Literature Survey:

Objective: To analyze existing research on ambulance routing, emergency triage, hospital resource prediction, and dispatch visualization, identifying current gaps in developing a unified, intelligent emergency response system.

Reviewed Research Papers

1. Smart Ambulance Routing Using Green AI and Edge Computing

This paper explores real-time ambulance tracking using IoT and Green AI principles. It emphasizes cost-efficient routing through low-power edge devices. However, it lacks integration with patient condition or hospital load data.
Read Paper

---

2. Smart Ambulance Route Optimization System – IRJET

Introduces an optimized ambulance dispatch system utilizing GPS, Google Maps API, and traffic signal control. Focus is on timely arrival, but triage or hospital suggestions are absent.
Read Paper

---

3. Ambulance Routing with CNN-SVM Models in Urban Traffic – Nature

Applies convolutional neural networks and SVMs for dynamic route optimization and patient urgency estimation. Highlights scalability but omits real-time triage workflows.
Read Paper

---

4. QoS-Aware Disaster Triage and Routing Optimization – Springer

Proposes an integrated framework using machine learning to predict triage level and route ambulances accordingly in disaster scenarios. Offers early attempts at unification of functions.
Read Paper

---

5. JumpSTART Triage in Pediatric Mass Casualty Response – PubMed Central

Describes pediatric-specific triage rules under JumpSTART protocols. Lays foundation for automated triage logic but remains manual in nature.
Read Paper

---

6. Evaluation of Triage System Accuracy in Mass Casualty Incidents – PMC

Presents a meta-analysis of current triage system accuracy under pressure. Points out errors and the need for AI-driven automation in real-time deployments.
Read Paper

7. Explainable ML for ICU Resource Prediction – arXiv

Develops a pipeline for ICU readmission and resource forecasting using explainable AI. Valuable for hospital readiness but not tied to live emergency dispatch.
Read Paper

---

8. AI-Based Emergency Call Triage Using Natural Language Processing – Science Partner Journals

A proof-of-concept that applies machine learning to triage emergency calls based on severity using call transcripts. Lacks integration with routing or hospital databases.
Read Paper

---

9. Real-Time Hospital Recommendation System with Google Maps API – BMC Health Services Research

A web-based tool suggesting optimal hospitals based on location and traffic data. Though real-time, it does not assess ICU load or patient condition dynamically.
Read Paper

---

10. Forecasting Emergency Call Demand Using ML – ScienceDirect

Uses ambulance call history to model future emergency trends. Effective for planning, but not directly involved in triage or dispatch workflows.
Read Paper

Key Insights and Gaps Identified

Aspect	Findings
Routing Optimization	Strong AI-based models exist but lack patient condition inputs.
Triage Logic (START/JumpSTART)	Mostly manual, with minimal tech-enabled implementation.
ICU/Resource Forecasting	Developed in silos, not tied to dispatch or EMS workflows.
Dashboard Visualization	Exists in Tableau and academic simulations, but lacks real-time triage.
Integrated Solutions	No end-to-end, low-cost platform integrating all four components.

Conclusion

The literature highlights significant progress in individual domains like ambulance routing, triage systems, and ICU forecasting. However, a **fully integrated platform**—incorporating **AI-based triage, hospital recommendation, live route optimization, and real-time dashboards**—remains missing. This presents a strong opportunity for impactful, scalable innovation in emergency response systems.

Comprehensive Review & Critical Analysis – Paper 1 [Read Paper]

Title: ***Greenvoy: A Survey on Smart Ambulance Routing through Green AI and Edge Intelligence***

Authors: Shalini S., C. Nandini, Geetha Shree R., M. Yasaswini, Neetha Jain, Anusha P.
Published: *International Journal of Science, Engineering and Technology*, 2025 (ijset.in, ijset.in)

---

1. Objective & Scope

This paper conducts a thorough examination of contemporary *Smart Ambulance Systems* (SAS) that integrate IoT sensors, low-power Green AI methods, and edge-based inference models. Its primary goal is to assess how these technologies enable efficient real-time ambulance routing, patient vitals monitoring, and emergency service coordination, with an emphasis on minimizing energy use and reducing latency. (ijset.in)

---

2. Key Components Reviewed

- **IoT-enabled data collection**: Biomedical sensors (e.g., MAX30100) for continuous patient vitals, coupled with GPS/GSM modules for location and communication.
- **Edge processing**: Edge-AI devices near ambulances analyze and transmit critical data while limiting dependency on cloud, reducing data latency.
- **Routing intelligence**: Applications of ML, especially reinforcement learning algorithms, to perform dynamic route decision-making based on traffic, energy metrics, and proximity to hospitals.
- **Cloud and API integration**: Utilizes services—like Google Maps—for live traffic, enabling improved situational awareness and data sharing. (ijset.in)

---

3. Major Findings

- **Routing Accuracy**: Green AI methods can effectively find time- and energy-efficient paths, particularly under traffic constraints.
- **Edge Viability**: Deploying ML inference at edge nodes achieves sub-100 ms responses—critical for emergency use—while cutting down bandwidth requirements.
- **Patient Monitoring**: Live telemetry provides hospitals with early warning of patient deterioration.
- **System Gaps**: Despite innovations, few SAS implementations factor in **hospital load data** or **triage assessments**, limiting end-to-end decision support.

---

4. Strengths

- **Holistic survey**: Covers full spectrum—from hardware (sensors, communication) to software (ML routing, cloud integration).
- **Green AI focus**: Emphasizes energy-efficient computation, which is critical for scalability in resource-constrained settings.
- **8-challenge taxonomy**: Clearly outlines technical and operational obstacles, from scalability and security to standardization. (ijset.in, arxiv.org, ijset.in)

---

5. Weaknesses & Limitations

- **Overreliance on Simulations**: Recommendations are based mainly on prototype or simulation results; real-world implementation data is scarce.
- **Lack of Clinical Metrics**: Does not assess how SAS interventions affect patient outcomes such as mortality, morbidity, or hospital readiness.
- **System Fragmentation**: Highlights disconnect between routing logic and hospital resource planning or triage protocols.
- **Economic Viability**: Offers limited cost–benefit analysis for deploying SAS in low-resource or rural settings.

---

6. Critical Analysis

The paper excels in delineating current technological enablers of smart ambulance systems, particularly emphasizing the promise of Green AI and edge computing. These advances are vital in balancing performance with sustainability. However, the review stops short of evaluating the **clinical integration**—i.e., how this data informs real-time triage decisions or hospital load balancing, a critical omission for developing truly intelligent, end-to-end emergency response systems.

---

7. Contribution to Your Research

- **System blueprint**: Offers a layered architecture (sensors → edge → cloud → hospital) that you can adapt.
- **Green AI techniques**: Reinforces your direction towards low-cost, low-power ML—essential for scalable deployment.
- **Identified gap**: Provides explicit grounding to highlight that *dispatch systems rarely incorporate real-time triage or hospital-load data*—a major focus area for your work.

---

8. Recommendations for Extension

- **Pilot deployment**: Run small-scale trials to gather empirical data on response time, resource usage, and patient outcomes.
- **Add triage module**: Integrate a lightweight triage algorithm (e.g., on edge or in-cab tablet) fed from vitals/EMS input.
- **Hospital coordination API**: Introduce a RESTful interface for live hospital load and bed availability to influence routing.

🔗 **Read the full paper:** https://www.ijset.in/wp-content/uploads/IJSET_V13_issue3_227.pdf

---

Comprehensive Review & Critical Analysis – Paper 2 [Read Paper]

Title: *Smart Ambulance Route Optimization System*

Authors: A. R. Nair, R. R. Patil, M. R. Deshmukh
Published in: *International Research Journal of Engineering and Technology (IRJET)*, Vol. 12, Issue 4, Apr. 2025 (IRJET)

---

1. Objective & Scope

This work presents a smart ambulance dispatch solution focused on alleviating urban traffic delays. Key objectives include leveraging real-time GPS tracking, IoT-enabled traffic signal control, AI-driven routing, and centralized dashboard for efficient emergency transit (IRJET). The system aims to significantly reduce ambulance response times by optimizing traffic light sequencing and route selection.

---

2. System Architecture & Features

- **Real-Time GPS Tracking:** Provides continuous location updates to a cloud-based control center.
- **Traffic Signal Preemption:** Integrates IoT-enabled signals and AI analytics to prioritize ambulances at intersections.
- **Route Optimization:** Uses Google Maps API and ML models to predict traffic congestion and suggest live route adjustments.
- **Central Dashboard:** Enables traffic authorities to visualize ambulance locations and dynamically control routes and signals (IRJET).
- **V2X Communications:** Vehicle-to-infrastructure messaging allows proactive traffic signal changes.
- **Scalability Concept:** System design extends to other emergency vehicles like fire trucks and police vans (IRJET).

---

3. Key Findings

- **Response Efficiency:** System simulation indicated up to ~30% decrease in travel time via traffic signal prioritization.
- **Predictive Routing:** ML-driven congestion forecasting augmented routing decisions, improving dispatch success.
- **Operational Insights:** Central dashboard enhanced inter-agency coordination and permitted manual overrides when required (IRJET, arXiv).

---

4. Strengths

- **Multi-technology Integration:** Combines GPS, IoT traffic lights, V2X, cloud analytics, and AI for a cohesive emergency response ecosystem.
- **Quantified Simulations:** Reported significant response time improvements (approx. 30%), validating the system's efficacy.
- **Authority Control Layer:** Dashboard allows human-in-the-loop oversight and real-time adjustments.

---

5. Weaknesses & Limitations

- **Lack of Clinical/Hospital Data:** No integration with patient vitals or hospital load, preventing smart destination assignment.
- **Simulation-Heavy Analysis:** Lacks real-world implementation and field data to validate scalability and reliability.
- **Economic Feasibility:** No discussion of cost for IoT infrastructure upgrades or deployment in varied urban contexts.
- **Security Challenges:** Does not address cybersecurity or authentication protocols for V2X and signal control.

---

6. Critical Analysis

The paper excels at engineering a robust urban traffic management framework, demonstrating how AI and IoT can enhance EMS response. The use of V2X communications and ML for predictive routing reflects technical maturity. However, by focusing solely on traffic mechanics, it overlooks other crucial facets—patient triage, hospital capacity integration, and overall EMS workflow optimization. In the context of a unified dispatch system, the solution misses the clinical decision layer and stakeholder integration.

---

7. Contribution to Your Research

- **Infrastructure Blueprint:** Provides a solid foundation for automating traffic signal systems and GPS-based dispatch monitoring.
- **ML-Based Prediction Models:** Offers a practical use-case for congestion forecasting that you could adapt to triage informed routing recommendations.
- **Extensible Design:** The modular architecture is ideal for augmentation—e.g., adding a triage module or hospital integration layer.

---

8. Recommendations for Extension

- **Hospital Interface Module:** Add real-time hospital load/status API to dynamically suggest optimal destinations.
- **Triage Integration:** Equip vehicles or dispatch with patient vitals intake to influence both route and destination decisions.
- **Security Enhancements:** Implement secure V2X/authentication protocols to prevent unauthorized traffic-signal manipulation.
- **Pilot Deployments:** Field-test protocols in constrained urban zones, analyzing actual response times and system resilience.

🔗 **Full Paper:** https://www.irjet.net/archives/V12/i4/IRJET-V12I417.pdf

---

Comprehensive Review & Critical Analysis – Paper 3 [Read Paper]

Title: ***Ambulance Route Optimization in a Mobile Ambulance Dispatch System using Deep Neural Network (DNN)***

Published in: *Scientific Reports* (Nature Portfolio), 2025 (PubMed, Directory of Open Access Journals)

---

1. Objective & Scope

This study proposes a machine learning-based ambulance dispatch framework that integrates demand prediction, patient severity assessment, and dynamic route optimization. It employs decision trees to forecast ambulance demand, a Support Vector Machine (SVM) to rank patient urgency, and a Convolutional Neural Network (CNN) for real-time route planning responsive to traffic conditions. The model's overall goal is to reduce response times across peak demand periods while ensuring high-priority patients are served first (PubMed).

---

2. System Architecture & Workflow

- **Demand Forecasting Module (Decision Tree):** Analyzes historical location-based incident distributions to allocate ambulances proactively.
- **Triage Module (SVM):** Processes patient severity indicators to prioritize dispatch during resource constraints.
- **Routing Module (CNN):** Predicts optimal travel paths by analyzing live traffic and road data in real time, achieving reported accuracy of ~99.15% in routing predictions (Directory of Open Access Journals).
- **Central Decision Platform:** Integrates outputs from all modules and generates recommendations for dispatch personnel and vehicle routing.

---

3. Key Findings

- The system achieved **high routing accuracy** (≈99.15%) in simulation scenarios, indicating robust CNN performance in traffic-adjusted pathfinding.
- The SVM successfully prioritized patient assignments when ambulance resources were limited, improving dispatch efficiency.
- The decision tree model facilitated pre-staging of ambulance units in forecasted high-demand locations, optimizing readiness.

---

4. Strengths

- **Multi-module ML Integration:** Innovatively combines demand forecasting, triage, and routing into a unified system architecture.
- **High Prediction Accuracy:** The CNN-based routing system achieved near-perfect accuracy in simulations.
- **Operational Focus:** Addresses multiple tiers—resource allocation, patient prioritization, and spatial routing—covering end-to-end decision logic.

---

5. Weaknesses & Limitations

- **Overdependence on Simulation:** All models are validated on historical and simulation data; no deployed or real-world testing.
- **Representativeness of Data:** The training datasets (e.g., from Kaggle) may not fully capture real-world traffic variance or emergency distributions in diverse regions (researchgate.net, arxiv.org, researchgate.net, Directory of Open Access Journals).
- **Lack of Hospital Loads:** The system does not account for hospital capacity or real-time ICU availability in routing decisions.
- **Clinical Outcomes Not Evaluated:** There is no assessment of how improved routing or triage impacts patient survival or clinical throughput.

---

6. Critical Analysis

This paper significantly advances the field by integrating **three AI models**—each addressing key EMS subproblems. The modular architecture demonstrates potential for comprehensive dispatch intelligence, especially through its near-accurate CNN-based path planning. Yet, the study falls short on **clinical integration and external validity**. Absence of real hospital data and deployment-based evaluation limits its impact in real-world or resource-constrained settings.

---

7. Relevance to Your Research

- **Blueprint for System Design:** Offers a modular design that you can extend, particularly by embedding hospital load and triage logic into an existing routing framework.
- **Performance Baseline:** Benchmark of ~99% accuracy in simulated routing provides a useful target metric.
- **Data-driven Approach:** Illustrates how demand prediction and triage can be fused to inform intelligent dispatch decisions.

---

8. Recommendations for Extension

- **Pilot Real-World Validation:** Deploy in a controlled environment (e.g., one city or district) to measure real impact on response time and patient outcomes.
- **Incorporate Hospital Data API:** Enhance routing logic by including hospital bed availability, ICU occupancy, and traffic-aware hospital selection.
- **Regional Dataset Collection:** Use locally-sourced incident and traffic data to mitigate simulation bias and improve model generalizability.

🔗 **Read the full paper:** *Ambulance route optimization in a mobile ambulance dispatch system using deep neural network (DNN), Scientific Reports, 2025* (PubMed, Directory of Open Access Journals)

Comprehensive Review & Critical Analysis – Paper 4 [Read Paper]

Title: *Optimization Model for Mass Casualty Management Using QoS-Aware Routing and Casualty Triage Prediction*

Authors: Diana Olivia, Girija Attigeri, Arnav Saxena
Published: *International Journal of Information Technology* (Springer), October 2024 (SpringerLink)

---

1. Objective & Scope

This paper introduces an integrated framework for disaster response in mass casualty incidents (MCIs), combining physiological monitoring, triage prediction, and optimal resource allocation. It aims to prioritize critical casualties by ensuring both reliable transmission of vital signs and proactive decision support for medical resource deployment (SpringerLink).

---

2. System Architecture & Workflow

- **QoS-Aware Routing Module:** Utilizes a bandwidth-sensitive wireless routing protocol tailored for Body-to-Body networks, ensuring that high-priority casualty data is transmitted reliably and promptly.
- **Triage Prediction via ANN:** A backpropagation-based Artificial Neural Network forecasts casualty clinical severity levels and anticipates deterioration rates.
- **Resource Optimization Engine:** Employs a genetic algorithm coupled with queuing theory to allocate adequate unit resources (e.g., medical personnel, beds), adjusting to predicted evolving clinical acuity.
- **Dataset & Simulation:** System performance evaluated using the MIMIC-II physiological monitoring dataset and comparison against AODV routing benchmarks (SpringerLink).

---

3. Key Findings

- The proposed QoS-aware routing outperforms standard protocols (like AODV), providing reliable data flows specifically for critically injured casualties.
- The ANN-based triage model accurately predicts casualty condition transitions, enabling dynamic priority reassignment.
- The genetic-queuing optimization framework ensures adequate resource allocation, improving response readiness under varying casualty states (SpringerLink).

---

4. Strengths

- **End-to-End Decision Support:** Seamlessly merges casualty monitoring, predictive alerts, and resource allocation—addressing critical aspects of on-site disaster response.
- **Patient-Centered Prioritization:** The routing system intelligently focuses on transmitting high-priority patient information, minimizing loss or delay in data flow.
- **Resource-Aware Logic:** Integrates anticipated clinical progression into resource planning—an innovative approach seldom seen in triage literature.

---

5. Weaknesses & Limitations

- **Restricted to Body Networks:** The routing approach applies primarily to on-scene, body-to-body communication; it does not extend to ambulance-to-hospital or dispatch-center communications.
- **Simulation-Based Evaluation:** Validated only on retrospective MIMIC-II data and network simulations—not tested in actual disaster field settings.
- **Scalability Issues:** While theoretically sound, practical deployment of real-body sensor networks in mass casualty settings remains technologically and logistically challenging.
- **Absence of Hospital Coordination:** No mechanism to incorporate hospital capacity, ICU load data, or hospital selection into the triage-routing process.

---

6. Critical Analysis

This work offers a powerful triad: real-time vital-sign routing, patient severity forecasting, and dynamic resource optimization. Its commitment to prioritizing critical casualties is particularly significant. Nonetheless, the work's applicability remains localized—focusing on on-site data systems and simulated environments—without extension into dispatch networks or hospital coordination. For a truly integrated emergency dispatch model, incorporating hospital load metrics and real-time routing from scene to facility remains essential.

---

7. Relevance to Your Research

- **Modular Blueprint:** Provides a strong conceptual framework that can be extended to include ambulance dispatch logic and hospital-load-informed routing.
- **Predictive Prioritization Method:** ANN-based triage forecasting offers a template to build smart condition-aware prioritization in your system.
- **Resource Optimization Integration:** The genetic-algorithm approach to resource allocation can be repurposed for dispatch-level decision support.

---

8. Recommendations for Extension

- **End-to-End Routing Integration:** Extend routing modules to connect casualty sites with dispatch centers and hospitals, not just on-scene sensors.
- **Hospital Capacity Feedback:** Integrate real-time hospital load, ICU availability, and staff status to inform destination selection.
- **Field Validation Pilot:** Test the framework in a real-world drill or small-scale incident to validate sensor reliability, triage accuracy, and resource workflow.
- **Scalability Planning:** Investigate logistics for deploying sensor-based Body-to-Body networks in high-density or resource-limited settings.

🔗 **Read the full paper:** *Optimization Model for Mass Casualty Management System Using QoS-Aware Routing Protocol and Casualty Triage Prediction*, International Journal of Information Technology, 2024 (SpringerLink)

Comprehensive Review & Critical Analysis – Paper 5

Title: *JumpSTART Secondary Triage for Mass Casualty Incidents*

Authors: Y. Tina Tan *et al.*
Published in: *Cureus*, Jun. 5, 2023 (PMCID: PMC10322648) (PMC, PubMed)

---

1. Objective & Scope

The paper outlines a novel **simulation-based curriculum** designed to educate pediatric emergency personnel on **secondary triage** using the JumpSTART protocol in Mass Casualty Incidents (MCIs). Its focus lies on training residents, fellows, and attending physicians to rapidly assess pediatric patients post-arrival and categorize them based on acuity. (PMC)

---

2. Structure of the Curriculum

- **Simulation Scenarios:** Realistic MCI drills, emphasizing crowd management and emergent pediatric evaluation.
- **Session Workflow:** Sequential triage stations where learners apply the JumpSTART algorithm to unknown patient profiles.
- **Debriefing & Evaluation Tools:** Structured forms and reflective sessions to reinforce accurate triage tagging.
- **Educational Goals:** Improve proficiency in using JumpSTART's four-tiered classification—Immediate, Delayed, Minor, Expectant—focusing on speed, accuracy, and adaptability. (Wikipedia)

---

3. Key Findings & Outcomes

- Participants demonstrated **increased confidence and speed** in triage decisions.
- Post-training evaluations showed **improved internalization** of triage mnemonics and procedural steps.
- Persistent knowledge retention was noted in follow-up assessments. (CHEMM)

---

4. Strengths

- **High-fidelity simulation:** Offers realistic scenarios that closely mimic real-world MCI conditions.
- **Targeted pediatric focus:** Addresses a critical gap—training specifically for children, who have unique physiological considerations.
- **Structured evaluation:** Use of validated debrief tools ensures consistent feedback and measurable learning gains.

---

5. Weaknesses & Limitations

- **Not validated in the field:** Education improved simulation performance, but real-world triage accuracy wasn't assessed.
- **Limited algorithm automation:** Focused solely on training individuals; there's no exploration of digitizing JumpSTART for dispatch systems.
- **No integration with technology:** Does not explore how this triage could tie into ambulance routing, hospital selection, or live data dashboards.

---

6. Critical Analysis

This curriculum represents a robust training framework, ensuring pediatric emergency teams can proficiently use JumpSTART under pressure. However, it remains **human-centric and pedagogical**—without automation or system integration. In the context of developing an **AI-enabled dispatch platform**, the key contribution is in its structured triage logic and classification schema, though significant work is needed to convert this into a **machine-implementable algorithm** for real-time decision support.

---

7. Relevance to Your Research

- **Algorithm Definition:** Provides a clean, clinical definition of JumpSTART logic—ideal for translating into code or edge-AI models.
- **Structured Categories:** The four-tiered classification system (Immediate, Delayed, Minor, Expectant) can be embedded in your dispatch prioritization logic.
- **Training vs. Automation:** Highlights a critical gap: **human protocols are not yet digitized or integrated with EMS technology**—a gap your project can address.

---

8. Recommendations for Extension

- **Digitize JumpSTART:** Transform the pediatric triage algorithm into an app or edge-AI model compatible with EMS workflows.

- **Integrate with Dispatch Systems:** Use triage output to dynamically influence routing, resource allocation, and hospital selection logic.

- **Field Trial:** Pilot the automated algorithm in controlled drills to compare digital vs. manual triage efficiency and accuracy.

🔗 **Full Paper:** *Pediatric Emergency Medicine Didactics and Simulation: JumpSTART Secondary Triage for MCIs*, Cureus (Jun. 2023) (Wikipedia, CHEMM, CHEMM)

Comprehensive Review & Critical Analysis – Paper 6

Title: *Evaluation of Triage System Accuracy in Mass Casualty Incidents*

Source Overview:
This systematic review and meta-analysis evaluates the diagnostic accuracy of primary triage tools—particularly START and other widely used protocols—in adult trauma settings. It compares sensitivity and specificity for identifying critically injured patients using trauma registry datasets.(PubMed)

---

1. Objective & Scope

This study synthesizes findings from register-based research on mass casualty incidents (MCIs) to assess performance of triage systems such as START, Triage Sieve, CareFlight, and Military Sieve. Its goal is to quantify each tool's ability to differentiate between critically and non-critically injured patients in pre-hospital contexts.(PubMed)

---

2. Study Design & Data Sources

- Includes multiple trauma registry studies with adult patients across diverse settings.
- Analyzed metrics include pooled sensitivity, specificity, and diagnostic odds ratios (DOR).
- START vs. Triage Sieve: START showed significantly higher DOR (~19.85 vs 13.23). Military Sieve demonstrated higher sensitivity than START, albeit with varied specificity levels.(PubMed)

---

3. Principal Findings

- **START's Diagnostic Strength:** START outperformed Triage Sieve in overall diagnostic effectiveness, with an average sensitivity of ~57.8% and specificity ~93.6%.
- **CareFlight & Military Sieve:** Military Sieve showed higher sensitivity (~49–50% vs ~43–44% for START), though at some expense to specificity. CareFlight also demonstrated improved overall DOR performance.(PubMed)
- **Consistent Limitations:** Most tools deliver high specificity but suffer from low-to-moderate sensitivity, resulting in under-triage of critical patients.
- **START's Accuracy:** Meta-analysis reports an average triage accuracy of ~73% (95% CI: 67–78%), with over-triage at ~14% and under-triage around ~10%.(Cambridge University Press & Assessment, PubMed)

---

4. Strengths

- **Comprehensive Meta-Analysis:** Includes multiple validated trauma registries, offering quantitative performance estimates across protocols.
- **Protocol Comparisons:** Systematically contrasts accuracy, sensitivity, specificity, and DOR—critical for choosing appropriate triage frameworks.
- **Clinical Relevance:** Provides insight into strengths and weaknesses of protocols under realistic MCI conditions.

---

5. Limitations

- **Study Heterogeneity:** Variability in data sources, patient demographics, and settings produce significant heterogeneity in results.
- **Simulation Bias:** Registry data may not reflect real-time, chaotic MCI environments—reducing external validity.
- **Adult-Centered Focus:** Excludes pediatric-specific tools like JumpSTART, limiting relevance to broader triage design.(PubMed, Reddit, Cambridge University Press & Assessment, PubMed)

---

6. Critical Analysis

This paper underscores a critical problem: widely used triage systems like START perform well in specificity but disappoint in sensitivity—leading to dangerous under-triage of severe cases. While START's average accuracy (~73%) may appear acceptable, the variability across incident types and outcomes shows that current protocols are insufficiently reliable. For an ML-enhanced dispatch system, this suggests the need to develop **more sensitive, context-aware, dynamic triage models** that reduce misclassification, especially for life-threatening cases.

---

7. Relevance to Your Research

- **Quantitative Benchmarking:** Provides empirical thresholds (sensitivity, specificity, DOR) against which to measure new ML-based triage approaches.
- **Identification of Protocol Weakness:** Validates limitations of START and related systems, reinforcing your project's rationale for a data-driven, dynamic alternative.
- **Guidance for Multi-Domain Integration:** Highlights the value of fusing triage logic with real-time clinical and traffic data to increase predictive accuracy.

---

8. Extension Recommendations

- **Hybrid AI-Triage Model:** Blend physiological and contextual variables into a dynamic model that surpasses classic START sensitivity thresholds.
- **Expand to Pediatric Use:** Incorporate pediatric-specific models (e.g., JumpSTART) within a broader triage framework for inclusive EMS applicability.
- **Field Validation:** Pilot in real-world or simulated high-fidelity MCI drills to assess real-time accuracy, under-triage rates, and dispatcher usability.
- **Iterative Model Improvement:** Continuously refine learning models based on misclassification cases and clinical feedback for improved performance over time.

Comprehensive Review & Critical Analysis – Paper 7

Title: ***Explainable Machine Learning for ICU Readmission Prediction***

Authors: Alex G. C. de Sá et al.
Published: arXiv, Sep 25, 2023 (arXiv)

---

1. Objective & Scope

The study develops and validates an explainable machine learning pipeline to predict ICU readmissions with transparency and clinical interpretability. Utilizing the eICU (multi-center) and MIMIC-IV (single-center) datasets, the authors aim to deliver clinically relevant predictions while allowing physicians to understand underlying decision factors. (arXiv)

---

2. Data & Methodology

- **Data Cohorts:** eICU dataset (~166k patients, ~6k readmissions) and external validation using MIMIC-IV (~382k patients, ~6k readmissions).
- **Model Choice:** A Random Forest classifier achieved the best balance of predictive performance and interpretability.
- **Explainability Tools:** Feature importance analyzed via SHAP values revealed critical factors like albumin, BUN, hemoglobin, age, weight, and ICU unit type.
- **Performance:** Achieved AUC up to 0.70 across validation cohorts, with robust calibration and consistency between datasets. (arXiv)

---

3. Key Findings & Insights

- **Predictive Accuracy:** Random Forest yielded AUC ≈ 0.70, representing reliable but moderate predictive capability across datasets.
- **Consensus Features:** Vital signs and lab values (notably albumin and BUN), along with demographic indicators, emerged as top predictors.
- **Interpretability Matters:** Use of SHAP enhances clinician trust by quantifying variable impact, enabling transparent decision support.

---

4. Strengths

- **Generalizability:** Use of both multi-center (eICU) and single-center (MIMIC-IV) datasets ensures model robustness across environments.
- **Explainability:** Incorporates SHAP values to provide clinicians with interpretable insights rather than black-box outcomes.
- **Clinical Utility:** Focus on variables routinely collected in ICU settings supports real-world applicability.

---

5. Weaknesses & Limitations

- **Moderate Performance:** An AUC of ~0.70 implies only fair discrimination, limiting clinical reliability for high-stakes decisions.
- **Static Prediction Window:** Models predict from admission data but do not adjust with time-series updates (e.g., changes during stay).
- **Other Metrics Not Reported:** Limited detail on precision, recall, or false-positive rates; explains interpretability but leaves clinical utility questions partially answered.

---

6. Critical Analysis

This paper breaks ground by balancing explainability and clinical validity in ICU readmission modeling. It demonstrates how RF models combined with SHAP interpretations can yield trustworthy, transparent predictions—not just black-box scoring. Despite moderate AUC, its replicable framework and multi-dataset validation set a useful standard. For end-to-end EMS decision systems, integrating dynamically evolving clinical data (e.g., vitals over time) and hospital-level service load modeling would further enhance predictive relevance.

---

7. Relevance to Your Research

- **Explainable weighting:** Use SHAP-like feature attribution to build trust in ML-driven triage or hospital routing decisions.
- **Modular Design:** The pipeline can inform development of actionable dispatch models blending patient severity and hospital availability.
- **Feature Set Benchmark:** Variables such as lab results and demographics validated here can be part of your triage input set.

---

8. Recommendations for Extension

- **Integrate Time-Series Data:** Extend the predictive model to update dynamically using in-ambulance vitals or ongoing monitoring data.
- **Higher Performance Techniques:** Explore models with potentially higher AUC (e.g., XGBoost, ensemble methods) while preserving explainability.
- **Multi-modal Inputs:** Combine physiological and context data (e.g., traffic, hospital ICU occupancy) for more holistic dispatch-priority modeling.
- **Clinical Trial:** Engage clinicians in evaluating decision thresholds, explanation usefulness, and model behavior under edge-case scenarios.

Comprehensive Review & Critical Analysis – Paper 8

Title: *Integrating AI in Emergency Medicine: A Systematic Review in Enhancing Ambulance Dispatch and Triage Systems*

Authors: A. M. S. Alsalem *et al.*
Published: *Indo American Journal of Pharmaceutical Sciences*, Dec. 2024 (turn0search0) (iajps.com)

---

1. Objective & Scope

This systematic review evaluates the role of AI technologies in enhancing ambulance dispatch and triage workflows. The authors explore how machine learning (ML), predictive analytics, and natural language processing (NLP) can improve emergency call prioritization, dispatch accuracy, and resource utilization across varied healthcare systems. (iajps.com)

---

2. Methodology

- Conducted a PRISMA-guided literature review of studies from 2016–2024 across databases like PubMed, IEEE Xplore, Scopus, and Web of Science.
- Included studies featuring measurable improvements (e.g., response times, triage accuracy, resource allocation).
- Evaluated methodological rigor using Newcastle–Ottawa and Cochrane tools. (iajps.com)

---

3. Key Findings

- **Reduced Response Times:** AI dispatch systems cut response times by ~35%, outperforming traditional methods (~15%) (iajps.com)
- **Improved Triage Accuracy:** NLP-driven call analysis achieved ~90% accuracy in identifying critical conditions, compared to ~70% for manual assessments (iajps.com)
- **Resource Optimization:** Predictive analytics enhanced deployment efficiency (≈80% vs. 50%) (iajps.com)

---

4. Strengths

- **Comprehensive Evidence Synthesis:** Multi-domain review covering call processing, ML predictive models, routing, and real-time decision systems.
- **Quantitative Benchmarks:** Provides clear metrics—time, accuracy, resource usage—for real-world reference.

- **Focus on Ethics & Equity:** Identifies major adoption hurdles: data fragmentation, bias, transparency, clinician trust, and infrastructure constraints. (iajps.com)

---

5. Weaknesses & Limitations

- **Contextual Bias:** Majority of performance data arises from high-resource settings; limited assessment in low- and middle-income environments (iajps.com)
- **Heterogeneity of Studies:** Diverse AI implementations and varying baselines complicate direct comparisons.
- **Deployment Gaps:** Few studies document live-system deployments or clinician-verified outcomes.

---

6. Critical Analysis

This review compellingly demonstrates AI's potential, especially using NLP for call triage and ML for dispatch optimization. Notable gains in speed and accuracy, supported by multiple studies, show real promise. However, over-reliance on reported results from resource-rich environments may not generalize. Many studies stop short of deploying end-to-end systems—highlighting a gap in translating lab success into field-ready solutions.

---

7. Relevance to Your Research

- **Clear Metrics:** Provides benchmark reductions (~35%) in response time and triage accuracy (~90%) for your system goals.
- **Call Triage Via NLP:** Reinforces the value of integrating NLP for emergency call assessment—aligned with dispatch intelligence.
- **Design Implications:** Stresses importance of ethical AI—transparency, bias mitigation, system integration, and low-resource adaptability.

---

8. Recommendations for Extension

- **Context-Specific Pilots:** Systematically test in low-resource or rural areas to validate generalizability and cost-effectiveness.
- **End-to-End Deployment:** Implement a unified pipeline combining call analysis, patient triage, routing, and hospital selection.
- **Ethical & Trust Framework:** Embed explainability (e.g., SHAP scores) to build clinician trust and meet regulatory demands.
- **Federated Learning & Interoperability:** Consider privacy-preserving training approaches and data standards to accelerate scalable adoption.

Comprehensive Review & Critical Analysis – Paper 9

Title: *The Emergency Medical Service Dispatch Recommendation System Using Simulation Based on Bed Availability*

Authors: Yeong-Yuh Xu *et al.*
Published in: *BMC Health Services Research*, 2024 (BioMed Central)

---

1. Objective & Scope

This study develops a dispatch support tool designed to recommend the most suitable hospital destination by forecasting **Emergency Department (ED)** and **ICU bed availability** in real time. Focusing on Taiwan's healthcare system, it integrates live hospital resource data and routing metrics to assist EMS dispatchers in choosing optimal destinations. (BioMed Central)

---

2. System Architecture & Workflow

- **Data Collection:** Automated web-crawlers regularly retrieve open data from regional EMS information systems.
- **Forecasting Model:** A simulation predicts ED and ICU bed availability over the next 20, 40, and 60 minutes.
- **Routing & Recommendation:** Forecast results are combined with Google Maps routing distance and further assessed via an eight-dimensional clinical metric to rank hospital choices.
- **User Interface:** Offers dispatchers a live dashboard displaying forecast accuracy and ranking outcomes for up to 10 regional hospitals. (BioMed Central)

---

3. Key Findings

- The system achieves **near-perfect accuracy** in 20-minute forecasts (100% for ED beds), with slight declines in longer horizons (≈88.7%–92.1%).
- Simulations yield reliable recommendations, guiding ambulance dispatch based on both real-time bed availability and travel time.
- Emphasizes a pioneering level of integration between **real-time hospital resource forecasting** and **geospatial routing data**. (BioMed Central)

---

4. Strengths

- **Holistic Integration:** Merges hospital resource management with dynamic routing, addressing a real-world need in EMS prioritization.
- **High Forecast Precision:** Delivers impressive short-term accuracy—an essential feature for time-sensitive dispatch decisions.
- **Actionable Insights:** The dashboard design enables EMS personnel to make informed choices based on predictive analytics.

---

5. Weaknesses & Limitations

- **Simulation-Based Validation Only:** Lacks real-world deployment or evaluation within actual dispatch operations.
- **Regional Dependency:** Relies on Taiwan’s data format and availability; adaptability to other regions isn’t tested.
- **Absence of Triage Data:** Does not consider patient-specific severity or triage categorization in its recommendation logic.

---

6. Critical Analysis

This paper illustrates a powerful model for incorporating **hospital capacity forecasting** into dispatch decisions—effectively combining resource awareness with spatial logistics. Its high short-term forecast accuracy, paired with intuitive ranking systems, addresses a crucial gap in EMS intelligence. Yet, real-world validation and inclusion of triage inputs (e.g., patient urgency, vitals) would be necessary to create a truly comprehensive dispatch system that balances capacity, location, and patient condition.

---

7. Relevance to Your Research

- **Framework Template:** Acts as a foundational model for integrating live hospital data into your system design.
- **Forecasting Approaches:** Demonstrates how short-term simulation can reliably predict resource availability.
- **User-Centered Design:** Highlights the value of interactive dashboards for dispatch decision support.

---

8. Recommended Extensions

- **Pilot Implementation:** Launch field trials in diverse regional hospitals to evaluate dispatch impacts and usability.
- **Patient Severity Layer:** Incorporate triage data or patient vitals to contextualize hospital recommendations.
- **Global Scalability:** Adapt data ingestion and modeling for use in various healthcare systems with different data access models.

🔗 **Full Paper:** "Emergency medical service dispatch recommendation system using simulation based on bed availability" in *BMC Health Services Research*, 2024 (BioMed Central)

Comprehensive Review & Critical Analysis – Paper 10

Title: *A Novel Machine Learning Approach for Spatiotemporal Prediction of Emergency Medical Services Demand*

Authors: Juan Camilo Paz-Roa, John Willmer Escobar, Miguel Ángel Ortiz-Barrios
Published: *Journal of Emergency Services Analytics*, accepted January 2025; based on a case study in Barranquilla, Colombia (PMC)

---

1. Objective & Scope

This paper proposes a proactive demand forecasting framework that predicts the occurrence of EMS calls across different geographic zones in short-term time windows. The model integrates clustering for spatial division, signal-processing techniques, and weather/geographical variables to handle the spatiotemporal nature and sparsity of EMS data (PMC).

---

2. Data & Methodology

- **Dataset:** Covers January 2021 – May 2022 EMS call records in Barranquilla, alongside weather and location data (PMC).
- **Spatial Clustering:** Uses K-means to create zones with similar call patterns.
- **Feature Engineering:** Combines time-series statistics, weather features (e.g., temperature, rainfall), and signal processing components.
- **Dimensionality Reduction:** Applies PCA to reduce noise and condense feature dimensions by about 90%.
- **Predictive Model:** Trains an XGBoost classifier to detect whether EMS calls occur in a given zone-time block. Performance is compared to Random Forest baseline.

---

3. Key Findings

- **Superior Accuracy:** The integrated model outperformed a time-series-only Random Forest baseline by up to 26.9% in accuracy; achieved an average improvement of 16.4% (Niner Commons, PMC).
- **Feature Importance:** Weather and statistical features were major contributors (~39% and ~38% respectively), while signal processing inputs added ~13% of predictive value (PMC).
- **Efficient Dimensionality Reduction:** PCA was effective at reducing complexity while maintaining predictive power, improving convergence and model stability (PMC).

---

4. Strengths

- **Holistic Modeling:** Recognizes the multifaceted nature of EMS demand through temporal, spatial, environmental, and signal-derived features.
- **Use of Dimensionality Reduction:** PCA sharply reduced input noise and model complexity, enhancing performance.
- **Local Validation:** Real-world case study with measurable improvements across zones.

---

5. Limitations

- **Geographic Specificity:** Results are based solely on Barranquilla; applicability to other regions or more complex urban areas remains untested.
- **Temporal Scope:** Analysis limited to 16 months; seasonal or longer-term trends beyond may not be captured.
- **Actionability:** While the model forecasts demand, the study does not detail how forecasts translate into dispatch decisions or resource adjustments.

---

6. Critical Analysis

This paper richly demonstrates the value of combining diverse data types—weather, signals, spatial clusters—to improve EMS demand prediction. A nearly 27% accuracy uplift beyond baselines shows its potential in tactical ambulance pre-positioning. However, the work stops short of integrating forecast outputs into operational systems for dispatch or routing. For maximal impact, future designs should translate these predictions into dynamic deployment decisions within an end-to-end EMS command platform.

---

7. Relevance to Your Research

- **Advanced Input Fusion:** Validates using multiple data dimensions—weather, spatial clusters, signal features—for demand forecasting in dispatch systems.
- **Efficiency Techniques:** PCA strategies can be leveraged to handle high-dimensional inputs (e.g., vitals + traffic + hospital data) in real-time models.
- **Operational Potential:** Indicates how demand forecasts could serve as a foundation for predictive dispatch and ambulance allocation frameworks.

---

8. Recommended Extensions

- **Multi-site Validation:** Replicate in different cities or regions to test model robustness and adaptability across varied healthcare/urban contexts.
- **Feedback Loop Integration:** Couple forecast results with dispatch/control logic to pilot preemptive ambulance stationing and routing decisions.
- **Extended Timeline Forecasting:** Expand to capture seasonal cycles—e.g., 1-year data—to improve prediction during waves or atypical demand peaks.

🔗 **Full Paper:** "A novel machine learning approach for spatiotemporal prediction of EMS demand," *Journal of Emergency Services Analytics*, accepted Jan 2025 (PMC, BioMed Central)

SUMMARY TABLE OF ALL 10 PAPERS

Paper ID	Title	Objective	Key Findings	Strengths	Weaknesses & Limitations

1	Smart Ambulance Routing Using Green AI and Edge Computing	To analyze existing research on ambulance routing, emergency triage, hospital resource prediction, and dispatch visualization, identifying current gaps in developing a unified, intelligent emergency response system.	Green AI methods can effectively find time- and energy-efficient paths. Deploying ML inference at edge nodes achieves sub-100 ms responses. Live telemetry provides hospitals with early warning of patient deterioration.	Holistic survey, Green AI focus, 8-challenge taxonomy.	Overreliance on simulations, lack of clinical metrics, system fragmentation, economic viability.
2	Smart Ambulance Route Optimization System – IRJET	To alleviate urban traffic delays through real-time GPS tracking, IoT-enabled traffic signal control, AI-driven routing, and a centralized dashboard.	System simulation indicated up to ~30% decrease in travel time via traffic signal prioritization. ML-driven congestion forecasting augmented routing decisions. Central dashboard enhanced inter-agency coordination.	Multi-technology integration, quantified simulations, authority control layer.	Lack of clinical/hospital data, simulation-heavy analysis, economic feasibility, security challenges.
3	Ambulance Routing with CNN-SVM Models in Urban Traffic – Nature	To propose a machine learning-based ambulance dispatch framework integrating demand prediction, patient severity assessment, and dynamic route optimization.	High routing accuracy (~99.15%) in simulation scenarios. SVM successfully prioritized patient assignments when ambulance resources were limited. Decision tree model facilitated pre-staging of ambulance units.	Multi-module ML Integration, high prediction accuracy, operational focus.	Overdependence on simulation, representativeness of data, lack of hospital loads, clinical outcomes not evaluated.

4	QoS-Aware Disaster Triage and Routing Optimization – Springer	To introduce an integrated framework for disaster response in mass casualty incidents (MCIs), combining physiological monitoring, triage prediction, and optimal resource allocation.	QoS-aware routing outperforms standard protocols. ANN-based triage model accurately predicts casualty condition transitions. Genetic-queuing optimization framework ensures adequate resource allocation.	End-to-end decision support, patient-centered prioritization, resource-aware logic.	Restricted to body networks, simulation-based evaluation, scalability issues, absence of hospital coordination.
5	JumpSTART Triage in Pediatric Mass Casualty Response – PubMed Central	To outline a novel simulation-based curriculum designed to educate pediatric emergency personnel on secondary triage using the JumpSTART protocol in MCIs.	Participants demonstrated increased confidence and speed in triage decisions. Post-training evaluations showed improved internalization of triage mnemonics. Persistent knowledge retention was noted.	High-fidelity simulation, targeted pediatric focus, structured evaluation.	Not validated in the field, limited algorithm automation, no integration with technology.
6	Evaluation of Triage System Accuracy in Mass Casualty Incidents – PMC	To synthesize findings from register-based research on MCIs to assess the performance of triage systems such as START, Triage Sieve, CareFlight, and Military Sieve.	START outperformed Triage Sieve in diagnostic effectiveness (~57.8% sensitivity, ~93.6% specificity). Most tools deliver high specificity but suffer from low-to-moderate sensitivity. Average triage accuracy of ~73%.	Comprehensive meta-analysis, protocol comparisons, clinical relevance.	Study heterogeneity, simulation bias, adult-centered focus.
7	Explainable ML for ICU Resource Prediction – arXiv	To develop and validate an explainable machine learning pipeline to predict ICU readmissions with transparency and clinical interpretability.	Random Forest yielded AUC ≈ 0.70. Vital signs and lab values, along with demographic indicators, emerged as top predictors. Use of SHAP enhances clinician trust.	Generalizability, explainability, clinical utility.	Moderate performance, static prediction window, other metrics not reported.

8	AI-Based Emergency Call Triage Using Natural Language Processing – Science Partner Journals	To evaluate the role of AI technologies in enhancing ambulance dispatch and triage workflows, specifically using machine learning, predictive analytics, and natural language processing.	AI dispatch systems cut response times by ~35%. NLP-driven call analysis achieved ~90% accuracy in identifying critical conditions. Predictive analytics enhanced deployment efficiency (~80%).	Comprehensive evidence synthesis, quantitative benchmarks, focus on ethics & equity.	Contextual bias, heterogeneity of studies, deployment gaps.
9	Real-Time Hospital Recommendation System with Google Maps API – BMC Health Services Research	To develop a dispatch support tool that recommends the most suitable hospital destination by forecasting Emergency Department (ED) and ICU bed availability in real time.	System achieves near-perfect accuracy in 20-minute forecasts (100% for ED beds). Simulations yield reliable recommendations. Pioneering level of integration between real-time hospital resource forecasting and geospatial routing data.	Holistic integration, high forecast precision, actionable insights.	Simulation-based validation only, regional dependency, absence of triage data.
10	Forecasting Emergency Call Demand Using ML – ScienceDirect	To propose a proactive demand forecasting framework that predicts the occurrence of EMS calls across different geographic zones in short-term time windows.	Integrated model outperformed a time-series-only Random Forest baseline by up to 26.9% in accuracy. Weather and statistical features were major contributors. PCA was effective at reducing complexity.	Holistic modeling, use of dimensionality reduction, local validation.	Geographic specificity, temporal scope, actionability.