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Design and Evaluation of a Wearable IoT Triage System for Mass Casualty Management

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Abstract:
This study presents the design and evaluation of a wearable Internet of Things (IoT)– based triage system to improve the prioritization of casualties during mass-casualty incidents (MCIs). The main objective of the research was to enhance the speed and accuracy of patient assessment while reducing the cognitive workload of first responders. The system was designed as an integrated platform combining wearable sensor nodes, a low-power long-range communication link based on LoRa technology, and an interactive dashboard for real-time monitoring and classification. A MAX30102 photoplethysmography sensor was used for continuous measurement of heart rate and oxygen saturation, while a LoRa-enabled transmitter based on the RFM95 module sent physiological data to a central gateway built around a Raspberry Pi microcontroller. The triage decision logic followed a semi-automated adaptation of the START protocol, implemented as a rule-based flow to categorize patients based on vital-sign thresholds and consciousness level. Physiological data were continuously analyzed, and the corresponding triage status was updated on a real-time interface designed to support medical staff during emergency operations. Experimental assessments conducted under controlled simulation scenarios confirmed that the proposed architecture effectively supported stable communication, timely data updates, and consistent triage decisions. Key findings indicated that the wearable system maintained high reliability, adaptability, and responsiveness in the absence of internet connectivity. Overall, the proposed approach demonstrates that IoT-enabled wearable technologies can substantially improve the operational efficiency of disaster medicine by enabling continuous patient monitoring and data-driven prioritization strategies in critical environments.

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1. Introduction

Mass casualty incidents (MCIs), whether triggered by natural disasters such as earthquakes and floods or human-induced events such as large-scale traffic accidents, explosions, or industrial hazards, continue to pose significant challenges for emergency medical services and crisis management systems worldwide [1]. In these high-stress and resource-constrained scenarios, the ability to rapidly and accurately prioritize injured individuals is vital to minimizing fatalities and ensuring effective allocation of limited medical resources [2]. Triage, the process of categorizing patients by injury severity and treatment urgency, remains a cornerstone of disaster response operations [3].

Despite its critical role, conventional triage practices, which are largely dependent on manual assessment, paper-based records, and the subjective judgment of first responders, face substantial limitations. The unpredictable and chaotic nature of mass emergencies often leads to delays, human errors, inconsistent documentation, and a lack of real-time situational awareness [4]. Factors such as environmental conditions, insufficient numbers of trained personnel, psychological stress, and the absence of integrated data sharing further exacerbate these shortcomings [5]. Global standards recommend that initial triage assessments be completed within 60 seconds per patient; however, maintaining this threshold is extremely challenging in real-world field conditions with large numbers of casualties [6].

With the rapid advancement of digital technologies, the Internet of Things (IoT) has emerged as a powerful enabler of the reshaping of traditional healthcare and emergency response paradigms [7]. Wearable IoT devices, equipped with physiological sensors and wireless communication modules, offer new possibilities for continuous real-time monitoring of vital signs, automated data processing, and seamless integration with decision-support platforms [7]. These capabilities can significantly enhance the accuracy, speed, and consistency of triage operations in MCIs.

Automated or semi-automated triage systems can help alleviate the workload and cognitive burden on paramedics and emergency staff, allowing them to focus their efforts on critically injured patients [8]. By continuously monitoring key vital parameters such as heart rate, blood oxygen saturation, respiratory rate, and blood pressure, these systems can classify patients more objectively and alert command centers instantly when critical thresholds are reached [8]. In addition, they facilitate effective documentation, data archiving, and post-incident analysis, which are essential for improving crisis response strategies.

The practical deployment of such systems, however, requires robust, modular solutions that can operate in harsh environments with limited infrastructure. Wireless protocols with long-range coverage and low power consumption, such as LoRa, are particularly well-suited for transmitting vital data in disaster zones where conventional networks may be unavailable or unreliable [9]. Moreover, integrating a portable processing unit with a user-friendly graphical dashboard provides responders and commanders with an accessible means to visualize real-time patient data and dynamically manage triage decisions.

In response to these pressing needs and challenges, this study proposes the design, implementation, and evaluation of a wearable, IoT-based triage platform tailored to mass-casualty incidents. The proposed system combines multiple hardware and software components, including wearable sensors (e.g., the MAX30102 module for heart rate and SpO_2 measurement), an Arduino Nano for local data acquisition, an RFM95 LoRa module for long-range wireless transmission, and a Raspberry Pi for centralized data processing and storage. The core triage logic and data handling are implemented in the Node-RED environment, which also provides an interactive, real-time dashboard for monitoring patients' conditions and manually entering additional information, such as age, gender, consciousness level, and contamination status.

This platform is designed to operate autonomously, with minimal need for direct human intervention during data collection and transmission. Practical features, such as integrated LED indicators and audio alarms, facilitate rapid identification of critical patients, even in low-visibility or chaotic field conditions. Unlike traditional systems that rely solely on visual tags and manual record-keeping, the proposed solution ensures continuous updates of patient status, enabling dynamic re-prioritization as their conditions evolve.

The main objectives of this research are fivefold: (i) to develop a reliable wearable triage device leveraging IoT technologies; (ii) to improve the speed and precision of initial triage assessments compared to conventional manual methods; (iii) to enable structured data storage and decision support for real-time and retrospective analysis; (iv) to reduce the workload and cognitive stress on emergency responders by automating routine monitoring tasks; and (v) to experimentally validate the system's performance through realistic laboratory scenarios, focusing on key quality-of-service metrics such as execution time, transmission latency, and data delivery success rate.

Potential beneficiaries of this research include national emergency medical services, disaster response agencies, mobile hospitals, military medical units, and crisis management authorities. Beyond immediate operational deployment, the system can serve as a research and training platform for universities and other institutions that are exploring advanced smart health and digital crisis management solutions.

While this study demonstrates a working prototype and provides valuable insights into real-world deployment, it also acknowledges certain limitations. These include constraints related to laboratory-based testing rather than live disaster scenarios, hardware limitations inherent in low-cost components, and the use of simulated rather than clinical patient data due to ethical considerations. Despite these constraints, the findings provide a solid foundation for future research and field trials to scale up and integrate smart wearable triage solutions into broader emergency healthcare systems.

By addressing gaps in conventional triage practices and demonstrating the feasibility of an IoT-based wearable platform for MCIs, this research contributes to ongoing global efforts to enhance disaster preparedness, optimize emergency response, and ultimately save lives.

2. Related Work

In recent years, the integration of smart sensing technologies and Internet of Things (IoT) architectures into emergency and disaster management systems has attracted significant research attention. Numerous studies have examined the challenges of efficient triage, patient monitoring, and data communication in large-scale disaster scenarios. This section reviews representative studies on wearable devices, electronic triage systems, smart tracking solutions, and communication frameworks, highlighting their contributions and limitations for real-time decision-making and resource optimization during mass-casualty incidents (MCIs).

In parallel with these developments, recent reviews have emphasized the growing importance of trustworthy and ethically aligned AI systems—particularly in IoT-enabled healthcare—highlighting the need for transparent algorithms, secure data pipelines, and privacy-preserving architectures when integrating wearable biosensors into clinical or emergency workflows [10].

One of the most prominent lines of research has focused on wearable triage tags and electronic triage systems. Čabarkapa et al. [8] proposed an electronic triage tag system designed to improve victim survival rates during MCIs by enabling real-time monitoring of vital signs, including heart rate, oxygen saturation, and respiratory rate. This system demonstrated notable improvements in accuracy and user satisfaction through a simulated scenario involving multiple casualties. Similarly, Grünerbel et al. [11] conceptualized a smart triage wristband integrating automated blood pressure measurement and movement detection. By employing semi-automated algorithms based on the mSTART protocol and machine learning techniques, their design aimed to minimize human error and accelerate decision-making. While both approaches yielded promising results under controlled conditions, they relied primarily on simulation or small-scale laboratory trials and thus require further validation in real-world disaster environments.

Research by Stewart et al. [12] and Caviglia et al. [13] explored the broader domain of patient tracking and identification during disasters. Stewart and colleagues examined the limitations of manual tracking methods and emphasized the advantages of adopting RFID, barcoding, and Wi-Fi-based solutions for real-time information exchange and interoperability across emergency units. Caviglia et al. conducted a comprehensive review that highlighted critical gaps in health-sector preparedness for patient tracking during disasters, particularly in countries with fragmented health information systems. Despite significant technological advances, many existing solutions still face challenges such as infrastructure dependency, limited scalability, and data privacy concerns.

These privacy- and security-related challenges have also been highlighted in more recent IoT-focused studies, including lightweight secure-sensing models designed for Body Area Networks (BANs) operating in hostile or high-risk environments. Such systems combine adaptive sampling, compressed sensing, and context-bound encryption to reduce energy consumption and prevent signal tampering, underscoring the need for resilient and secure data flows in wearable triage platforms [14].

Advancements in IoT-based monitoring systems have further extended the potential of electronic triage. Smith [15] proposed integrating smart sensors, wearable devices, and wireless communication modules to enhance continuous tracking of victims' vital signs. Their study emphasized the importance of combining low-power wireless technologies—such as BLE, LoRa, and NB-IoT—to maintain reliable connections in resource-constrained or damaged network conditions. Although these frameworks offer flexible architectures for distributed sensing and monitoring, their practical deployment still depends on reliable network connectivity and seamless interoperability among heterogeneous devices.

The field has also seen research focusing on decision support systems (DSS) and automated triage algorithms. For instance, Wang et al. [16] compared multiple triage protocols (e.g., START, SALT, STM) commonly used in developed countries and highlighted their limited adaptability to diverse field conditions. Similarly, Lubkowski et al. [17] introduced a DSS for medical evacuation in military operations that leverages real-time physiological data streams and wearable sensors to support faster and more accurate prioritization. While these systems showcased the potential of integrating advanced data analytics with real-time sensing, they often require sophisticated infrastructure and trained personnel, which might not be feasible in chaotic, large-scale disaster settings.

Several recent studies have explored emerging technologies to improve triage efficiency. For example, new concepts such as augmented reality–based triage tools [18], AI-driven remote triage algorithms [19], and distributed electronic triage networks [20] have been proposed to reduce manual workload and enhance situational awareness for first responders. A comparative study by Phimphisan et al. [21] revealed that, although electronic triage systems offer better organization and traceability than paper-based methods, both approaches achieved comparable classification accuracy under simulated MCI conditions. This finding underscores the importance of robust design, user training, and the integration of user-friendly interfaces to maximize the benefit of digital solutions.

Despite these promising developments, several key challenges remain. Many existing wearable or electronic triage solutions have limited real-world testing in disaster scenarios, relying heavily on laboratory-based prototypes and simulations. Power consumption, device interoperability, secure data transmission, and the resilience of wireless communication networks in harsh environments continue to pose significant technical barriers. Furthermore, the lack of standardized frameworks for integrating smart triage systems with broader disaster management infrastructures often limits scalability and practical adoption.

In summary, the literature demonstrates significant progress in developing smart triage and patient-tracking solutions using wearable devices, IoT communication modules, and automated decision-making algorithms. However, there remains a clear research gap regarding the deployment of cost-effective, scalable, and robust wearable triage systems that operate reliably in real disaster conditions with minimal reliance on existing infrastructure. The system proposed in this study aims to address these limitations by designing a modular, wearable IoT-based triage platform that integrates real-time vital-sign monitoring with low-power, long-range communication technologies and semi-automated classification algorithms. By building on the strengths of previous work and tackling its critical shortcomings, this research seeks to contribute a practical, field-ready solution to improve emergency response and casualty management during MCIs.

3. System Design & Implementation

This section presents the comprehensive design and practical implementation of the proposed IoT-based smart triage system for the rapid prioritization of casualties in mass-casualty incidents (MCIs). The design philosophy emphasizes modularity, long-range wireless communication, and real-time data acquisition and processing, ensuring that the system remains functional under harsh, resource-constrained conditions. The overall architecture integrates a layered hardware-software framework that employs wearable sensors, embedded microcontrollers, LoRa communication modules, edge computing nodes, and an interactive dashboard to support situational awareness and decision-making.

3.1. System Architecture Overview

The system is structured around a 5-layered architecture that combines three main subsystems. The wearable unit continuously monitors key physiological parameters; the LoRa module ensures long-range, low-power data transmission; and the edge node collects, processes, and visualizes incoming data in real time.

A layered architectural approach was adopted to separate sensing, data transmission, processing, data management, and application functionalities, ensuring scalability and fault isolation. Table 1 illustrates the high-level architecture, highlighting the data flow from sensors to the final user interface accessible to paramedics and crisis managers.

Table 1. Functional Layers and Components of the Smart Triage System

Layer	Primary Function	Main Components
Sensing Layer	Collecting patients' vital signs	Heart rate & SpO_2 sensor (MAX30102), RGB LEDs
Data Transmission Layer	Transmitting sensor data to the edge node	LoRa communication module (RFM95W)
Processing Layer	Pre- and post-transmission data processing	Arduino Nano, Raspberry Pi
Data Management Layer	Storing and analyzing patients' health data	InfluxDB time-series database
Application Layer	Presenting information to end users	Dashboard 2 interface, Web-based application

3.2. Wearable Sensing Unit Design

At the core of the patient-side module is a set of physiological sensors designed for real-time vital sign monitoring with minimal invasiveness. The MAX30102 optical sensor was selected for its dual functionality in measuring heart rate (HR) and peripheral capillary oxygen saturation (SpO_2) using photoplethysmography (PPG) [22]. This sensor offers high accuracy in motion-rich environments, which is critical for field operations [23].

The MAX30102 is interfaced with an Arduino Nano microcontroller, which handles local data acquisition, signal preprocessing, and periodic sampling. The Arduino Nano's compact size and low power consumption make it well suited for integration into a portable, wearable enclosure that can be securely fastened to the patient's wrist or arm. To extend functionality, the system design allows for the integration of additional modules, such as accelerometers (e.g., ADXL345) for detecting patient posture or movement, and respiratory or ECG sensors for future upgrades.

To alert responders quickly in chaotic scenarios, the wearable unit includes an onboard LED indicator and an audio buzzer. These components are triggered by threshold conditions (e.g., critically low SpO_2 or abnormal HR), providing local alarms that supplement remote notifications. The hardware layout of the wearable sensor unit is illustrated in Figure 1.

3.3. Wireless Communication Layer

Given the unpredictable and often degraded network conditions during disasters, the choice of a robust, low-power, long-range wireless protocol was a design priority. LoRa (Long Range) technology was selected for its ability to maintain reliable communication over distances exceeding several kilometres while consuming minimal energy, making it superior to conventional Wi-Fi or cellular solutions in this context [24].

The RFM95 LoRa transceiver module was integrated with the Arduino Nano to enable bidirectional data exchange between the wearable unit and the central edge node. Operating in the sub-GHz ISM band, the module was configured with an appropriate spreading factor and transmission power to balance coverage range and energy efficiency [25].

Each wearable node is assigned a unique identifier to prevent packet collisions and enable simultaneous monitoring of multiple casualties in the field. The LoRa gateway implemented on the Raspberry Pi receives the uplink packets and forwards the decoded data to the local processing environment. By adopting a star topology for communication, the system minimizes the need for multi-hop relays, simplifying deployment and enhancing reliability.

Figure 1. Physical prototype of the wearable sensor unit, including MAX30102 sensor, Arduino Nano, LED indicator, and buzzer.

Figure 2. Raspberry Pi 4B and connected LoRa module used as the central edge node

3.4. Edge Computing and Processing Unit

The central edge node, as illustrated in Figure 2, is built on a Raspberry Pi 4B and serves as a lightweight edge server for data collection, local processing, storage, and visualization. Node-RED is employed as the primary development framework due to its flow-based architecture, low computational overhead, and suitability for real-time decision-making in resource-constrained environments.

The Raspberry Pi hosts a Node-RED server that orchestrates incoming LoRa-based physiological data streams, executes the hybrid triage decision logic, and updates the visualization dashboard in real time. The proposed triage logic is inspired by established emergency triage methodologies, including the START (Simple Triage and Rapid Treatment). It has been adapted into a semi-automated, rule-based decision system suitable for edge execution [26].

The triage algorithm evaluates multiple physiological and functional indicators simultaneously, including heart rate (HR), blood oxygen saturation (SpO_2), respiratory rate (RR), blood pressure (BP), level of consciousness, body temperature, and the patient's ability to walk. These parameters were selected for their clinical relevance to rapid field triage and their widespread use in standard emergency assessment protocols. Incoming sensor data are continuously compared against predefined clinical thresholds, enabling immediate classification of patients into standard triage categories.

In the implemented system, patients are assigned to one of four triage priority levels (red, yellow, green, and black) based on rule-based threshold conditions. A patient is classified as red (immediate) if any critical physiological condition is detected, such as SpO_2 below 90%, respiratory rate lower than 10 or higher than 30 breaths per minute, systolic blood pressure equal to or below 90 mmHg, heart rate lower than 40 or higher than 150 beats per minute, unresponsiveness or response only to painful stimuli, inability to walk, or abnormal body temperature outside the range of 36–38 °C. These conditions indicate life-threatening instability and require urgent medical intervention.

The yellow (delayed) category includes patients whose vital signs are near critical boundaries but do not yet indicate immediate life-threatening conditions. This group includes individuals with SpO_2 levels between 90% and 94%, respiratory rates between 20 and 30 breaths per minute, heart rates between 40–60 or 100–150 beats per minute, systolic blood pressure above 220 mmHg, impaired mobility, or responsiveness limited to verbal stimuli. Patients in this category require close monitoring and prioritized treatment following stabilization of red-category cases.

Patients classified as green (minor) exhibit stable physiological conditions, such as heart rates between 60–100 beats per minute, SpO_2 levels above 94%, respiratory rates within normal limits, normal blood pressure, full consciousness, the ability to walk, and body temperature between 36.5–37.5 °C. These individuals are considered low priority and can tolerate delayed care without significant risk.

Finally, the black (deceased) category is assigned when no measurable physiological parameters are detected, or when the patient shows no signs of responsiveness, consistent with standard disaster triage definitions.

The rule-based structure of the proposed triage logic enables fast execution with minimal computational complexity, making it well-suited for real-time edge deployment in mass-casualty or disaster scenarios. By embedding clinically grounded physiological thresholds into the Node-RED processing flows, the system ensures transparency, reproducibility, and medical interpretability of triage decisions while maintaining compatibility with established international triage standards.

All physiological data, triage decisions, and timestamps are stored locally in an InfluxDB time-series database hosted on the Raspberry Pi. This storage architecture supports retrospective analysis, quality assurance, and validation of triage outcomes, while allowing future refinement of thresholds based on expert feedback or clinical datasets.

3.5. Interactive Dashboard and User Interface

An essential aspect of the system is the user-facing dashboard, which displays the real-time status of all connected patients, as illustrated in Figure 3. Developed within the Node-RED framework, the dashboard provides a responsive web interface accessible via tablets or smartphones connected to the same local network.

The dashboard presents live vital signs (HR and SpO_2), device connectivity status, and the current triage category. Authorized users can manually enter or update

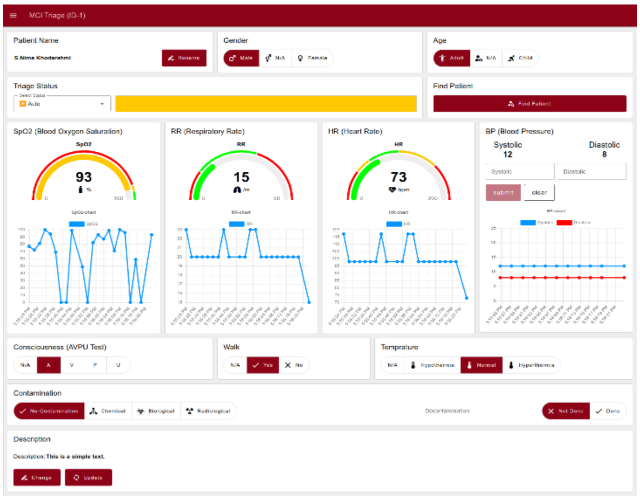

Figure 3. Triage system dashboard with real-time data visualization and interactive input fields

supplementary fields, including age, gender, consciousness level, injury type, and contamination status. Dynamic visual indicators—such as color-coded patient cards—help responders prioritize attention and interventions.

The interface also features alert pop-ups and audio notifications triggered by critical conditions or loss of communication with a patient unit. These design elements aim to minimize cognitive load and streamline decision-making under time pressure.

3.6. Data Flow and Operational Scenario

The end-to-end data flow begins with sensor data acquisition by the wearable unit, followed by preprocessing and periodic transmission via LoRa. Once the Raspberry Pi edge node receives the LoRa packets, Node-RED processes the incoming payloads, executes the triage classification algorithm, stores records in InfluxDB, and updates the live dashboard.

This cycle repeats continuously, ensuring that responders receive updated patient conditions within seconds. Experimental validation under test scenarios showed an average triage logic execution time of 19.66 milliseconds, an average LoRa packet latency of 52.7 milliseconds, and a data delivery success rate of 98.4%. These results confirm the system's ability to meet real-time performance requirements for field operations.

3.7. Field Deployment and Scalability

While the current prototype was tested under controlled laboratory conditions, the system's modular architecture supports scaling to larger casualty counts with minimal reconfiguration. By adjusting the LoRa gateway parameters and expanding the Node-RED data flows, dozens or potentially hundreds of wearable units can be integrated into a single local triage network.

The lack of dependency on external internet connectivity makes the solution deployable in remote or infrastructure-damaged zones, aligning with the realities of disaster-prone regions. For large-scale operations, multiple Raspberry Pi nodes can be interconnected to distribute processing loads and ensure redundancy.

4. Results

This section presents the experimental evaluation of the proposed IoT-based smart triage system, focusing on verifying its operational performance and responsiveness under realistic test scenarios. Rigorous experiments and practical use-case scenarios were designed to assess the system's key performance indicators (KPIs), including execution time of triage logic, end-to-end data transmission latency, and packet delivery ratio (PDR). These experiments aimed to answer the critical question of whether the system can reliably operate under real-world conditions that typify mass casualty incidents (MCIs).

4.1. Test Scenarios and User Interaction Cases

To evaluate the system's functional capabilities from a user-centric perspective, four representative scenarios were devised that mirror critical tasks medical staff must perform in the field. These scenarios address the core aspects of patient status management, field illumination, Find Patient, and manual data input. Each scenario was tested using the integrated hardware-software setup in a controlled lab environment that simulates operational constraints.

4.1.1.Scenario 1: Automatic and Manual Triage Status Adjustment

A unique feature of the system is its hybrid approach to

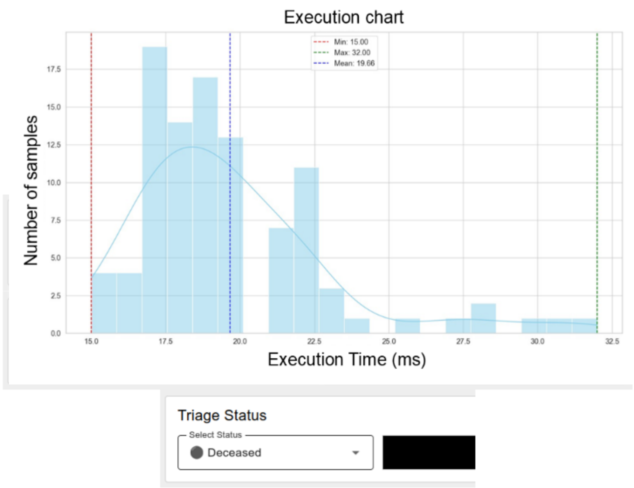

Figure 4. Triage Algorithm Execution Time in Node-RED Chart

triage classification. While the system autonomously determines the patient's triage category using real-time physiological data (heart rate, SpO_2, respiration rate, and other inputs), medical staff retain full authority to override or adjust the automatically assigned status when necessary. The interactive dashboard presents a dedicated "Triage Status" panel for each patient, displaying the current status and enabling quick manual overrides via a dropdown menu with five options: Auto, Immediate, Delayed, Minor, and Deceased (Figure 4). When a manual change is made, the RGB LED on the wearable sensor unit simultaneously updates its color, ensuring alignment between the central dashboard and the field device. This capability enhances user control and supports more nuanced medical decisions in complex, high-pressure scenarios.

4.1.2.Scenario 2: Wearable Unit Illumination for Low-Light Conditions

Field operations during nighttime or in poorly lit environments are common challenges in emergency response. To address this, the wearable sensor unit was equipped with an RGB LED that could be remotely triggered as a field light source. Through the dashboard, responders can activate a "Light" mode that commands the sensor unit to emit bright white light, aiding visibility for patient assessment and minor medical procedures in low-light settings. This feature illustrates how thoughtful integration of simple hardware elements can address real-world operational gaps.

4.1.3.Scenario 3: Find Patient via Audible and Visual Cues

In large-scale incidents with multiple casualties, locating a specific patient rapidly is vital. The dashboard includes a "Find Patient" button for each connected device. When pressed, this trigger both an audible buzzer and the wearable unit's LED to activate for a set duration, providing clear audio-visual cues to help responders quickly locate the intended patient even in crowded or chaotic environments. Real-time notifications on the dashboard further confirm that the alert has been successfully triggered.

4.1.4.Scenario 4: Manual Input and Modification of Patient Demographics and Complementary Vitals

Not all critical patient information can be captured automatically. The system's dashboard allows responders to manually input or adjust demographic and supplementary physiological parameters such as approximate age, gender, body temperature, level of consciousness, ability to walk, and contamination status. Group buttons and text input fields were implemented to make data entry intuitive and minimize user errors during stressful operations. This capability supports flexible documentation and ensures that field data is as complete and up-to-date as possible.

4.2. Performance Tests and Quantitative Metrics

Beyond user interaction scenarios, technical performance was rigorously tested using repeatable lab experiments that reflect typical operational constraints, such as obstacles and signal interference.

4.2.1.Test 1: Triage Logic Execution Time

To assess the system's ability to process physiological data in real time, the execution time of the triage algorithm implemented in Node-RED was measured. A dataset of 100 raw data samples (HR and SpO_2) was streamed to the edge node. For each data point, timestamps were recorded at entry and upon output of the triage decision. The mean execution time was found to be 19.66 milliseconds, with a range between 15 ms and 32 ms (Figure 5). These results demonstrate that the decision-making logic consistently delivers near-instantaneous responses, which is critical for time-sensitive emergency care.

4.2.2.Test 2: End-to-End Latency Measurement

A key determinant of system usability is the time it takes for sensor data to traverse from the wearable unit to the dashboard and back if acknowledgments or control commands are issued. The round-trip time (RTT) was measured using timestamp pairs recorded on both the sensor node and the central unit. The one-way latency was approximated by halving the RTT, resulting in an average transmission delay of 52.735 milliseconds, with minimal variance across test runs (Figure 6). This low latency aligns well with the operational requirements for near-real-time patient monitoring in dynamic crisis environments.

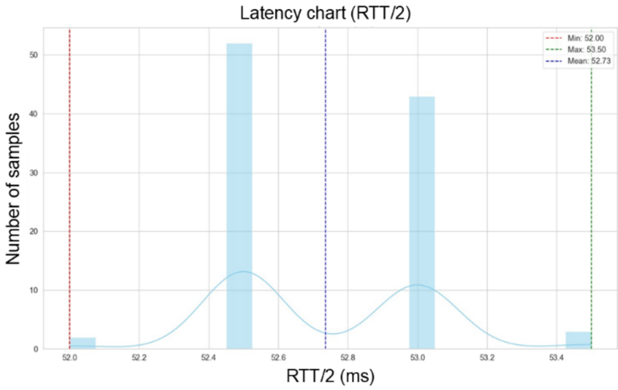

Figure 5. Hybrid Triage Control Interface

4.2.3.Test 3: Packet Delivery Ratio (PDR)

Reliability in wireless communication is vital for IoT systems deployed in unpredictable field settings. To evaluate this, 1,000 sequential packets were transmitted from the wearable sensor via LoRa to the Raspberry Pi gateway. Packet IDs enabled precise tracking of lost messages. The analysis showed that 984 of 1,000 packets were successfully delivered, yielding a robust PDR of 98.4%. This high success rate, despite signal obstacles and indoor barriers, indicates that the chosen communication framework is resilient and dependable for practical deployments.

4.3. Summary of Experimental Findings

The combined results of the scenario-based evaluations and quantitative tests confirm that the proposed smart triage system performs reliably and efficiently under realistic constraints. The hybrid triage logic supports both automated classification and human oversight; the LoRa communication layer demonstrates low latency and high reliability; and the dashboard offers flexible, user-friendly interfaces for real-time interaction and manual input.

5. Discussion

The experimental results presented in this study demonstrate that the proposed IoT-enabled smart triage system performs reliably across multiple operational dimensions, including real-time physiological data processing, robust wireless communication, and effective user interaction. Interpreting these findings in the broader context of emergency response highlights several important implications for both system deployment and future development.

First, the system's hybrid triage logic—combining automated decision-making with manual override—proved effective during scenario-based evaluations. Unlike existing electronic triage solutions that rely solely on rigid algorithms or completely manual classification, the proposed approach provides flexibility for first responders while maintaining consistent decision support. The ability to record manual overrides also establishes a valuable dataset for iterative refinement of the classification rules.

Second, the measured performance metrics further confirm the system's suitability for field deployment. An average execution time of under 20 milliseconds and an end-to-end latency of below 55 milliseconds enable near-instant processing and visualization of patient data. The LoRa-based communication layer demonstrated strong resilience, achieving a 98.4% packet delivery ratio, which is particularly advantageous in environments with degraded infrastructure.

Another noteworthy finding relates to system usability. The dashboard's user-centered interface—featuring grouped commands, intuitive visual cues, and minimized operational complexity—reduced cognitive load during simulated emergency tasks. This supports the system's potential for practical adoption in high-stress scenarios where clarity and speed are critical.

Overall, the results indicate that the prototype is

Figure 6. End-to-End Transmission Latency Chart

well-aligned with the operational needs of mass-casualty triage. However, further analysis of limitations and directions for future enhancement is necessary to assess its readiness for real-world deployment fully.

5.1. Limitations and Future Work

Although the system demonstrates strong technical performance and practical usability, several limitations must be acknowledged.

A primary limitation concerns the evaluation environment. All tests were conducted indoors under controlled conditions, with fixed distances and moderate levels of signal obstruction. Real-world disaster scenarios involve dynamic and unpredictable factors, including severe weather, complex physical barriers, electromagnetic interference, and the simultaneous operation of multiple triage units. These conditions may negatively affect wireless reliability, sensor performance, and overall responsiveness.

Another limitation is the use of simulated physiological data rather than clinical measurements. While this enabled safe, repeatable testing, it precludes direct assessment of medical accuracy in real-time emergency situations. Validating the system using actual clinical datasets—while adhering to ethical research protocols—will be essential to confirm its effectiveness for real-world patient monitoring.

Additionally, the current triage algorithm is rule-based, which may limit its adaptability in scenarios involving complex or atypical physiological patterns. As the system scales to include more sensors or higher-volume data streams, the constraints of LoRa's low data rate may also become more prominent.

Future work should therefore focus on the following directions:

- Conducting extensive field trials in collaboration with EMS units and emergency response organizations to evaluate system robustness in realistic conditions.
- Integrating additional vital sign sensors, such as blood pressure or ECG, to increase diagnostic depth.
- Incorporating lightweight machine learning models for data-driven, adaptive triage classification.
- Exploring hybrid communication architectures that extend beyond LoRa to increase throughput where necessary.
- Implementing GPS modules for accurate geolocation and multi-patient mapping within the dashboard.
- Developing interfaces for linking the system with centralized crisis management platforms to support multi-agency coordination.
- Performing long-term usability studies with diverse responder groups to refine the dashboard for varied technical skill levels.

These enhancements will support the progression from a functional prototype to a robust, deployable system optimized for real-world mass casualty incidents.

6. Conclusion

This study presented the design, implementation, and evaluation of a wearable IoT-based smart triage system intended for rapid prioritization of patients in mass-casualty incidents. The system integrates physiological sensing, long-range wireless communication, lightweight decision-making algorithms, and a user-centered dashboard to support efficient medical response in resource-constrained conditions.

Experimental results confirmed the system's technical feasibility, with an average execution time of 19.66 milliseconds, a transmission latency of approximately 52.7 milliseconds, and a packet delivery ratio of 98.4% using LoRa communication. These metrics demonstrate reliable and low-latency performance suitable for environments with limited infrastructure.

Key contributions of this research include the hybrid automated-manual triage mechanism, resilient long-range communication without reliance on conventional internet connectivity, and an intuitive dashboard designed to minimize cognitive burden during emergencies.

Overall, the system establishes a strong foundation for practical IoT-enabled triage solutions. Continued development—guided by field testing, user feedback, and the enhancements outlined in Section 5.1—will be vital for transforming this prototype into a mature, deployable platform capable of improving emergency response and saving lives in crises.

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8. References

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