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# AI Emergency Response Agent: A Literature Survey and Proposed Framework for Autonomous Real-Time Emergency Assistance

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Guide

Abstract

Manual communication is often used during emergency medical situations, causing a delay in receiving the correct help. During an emergency, the individual needs to recognise the situation, tell someone where they are, determine which hospital would be best, organise an ambulance, and decide what first aid to give. Each of these can cause delays. Recent studies have looked into implementing machine learning, large language models (LLMs), and multi-agent systems into emergency situations in order to improve various parts of the emergency situation. However, most models only focus on certain tasks. Sixteen studies were reviewed between 2018 and 2026 covering emergency triage prediction, using large language models in multi-agent decision support, ambulance dispatch, ambulance booking, first-aid chatbots, and medical resource recommendation. Nine key studies were compared using a year-based survey matrix. Five main issues were found to be issues within the current systems. These include: limited scope, lack of capability in autonomous agents, lack of real-time integration between location services, hospitals, ambulance and emergency contacts, missing privacy, security and trust issues, and lack of validation in real-life scenarios. In order to overcome these issues this paper proposes an emergency taxonomy linking different types of emergencies to the right priority in first aid and capabilities in hospitals. It also proposes a way of prioritising resources using a scoring system based around how urgent the emergency is. A conceptual model of a five-module AI Emergency Response Agent was also proposed which has not yet been implemented. An appropriate evaluation protocol will be discussed in future work.

Keywords : AI emergency response agent, autonomous agents, emergency triage, first-aid guidance, hospital recommendation, large language models, multi-agent systems, GPS tracking, literature survey.

## I. Introduction

If someone collapses, has been involved in a road traffic accident or has been poisoned it can make a significant difference if they receive aid within the first few minutes. If patients can be identified as being in an emergency and given basic life support quickly, then the patient will have better outcomes

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[8]. Unfortunately, emergencies can be complex processes, requiring patients to identify the issue, provide accurate information about where they are, find a suitable hospital, call for an ambulance and know what to do with first aid until professionals arrive. This can cause delays in receiving aid from professionals, especially when the victim cannot communicate or others are confused about what to do.

Artificial intelligence (AI) can help aid this process. There have been studies that explore using machine learning models to predict patient outcomes within the emergency department triage [1, 2], developing multi-agent systems based on large language models (LLMs) to aid with triage and treatment planning [3], using LLMs to aid with emergency call outs and public communication [4], developing wearable technologies to aid EMS responders [5] and developing mobile applications to connect users with ambulance services [7]. Although these are useful solutions most only focus on one part of the emergency.

This paper therefore asks a focused question: what would an AI system have to look like to detect an emergency, locate the user, recommend a suitable hospital and ambulance, guide first aid and notify the right people in one autonomous, auditable chain? Our contributions are:

- A structured review of sixteen works (2018–2026) and a year-wise literature survey matrix comparing methodology, key findings and limitations (Section III).
- An emergency taxonomy linking emergency types to first-aid priorities and hospital capabilities (Section II).
- A gap analysis that identifies five unmet requirements (Section IV).
- An urgency-scoring and resource-ranking formulation and a five-module conceptual framework that address those gaps, together with a proposed evaluation protocol (Sections V and VI).

The work is deliberately limited to literature survey and gap analysis. No model is trained, no patient data are used and no field trial is conducted; Section VII states the consequences of this scope.

## II. Emergency Response Landscape and Taxonomy

### *A. The emergency response chain*

An emergency response can be viewed as six linked stages: (1) detection and reporting, (2) location sharing, (3) dispatch and hospital selection, (4) bystander first aid, (5) notification of relatives and the receiving hospital, and (6) hospital handover and triage. Delay can accumulate at every stage, and the stages are normally coordinated by people over a voice call. Hospital-side triage uses five-level acuity scales: Raita *et al.* compare learned models with the Emergency Severity Index (ESI) [2], and Han and Choi build on the Korean Triage and Acuity Scale (KTAS) [3]. These scales begin at the hospital door; the earlier stages (1)–(5) are less well served by AI, which motivates the framework in Section V.

### *B. Emergency taxonomy*

Table I lists the eight emergency classes considered in this work, the indicators a user or device can report, the first-aid priority, and the hospital capability the receiving facility should have. The mapping is proposed here from general first-aid practice and should be validated by medical professionals against current guidelines before any use.

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**Table I.** Emergency Taxonomy Linking Reported Indicators, First-Aid Priority and Required Hospital Capability

| Emergency class | Typical reported indicators | First-aid priority (summary) | Hospital capability |
|---|---|---|---|
| **Cardiac emergency** | Chest pain, pain spreading to arm, collapse, no pulse | Call emergency services; start chest compressions if unresponsive and not breathing normally; use an AED if available | Cardiology / cardiac care |
| **Stroke** | Face drooping, slurred speech, arm weakness, sudden severe headache | Call emergency services; note the time symptoms began; keep the person still; give nothing by mouth | Neurology, brain imaging |
| **Road accident / trauma** | Collision, fall from vehicle, head injury, limb deformity | Call emergency services; do not move the person unless in danger; control visible bleeding | Trauma centre |
| **Severe bleeding** | Blood loss that will not stop, deep wound | Apply firm direct pressure with a clean cloth; keep it in place | Trauma / surgery |
| **Burns** | Fire, scald, electric shock, blistering skin | Cool with clean running water; cover loosely; avoid ice and ointments | Burns unit |
| **Choking** | Cannot cough or speak, grasping throat, turning blue | Back blows and abdominal thrusts as appropriate for age; call emergency services | Emergency department |
| **Seizure** | Uncontrolled shaking, loss of awareness | Protect from injury; do not restrain or place anything in the mouth; time the seizure | Neurology / emergency dept. |
| **Poisoning** | Swallowed chemicals or tablets, gas exposure | Call emergency services or a poison centre; keep the container; do not induce vomiting unless advised | Toxicology / Intensive Care |

*The first-aid recommendations provided in this table are intended as a general guide. Official first-aid guidelines should always be consulted to ensure that the advice is accurate and up to date, particularly when treating children.*

## III. Literature Review

### *A. Method*

The retained works were published in IEEE conferences, Springer and Nature Portfolio journals, PLOS ONE and on arXiv, and were identified for the topics of AI-based emergency triage, LLM and multi-agent decision support, first-aid guidance, ambulance and hospital recommendation, and emergency

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dispatch assistance. Sixteen works published between 2018 and 2026 were retained: nine primary studies that propose or evaluate a method or system [1–9], two reviews [10, 11], and five further works [12–16] that are described only at the level of their stated scope. For each primary study we extracted the methodology, the key finding and the stated or evident limitation, and compared them in Table II. Studies are ordered by year.

*B. Survey matrix*

Table II compares the nine primary studies by methodology, key findings and limitations.

*C. Synthesis*

**Hospital-side triage prediction.** Hong *et al.* and Raita *et al.* show that learned models can predict admission and critical-care needs at triage, and that they can outperform the conventional ESI [1, 2]. Both start when the patient is already at the hospital, and both are limited to the datasets on which they were built.

**LLM and multi-agent decision support.** Han and Choi demonstrate that splitting emergency-department work among role-specific LLM agents improves triage accuracy over a single agent [3]. Otal *et al.* move earlier in the chain, classifying incoming emergency messages, giving instructions and notifying agencies with location [4]. ESARS uses a multi-agent design for situation awareness from social-media data [6]. These are the closest precedents for an agentic emergency system, but each covers a different slice.

**Responder-side assistants.** CognitiveEMS [5] and IRIS-AI [9] show that real-time recommendation is feasible, but their users are trained EMS responders and fire commanders rather than the person in the emergency.

**Citizen-facing tools.** The ambulance application of Samuel *et al.* combines location with ambulance availability and arrival time [7], which is the logistics part of the problem, but it does not understand what the emergency is. First-aid guidance is studied separately: chatbots can help but their correctness varies [8], and a further work proposes a context-aware chatbot for personalised first-aid guidance [14].

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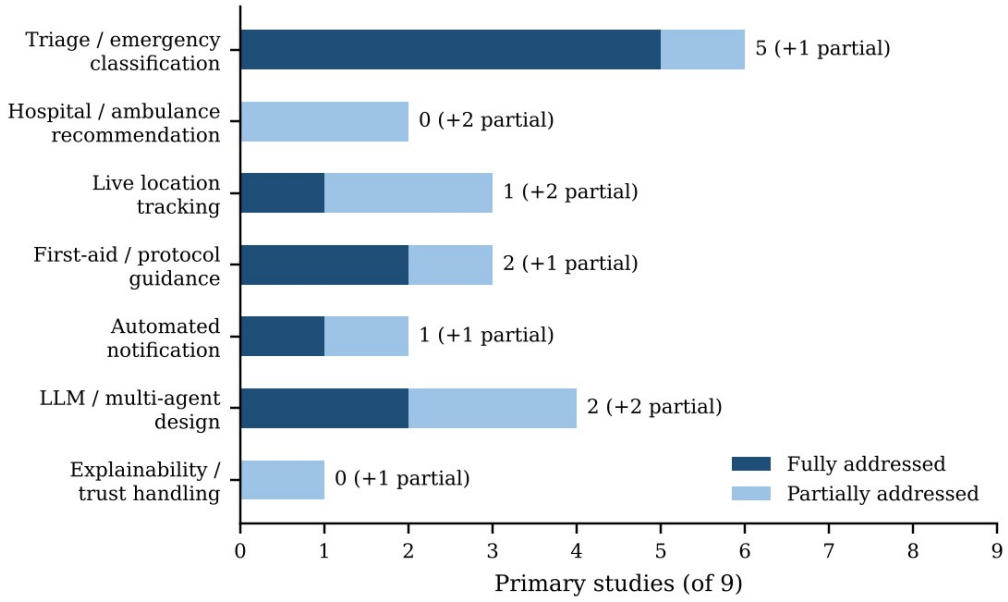



**Figure 1.** Number of the nine primary studies that address each capability, derived from Table III.

**Reviews and related works.** Correia *et al.* review AI in emergency medicine with a focus on emergency imaging, and stress privacy, bias and the need for validation across settings [10]. A scoping review of AI agents in healthcare identifies 43 studies, most of them published in 2025, which indicates how new agentic approaches are [11]. As their titles indicate, further works address transparency and accountability in AI for emergency management [12], an AI emergency-response and disaster-management system [13], the safety of generative AI agents [15], and the combination of LLMs, multi-objective optimisation and reinforcement learning for urban emergency response [16].

Table III condenses the matrix into a capability comparison. Its entries are derived from Table II and from the study descriptions; “Yes” means the capability is addressed, “Part” that it is addressed in part, and “No” that it is not addressed.

## IV. Research Gaps and Challenges

Reading Tables II and III together, triage or emergency classification is the best-covered capability (five of nine studies fully, one in part), whereas no study fully addresses hospital or ambulance recommendation or explainability and trust (Fig. 1). The broadest study, Otal *et al.* [4], fully covers three of the seven capabilities and touches five, and none combines the full set. Five gaps follow.

**Gap 1: single-function systems.** Most existing solutions focus on one task, such as triage prediction [1, 2], ambulance booking [7], situation awareness [6] or first-aid guidance [8]. Each is useful, but the person in the emergency must still bridge the gaps between them.

**Gap 2: limited autonomous agent behaviour.** Many systems depend on manual decisions and do not use agents that can plan, reason and execute several tasks on their own. Although multi-agent systems have been proposed in previous studies [3, 6], they mainly support hospital staff and decision-makers rather than directly assisting victims during an emergency.

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**Gap 3: limited real-time integration.** GPS, hospitals, ambulances, emergency contacts and first-aid guidance are rarely brought together on one platform. Location-based tools [7] can help users find or access emergency services, but they generally do not assess the nature of the emergency. Similarly, tools designed to understand emergencies [4] do not necessarily compare hospitals or recommend the most suitable facility.

**Gap 4: Privacy, Security and Trust.** Ensuring the protection of patient privacy, security, and trust in the AI solution are important issues [10, 12]. If an AI agent requires access to user location and health information then this must be done with appropriate consent, only collect and share the necessary data, and keep clear logs.

**Gap 5: Lack of real world validation.** Many proposed AI solutions have only been validated in simulated environments, therefore there is a need to be able to validate at scale [3, 11].

A common requirement across all the areas is to ensure safety. LLM generated first aid guidance may be incorrect or incomplete [8], therefore the AI agent must know when it does not have confidence and pass it to a human.

**Table II.** Year-Wise Literature Survey Matrix

| Author, year | Methodology and key findings | Limitations |
|---|---|---|
| **Hong et al., 2018 [1]** | Machine learning (XGBoost) on triage information and patient history to predict hospital admission at emergency-department triage; prediction is more accurate when patient history is included. | Limited to specific hospital datasets. Operates at the hospital door; no location, dispatch or first-aid role. |
| **Raita et al., 2019 [2]** | Machine-learning models for emergency-department triage; they outperform the traditional Emergency Severity Index (ESI) in predicting critical-care needs. | Requires validation in various hospitals. Hospital only. |
| **Han & Choi, 2024 [3]** | Multi-agent clinical decision support built on an LLM (Llama3-70b) with CrewAI and LangChain; four agents (triage nurse, emergency physician, pharmacist, ED coordinator) support KTAS-based triage and treatment planning, and show higher accuracy than a single-agent baseline in specialist assessment. | Requires integration and full testing in hospitals. Emergency department setting; no pre-hospital location or dispatch. |

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| Author, year | Methodology and key findings | Limitations |
|---|---|---|
| **Otal et al., 2024 [4]** | LLaMA2 identifies and classifies emergency situations from social-media posts and direct emergency messages, offers instructions to telecommunicators and to the public, and triggers workflows that notify agencies with caller location and emergency information. | No hospital or ambulance recommendation; the system is designed for US 911 dispatch. Testing of the LLM reliability during deployment is yet to be completed. |
| **Weerasinghe et al., 2024 [5]** | CognitiveEMS: wearable assistant on AR smart glasses with edge computing; speech recognition tuned for emergency conversations (WER 0.290 vs. 0.618 for a state-of-the-art baseline), EMS protocol prediction and action recognition. | Designed for professional EMS responders with specialised equipment; no patients and bystanders. No hospital ranking or notifying contacts. |
| **Sako et al., 2024 [6]** | ESARS: situation-aware multi-agent system that uses geolocation-enabled social-media streams to give decision-makers real-time emergency alerts and reports through a web interface. | Answers needs of decision-makers, not specific victims. Relies on social media data. No first-aid recommendation or hospital rankings. |
| **Samuel et al., 2024 [7]** | Android application that uses location-based services to find available ambulances, show estimated arrival times, book an ambulance and track it in real time. | Allows for booking ambulances only; no emergency verification, first-aid help or hospital recommendations; user must start everything. |
| **Aqavil-Jahromi et al., 2025 [8]** | Evaluates GPT, Bard and Bing chatbots in basic-life-support scenarios; chatbots give useful first-aid guidance but should support, not replace, medical professionals. | The accuracy of the program can vary; hallucination is still a problem. No connection with location; dispatch or notifications. |
| **Mercadé et al., 2025 [9]** | IRIS-AI: AI recommender of resources for emergency decision support in fire departments. | Fire service domain for command's staff only; not for medical emergencies or untrained users. |

*Entries are taken from the abstracts and explanations of the works as published; summaries of entries [8], and the expert commentary [3] are provided as stated.*

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## V. Proposed Conceptual Framework

### *A. Urgency scoring and resource prioritization*

Let $x$ denote the user's report (textual, voice and sensor data if available). An emergency class $c$ can be drawn from Table I. A classifier provides posterior probabilities $P(c \mid x)$. We define the confidence and margin

$$\kappa = \max_c P(c \mid x), \quad m = P(c_{(1)} \mid x) - P(c_{(2)} \mid x) \quad (1)$$

where $c(1)$, $c(2)$ are the two most probable classes. Urgency is scored from three measurements: the base severity $Sc$ of the predicted class, the abnormality $V$ of any vital-sign or sensor reading (set to zero, with the remaining weights renormalised, if none is available), and the elapsed time $T$ since onset:

$$U = w_S\varphi_S(S_c) + w_V\varphi_V(V) + w_T\varphi_T(T) \quad (2)$$

where the weights are non-negative and sum to one, and each $\varphi$ maps its input to [0, 1], so $U \in [0, 1]$. The score is discretised into an urgency band by ordered thresholds,

$$b = k \text{ if } \tau_k \le U < \tau_{k+1}, \quad k = 1, \ldots, 5 \quad (3)$$

with band 5 the most urgent (Table IV). For each candidate hospital $j$ within a search radius, the resource agent computes a cost from the travel time ETA$j$ (from live GPS and a routing service), the reported availability $A$j ∈ [0, 1], and the capability match $M$j,c ∈ {0, 1} from Table I:

$$C_j = \alpha\,\mathrm{ETA}_j + \beta(1 - A_j) + \gamma(1 - M_{j,c}) \quad (4)$$

$$j^* = \operatorname{argmin}_j C_j$$

Ambulances are ranked by ETA alone. First-aid guidance is released only when

$$\kappa \ge \kappa_0 \quad \text{and} \quad m \ge m_0 \quad (5)$$

otherwise the agent gives generic safe instructions, asks a clarifying question and escalates to a human dispatcher. The weights $w$, coefficients $\alpha$, $\beta$, $\gamma$ and thresholds $\tau$, $\kappa 0$, $m0$ are parameters to be calibrated with clinicians and real data; this paper does not set them.

### *B. Architecture*

The framework has five modules and a supervising orchestrator (Fig. 2), each aimed at one or more of the gaps in Section IV.

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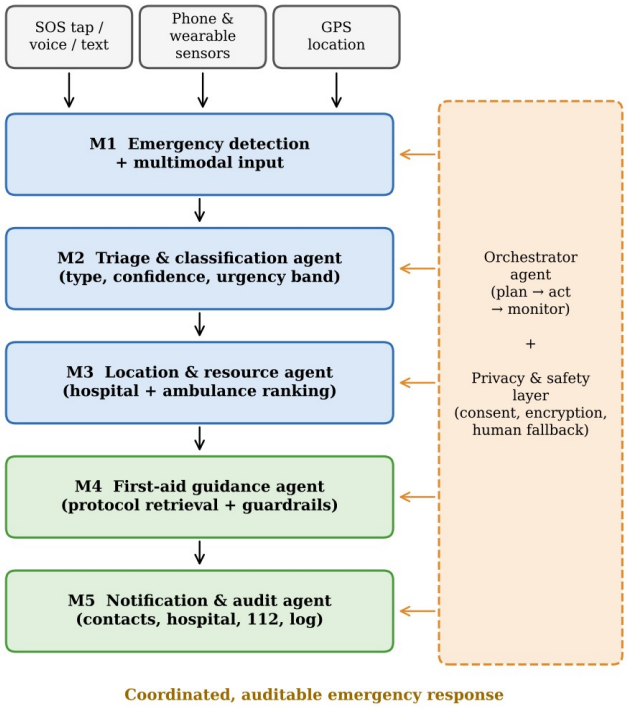



**Figure 2.** Conceptual framework. Modules M1–M3 (blue) sense and understand the emergency, M4–M5 (green) guide and notify, and the orchestrator with its privacy and safety layer (orange) coordinates and supervises them.

**M1: emergency detection and multimodal input (Gap 3).** An SOS tap, a voice or text report, and, where available, phone or wearable sensor signals start an incident. Accepting several input types lets the agent work for users who cannot type, and the module must tolerate a missing channel.

**M2: Triage/Classify.** An ML-based or LLM-based classifier assigns a class from Table I to the report using posterior probabilities (Equation 1). Urgency bands are determined using Equations 2 and 3. LLM generated outputs cannot always be trusted [8] so an ML-based classifier is used as a check. If the confidence of the classification is low then this is highlighted.

**M3: Locating Resources.** The agent tracks GPS location and locates nearby hospitals and ambulances. Using Equation 4 the hospitals are ranked so they can send the patient to a suitable nearby hospital.

**M4: First Aid Advice.** Advice is taken from a carefully curated database that has been reviewed by clinicians. This advice may be rewritten by an LLM for clarity. Equation 5 acts as a filter. If the system is unsure which class the emergency belongs to then advice will not be given. All advice given can be traced back to the protocol.

**M5: Notify/Audit.** The agent notifies the emergency contacts, ambulance service and receiving hospital with the live location and details of the emergency. Each incident is recorded with the inputs, versions of modules used and decisions made.

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**Orchestrator & Privacy.** The orchestrator uses a plan-do-monitor approach. It decides which modules are required. Where possible modules are run in parallel. The orchestrator monitors for any issues such as no internet connection or ambulance not taking the request. If there is a problem with the system then it will re-plan. A privacy and safety layer will be included where explicit consent is given. Less data will be recorded, encrypted, with time limits. There will also be a human in the loop. This complies with data protection laws such as the Digital Personal Data Protection Act, 2023 in India [17].

**Table III.** Capability Comparison of Primary Studies

| Study | Triage | Recommendation | Localization | First aid | Notification | Agents | Explainability / Trust |
|---|---|---|---|---|---|---|---|
| Hong 2018 [1] | Yes | No | No | No | No | No | No |
| Raita 2019 [2] | Yes | No | No | No | No | No | No |
| Han & Choi 2024 [3] | Yes | No | No | No | No | Yes | No |
| Otal 2024 [4] | Yes | No | Part | Yes | Yes | Part | No |
| Weerasinghe 2024 [5] | Yes | No | No | Part | No | Part | No |
| Sako 2024 [6] | Part | No | Part | No | Part | Yes | No |
| Samuel 2024 [7] | No | Part | Yes | No | No | No | No |
| Aqavil-J. 2025 [8] | No | No | No | Yes | No | No | Part |
| Mercadé 2025 [9] | No | Part | No | No | No | No | No |
| **Proposed system design** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** |

*Triage: emergency triage/classification; Recommendation: hospital or ambulance recommendations; Localization: real-time localization; First aid: first-aid or protocols; Notification: automated*

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*notifications; Agents: LLM or multi-agents; Explainability/Trust: explainability/trust handling. The bottom row is a design goal, not an achievement.*

**Table IV.** Proposed Urgency Bands and Agent Actions

| Band | Example situation | Agent's suggested action |
|---|---|---|
| 5 | Unresponsive, not breathing normally | Automatically call emergency number, ambulance, provide live location, pre-alert hospital, alert contacts, initiate guidance |
| 4 | Stroke, heavy bleeding | Send ambulance, prioritize suitable hospitals, guidance, contacts |
| 3 | Bone fracture, moderate burn | Recommend suitable hospital and directions, guidance, contacts if needed |
| 2 | Small injury, mild symptoms | Nearby facility/tele-consultation, monitor |
| 1 | Non-urgent question | Self-care guidance, no alert |

*These bands are illustrative and roughly based on the five-tiered triage system, such as ESI [2] and KTAS [3]. Clinicians will have to determine the actual map.*

## VI. Proposed Evaluation Protocol

The framework has not been built, so no results are reported. To keep the claims testable, we propose the following protocol for the implementation stage.

- **Classification quality:** accuracy, macro-F1 and per-class recall for the classes in Table I, with particular attention to the under-triage rate for life-threatening classes.
- **Guidance safety:** clinician review of guidance for correctness, a count of unsafe or incorrect instructions, and the rate at which the agent correctly withholds guidance when uncertain.
- **Resource recommendation:** ETA error and the share of cases routed to a capable, available facility, compared with a nearest-hospital baseline in simulation on a public road network and hospital directory.
- **End-to-end latency and reliability:** time from trigger to delivered notifications, and behaviour under poor connectivity.
- **Advantage of response time:** simulations for dispatch followed by drills under ethical approval in comparison with the manual system with respect to ambulance dispatch time and hospital pre-alert.

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- **Privacy and security:** threat modelling, data-minimisation audit and consent-flow review.
- **Usability and false alarms:** usability testing with lay users, including older adults and speakers of local languages, and the rate of false emergency triggers.

Because real patient data will not be available at the start, initial experiments would use public triage datasets and scripted scenarios, with any real-world pilot requiring ethics and regulatory approval.

## VII. Limitations and Scope

The paper reviews sixteen works, which is enough to expose recurring gaps but is not an exhaustive systematic review; extending the corpus is a natural next step. The capability comparison in Table III is based on published abstracts and descriptions and may miss features that a paper implements but does not emphasise, and the five further works [12–16] are characterised only by their stated scope and should be re-read in full. Some of the primary sources are from hospital, US and Korean contexts, thus their conclusions might not apply directly to Indian pre-hospital emergency response systems. The framework is conceptual: the weights and thresholds in Eqs. (2)–(5) are uncalibrated, the taxonomy in Table I is a proposed interpretation that should be validated by medical professionals, and no experiment supports any performance claim. Software implementation, model training, clinical validation and field deployment are outside the scope of this stage.

## VIII. Conclusion and Future Work

Emergency response still relies on manual communication that adds delay when time matters most, while the AI literature reviewed here largely automates one stage at a time. Comparing sixteen works showed that none of the nine primary studies fully combines emergency understanding, location tracking, resource recommendation, first-aid guidance and notification, and that no study fully addresses hospital or ambulance recommendation. We addressed this with an emergency taxonomy, an urgency-scoring and resource-ranking formulation, and a five-module framework with an orchestrator and a privacy and safety layer.

The next stage is implementation, beginning with the triage and classification module (M2) and a location and resource prototype (M3), followed by a clinician-reviewed guidance base (M4), calibration of the weights and thresholds, and evaluation under the protocol in Section VI.

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