and methodologically defensible.

2.2 CONCEPTUAL FRAMEWORK DEVELOPMENT

The conceptual framework was developed through a structured review of literature on artificial intelligence in disaster management, post-disaster infrastructure recovery, facilities management decision-making, and decision-support systems. Key concepts and decision factors were extracted and synthesised to define the core components of the Action-First AI framework (Table 01). The framework was organised into five interrelated operational layers: Input layer, Facilities management knowledge layer, Decision layer, Action layer, and Outcome layer. This layered structure was adopted to reflect the sequential logic of post-flood recovery decision-making and to align the framework with decision-support system thinking, in which data inputs, domain interpretation, decision rules, operational actions, and performance outcomes are treated as distinct but connected elements. In post-flood facilities management, decisions do not arise directly from damage data alone. Rather, raw post-disaster information must first be interpreted through facilities management knowledge, including service criticality, infrastructure interdependencies, accessibility conditions, and operational constraints, before repair priorities can be generated and translated into action (Wickramaarachchi & Lakshani, 2026). The framework, therefore, moves from situational inputs to knowledge-based interpretation, then to prioritisation, implementation, and recovery outcomes.

More specifically, the Input layer captures the immediate post-flood condition of assets and the surrounding disruption context (Wang et al., 2025). The Facilities management knowledge layer represents the domain-specific criteria used to interpret these inputs, particularly the importance of essential services, system interdependencies, and operational feasibility (Mao & Liu, 2024). The Decision layer translates this knowledge into prioritisation logic for repair sequencing (Gokalp et al., 2021). The Action layer represents the implementation stage, where prioritised decisions are translated into repair actions and resource allocation (Wang et al., 2025). The Outcome layer reflects the intended effects of these actions, especially service restoration and wider societal benefit. The layered design was therefore selected as a process-oriented representation of how post-flood repair prioritisation progresses within facilities management environments, rather than as an arbitrary classification of variables. Table 01 summarises the key constructs derived from the literature and demonstrates how they informed the framework design. Validation was treated as a separate framework evaluation component of the research process rather than as an operational layer of the framework itself. The resulting conceptual framework, illustrated in Figure 01, provides a structured representation of how Action-First AI can support prioritised asset repair and service restoration in post-flood contexts.

Table 1, Key Variables of the Framework

Framework layer	Extracted construct	What the literature suggests	How it is used in this study	Key sources
Input layer	Damage status & disruption context	Recovery decisions depend on post-disaster damage states and evolving conditions	Assets have damage level, repair duration, access constraints as inputs	(Vugrin et al., 2010; Wang et al., 2025)
FM knowledge layer	Service criticality	Essential services require differentiated priority; recovery should focus on service function	Assign criticality weights by sector (health, water, power, transport)	(Mao & Liu, 2024; Wang et al., 2025)
FM knowledge layer	Infrastructure interdependency	High-ranked assets may not improve recovery if dependencies remain down	Include interdependency/accessibility logic; “enabling assets” elevate priority	(Mao & Liu, 2024; Vugrin et al., 2010)
Decision layer	Repair sequencing importance	Repair order strongly shapes recovery outcomes (not just total repairs)	Prioritisation produces ranked repair list (action-first sequence)	(Gokalp et al., 2021; Vugrin et al., 2010)
Decision layer	Population impact	Resource allocation should consider who benefits and how many are affected	Population dependency integrated as a scoring factor	(Wood, 2025; Kolivand et al., 2025)
Decision layer	Explainability & human oversight	Disaster decisions require interpretable outputs and human-in-the-loop governance	Use transparent priority scoring and justification in dashboard outputs	(Domfeh & Dancy, 2025; Dcruz et al., 2025)

Action layer	Resource constraints & operational feasibility	Repair scheduling depends on limited crews and feasibility constraints	Include crew/resource availability and repair durations in implementation design	(Vugrin et al., 2010; Wang et al., 2025)
Outcome layer	Service restoration as the outcome focus	Recovery success should be measured by restoration of services and access	Dashboard reports prioritised actions, service restoration indicators	(Sprague, 1980; Kolivand et al., 2025)
Framework evaluation component	Expert-based validation of DSS	DSS and expert systems commonly validated via expert utility/relevance assessment	Framework validated via expert review survey and qualitative feedback	(Borenstein, 1998)

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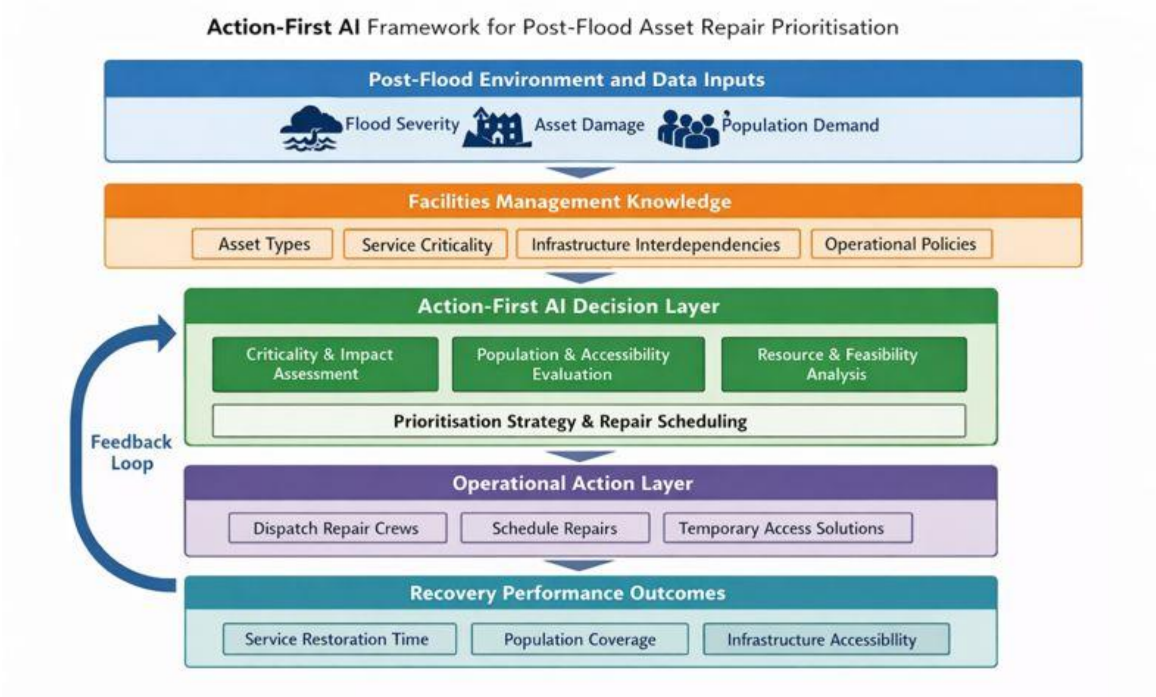

Figure 1, Initial Action-First AI framework for post-flood asset repair prioritisation

2.3. QUALITATIVE EXPERT REVIEW STRATEGY

To validate the conceptual framework and explore its practical applicability, a qualitative expert review was conducted. Expert review is widely used in design science research to evaluate conceptual artefacts in contexts where empirical implementation is not yet feasible or data availability is limited. The expert review aimed to: assess the conceptual clarity and relevance of the proposed framework, identify practical challenges and opportunities for integrating the framework into existing FM systems, and to generate insights to inform the conceptual flow model and dashboard design. A purposive sampling strategy was adopted to ensure representation from key stakeholder groups involved in post-flood infrastructure management and digital systems.

The review evaluated the artefact against seven criteria: conceptual clarity, logical coherence, completeness, contextual relevance, feasibility of implementation, transparency of prioritisation logic, and perceived usefulness for decision support.

2.4. PROFILE OF EXPERT RESPONDENTS

Experts were selected based on the criteria: a minimum of five years of professional experience, involvement in disaster management, facilities management, infrastructure engineering, or digital systems, and familiarity with decision-making processes in complex operational contexts.

Table 2, Profile of the Respondents

Participant Code	Category	Role / Background	Years of Experience	Key Expertise Areas
DM1	Disaster Management	Senior disaster risk management officer, national agency	18	Disaster response coordination, flood recovery planning, resilience policy
DM2	Disaster Management	Emergency response coordinator, regional authority	12	Emergency operations, infrastructure disruption management
DM3	Disaster Management	Civil protection officer	9	Disaster preparedness, inter-agency coordination
DM4	Disaster Management	Academic researcher in disaster risk reduction	15	Disaster resilience, infrastructure recovery, risk assessment
DM5	Disaster Management	NGO programme manager	11	Community-based disaster recovery, humanitarian logistics
DM6	Disaster Management	Infrastructure resilience consultant	20	Critical infrastructure protection, post-disaster planning
FM1	Facilities Management	Facilities manager, public hospital	14	Healthcare facility operations, maintenance

				planning, emergency response
FM2	Facilities Management	Asset management engineer, utility provider	17	Infrastructure asset management, lifecycle planning
FM3	Facilities Management	Senior FM professional, transport authority	22	Transport infrastructure maintenance, service restoration
FM4	Facilities Management	Maintenance manager, municipal council	10	Public infrastructure maintenance, resource allocation
FM5	Facilities Management	Facilities manager, private FM firm	8	Building services management, operational planning
FM6	Facilities Management	Infrastructure engineer, power sector	19	Power network maintenance, outage management
FM7	Facilities Management	Construction and maintenance consultant	25	Critical infrastructure repair, project management
IT1	IT / Digital Systems	Software architect, infrastructure systems	16	System integration, decision-support systems
IT2	IT / Digital Systems	BIM specialist, construction technology firm	7	BIM-based FM, digital twins, data modelling
IT3	IT / Digital Systems	CMMS/CAFM systems engineer	13	FM software platforms, asset databases
IT4	IT / Digital Systems	Data analytics specialist	9	Data-driven decision support, AI applications
IT5	IT / Digital Systems	Digital transformation manager, infrastructure organisation	21	Smart infrastructure, digital strategy
IT6	IT / Digital Systems	University lecturer in information systems	14	Decision-support systems, AI in built environment
IT7	IT / Digital Systems	Software developer, smart city projects	6	Web-based platforms, dashboard design

2.5. DATA COLLECTION

Qualitative data were collected through semi-structured expert interviews and open-ended questionnaire responses. The interview protocol focused on three main themes: evaluation of the conceptual framework (clarity, relevance, completeness), perceived feasibility of applying the framework in real post-flood FM contexts, and suggestions for system integration, decision logic refinement, and user interface design.

2.6. QUALITATIVE DATA ANALYSIS

The qualitative data were analysed using thematic analysis. Expert responses were systematically coded to identify recurring themes related to: validation of framework components; practical constraints in post-flood decision-making; data requirements and integration with FM systems; expectations for AI-enabled decision-support tools; and preferred features of the conceptual flow model and dashboards. These themes were used to refine the conceptual framework and to inform the design of the conceptual flow model and prototype dashboards.

2.7. DERIVATION OF CONCEPTUAL FLOW MODEL AND PROTOTYPE DECISION-SUPPORT DASHBOARD

Based on the insights generated from the expert review, a conceptual flow model was developed to illustrate how the Action-First AI framework could be embedded within existing FM environments. The architecture reflects expert-identified requirements regarding data flows, decision processes, and user interaction. Similarly, a prototype dashboard design was conceptualised to demonstrate how FM professionals could interact with the framework in practice. The dashboard features were derived directly from expert recommendations concerning usability, transparency, and decision-support needs in post-flood contexts. These system design artefacts are presented in section 3.7 as outcomes of the qualitative expert analysis rather than as fully implemented technical systems.

3. Results: Qualitative Expert Analysis

3.1. OVERVIEW OF QUALITATIVE FINDINGS

The qualitative analysis of expert interviews revealed strong support for the proposed Action-First AI framework and highlighted practical considerations for its implementation in post-flood facilities management contexts. Thematic analysis identified five overarching themes corresponding to the interview protocol: (i) conceptual validity of the initial framework, (ii) operational feasibility in post-flood environments, (iii) practical constraints and contextual challenges, (iv) integration with existing FM systems, and (v) design expectations for the conceptual flow model and decision-support dashboards.

3.2. THEME 1: VALIDATION OF THE CONCEPTUAL FRAMEWORK

Experts generally perceived the conceptual framework as logically structured and aligned with real-world decision-making processes in post-flood facilities management. Participants highlighted that the layered structure linking data inputs, facilities management knowledge, decision logic, operational actions, and recovery outcomes reflects the sequential nature of post-disaster recovery.

Table 3, Expert Insights on Conceptual Framework Validation

Theme	**Expert category**	**Representative excerpt**	**Implication for framework refinement**
Conceptual clarity	FM expert (FM3)	"The structure makes sense because we usually start from damage information and then decide which services must be restored first."	Confirms layered structure of the framework
Relevance to practice	Disaster expert (DM2)	"Prioritising hospitals and water systems before roads reflects what we actually try to do during floods."	Validates inclusion of service criticality and population impact
Completeness	FM expert (FM6)	"The framework covers most technical aspects, but operational and resource constraints also affect decisions."	Suggests adding operational and resource considerations
Need for human oversight	IT expert (IT4)	"AI should support decisions, not replace them, especially in emergency situations."	Reinforces human-in-the-loop principle

3.3. THEME 2: FEASIBILITY OF APPLYING THE FRAMEWORK IN REAL POST-FLOOD CONTEXTS

Experts expressed cautious optimism regarding the feasibility of implementing the Action-First AI framework in real-world post-flood contexts. While participants acknowledged the potential value of structured prioritisation, they emphasised that practical implementation depends on data availability, institutional capacity, and digital maturity of FM systems.

Table 4, Expert Views on Implementation Feasibility

Theme	**Expert category**	**Representative excerpt**	**Implication for conceptual flow model**
Data availability	Disaster expert (DM5)	"During floods, we rarely have complete data; the system must work with partial information."	Need for flexible data input and uncertainty handling
Institutional readiness	FM expert (FM2)	"Many organisations still rely on manual records, so integration must be gradual."	Suggests modular system architecture
Practical usefulness	Disaster expert (DM1)	"Even a simple prioritisation tool would be better than relying only on experience."	Supports incremental implementation approach
Technical feasibility	IT expert (IT1)	"The logic is feasible if integrated as an add-on	Guides integration strategy with existing FM systems

		module rather than a standalone AI system."	

3.4. THEME 3: CONSTRAINTS AND CONTEXTUAL CHALLENGES IN POST-FLOOD DECISION-MAKING

Experts identified several contextual challenges that influence post-flood facilities management decisions. These include limited resources, political pressures, accessibility issues, and interdependencies between infrastructure systems.

Table 5, Contextual Constraints Identified by Experts

Constraint type	**Expert category**	**Representative excerpt**	**Implication for framework**
Resource limitations	FM expert (FM4)	"We never have enough crews or equipment to repair everything at once."	Supports inclusion of resource feasibility analysis
Accessibility barriers	Disaster expert (DM3)	"Sometimes we cannot reach critical assets because roads are blocked."	Validates accessibility assessment in decision layer
Political and social pressure	Disaster expert (DM6)	"Certain areas receive priority due to public or political attention."	Suggests need for transparency in prioritisation logic
Infrastructure interdependencies	IT expert (IT6)	"Restoring one system often depends on another being operational first."	Reinforces interdependency modelling in the framework

3.5. THEME 4: INTEGRATION WITH EXISTING FM SYSTEMS

Experts consistently emphasised that the success of the proposed framework depends on its ability to integrate with existing FM software and organisational workflows. Rather than developing a standalone AI system, participants recommended embedding the framework as a decision-support layer within current FM platforms.

Table 6, Expert insights on FM system integration

Integration aspect	**Expert category**	**Representative excerpt**	**Design implication**
Data sources	IT expert (IT3)	"Most required data already exists in CMMS or BIM systems, but it is fragmented."	Need for data aggregation layer
System compatibility	IT expert (IT5)	"The framework should be compatible with CAFM or CMMS platforms rather than replacing them."	Supports modular architecture design

User workflow	FM expert (FM1)	"If the system fits our existing workflow, it is more likely to be used."	Guides dashboard design
Scalability	IT expert (IT7)	"The system should be scalable so it can evolve with digital maturity."	Suggests layered and extensible architecture

3.6. THEME 5: EXPECTATIONS FOR CONCEPTUAL FLOW MODEL AND DASHBOARD DESIGN

Experts articulated clear expectations regarding the features and usability of an AI-enabled decision-support system for post-flood facilities management. Participants emphasised the need for simplicity, transparency, and actionable outputs.

Table 7, Expert-Driven Requirements for Architecture and Dashboard Design

Design dimension	**Expert category**	**Representative excerpt**	**Resulting design feature**
Transparency	Disaster expert (DM4)	"Users must understand why an asset is prioritised."	Explainable priority scoring
Usability	FM expert (FM5)	"The dashboard should show clear priorities, not complex analytics."	Ranked repair list and visual indicators
Decision support	FM expert (FM7)	"We need recommendations, not just data."	Automated repair sequencing
Human oversight	IT expert (IT2)	"Decision-makers must be able to override AI suggestions."	Human-in-the-loop controls
Situational awareness	Disaster expert (DM1)	"We need a real-time overview of service restoration."	Recovery status visualisation

These requirements were synthesised to develop the conceptual flow model and prototype dashboard design presented in Sections 3.7.2 and 3.7.3. The expert review confirmed the overall structure of the initial conceptual framework but also highlighted the importance of organisational, human, and data-related factors in post-flood decision-making. Based on these insights, the framework was refined to explicitly incorporate human oversight, operational constraints, data uncertainty, and system integration considerations. Figure 02 presents the revised Action-First AI framework reflecting expert feedback.

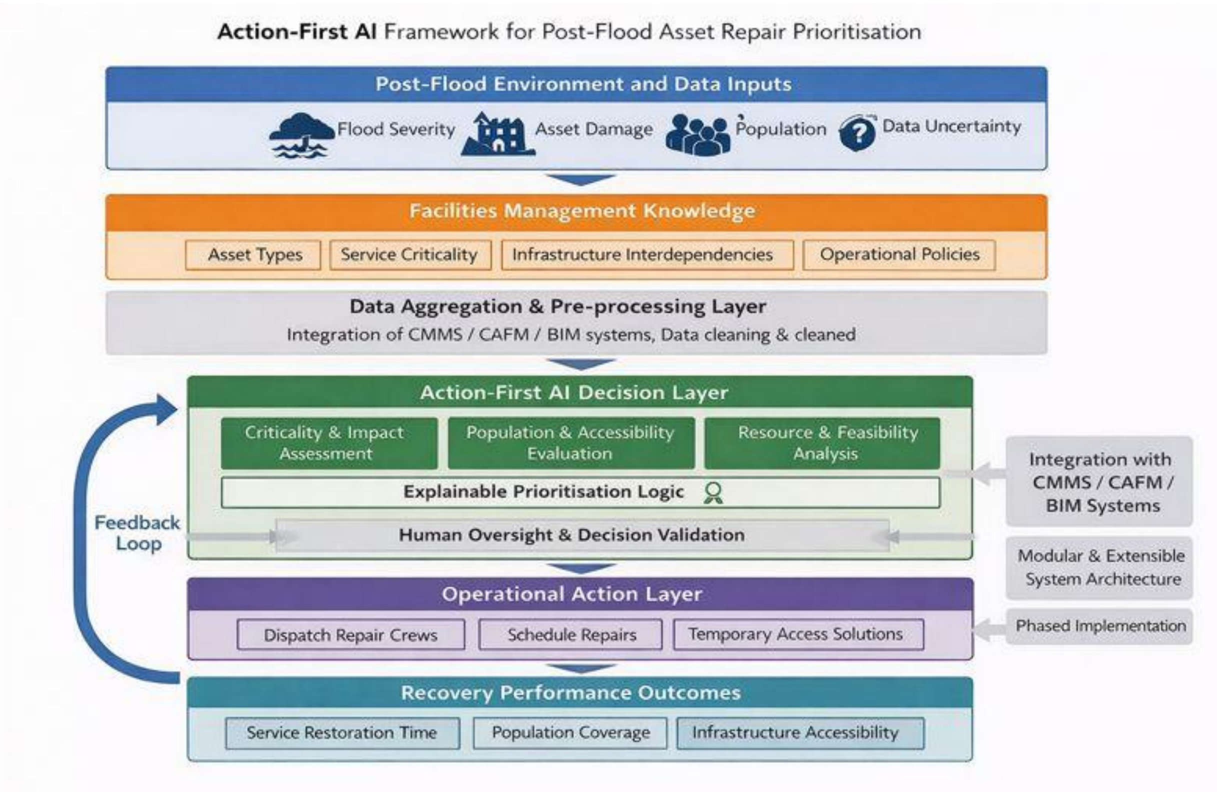

Figure 2, Refined Action-First AI framework

3.7. CONCEPTUAL FLOW MODEL AND PROTOTYPE DECISION-SUPPORT DASHBOARD

The qualitative expert review revealed that the practical relevance of the Action-First AI framework depends not only on its conceptual soundness but also on its ability to be embedded within existing FM environments and decision-making workflows. Experts emphasised that post-flood prioritisation decisions are shaped by fragmented data sources, organisational constraints, and the need for transparent and human-centred decision support.

In response to these insights, a conceptual flow model and a prototype decision-support dashboard were developed as design artefacts that translate the refined framework into an operationally meaningful structure. These artefacts are not intended to represent a fully implemented AI system; rather, they serve as conceptual blueprints illustrating how the framework could be practically operationalised within FM contexts.

3.7.1. Expert-Informed Design Principles

The thematic analysis of expert responses identified several key principles that guided the conceptual flow model and dashboard design:

1. Integration with existing FM systems: The framework should complement, rather than replace, current CMMS, CAFM, and BIM platforms.
2. Data aggregation and flexibility: The system should be capable of integrating fragmented and incomplete post-flood data.
3. Human-in-the-loop decision-making: AI outputs should support professional judgement rather than automate decisions.
4. Transparency and explainability: Prioritisation logic must be interpretable by FM professionals and stakeholders.
5. Modularity and scalability: The system should support incremental implementation and future digital expansion.

These principles directly shaped the structure of the conceptual architecture and the functional features of the prototype dashboard.

3.7.2. Conceptual Flow Model

Figure 03 presents the conceptual system architecture derived from expert insights and the refined Action-First AI framework. The architecture is organised into layered components that reflect both technical data flows and organisational decision processes in post-flood facilities management. Rather than representing a fully implemented AI system, the architecture serves as a conceptual blueprint illustrating how AI-inspired prioritisation logic could be embedded within existing facilities management environments.

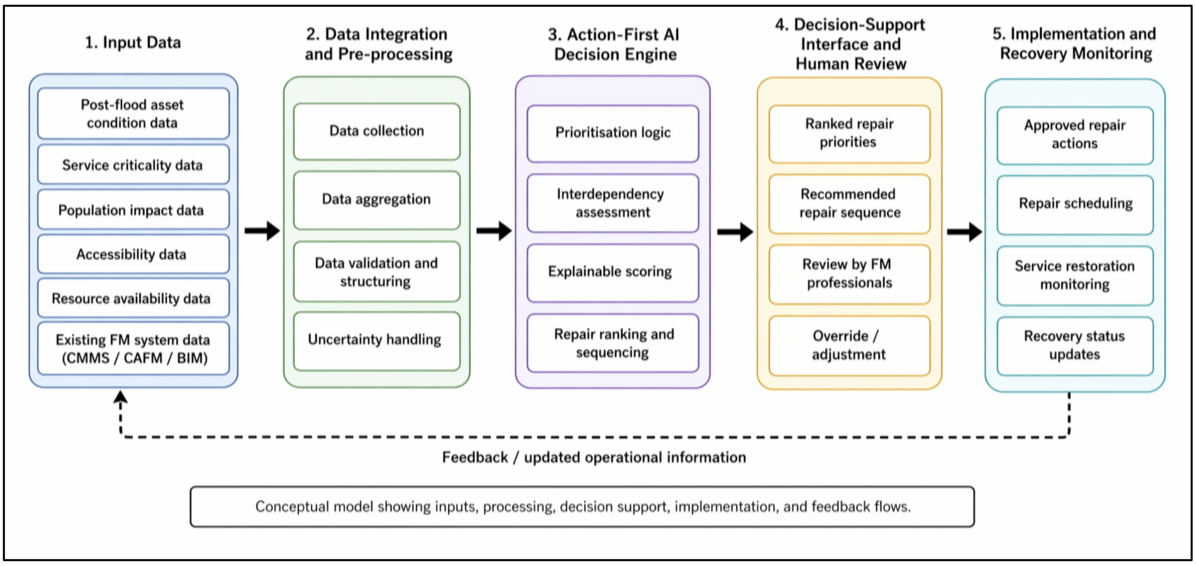

Figure 3, Conceptual flow model for Action-First AI in post-flood facilities management

3.7.3. Prototype Decision-Support Dashboard

Following the conceptual system architecture, the next step is to demonstrate how the proposed Action-First AI framework could be operationalised from the perspective of end users. While the system architecture illustrates the underlying data flows, decision processes, and integration mechanisms within facilities management environments, it does not directly convey how practitioners would experience these processes in real-world post-flood scenarios. To address this gap, a prototype decision-support dashboard was developed as a user-facing representation of the architecture. The dashboard translates the internal logic of the Action-First AI framework into actionable visual outputs, enabling facilities management professionals to interpret prioritisation results, evaluate operational constraints, and support informed post-flood decision-making.

Figure 04 illustrates the prototype decision-support dashboard designed to support post-flood facilities management decisions using the Action-First AI framework. The dashboard visualises framework-generated prioritisation outputs alongside contextual information, including asset damage levels, population impact, resource availability, and repair schedules. It also incorporates human-in-the-loop features that allow professionals to review and adjust prioritisation sequences, and feedback mechanisms that link operational outcomes to the decision process. By integrating analytical outputs with intuitive visual interfaces, the dashboard demonstrates how AI-inspired decision logic can be translated into practical tools for enhancing transparency, coordination, and responsiveness in post-flood infrastructure recovery, while aligning with existing FM workflows.

Figure 4, Prototype Decision-Support Dashboard

3.8. COMPARISON WITH EXISTING AI-BASED DISASTER MANAGEMENT AND DECISION SUPPORT SYSTEMS

The proposed Action-First AI framework differs from much of the existing AI literature in disaster management by shifting the focus from prediction and assessment toward operational repair prioritisation. Recent review studies show that AI applications in disasters are often centred on prediction, risk assessment, early warning, data fusion, and explainability, while decision-support system research has also tended to focus more strongly on preparedness and response than on recovery. Against this background, the present framework contributes by positioning AI as an action-oriented and explainable support mechanism for post-flood repair sequencing within facilities management rather than as a predictive end in itself (Albahri et al., 2024; Elkady et al., 2024).

The framework also differs from optimisation-based disaster decision-support studies that address restoration sequencing across critical infrastructure systems. Existing work has shown the value of mathematical and stochastic decision-support models for prioritising critical societal services, handling interdependencies, and coordinating specialised repair crews across multiple lifelines. These approaches provide strong analytical foundations for post-disaster restoration planning. However, they are typically developed at lifeline or network level and are not primarily framed around facilities management workflows, user-facing explainability, or integration into FM environments. By contrast, the proposed framework is tailored to post-flood facilities management contexts and combines service criticality, population impact, accessibility, interdependencies, and operational feasibility within an interpretable prioritisation structure (Shahverdi et al., 2025).

Compared with broader digital disaster management and geospatial decision-support platforms, the proposed framework is narrower in scope but more operationally focused. For example, collaborative spatial decision-support systems have been developed to integrate geospatial resources, domain knowledge, and multi-actor coordination for disaster response, while more recent digital risk twin concepts seek to provide integrated, cross-sectoral disaster risk management environments through combined automated and manual data collection and human-in-the-loop decision-making. These approaches make important contributions to data integration, coordination, and situational awareness. The relative advantage of the Action-First AI framework lies in its targeted emphasis on post-flood asset repair prioritisation within existing facilities management environments, particularly through its intended compatibility with CMMS, CAFM, and BIM-linked workflows and its focus on clear and reviewable prioritisation outputs (Fang et al., 2023; Ghaffarian, 2025).

Taken together, these comparisons suggest several relative strengths of the proposed framework. First, it offers closer alignment with day-to-day facilities management practice than many existing AI or infrastructure-level restoration models. Second, it places stronger emphasis on transparent, human-centred, and socially responsive prioritisation rather than purely technical optimisation. Third, it appears suitable for fragmented and data-scarce post-flood contexts because it is conceived as a modular decision-support layer rather than a fully autonomous, data-intensive AI system. These should, however, be understood as conceptual and design-level advantages at this stage, since the present study validates the framework through expert review rather than through full technical implementation or comparative performance testing (Albahri et al., 2024; Elkady et al., 2024; Ghaffarian, 2025).

4. Conclusion

This study proposed and evaluated an Action-First AI approach for post-flood facilities management, addressing a critical gap between AI-driven analytics and operational decision-making in disaster recovery. The findings highlight several key contributions. Conceptually, the study introduces an Action-First AI paradigm that shifts the focus of disaster-related AI from prediction to operational prioritisation. Theoretically, it bridges artificial intelligence, disaster management, and facilities management into a unified decision-support framework. Methodologically, it demonstrates the value of expert-based validation and design science approaches in developing AI-inspired frameworks in data-scarce contexts. Practically, it provides a conceptual blueprint for embedding AI-enabled decision support within facilities management systems, particularly in developing-country contexts such as Sri Lanka. While the study does not involve the technical implementation of an AI system, it offers a robust foundation for future development. The proposed framework, conceptual flow model, and dashboard can guide software developers, IT specialists, and facilities management organisations in translating conceptual design into operational digital tools. Future research should focus on practical implementation, integration with real-world FM systems, and empirical evaluation using post-flood datasets to assess the effectiveness, usability, and impact of the proposed approach. Overall, this research demonstrates that Action-First AI has significant potential to enhance the speed, transparency, and equity of post-flood infrastructure recovery. By aligning AI-inspired decision logic with facilities management practices and human judgment, the study offers a novel, practically grounded pathway to advance AI-enabled disaster recovery and resilient infrastructure management. The novelty of the study lies in framing AI not as a predictive end in itself, but as an explainable and action-oriented decision-support approach tailored to post-flood facilities management and embedded within existing FM workflows.

5. References

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