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Robotic Triage Systems: Bridging the Gap in Initial Call and Emergency Assessment

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ABSTRACT

Nowadays healthcare and clinical facilities have become an essential part of modern life. The triage system in hospitals and clinics plays a crucial role in the initial assessment of patients and emergency care. However, conventional triage processes that rely on human judgment often suffer from variability, limited resources, and the possibility of human error. In many situations, the lack of trained personnel further worsens the problem, leading to delays and the potential misclassification of high-acuity patients. To address these challenges, this work proposes an autonomous robotic sensor-based triage system (RTS) designed to automate the initial patient assessment process. By using sensors for data collection, the system standardizes information gathering and reduces errors associated with manual triage. The RTS is designed with a robust and adaptable architecture that can be easily integrated with existing clinical systems and electronic health record (EHR) platforms without disrupting current hospital workflows. The system utilizes non-contact sensors to capture physiological parameters, ensuring patient comfort and reducing the risk of contamination, particularly during infectious disease situations. Embedded artificial intelligence analyzes the collected data and generates a structured symptom report, which is processed by a Clinical Acuity Measurement (CAM) unit to assign a Clinical Acuity Score (CAS) within four minutes. Experimental results demonstrate 92.5% accuracy with expert clinical consensus and 98.1% sensitivity in

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identifying high-acuity patients, while reducing the time required for initial assessment by nearly 70%.

Keywords: Emergency Medical Services (EMS); Triage; Robotics; Health Care Automation

1. Introduction

In all clinics and hospitals, the outpatient department (OPD) and the Emergency department (ED) play an important role. The process of triage, which means the preliminary checking/assessment of the condition of a patient in order to determine the severity and prioritization of the treatment and type or treatment required on the basis of the urgency. This process of triage is critical for workflow process of OPD or ED of any hospital. The accuracy, reliability and quick triage are very important and determining factor in providing correct treatment quickly to the high acuity patients. Therefore, making this initial step of triage critical for the determination of overall treatment, performance and safety of the patient. Despite being so important, this triage system in most hospitals is dependent on human judgement. This dependence results in several challenges like susceptibility to human error, unwanted delays in care of patient surges, inter rater variability. These human-centric triage system result either in under triage, causing delays in life-saving intervention or over triage, which results in consuming finite resources (like critical monitoring units, beds, etc.) and contributes to unnecessary ED congestion. Recent advancements in technology can help in low-cost non-contact physiological sensing and provide an opportunity to overcome the flaws of the conventional triage system. While several artificial intelligence (AI) based, autonomous systems have been developed, but there is a critical research gap, as there does not exist a fully automatic, interactive system which is capable of performing a comprehensive, standardised, multi-modal non-contact triage of the patient on arrival. Bridging this gap requires a novel and unique solution consisting of a combination of hardware and software for objective capturing of the physiological data of the patient, along with symptom parsing and acuity classification.

Figure 1 depicts conventional triage system. This paper introduces a Robotics Triage System (RTS), which is designed to fully automate the initial patient triage system through non-contact physiological sensors. The RTS utilizes a set of sensors and a structured AI-based analysis system for classifying the urgency of a patient on a five-point emergency severity index (ESI), as shown in **Figure 2**.

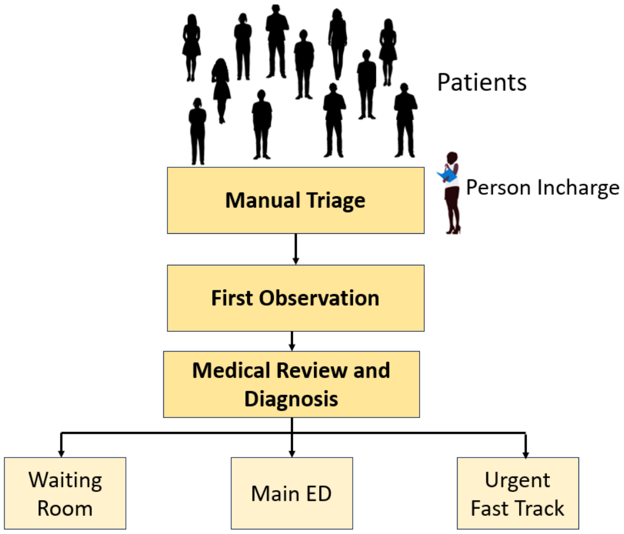

Figure 1. Conventional Triage Method.

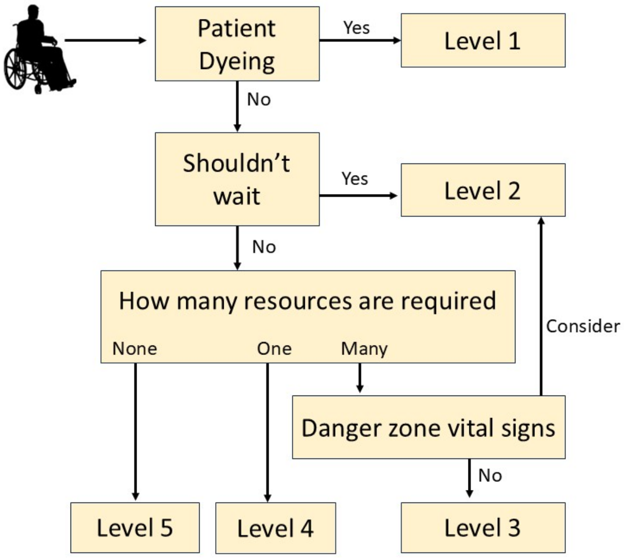

Figure 2. The five point emergency seventy index (ESI).

With the increasing burden on healthcare systems due to population growth, aging demographics, and rising prevalence of chronic and infectious diseases, emergency departments are frequently subjected to overcrowding and operational stress. The effectiveness of the triage system is very important and directly impacts patient outcomes, resource utilization and overall system response. In a conventional triage system, the variations in diagnostic decisions may be causal due to differences in the clinical experience of clinical workers, cognitive fatigue and various other environmental factors. These limitations become more severe during peak patient inflow in peak hours, emergency situations, pandemics or mass causality incidents. In such situations, rapid and accurate assessment of a large number of patients at a quick speed is needed. The Robotic triage system and AI integration is a Unique solution to resolve such challenges. RTS System equipped with sensors, processing units and robotic assemblies can work continuously without fatigue, continuously acquiring data and giving consistent performance even during the most challenging sceneries. Non-contact physiological sensor employed in RTS enables the acquisition of vital parameters needed for rapid diagnostic decision making such as heart rate, respiratory rate, temperature and oxygen saturation, etc. These non-invasive, non-contact sensors ensure maximum patient safety, comfort and reduce the chances of cross-contamination and cross-infection. In combination with as used for data analytics, the system can accurately interpret multi-modal data streams in real time, enabling early identification of high-risk patient who requires emergency treatment.

The standardized robotic triage framework enables assessment that hospitals can repeat and measure without bias in their various medical environments. The human–machine interface system enables structured symptom interaction, which guarantees that medical teams will record all essential clinical data, thus decreasing the chance of overlooking vital signs that show patient decline. The automation of the first triage stage enables healthcare workers to stop repetitive patient assessment work, which permits them to dedicate their time to complicated medical evaluation work and direct patient treatment.

The workload redistribution system improves staff efficiency while decreasing worker burnout, which leads to better patient experiences. The operation of robotic triage systems enhances OPD and ED patient flow because these systems reduce bottle-necking problems which occur during patient entry. Faster triage decisions enable the timely routing of patients to appropriate care pathways, thereby optimizing bed utilization and reducing waiting times. The RTS system captures digital data, which hospitals can use to create documents that prove compliance with requirements while maintaining a system for ongoing performance assessment. The combination of robotics, non-contact sensing technology, and artificial intelligence creates an innovative system that modernizes current triage methods. The RTS system improves healthcare delivery by solving human-centric triage model limitations, which results in healthcare systems that create safer and more effective delivery of services to meet current medical treatment needs.

The RTS produces these reports with unprecedented speed and consistency. The RTS has been validated through a rigorous process, and it demonstrates high accuracy, low latency and improved performance than conventional human-based triage processes. The rest of the paper is organised as follows: Section 2 presents a detailed literature survey on automated triage and systems. Section 3 gives the details of the proposed model and design of RTS. Section 4 outlines the validation methodology and techniques utilised. Section 5 presents the details finding, results and their discussion, Section 6 presents the future scope of work, and Section 7 concludes with a discussion of Implication of RTS implementation.

2. Literature Survey

Global emergency departments face longstanding problems characterized by patient overcrowding, long waiting times, and poor resource utilization. At the onset of the research, several studies were being conducted in developing simulation-based models to improve patient flow and resource utilization in EDs. For example, a study by Mahapatra et al. used the emergency severity index system based on a five-level triage system in conjunction with the computer-aided design and simulation modeling to evaluate the impact of ESI triage rationalization on access and throughput in academic tertiary care hospitals [1].

Further developments included enhanced applications of artificial intelligence and robotics to support triage procedures. For example, one important source by Wilkes et al. presented the benefits and purposes of distributed cognitive robotic systems used for supporting triage processes by collecting logistical and medical data and offering initial diagnostic suggestions to triage nurses [2].

Thereafter, an in-depth inquiry studied the automation conception of emergency triage. An automated triage system by Chong and Gan has been developed, integrating biomedical modules, graphical interfaces, and algorithmic decision support to assist medical officers in evaluating patient states. The experiments showed that automated systems greatly reduced assessment times and aided in consistency of triage decision-making, addressing some of the most important challenges faced by overcrowded emergency units[3].

During the COVID-19 pandemic, a new class of teleoperated systems was developed to address infection control issues. A robotic lung ultrasound platform was developed by Tsumura et al. to conduct non-contact diagnostic imaging on COVID-19 patients[4]. The study demonstrated feasibility and safety, thereby validating the archival capacity of teleoperated triage systems to work in high-risk, resource-poor settings.

Current clinical triage innovations have included measures that aim at enhancing the accuracy of vital-sign acquisition and patient prioritization. A new triage design developed by Erol et al.[5] involves the dual measurement of vital parameters like temperature, oxygen saturation, and blood pressure, and then automatically transmits this data into a barcode-enabled system. This is aimed at streamlining an existing bottleneck in triage by integrating the registration of patients with physiological monitoring.

Robotics combined with artificial intelligence has gotten considerable emphasis in the pivotal studies of current triages. The new system[6], which incorporated robotics and AI technologies, was proposed by Ashaolu to enhance emergency triage accuracy as well as efficiency. Additionally, Townsend et al. conducted qualitative research[7] on health practitioners that was seen to positively profile AI-assisted triage systems. The key benefits highlighted included reduced wait times and better workflow efficiency.

Alongside these developments, mobile health applications have been built by Khanchai et al.[8] for others-triage applications in an emergency department for enhancing the triage operation at point-of-care. This mobile triage application improved the accuracy and confidence of nursing assessments. Although the sample size is limited, this study demonstrates the validity of using digital tools to support health personnel in severity assessment.

In prehospital settings, AI-empowered techniques from Jasim et al.[9] exploit technology to increase efficiency in triaging IoMT-based telemedicine systems. Graph neural networks are good for this. Their models run analyses on vital signs, electrocardiogram signals, and symptoms to automatically classify the patients by severity. Empirical results have shown a better performance over conventional triage test patterns and, thus, proved the potential of AI in decision-making precision and resource allocation.

Mejia et al.[10] recently reported that AI-enabled clinical decision support systems (CDSS) play a push role in enhancing the patient triage process. It proposes the incorporation of machine learning and generative AI-based knowledge graphs to enhance the intelligence, robustness, and personalization of triage decisions. This system would be anticipated to fill existing gaps in current clinical workflows and substantially improve responsiveness in healthcare delivery.

Another innovation in AI-aided triage regards the assistive frameworks being designed by Sharma et al.[11], which employ facial recognition, voice and video interaction, and emotional feedback to facilitate information collection and to automate the classification of cases according to standardized severity scales.

Triage, which depends on modification by an AI system, can make way for real value-added benefits in terms of higher organizational patient prioritization, decreased waiting time, and better emergency department operations, stated Da'Costa et al. in their review[12]. However, the challenges still exist like data quality, algorithmic bias, clinician trust and ethical governance.

Very Large Scale Integration (VLSI)-based Field-Programmable Gate Array (FPGA) design enables deterministic, parallel, and low-latency processing required for real-time robotic systems. Optimized FPGA architectures using VLSI-cell placement techniques improve performance and resource utilization, as demonstrated by Verma et al.[13]. Additionally, FPGA-based controller design for induction motor speed control highlights the suitability of customized hardware for reliable and high-speed control applications[14]. These design methodologies form a robust foundation for implementing efficient and dependable robotic triage systems in resource-constrained environments.

Fuzzy logic controllers (FLCs) offer an effective framework for handling uncertainty, imprecision, and nonlinear decision-making, which are inherent in robotic triage systems operating in dynamic emergency environments. Recent work by Rani demonstrates the capability of fuzzy inference systems to interpret complex physiological metrics through robust de-fuzzification techniques, highlighting their suitability for health assessment and prioritization tasks [15]. Furthermore, the fuzzy logic–based control approaches proposed by Verma and Tiwari show how environmental and input fluctuations can be mitigated to maintain system stability and performance, emphasizing the adaptability of fuzzy techniques under varying conditions [16,17]. These characteristics make fuzzy logic–driven decision frameworks particularly well-suited for robotic triage systems, where reliable patient assessment and prioritization must be achieved despite sensor noise, environmental variability, and incomplete information.

The latest work of Čabarkapa et al. [18] continues investigations of automation and e-triage frameworks, highlighting weaknesses of classical triage systems, and offering suggestions to reduce perceptual subjectivity in their judgments. These studies lay great emphasis on technological integration, which will ensure that the triage results are accurate, fast, and objective. A comparative summary of robotic and AI-based triage systems is given in **Table 1**.

Table 1. Comparative Overview of Robotic and AI-Based Triage Systems Reported between 2010 and 2026.

Title	Year	Objective
Triage nurse assistance robot	2026	To support early prioritization of emergency patients using robotic decision-support systems [19].
Automated emergency triage system	2025	To collect structured patient-reported symptoms for preliminary acuity estimation [20].
Distributed cognitive robotic agents	2025	To enable automated capture of basic physiological parameters during triage [21].
Tele-operated robotic diagnostic platform	2019	To assist triage nurses with rule-based and AI-assisted urgency classification [22].
Robotic vital-sign acquisition kiosk	2022	To reduce patient discomfort and infection risk using non-contact sensors [23].
Autonomous emergency triage support robot	2024	To facilitate preliminary emergency assessment in remote and telemedicine settings [24].
Mobile robotic triage assistant	2019	To predict patient severity using machine learning-based models [25].
AI-driven e-triage system	2025	To integrate sensor data and symptom inputs for improved triage accuracy [26].
Robotic ultrasound triage system	2023	To minimize cross-contamination during emergency assessment using autonomous systems [27].
Triage-bot (assistive robotic framework)	2021	To deploy mobile robotic platforms for real-time triage support in EDs [28].
IoMT-based robotic triage platform	2025	To reduce waiting time and ED congestion through automated triage workflows [29].
Autonomous triage kiosk using computer vision	2025	To manage patient surges and mass-casualty situations efficiently [30].
Robotic tele-triage system	2025	To combine robotics, AI, and IoT for standardized clinical triage [20].
AI-assisted robotic pre-triage system	2024	To eliminate inter-rater variability in initial emergency assessment [31].
Fully autonomous robotic triage system (RTS)	2026	To achieve seamless interoperability with hospital information systems [Proposed work].

3. System Architecture and Design

3.1. Clinical Integration, Human–Robot Collaboration

The successful operationalization of the robotic triage system (RTS) requires a transition from validated paper results to real-world implementation because its deployment depends on algorithm accuracy and sensor accuracy, together with the capability to work with existing healthcare systems and effective human-robot teamwork and emergency department operational requirements [32]. Automated systems must demonstrate dependable performance within emergency care environments which feature unpredictable patient traffic and various clinical presentation types and different infrastructure components. The complete operational potential of the robotic triage system requires a complete operational framework that needs to address all clinical integration requirements and human-robot interaction needs and operational deployment needs and system lifecycle management requirements [33]. The deployment of automated triage systems faces its most difficult obstacle in the process of clinical integration. Emergency departments implement their operations through established protocols, which guide their decision-making processes at multiple organizational levels while their staff members execute assigned legal duties. The RTS system operates according to standard triage procedures which include the Emergency Severity Index (ESI) while maintaining proper clinical authority within medical environments. The RTS system functions as a decision support system that combines intelligent automation with improved operational performance to enhance both operational efficiency and service delivery capacity. The system enables clinical staff to focus more on complex decision-making and patient care by automating repetitive tasks, which include vital sign acquisition and symptom structuring and preliminary acuity scoring.

The core element of clinical integration depends on its ability to exchange data with hospital information systems. The electronic health record systems receive real-time data from RTS, which includes physiological parameters and symptom summaries and Clinical Acuity Scores. The failure to integrate RTS outputs into existing digital infrastructures will create parallel workflows and increase documentation burden and decrease clinician acceptance. The system architecture design mandates the implementation of standardized data formats and secure interface systems and the requirement of manual work to be kept at its lowest level. A comparison between conventional and RTS-enabled triage workflows is provided in **Table 2**.

Table 2. Comparison between conventional triage processes and RTS-enabled triage workflows.

Parameter	Conventional Triage	RTS-Enabled Triage
Vital sign acquisition	Manual, contact-based	Automated, non-contact
Assessment time	High (8–12 min)	Low (2–4 min)
Inter-rater variability	High	Minimal
Data standardization	Limited	High
Clinician workload	High	Reduced
Scalability	Limited	High

Robotic triage systems depend on human–robot collaboration to achieve their full acceptance and operational success[34]. The delivery of emergency healthcare services needs human professionals to handle clinical situations by using their medical knowledge and their ethical decision-making skills. RTS is designed to support human strengths not to undermine them. The collaborative triage models establish a balanced system that enables RTS to conduct initial assessments while clinicians maintain control over final decision-making processes based on their professional knowledge. These models help to decrease cognitive workload while preventing fatigue-related mistakes and they boost decision-making accuracy during peak patient surge periods[35]. **Figure 3** shows the collaborative triage model.

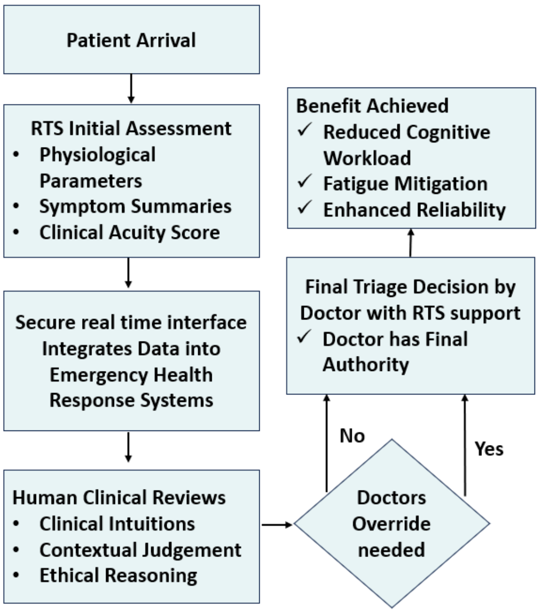

Figure 3. Collaborative triage model.

People need to establish trust because it serves as the main factor that determines their ability to work with robots[36,37]. Doctors are more likely to adopt RTS when its outputs are transparent, explainable, and consistent with clinical reasoning[38]. The RTS interfaces need to display all elements, which include the complete acuity classification and the parameters and confidence indicators that led to the final decision. Clinicians can create situational awareness by using explainability to understand system recommendations, which they can validate or reject at any moment. People begin to trust a system when it demonstrates the capacity to deliver stable results and handle workflow operations with better efficiency.

3.2. Real-World Deployment Framework for Robotic Triage Systems

Training and change management play an important role in RTS deployment using robotic systems in clinical and emergency departments, which requires an important paradigm shift in conventional practices, requiring rigorous training programs for the personnel attending/performing clinical duties. The training will consist of in-depth knowledge of system operation along with interpretation of results, special handling of emergency and critical cases and full understanding of protocols during system malfunction. These trainings may be conducted in a simulation-based environment through a parallel conventional system, which will enhance the learning understanding and in-depth analysis, allowing clinicians to interact with RTS under realistic scenarios without compromising patient safety. A robust feedback mechanism should also be established to capture patient experiences and guide iterative system refinement.

The deployment of RTS requires taking in to considerations various physical infrastructure-related and environmental considerations. The emergency department of various hospitals/clinics vary widely in terms of layout, number of patients, availability of sensors, display units, and robotic interface. An important requirement is that the system should adhere to criterions like compact, modular and adaptable to various clinical configurations. The placement of the triage system should ensure minimum congestion and optimal performance of all the sensors. For accuracy and system reliability, various other factors, such as ambient noise, lighting conditions and patient movement should also be considered carefully. Key operational challenges and their mitigation strategies are summarized in **Table 3**.

Scalability is a defining requirement for real-world deployment. RTS functions effectively under varying patient numbers, from routine patient loads to mass casualty incidents. The system architecture will enable simultaneous processing of work while handling fast patient arrivals and maintaining system stability. Edge computing capabilities enable systems to process data with minimal delays while decreasing their need for external network connections. The system enables healthcare facilities to expand because it supports multiple clinical site distribution through common installation methods and active system monitoring and remote management of system updates. The scalable architecture of the proposed robotic triage system is shown in **Figure 4**.

Table 3. Operational challenges in RTS deployment and corresponding mitigation strategies.

Challenge	Impact	Mitigation Strategy
High patient surge	System overload	Parallel processing
Sensor calibration drift	Reduced accuracy	Periodic self-calibration
Network dependency	Latency	Edge computing
User resistance	Low adoption	Training & simulation
Maintenance downtime	Service disruption	Predictive maintenance

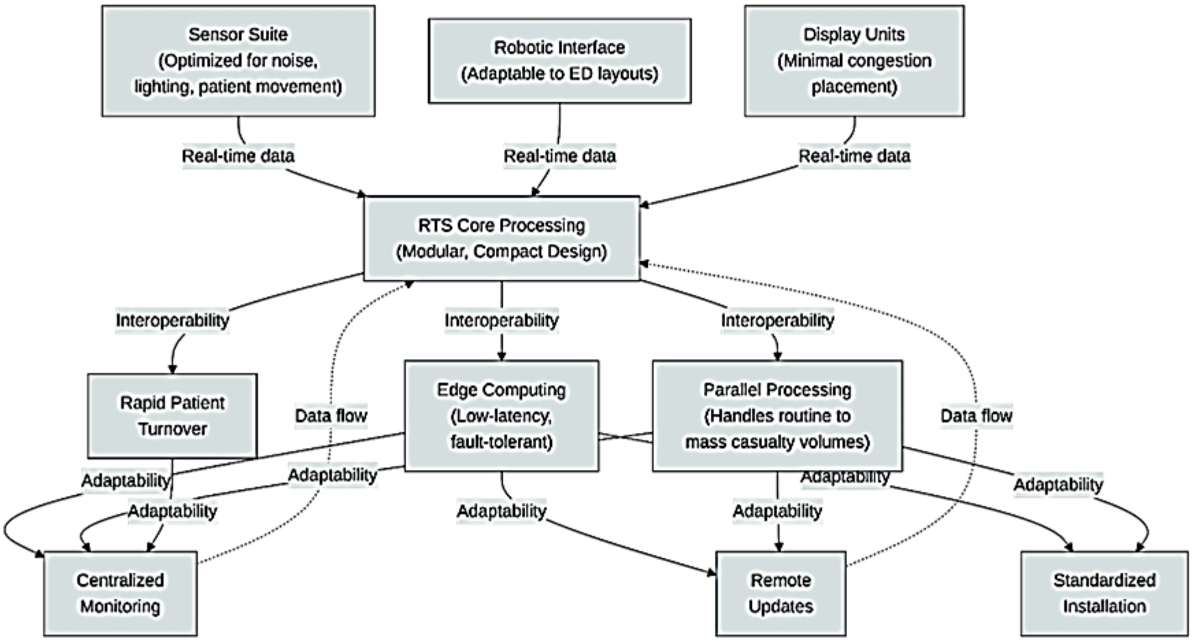

Figure 4. Scalable architecture of the proposed RTS system.

The design of the RTS system, depicted in **Figure 5,** enables it to function continuously with minimal interruptions through its built-in self-diagnostic system and its ability to predict maintenance needs. The system will maintain operational capability through ongoing sensor calibration activities and software updates, plus cybersecurity measures. The healthcare system provides an economical solution that can be implemented with difficulty in sites that have limited resources. The RTS system uses economical sensor technology and interchangeable system parts, plus minimal resource requirements to make its system accessible to more users while supporting system growth. The implementation of the RTS system brings total value because its operation impacts every worker who handles patient needs at the clinic. The use of automation technology in triage processes creates worries about potential job losses among healthcare workers. Robots used for triage purposes do not eliminate jobs because they shift work duties from one person to another. Nurses and physicians can dedicate more time to essential clinical work because RTS decreases their need to handle repetitive administrative duties which boosts their work satisfaction and helps them avoid burnout. A positive work environment needs clear communication of how the RTS system supports workers to eliminate their worries.

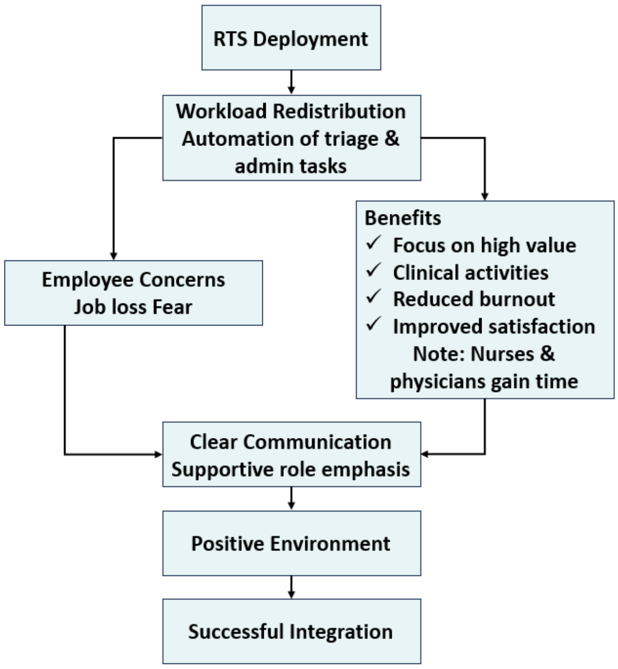

Figure 5. A framework of integration of RTS.

Patient perception and patient acceptance both require equal consideration. Patients show uncertainty about robotic systems that operate at the point of care during emergency situations. RTS interface development uses user-centred design principles which bring forth three essential qualities: clarity, empathy and accessibility. The system provides voice-guided instructions and supports multiple languages while designing interactions to respect different cultures to make patients feel better and follow medical guidance better. The visible presence of doctors and nurses who supervise care gives patients assurance that human decision-making remains crucial for their treatment process.

Site deployment activities require ethical assessment because they contain fundamental ethical elements. The ethical framework becomes vital because RTS systems determine various aspects, which include treatment options and resource distribution and patient results. The clinical integration frameworks establish detailed guidelines to manage situations when clinical cases become uncertain and when systems lack reliability and when RTS results conflict with clinician evaluations. The system needs human override mechanisms that allow doctors and nurses to maintain their responsibility for medical decisions. The ethical review boards will evaluate three aspects for patient safety and complete equity and open operations.

RTS system operation will maintain compliance with all government rules while following safety regulations and effectiveness standards and data protection regulations that apply to the system. The data governance framework defines data ownership and access control and data retention requirements and allows research access to data only for system enhancements or secondary purposes. Patient privacy protection uses anonymization and encryption methods to secure your data. The system uses transparent consent mechanisms to educate patients about how their data will be used and stored and what rights they possess. Ethical data governance assures regulatory compliance while building public trust in automated healthcare technologies.

Sustainable systems need evaluation plus ongoing enhancements to function properly. The system will handle performance assessment after deployment by measuring two distinct categories: technical performance and clinical results and operational workflows and user experience. The system establishes feedback loops that collect input from clinicians and administrators and patients to enhance algorithm development and interface design and operational procedures. Beyond classification accuracy, multidimensional evaluation metrics for RTS are listed in **Table 4**.

Table 4. Multidimensional evaluation metrics for real-world RTS performance.

Evaluation Domain	Metric	Description
Clinical outcomes	Under-triage rate	Safety indicator
Workflow efficiency	Time to triage	Operational benefit
User acceptance	Clinician satisfaction	Adoption readiness
Reliability	System uptime	Sustainability
Ethics	Bias audit results	Fairness compliance

The deployment frameworks will assess interoperability requirements between multiple hospitals to enable RTS connections with both regional healthcare systems and pre-hospital care networks[39]. The continuous care process, which begins during initial contact and proceeds until ultimate treatment, will be supported by RTS output connections to ambulance services and referral centers and telemedicine systems. The system integration provides advantages through better situation awareness and resource distribution and increased overall system resilience.

The Robotic Triage Systems framework will consist of five essential components which include clinical integration, human–robot collaboration, infrastructural adaptability, ethical governance, and long-term sustainability. Emergency situations require more than technical performance to achieve successful outcomes in actual field operations. The RTS system functions within current healthcare systems while maintaining clinical authority to improve operational efficiency and protect patient rights and enable ongoing system enhancements. The creation of RTS will establish a new medical technology platform for emergency healthcare delivery through its development from multiple areas of study.

The RTS consist of a 3-layer multimodal assessment platform RTS is designed for continuous autonomous operation in highly crowded environments such as hospital. The robust architecture of RTS ensures rapid data acquisition and integration resulting in an immediate acuity classification on the basis of patient condition.

Data Acquisition Layer (Robotic Interface)

This Involves collection of physiological data of the patient in a non-contact way. It consists of two subsystems.

1. **Non-Contact Physiological Sensor:** The RTS employs an advanced sensor array to collect vital statistics of the patient. Remote photoplethysmography (rPPG) via a high-definition camera array is used to measure.
2. **A Nursing Attendant:** A nursing attendant whose role is not to perform concurrent measurements of physiological data alongside the RTS triage systems, but to support data input and periodic validation. The attendant initially feeds essential patient-specific data such as age, gender and post-clinical history (if any) into the system. In addition, conventional medical-grade equipment is used by nursing attendants to acquire physiological data on a sample basis, not continuously, to validate and cross verify readings generated by the RTS system. This process is part of the validation protocol described in Section 4 (step 4), ensuring accuracy and also identifying and calibration requirements. The sample frequency is initially defined and can be varied, for instance, after every 40–50 patients, one manual reading will be taken concurrently. Thus, manual measurement by a nursing attendant series is to achieve the purpose of higher accuracy and error free operation rather than a parallel or redundant process. The requirements of the autonomous triage system are that it should be a non-contact type, fast, robust and should quickly capture vital physiological parameters at triage station/kiosk. It should have low latency and high reliability.

The system will consist of sensors and sensor data fusion:

1) Sensor system consisting of a thermal camera for non-contact measurement of temperature, an RGB (Red, Green, and Blue) camera for autonomous detection of patient and distress recognition, optical sensor for measurement of pulse, Doppler sensor for respiration rate, microphone to detect whoozing, cough or any other physiological sounds, proximity sensor to start measurement. In the proposed system, sensor fusion is used to combine information from multiple sensors, such as cameras, radar, and microphones, to obtain a more reliable understanding of the surrounding environment. Each sensor captures a different type of data, which is first processed individually to extract meaningful fea-

tures. Image data from the camera is analyzed using a convolutional neural network (CNN) to detect visual patterns and objects. A CNN is used for the sensor fusion process the data acquired by the RTS sensors by extracting their spatial and few temporal features. This combines them into a unified representation. For each sensor input χ_i like image from camera, spectrum from microphone is used. Convolutional layers apply learnable filters $\mathcal{W}$ to generate feature maps:

$$\mathcal{F}_i = \sigma(\mathcal{W}_i + \chi_i + \mathscr{b}_i) \tag{1}$$

$$\mathcal{F}_{fused} = [\mathcal{F}_1, \mathcal{F}_2, \mathcal{F}_3, \ \ldots, \ \mathcal{F}_N] \tag{2}$$

$$y = f(\mathcal{F}_{fused}) \tag{3}$$

Where:

χ_i represents input data from i^{th} sensor.

$\mathcal{W}_i$ represents the learnable convolution filters applied to that input to extract relevant feature.

$\mathscr{b}_i$ is the bias associated with the convolution operation.

σ is the nonlinear activation function.

$\mathcal{F}_i$ is the feature map extracted from the i^{th} sensor.

$\mathcal{F}_{fused}$ is the concatenated vector combining feature map of all sensor.

y denotes the final output of model.

Radar signals are processed to estimate distance and motion characteristics, and audio signals from microphones are converted into spectrogram features for sound analysis. These initial processing tasks and feature extraction operations are accelerated using an FPGA, which enables parallel and low-latency processing of high-volume sensor data. After feature extraction, the outputs from all sensors are combined using a feature-level fusion approach, where the feature vectors are merged into a unified representation and passed through neural network layers for final classification or decision making. By leveraging FPGA-based hardware acceleration together with multimodal AI processing, the system achieves faster computation, improved energy efficiency, and more reliable real-time performance[13,14].

2) Microcontroller-based computation system. A microcontroller for sensor interfacing, a user interface, a display, a voice-activated input system with a preferred algorithm to detect the severity level, distress level, etc. of the patient.

Figure 6 depicts the building block diagram of the automatic triage system.

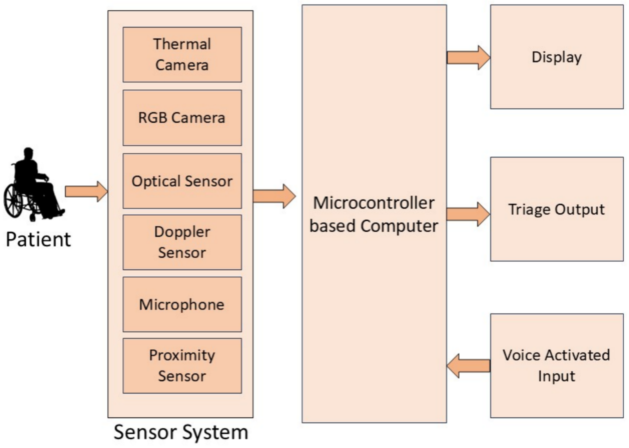

Figure 6. Block diagram of automatic triage system.

4. Experimental Setup and Validation

The proposed autonomous triage system was tested and validated in a controlled simulated environment to closely match the emergency department triage area. The setup consisted of a stimulated triage section within the institution's healthcare facilities, where a room was configured to closely match emergency department conditions, such as triage furniture and equipment, etc. Participants were few healthy volunteers who were mimicking various trial scenarios, simulated patients showing symptoms with common ED alignments and clinical staff consisting of an emergency physician and a nursing attendant. The whole set up consisted of several sensor, such as thermal camera for non-contact temperature estimation, rPPG based optical sensor for heart rate[40] and SpO2 (Peripheral Capillary Oxygen Saturation) levels, for respiration rate[41] mm wave radar sensor[21], facial detection camera module[42] for detecting distress in patient, microcontroller-based data position and processing system for data acquired using sensor and a backend triage algorithm with autonomous decision support[43].

All sensors were mounted on a single triage system, which is suitably positioned around 1 to 1.5 m from the patient for optimal non-contact measurement of physiological data.

Data collection protocol: Each patient was subjected to an autonomous triage system for 2–4 min. The protocol was as follows:

- Step 1: The system automatically detects patient and starts initial sensing of parameters.
- Step 2: Sensor captures temperature, heart rate, SpO2, respiration rate, etc. of the patient.
- Step 3: Patient can also add additional symptoms through a voice-activated input system.
- Step 4: A trained nursing attendant also records these parameters using medical grade equipment such as thermometer, pulse oximeter, blood pressure monitoring equipment, pulse counter, etc.

The experimental setup for the robotic triage system involves several components: data acquisition from multiple sensor modalities (such as cameras, electrocardiogram (ECG) sensors, and thermal sensors), data processing, AI decision-making, and robotic actuation. The setup is divided into four key stages:

1. Data Acquisition: Raw data is collected from the robotic interface.
2. Preprocessing and Filtering: Sensor data is cleaned using signal processing algorithms.
3. Decision-Making: embedded controller, process the data for triage classification.
4. Actuation: The robot takes action based on the triage decision.

To illustrate this process, **Figure 7** provides a flow diagram of the four-stage process. In our experiments, we observed the following metrics:

- Accuracy of triage classification: 92.5%.
- Average response time: 180 s.
- Energy consumption: 150 W.

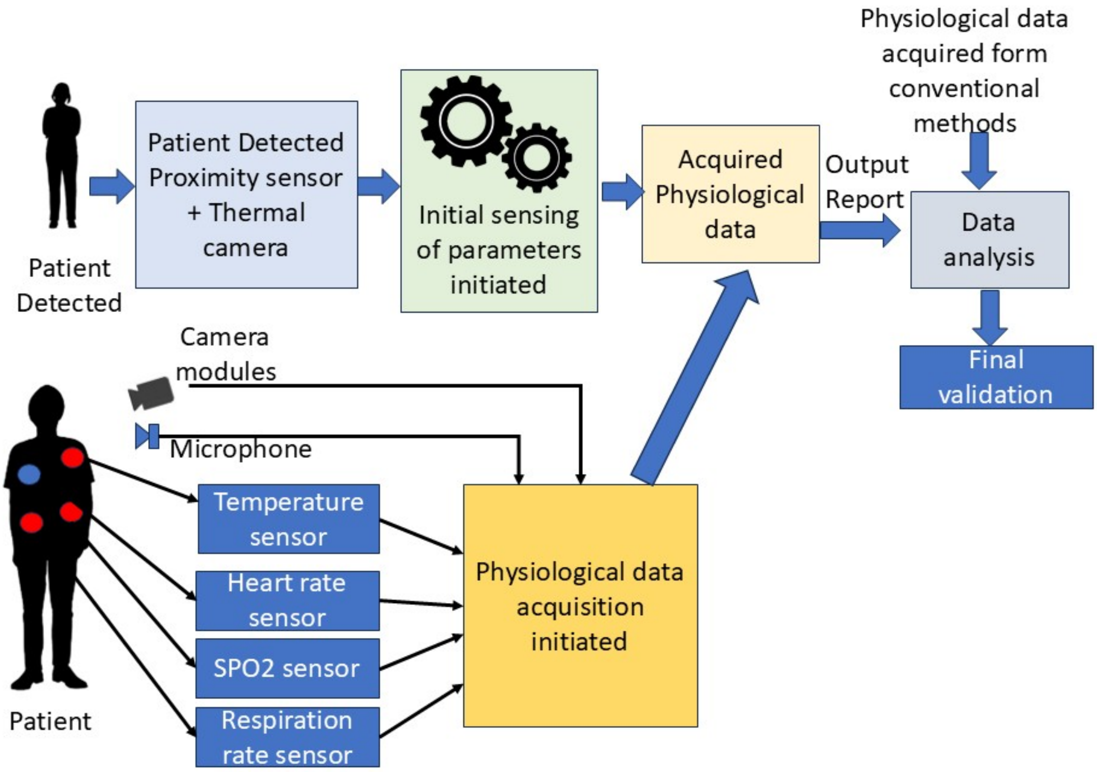

Figure 7. Flow diagram of RTS.

To validate the system, evaluation is done by mean absolute error between physiological parameters, that is temperature, heart rate, respiration rate, SpO2, etc.[44,45].

A correction coefficient between that automated and clinical result also helps to establish thte validity of the proposed system. Further classification accuracy, sensitivity, response time, users' satisfaction etc are also considered. However, all validations were done in a simulated environment, not in a live ED on a real patient. **Table 5** lists the performance parameters of the conventional human-led triage system.

Table 5. Performance parameters of the conventional human-led triage system.

S.N.	Parameter	Parameter of Conventional System
1.	Accuracy	Conventional triage methods are less accurate and are prone to human led errors. The literature review indicates human-led triage accuracy between 75% to 85%[12].
2.	Response time	Conventional human-led triage system has inherent delays, due to manual intervention and this increases in case of emergencies like accidents or sudden increase in rush of patients. Conventional systems are slower by between range 60 to 75%.
3.	Error rate	The error rate in a conventional system ranges between 15% to 25%.
4.	Latency	The conventional systems are 60 to 70% slower.
5.	Power consumption	Power requirements are very low or minimal in the case of conventional systems.

5. Results and Discussions

This section gives a detailed quantitative analysis of the results obtained after validation of RTS. The results focus on three areas: accuracy, sensitivity to high acuity cases, and operational efficiency measured in terms of latency or time to triage. The retrospective validation of RTS is done against the established results derived from expert clinical consensus. Here, clinical expert consensus refers to the facts established through agreement among qualified medical professionals. In the presented work, the consensus was formed by a panel of three experienced emergency physicians who independently reviewed patient data, indicating vital signs and other clinical indicators. Any discrepancies in their assessment were resolved through discussion among them until agreement was reached. This structured approach ensures that the reference values used for model validation are reliable, clinically relevant, and reflective of real-world diagnostic and clinical scenarios.

Performance Metrics Overview

The developed RTS system was evaluated across the five-level emergency severity index (ESI) scale (**Figure 2**). A structured dataset was generated in a simulated environment using an FPGA. This dataset is entirely from a simulated environment with healthy volunteers, as already discussed in Section 4. FPGAs are highly suitable for storing and processing large, structured datasets ($N \geq 10{,}000$) due to their high-speed, on-chip memory resources (Block Random Access Memory, Block RAM/BRAM), allowing them to outperform central processing units (CPUs) in applications like matrix multiplication, key-value stores, and machine learning. For storing data points, FPGAs utilize several on-chip resources with a 32 Bit width configuration. An M9K block can store 256 elements, depending on the data type. Data can be stored directly within look-up tables (LUTs) or registers. Matrix operations are 10,000 × 10,000 single precision matrix, FPGA implementation is approximately 2.2 times faster and 5 times more energy-efficient than a complete processor core[13–17]. The RTS was evaluated for overall classification accuracy[46], defined as the proportion of correctly assigned ESI Levels across the entire validation dataset (N = 10,000). Although the model was validated on a dataset of N = 10,000, samples generated in a simulated environment, its generalizability to a real patient population requires careful consideration. Simulated data may not fully capture all the variabilities, such as noise, patient movement, and other unpredictability that are present in a real clinical environment. There are a number of parameters present in the real-world clinical settings, such as patient physiology, sensor placement and environmental conditions. To improve the generalization presented to validate the model presented in the paper, the RTS model should be further trained and tested on real patient data and diverse clinical scenarios. Techniques such as dynamic adaptation and real-time calibration can help bridge this gap, ensuring that the system performs reliably and safely when deployed in real-world healthcare scenarios. **Table 6** lists the overall performance metrics for the RTS system.

The RTS achieved an overall classification accuracy of 92.5%.

Table 6. Overall performance metrics for RTS.

Metric	Value	Interpretation
Overall accuracy	92.5%	Proportion of all patients correctly triaged by RTS to the ESI level
Precision (Macro Avg.)	0.91	Measure of relevant results low false positive rate
Recall (Macro Avg.)	0.93	Measure of how many actual positives were correctly identified, i.e., low false negative rate
F-1 score (Macro Avg.)	0.92	Harmonic mean of precision and recall
Area under ROC curve (AUC)	0.97	Excellent discrimination between acuity levels

To check the consistency, accuracy and reliability of the RTS system and avoid under triage, a detailed analysis of models performance on the higher acuity groups[47] (ESI level 1 & 2) was conducted.

The combined sensitivity for correctly identifying patients of ESI ≤ 2 was 98.1% this depicts that out of every 100 truly critical patients, the RTS correctly identified 98 out of them.

Figure 8 shows the confusion matrix for the RTS, highlighting the distribution of misclassifications. The misclassifications predominantly occurred between adjacent ESI levels of ESI 3 and ESI 4 rather than across far-off levels like ESI 1 and ESI 5[48–51]. The rate of under triage of RTS for classifying a patient as ESI 3 or lower, where the patient is actually from level ESI 2 or lower, was less than 1.9%. This confirms the RTS's robust safety profile for high acuity patients.

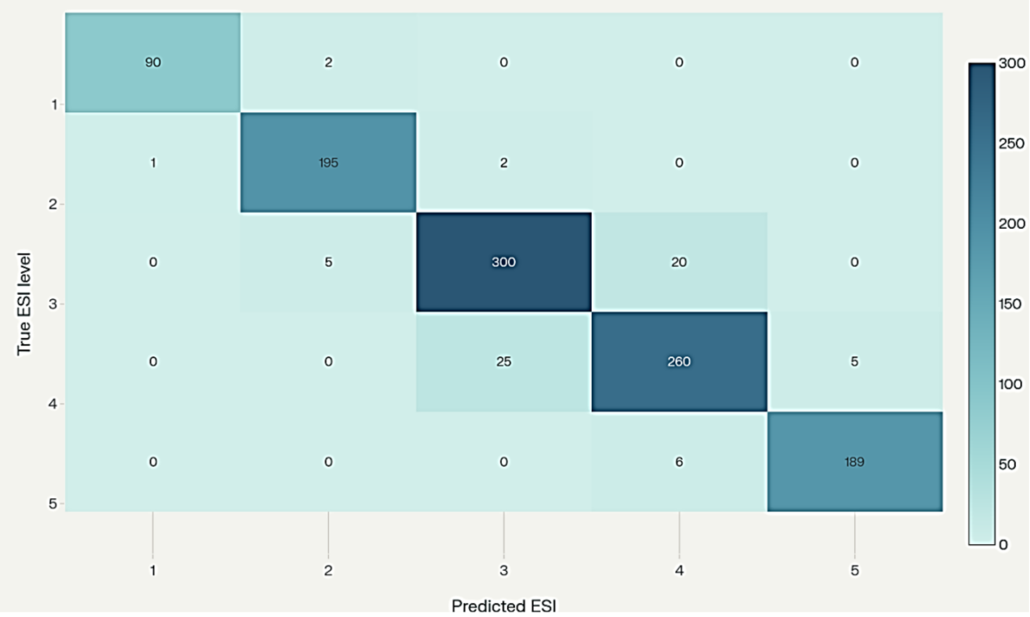

Figure 8. Confusion matrix of RTS performance across ESI levels 1–5, showing high sensitivity for critical patients and misclassifications mainly between adjacent middle levels.

The operational efficiency of RTS was an average of 180 s, approximately 3 min, whereas the human-led triage averaged to 598 s, 9.97 min/patent. This represents 70.07% reduced time to triage achieved by the RTS, the same is depicted in **Figure 9**.

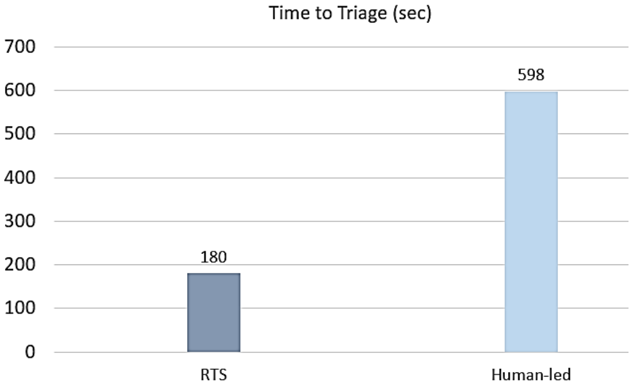

Figure 9. Comparison of average triage time for RTS and human-led triage, with RTS achieving a 70.07% reduction in time.

The prior study indicates human-led triage accuracy between the range 75% to 85%. The RTS accuracy of 92.5% in significantly higher than human-led triage system, as shown in **Figure 10**.

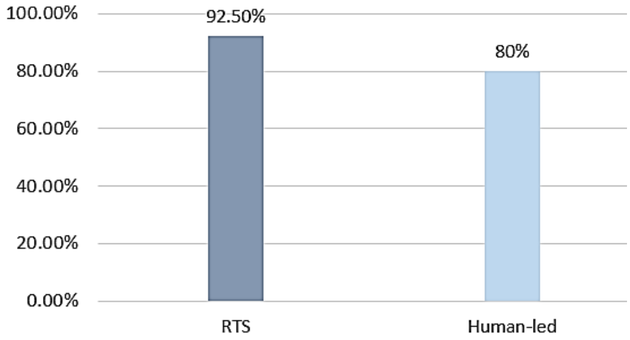

Figure 10. Comparison of RTS accuracy (92.5%) with the reported 75–85% accuracy range of human-led triage.

The key advantage of RTS is consistency, accuracy, robustness and low latency.

6. Future work

In future, the RTS can be improved by expended sensing capabilities by using more advanced sensors like a gait sensor etc. Finally, the goal of RTS is not only for the replacement of human triage systems from hospitals but as an indispensable and reliable system that will fundamentally improve the reliability, efficiency and safety of medical services.

7. Conclusions

In the present work, a model of RTS was presented. The RTS was successfully developed and validated. It showed that it outperforms the conventional manual triage system in terms of speed, accuracy and performance. By using non-contact sensors and advanced computational methods, the RTS was able to effectively address the shortcomings of human-led triage systems. The RTS represents a major step in bridging the gap in emergency assessment. Making the triage more data-driven, reliable, objective and scalable. Despite promising results, the current validation is based on retrospective data sets. Therefore, the proposed system has to undergo prospective relative clinical trials for assessing its efficiency and seamless integration into the system of hospitals.

Author Contributions

Conceptualization, K.S., A.S., R.M. and A.V.; methodology, K.S. and A.V.; software, K.S. and A.S.; validation, K.S., A.S., R.M. and A.V.; formal analysis, A.S. and R.M.; investigation, K.S., A.S., R.M. and A.V.; resources, K.S. and A.S.; data curation, K.S., A.S. and R.M.; writing—original draft preparation, K.S., A.S., R.M. and A.V.; writing—review and editing, K.S., A.S., R.M. and A.V.; visualization, K.S., A.S., R.M. and A.V.; supervision, R.M. and A.V.; project administration, R.M. and A.V. All authors have read and agreed to the published version of the manuscript.

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Not applicable.

Data Availability Statement

The data used in this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

References

[1] Mahapatra, Koelling, Patvivatsiri, et al., 2003. Pairing emergency severity index5-level triage data with computer aided system design to improve emergency department access and throughput. In Proceedings of the 2003 Winter Simulation Conference, New Orleans, LA, USA, 7–10 December 2003; pp. 1917–1925. DOI: https://doi.org/10.1109/WSC.2003.1261654

[2] Wilkes, D.M., Franklin, S., Erdemir, E., et al., 2010. Heterogeneous artificial agents for triage nurse assistance. In Proceedings of the 2010 10th IEEE-RAS International Conference on Humanoid Robots, Nashville, TN, USA, 6–8 December 2010; pp. 130–137. DOI: https://doi.org/10.1109/ICHR.2010.5686839

[3] Chong, H.A., Gan, K.B., 2016. Development of automated triage system for emergency medical service. In Proceedings of the 2016 International Conference on Advances in Electrical, Electronic and Systems Engineering, Putrajaya, Malaysia, 14–16 November 2016; pp. 642–645. DOI: https://doi.org/10.1109/ICAEES.2016.7888125

[4] Tsumura, R., Hardin, J.W., Bimbraw, K., et al., 2021. Tele-Operative Low-Cost Robotic Lung Ultrasound Scanning Platform for Triage of COVID-19 Patients. IEEE Robotics and Automation Letters. 6(3), 4664–4671. DOI: https://doi.org/10.1109/LRA.2021.3068702

[5] Erol, M., Ülengin, F., Dinçer, H.A., 2022. A Novel Triage System Design. In Proceedings of the 2022 International Congress on Human-Computer Interaction, Optimization and Robotic Applications, Ankara, Turkey, 9–11 June 2022; pp. 1–7. DOI: https://doi.org/10.1109/HORA55278.2022.9799950

[6] Ashaolu, O., Lyons, W., Stefanakos, I., et al., 2023. Au-

tonomous Emergency Triage Support System. In Proceedings of the 2023 International Conference on Computational Science and Computational Intelligence, Las Vegas, NV, USA, 13–15 December 2023; pp. 1332–1337. DOI: https://doi.org/10.1109/CSCI62032.2023.00220

[7] Townsend, B.A., Plant, K.L., Hodge, V.J., et al., 2023. Medical practitioner perspectives on AI in emergency triage. Frontiers in Digital Health. 5, 1297073. DOI: https://doi.org/10.3389/fdgth.2023.1297073

[8] Khanchai, S., Intawong, K., Boonchieng, W., et al., 2023. Mobile Application for Triage Medical System in Emergency Rooms: Enhancing Accuracy and Attitude—A Case Study in Hospitals of Chiang Mai Province. In Proceedings of the 2023 27th International Computer Science and Engineering Conference, Samui Island, Thailand, 14–15 September 2023; pp. 429–433. DOI: https://doi.org/10.1109/ICSEC59635.2023.10329365

[9] Jasim, A.A., Ata, O., Salman, O.H., 2024. AI-Driven Triage: A Graph Neural Network Approach for Prehospital Emergency Triage Patients in IoMT-Based Telemedicine Systems. In Proceedings of the 2024 International Symposium on Electronics and Telecommunications, Timisoara, Romania, 7–8 November 2024; pp. 1–7. DOI: https://doi.org/10.1109/ISETC63109.2024.10797314

[10] Mejia, J.M.R., Rawat, D.B., 2024. Exploring the Advancements of AI Enabled Clinical Decision Support Systems for Patient Triage in Healthcare. In Proceedings of the 2024 IEEE International Conference on E-health Networking, Application & Services, Nara, Japan, 18–20 November 2024; pp. 1–4. DOI: https://doi.org/10.1109/HealthCom60970.2024.10880833

[11] Sharma, D., Rashno, E., Zulkernine, F., et al., 2024. Triage-Bot: An Assistive Triage Framework. In Proceedings of the 2024 IEEE International Conference on Digital Health, Shenzhen, China, 7–13 July 2024; pp. 138–140. DOI: https://doi.org/10.1109/ICDH62654.2024.00033

[12] Da'Costa, A., Teke, J., Origbo, J.E., et al., 2025. AI-driven triage in emergency departments: A review of benefits, challenges, and future directions. International Journal of Medical Informatics. 197, 105838. DOI: https://doi.org/10.1016/j.ijmedinf.2025.105838

[13] Verma, A., Dhingra, S., Soni, M.K., 2009. VLSI-cell placement technique for Architecture of Field Programmable Gate Array (FPGA) design. Turkish Journal of Electrical Engineering and Computer Sciences. 17(3), 327–336. DOI: https://doi.org/10.3906/elk-0908-173

[14] Verma, A., Dhingra, S., Soni, M.K., 2009. Design and synthesis of FPGA for speed control of induction motor. International Journal of Physical Sciences. 4(11), 645–650. Available from: https://academicjournals.org/journal/IJPS/article-stat/93C172219712

[15] Rani, R., Verma, M., Verma, A., 2025. Application of Fuzzy Inference System for Interpreting Physical Fitness Metrics of Male and Female Trainee Athletes: De-Fuzzification through Hull and Sigma Scale Analysis. Journal of Electronic & Information Systems. 7(2), 13–24. DOI: https://doi.org/10.30564/jeis.v7i2.10609

[16] Verma, A., Tiwari, V.A., 2019. A fuzzy logic controller to minimize the effect of input temperature fluctuations on the deviation of relative humidity to avoid instrument's deterioration. International Journal of Research in Advent Technology. 7(6), 73–77. DOI: https://doi.org/10.32622/ijrat.76201948

[17] Verma, A., Tiwari, V.A., 2013. Optimum Fuzzy Based Approach to Improve the Instrument's Performance Affected by Environmental Conditions. Serbian Journal of Electrical Engineering. 10(2), 309–318. DOI: https://doi.org/10.2298/SJEE121219006V

[18] Čabarkapa, V., Čavoški, S., Vujović, V., et al., 2025. Automating Triage: Identifying Gaps in Traditional Approaches and Proposing Solutions. In Proceedings of the 2025 International Symposium INFOTEH-JAHORINA, East Sarajevo, Bosnia and Herzegovina, 19–21 March 2025; pp. 1–6. DOI: https://doi.org/10.1109/INFOTEH64129.2025.10959221

[19] Petrica, A., Marza, A.M., Barsac, C., et al., 2026. Artificial intelligence in emergency department triage: Perspective of human professionals. Frontiers in Digital Health. 7, 1693060. DOI: https://doi.org/10.3389/fdgth.2025.1693060

[20] Abdalhalim, A.Z., Ahmed, S.N., Ezzelarab, A.M., et al., 2025. Clinical Impact of Artificial Intelligence-Based Triage Systems in Emergency Departments: A Systematic Review. Cureus. 17(6), e85667. DOI: https://doi.org/10.7759/cureus.85667

[21] Hassanpour, A., Yang, B., 2025. Contactless Vital Sign Monitoring: A Review towards Multi-Modal Multi-Task Approaches. Sensors. 25(15), 4792. DOI: https://doi.org/10.3390/s25154792

[22] Rajkomar, A., Dean, J., Kohane, I.S., 2019. Machine learning in medicine. New England Journal of Medicine. 380(14), 1347–1358. DOI: https://doi.org/10.1056/NEJMra1814259

[23] Jorge, J., Villarroel, M., Tomlinson, H., et al., 2022. Non-contact physiological monitoring of post-operative patients in the intensive care unit. NPJ Digital Medicine. 5(1), 4. DOI: https://doi.org/10.1038/s41746-021-00543-z

[24] Ahmed, A.A., Mojiri, M.E., Daghriri, A.A., et al., 2024. The Role of Telemedicine in Emergency Department Triage and Patient Care: A Systematic Review. Cureus. 16(12), e75505. DOI: https://doi.org/10.7759/cureus.75505

[25] Choi, S.W., Ko, T., Hong, K.J., et al., 2019. Machine Learning-Based Prediction of Korean Triage and Acu-

ity Scale Level in Emergency Department Patients. Healthcare Informatics Research. 25(4), 305–312. DOI: https://doi.org/10.4258/hir.2019.25.4.305

[26] Krones, F., Marikkar, U., Parsons, G., et al., 2025. Review of multimodal machine learning approaches in healthcare. Information Fusion. 114, 102690. DOI: https://doi.org/10.1016/j.inffus.2024.102690

[27] Dantulurumuralidhar, V., Abrol, S., Rocque, M., et al., 2023. *CoVETED Study*: Contactless Vitals for Effective Triaging in Emergency Department—A System to Reduce Cross-Infection. Open Forum Infectious Diseases. 10(Suppl 2), ofad500.809. DOI: https://doi.org/10.1093/ofid/ofad500.809

[28] Chai, P.R., Dadabhoy, F.Z., Huang, H.-W., et al., 2021. Assessment of the Acceptability and Feasibility of Using Mobile Robotic Systems for Patient Evaluation. JAMA Network Open. 4(3), e210667. DOI: https://doi.org/10.1001/jamanetworkopen.2021.0667

[29] Faheem, M., Iqbal, A., 2025. Real-time clinical decision support with explainable AI: Balancing accuracy and interpretability in high-stakes environments. International Journal of Science and Research Archive. 16(1), 1204–1220. DOI: https://doi.org/10.30574/ijsra.2025.16.1.1992

[30] Tun, H., Rahman, H., Naing, L., et al., 2025. Trust in Artificial Intelligence–Based Clinical Decision Support Systems Among Health Care Workers: Systematic Review. Journal of Medical Internet Research. 27, e69678. DOI: https://doi.org/10.2196/69678

[31] Gershov, S., Raz, A., Karpas, E., et al., 2024. Towards an autonomous clinical decision support system. Engineering Applications of Artificial Intelligence. 127, 107215. DOI: https://doi.org/10.1016/j.engappai.2023.107215

[32] Abadi, A.S.S., Koguciuk, A., Jangas, M., et al., 2025. Advances in Nano-BioElectronics, Robotic Surgery, and Technologies for Medical and Healthcare. Journal of Electronic & Information Systems. 7(1), 1–21. DOI: https://doi.org/10.30564/jeis.v7i1.9353

[33] Yang, G.-Z., Cambias, J., Cleary, K., et al., 2017. Medical robotics—Regulatory, ethical, and legal considerations for increasing levels of autonomy. Science Robotics. 2(4), eaam8638. DOI: https://doi.org/10.1126/scirobotics.aam8638

[34] Topol, E.J., 2019. High-performance medicine: The convergence of human and artificial intelligence. Nature Medicine. 25, 44–56. DOI: https://doi.org/10.1038/s41591-018-0300-7

[35] Bajwa, J., Munir, U., Nori, A., et al., 2021. Artificial intelligence in healthcare: Transforming the practice of medicine. Future Healthcare Journal. 8(2), e188–e194. DOI: https://doi.org/10.7861/fhj.2021-0095

[36] Abbas, Q., Jeong, W., Lee, S.W., 2025. Explainable AI in Clinical Decision Support Systems: A Meta-Analysis of Methods, Applications, and Usability Challenges. Healthcare. 13(17), 2154. DOI: https://doi.org/10.3390/healthcare13172154

[37] Baharum, A., Ismail, R., Daruis, D., et al., 2025. Human-Robot Interaction-Healthcare: Systematic Review. Artificial Intelligence and Human-Computer Interaction. 404, 537–543. DOI: https://doi.org/10.3233/FAIA250160

[38] Sagona, M., Dai, T., Macis, M., et al., 2025. Trust in AI-assisted health systems and AI's trust in humans. npj Health Systems. 2, 10. DOI: https://doi.org/10.1038/s44401-025-00016-5

[39] Islam, S.M.R., Kwak, D., Kabir, M.H., et al., 2015. The Internet of Things for health care: A comprehensive survey. IEEE Access. 3, 678–708. DOI: https://doi.org/10.1109/ACCESS.2015.2437951

[40] Kim, C.-M., Choi, Y.-S., 2023. Facial Video-based Remote Photoplethysmography Signal Estimation with Vision Transformer. In Proceedings of the 2023 IEEE International Conference on Consumer Electronics-Asia, Busan, Korea, 23–25 October 2023; pp. 1–4. DOI: https://doi.org/10.1109/ICCE-Asia59966.2023.10326412

[41] Hao, Z., Wang, Y., Li, F., et al., 2025. Detection of vital signs based on millimeter wave radar. Scientific Reports. 15(1), 28112. DOI: https://doi.org/10.1038/s41598-025-09112-w

[42] Perpetuini, D., Filippini, C., Cardone, D., et al., 2021. An Overview of Thermal Infrared Imaging-Based Screenings during Pandemic Emergencies. International Journal of Environmental Research and Public Health. 18(6), 3286. DOI: https://doi.org/10.3390/ijerph18063286

[43] Esteva, A., Robicquet, A., Ramsundar, B., et al., 2019. A guide to deep learning in healthcare. Nature Medicine. 25, 24–29. DOI: https://doi.org/10.1038/s41591-018-0316-z

[44] Beam, A.L., Kohane, I.S., 2018. Big data and machine learning in health care. JAMA: Journal of the American Medical Association. 319(13), 1317–1318. DOI: https://doi.org/10.1001/jama.2017.18391

[45] Fawcett, T., 2006. An introduction to ROC analysis. Pattern Recognition Letters. 27(8), 861–874. DOI: https://doi.org/10.1016/j.patrec.2005.10.010

[46] Levin, S., Toerper, M., Hamrock, E., et al., 2018. Machine-Learning-Based Electronic Triage More Accurately Differentiates Patients with Respect to Clinical Outcomes Compared with the Emergency Severity Index. Annals of Emergency Medicine. 71(5), 565–574. DOI: https://doi.org/10.1016/j.annemergmed.2017.08.005

[47] Raita, Y., Goto, T., Faridi, M.K., et al., 2019. Emergency department triage prediction of clinical outcomes using machine learning models. Critical Care. 23(1), 64. DOI: https://doi.org/10.1186/s13054-019-2351-7

[48] Obermeyer, Z., Powers, B., Vogeli, C., et al., 2019. Dissecting racial bias in an algorithm used to manage the

health of populations. Science. 366(6464), 447–453. DOI: https://doi.org/10.1126/science.aax2342

[49] McCoy, L.G., Banja, J.D., Ghassemi, M., et al., 2020. Ensuring machine learning for healthcare works for all. BMJ Health & Care Informatics. 27(3), e100237. DOI: https://doi.org/10.1136/bmjhci-2020-100237

[50] Rajkomar, A., Dean, J., Kohane, I.S., 2018. Scalable and accurate deep learning with electronic health records. npj Digital Medicine. 1, 18. DOI: https://doi.org/10.1038/s41746-018-0029-1

[51] Jiang, F., Jiang, Y., Zhi, H., et al., 2017. Artificial intelligence in healthcare: Past, present and future. Stroke and Vascular Neurology. 2(4), 230–243. DOI: https://doi.org/10.1136/svn-2017-000101