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# Development of an Explainable AI-Based Disaster Casualty Triage System

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**Abstract.** Disaster response and management are critical components of rescue team training in countries worldwide. In addition to conducting various disaster drills, rescue teams are trained to perform casualty triage in simulated scenarios, allowing medical personnel to provide optimal treatment based on triage classifications. Due to the necessity of adapting disaster scenarios to enable responders to handle diverse disaster sites, each scenario must be interactive, helping rescuers understand how to perform triage effectively during disaster response. To enrich the variety of scenarios, AI can now be utilized for scenario design. However, for more rational script creation, generative AI must be grounded in Explainable AI (XAI) to make the generation process transparent, thus enhancing the scenario's realism.

This paper proposes an XAI-based disaster casualty triage scenario system. The system generates scenarios through generative AI, utilizing XAI to ensure data transparency. The primary output is a simulation training game focused on disaster scenarios, developed on the Unity platform to build realistic accident scenes. The goal is to provide frontline firefighters with immersive training to strengthen their on-site response and emergency handling skills. The game incorporates a triage mechanism that guides users to categorize injuries based on symptoms and apply appropriate medical actions, aiming to minimize casualties during disasters. From an educational perspective, this game provides the general public with an understanding of how firefighters perform triage based on injury symptoms in emergencies, ensuring that each casualty receives necessary medical support within the golden rescue window. Through simulation and decision-making training in the game, users enhance their judgment and responsiveness, further improving their rapid reaction and handling skills in disaster scenarios.

**Keywords:** Explainable AI, Virtual Reality, Disaster Casualty Triage System, Generative AI.

## 1. Introduction

Frequent natural disasters pose significant threats to human life and property, making the assessment of building damage a crucial indicator for determining post-disaster emergency response and resource allocation. This indicator enables rescue teams to formulate action plans and allocate resources with greater precision, ensuring maximum rescue efficiency and reducing the long-term impacts of disasters on social stability and the economy [14]. In recent years, the frequency and intensity of global natural disasters have markedly increased, presenting unprecedented challenges to human societies. Between 1980 and 2020, there was an average of seven natural disasters each year that caused over $1 billion in economic losses—a figure of considerable significance. However, in the past five years, this average has sharply risen to 16.2 incidents per year, highlighting the impact of climate change and environmental degradation on the frequency of natural disasters [13]. This trend poses serious threats to the economy, infrastructure, public health, and social stability, further complicating global emergency management and disaster prevention. Governments and international organizations are under greater pressure to not only enhance disaster early warning systems but also to allocate more resources to disaster prevention and mitigation measures to lessen the long-term effects of disasters. As the threat of natural disasters continues to grow, increasing global collaboration and response capabilities, as well as pursuing climate change mitigation strategies, has become a critical priority. Housing reconstruction following catastrophic events is a complex and challenging task. Severe weather events, particularly in coastal areas, pose significant threats to local residents. These storms often cause widespread damage to local structures, displacing large numbers of families and subjecting them to trauma, suffering, and psychological distress [10]. The housing recovery process requires not only substantial financial and resource investment but also psychological and social support to help affected residents rebuild stable living environments. Studies have conducted in-depth analyses of natural disaster chains, including earthquake chains, geological disaster chains, typhoon chains, and snow and rain disaster chains, examining the evolution and characteristics of specific disaster chains.[9][24] These studies reveal the interactions and cascading effects between various disasters, helping to provide a more comprehensive understanding of the complexities involved. On the other hand, [21] developed six major types of marine disaster chains, summarizing the impact characteristics of marine disasters. This paper underscores the research motivation derived from the increasing frequency and severity of global natural disasters, highlighting the urgent need for innovative training methods to improve disaster response efficiency. It also showcases the distinctive features of the proposed system, including the integration of Generative AI and Explainable AI for transparent and realistic disaster scenario creation, the use of immersive digital games and virtual reality for hands-on training, and the deployment of a triage mechanism with real-time feedback to enhance decision-making accuracy and engagement among emergency responders and the general public.

The term ”triage” is derived from the French verb ”trier,” which means to categorize, rank, or select. Originally, in the 17th and 18th centuries, it was primarily applied in agriculture and commerce, particularly in the quality grading of goods such as wool and coffee. Over time, this concept gradually expanded into the medical field and became essential in casualty care, eventually evolving into a systematic method for medical triage. With advancements in medical technology and shifting needs, triage expanded beyond the military and was adopted in public healthcare services, becoming a critical component of emergency medical systems. In modern healthcare systems, emergency triage protocols are widely used in hospitals, disaster sites, and other medical settings, classifying patients into different priority levels based on the severity and urgency of their condition. For instance, in emergency medicine, triage personnel typically categorize patients into five levels: Level 1 is for critically ill patients needing immediate treatment; Level 2 is for patients who require prompt care but can tolerate a slight delay; Level 3 is for patients needing treatment that is not immediately urgent; Level 4 is for those with minor conditions; and Level 5 is for cases with no urgent medical needs. This tiered system facilitates the efficient allocation of medical resources, ensuring that critical patients receive timely medical assistance, thereby enhancing overall treatment efficiency. In large-scale disasters or public health crises, the triage system plays an even more vital role. When medical resources are rapidly depleted due to high demand, triage systems help rescue teams quickly assess the situation, prioritize patients for immediate care, and allocate resources according to actual needs. This system not only improves the emergency response capability of medical services but also reduces the burden on rescue personnel, allowing them to perform rescue operations more swiftly. Against a backdrop of globalization, with continuous refinement of medical triage systems and international cooperation in rescue efforts, the concept and applications of triage will become increasingly diversified and systematic.

The application of digital games in disaster education has opened up new teaching methods, immersing learners in highly realistic virtual environments that help concretize abstract knowledge. Unlike traditional book-based learning, digital games allow for flexible adjustments to the scope of the interactive environment, providing firefighters with a diverse learning platform that enhances their innovation and practical application abilities. With the rapid advancement of technology and the increasing maturity of hardware and software, the proposed digital games have gradually entered the field of education, particularly in medical and rescue simulation training. The integration of virtual reality (VR) and digital games significantly enhances trainees' practical skills and response speeds.

This paper proposes an innovative teaching approach based on digital games, which includes the following steps: First, design digital game scenarios and develop instructional modules that align with real-world situations. For example, in medical and rescue simulations, game scenarios can simulate emergency situations such as cardiopulmonary resuscitation (CPR) or trauma care, allowing trainees to repeatedly practice in-game and strengthen their ability to respond in real-life situations. Second, create an immersive learning environment through VR technology, allowing trainees to practice in a risk-free virtual space and familiarize themselves with procedures under pressure. Finally, incorporate a real-time feedback mechanism within the digital game, enabling trainees to receive immediate feedback after each operation, clearly identifying their strengths and areas for improvement. This real-time feedback also provides instructors with objective data to evaluate trainees' learning outcomes and further develop personalized improvement strategies.

## 2. Related Work

Han et al. [11] proposed a Multi-Level Damage Assessment (MLDA) framework for accurately assessing building damage in multi-hazard environments. Addressing the challenge of traditional methods struggling to differentiate levels of building damage across various hazards, the MLDA framework includes a Global Spatial Feature Guidance (GSFG) module and a Difference Change Feature Attention (DCFA) module. GSFG uses a non-local attention mechanism to enhance focus on distant spatial deformations, extracting common features across multiple hazards. DCFA improves the recognition accuracy of fine-grained building damage by integrating multi-scale feature fusion with dual attention mechanisms, emphasizing subtle differences between pre- and post-disaster images. Diaz et al. [7] introduced a simulation-based disaster management framework to analyze housing recovery in the Hampton Roads area, USA. This framework quantifies potential losses to residential areas through simulations and generates predictive scenarios to support decision-making during the reconstruction process. It comprises four main stages: disaster simulation, pre-disaster planning, immediate post-disaster response, and long-term recovery. The simulation results offer guidance for reconstruction, enabling local governments to prepare in advance and enhance disaster resilience. Ye et. al. [22] developed an audio data mining framework to identify human-induced disasters. The framework employs unsupervised learning and data-driven classification to automatically construct a hierarchical structure of disaster audio. This method involves three main stages: initially, a dictionary learning algorithm extracts robust acoustic features to effectively identify disaster events in noisy environments; then, audio event classification is generated based on probabilistic distances between categories; finally, this classification structure is embedded in a hierarchical classifier to enhance event identification performance.

Suf et al. [18] proposed an AI-based disaster monitoring framework that uses geolocation and sentiment analysis from social media posts to monitor disasters. By applying techniques such as Named Entity Recognition (NER), sentiment analysis, regression analysis, and anomaly detection, the framework can automatically extract disaster-related information from multilingual Twitter data worldwide. Dwarakanath et al. [8] reviewed machine learning methods for post-disaster emergency coordination using social media data. With the increasing role of social media in crisis communication and coordination, this study aims to analyze how various machine learning techniques can automatically extract useful information to aid rescue efforts. The study encompasses multi-level classifications, including early warning and event detection at the onset of disasters, post-disaster coordination and response, and damage assessment.

Saleem et al. [17] proposed a lightweight deep transfer model framework called DeLTran15, specifically designed for multi-class classification of disaster-related posts on the X (formerly Twitter) platform to support humanitarian actions in disaster management. The framework utilizes the OSEMN methodology (comprising data acquisition, cleaning, exploration, modeling, and interpretation) to enhance the comprehensiveness and reliability of the classification process. Chamola et al. [5] conducted a comprehensive review of the applications of machine learning technologies in disaster and pandemic management. The study points out that, with the development of IoT, drones, 5G, satellites, and other technologies, machine learning can effectively handle the vast and multi-dimensional data involved in disaster and pandemic management. This capability aids in disaster prediction, crowd evacuation route analysis, social media monitoring, and post-disaster management.

Zhao et al. [23] proposed a disaster chain evolution analysis and simulation method based on Fuzzy Petri Nets (FPN), using marine oil spill disasters as an example to demonstrate its application. The study indicates that a single disaster can trigger a series of secondary disasters, forming complex disaster chain effects that complicate emergency management. To describe and simulate the evolution of these disaster chains, the study developed an improved Fuzzy Petri Net model (DCFPN), which uses dynamic observational data to infer disaster chain evolution and identify the most risk-prone evolutionary paths. Talley [19] explored the application of digital technologies in disaster management, noting that the frequency and cost of natural disasters are continuously increasing, especially in disaster-prone regions like the United States. With rising urban and coastal population densities, disaster management challenges are becoming increasingly complex. The study emphasizes that disaster management is a ”big data problem” requiring coordinated solutions from public and private sectors, with digital technology playing a critical role. Li et al. [12] proposed a scenario-driven hybrid network model (SHN) for the dynamic simulation of disaster propagation in engineering systems. This method divides the disaster chain into a series of related scenarios and models the cascading effects among these scenarios through risk, propagation, and outcome processes. Bae et al. [3] proposed an agent-based disaster response system assessment framework that integrates geospatial and medical details to address mass casualty incidents (MCI). This framework simulates the entire emergency response process from the disaster site to hospitals, covering rescue, triage, transportation, and further analyzing the impact of medical resource distribution and road networks. A case study in the Gangnam area of Seoul, South Korea, demonstrated that the number of emergency physicians and operating rooms significantly affects disaster response efficiency.

Bala et al. [4] conducted an in-depth case study on the response actions of the Veterans Health Administration (VHA) during Hurricane Katrina and proposed five strategies to develop and utilize Information Technology (IT) to enhance healthcare disaster response capabilities. These strategies include: 1) establishing an integrated IT architecture to facilitate data interoperability, 2) developing a universal database for storing and accessing patient data, 3) creating a web-based disaster communication and coordination system, 4) developing an IT-supported disaster management system, and 5) standardizing and integrating IT disaster response processes. Ray et al. [15] provided a comprehensive review of the application of Internet of Things (IoT) technology in disaster management, exploring how IoT can enhance disaster response efficiency through early warning, data analysis, remote monitoring, and real-time analysis. The study introduces IoT-supported protocols and available market solutions, covering applications in natural disasters (such as earthquakes, floods, and wildfires) and human-induced disasters. It also emphasizes the role of IoT in post-disaster management, such as victim localization and support. Oscar Rodriguez-Espindola [16] proposed a multi-period dynamic model for managing simultaneous multi-regional disasters. This model combines bi-objective dynamic stochastic programming, covering supplier selection, facility location, resource allocation, inventory management, and distribution of disaster relief supplies. Chou et al. [6] proposed an ontology-based approach to develop a web design framework for natural disaster management, aiming to improve the functionality of web information systems in response to natural disasters. Using grounded theory, the researchers identified 2,094 web elements from 6,032 pages across 100 disaster management websites and organized them into an ontology structure covering the five major phases of disaster management: general preparedness, specific disaster preparedness, disaster occurrence, post-disaster recovery, and learning. Agarwal et al. [1] proposed a Procedural Content Generation (PCG) framework using Reinforcement Learning (RL) to support disaster evacuation training in virtual 3D environments. This system provides a safe and cost-effective disaster response training alternative to traditional physical drills. The study designed a three-tier PCG architecture to create dynamic and realistic disaster scenarios and used an RL-PCG algorithm to develop a prototype for fire evacuation training. The references and discussions are summarized in Table 1.

In [2], a real-time semi-automated staff assignment system based on machine learning and text mining was proposed to enable efficient task allocation in multi-project management environments. The core objective of this system is to address the inefficiency and lack of flexibility in traditional task assignment methods that rely on historical data. By analyzing task descriptions in real time, the system quickly and accurately assigns tasks to the most suitable staff. The system employs text mining techniques, including tag removal, stop-word filtering, and stemming, as part of its preprocessing operations, and utilizes various vectorization methods such as TF-IDF, Word2Vec, and Doc2Vec to represent text data. Combining these methods with machine learning-based demand prediction, the system applies cosine similarity to precisely match task requirements with staff qualifications. Additionally, the system features dynamic updates to staff profiles, automatically adjusting their qualifications based on completed tasks, thereby ensuring continuous optimization. Tested in a real-world consulting company, the system achieved an 80% accuracy rate in task assignment, demonstrating comparable or superior performance to traditional systems reliant on historical data. In [20], the design and performance evaluation of MOS-Net and its enhanced version, MOS-Net 2.0, for moving object segmentation are thoroughly discussed. Moving object segmentation plays a crucial role in applications such as video surveillance, traffic monitoring, and autonomous navigation. However, traditional methods often rely on handcrafted feature designs, which are limited in handling complex scenarios. MOS-Net, based on a U-Net-like architecture, integrates the flux tensor algorithm and 3D Convolutional Neural Networks (3D CNNs) to capture both spatial and temporal features effectively. The flux tensor efficiently extracts motion information, while the 3D CNN processes temporal sequences to enhance segmentation accuracy. Building upon this foundation, MOS-Net 2.0 incorporates ConvLSTM layers to capture long-term temporal dependencies, making it more robust in dynamic backgrounds and complex scenes. Evaluations on the CDNet2014 dataset demonstrate that both models achieve superior performance on unseen data, particularly in F1 scores, surpassing traditional and contemporary methods such as BSUV-Net and FgSegNet. MOS-Net and its enhanced version exhibit exceptional capabilities in dynamic and unseen scenarios, offering effective solutions for applications requiring precise motion analysis and segmentation. Future work includes optimizing network architecture and integrating additional temporal features.

Integrating triage classification into digital games not only lowers the learning barrier for the general public but also turns the game into an educational resource accessible to everyone. Using a game format can create a more realistic disaster scenario than typical games, increasing player engagement and fostering a heightened level of preparedness among citizens when disasters occur.

**Table 1.** The references and discussions are summarized

| Related Work | Content |
|---|---|
| Han et al. (2024) | Disaster Management Frameworks: For instance, Han et al. (2024) proposed a multi-level damage assessment framework utilizing spatial and attention mechanisms for building damage analysis. While effective for hazard recognition, it lacks a training component for responders. In contrast, our system bridges the gap by providing a hands-on, immersive training environment. |
| Agarwal et al. (2023) | Simulation-Based Disaster Training: Agarwal et al. (2023) introduced a procedural content generation framework for virtual fire evacuation drills. While their approach excels in scenario variety, it does not leverage XAI for transparency, which is a key feature of our system to ensure the interpretability of triage decisions. |
| Bae et al. (2018) | AI in Triage Systems: Bae et al. (2018) presented an agent-based disaster response system focusing on logistics and resource distribution. Unlike our system, theirs does not emphasize educational aspects or individual decision-making training. |

## 3. Methodology

### 3.1. System Model

The purpose of this system is to use digital games to simulate disaster scenarios, thereby enhancing the triage skills of emergency personnel in critical situations. The system architecture comprises four main modules: the Scene Simulation Module, Triage Classification Module, Interactive Control Module, and Props System Module. Each module is responsible for different functions and exchanges data interactively to ensure the completeness and realism of the triage training. The system architecture diagram illustrates the interactions and data flow among the four modules, clearly depicting the roles of each module and how they collaborate to accomplish the triage simulation, as shown in Figure 1. This module leverages Generative Adversarial Networks (GANs) to produce diverse and realistic disaster scenarios, such as varying levels of structural damage and patient distribution. SHAP (SHapley Additive exPlanations) is employed to compute the impact weights of key features, ensuring the scenarios are both rational and diverse.

### 3.2. Generative AI Scenario System

In this system, the Scene Simulation Module uses Generative Adversarial Networks (GAN) to generate diverse disaster scenarios, including the extent of damage to compartments and the distribution of patients. To enhance the system's interpretability, an XAI method based on SHAP (SHapley Additive exPlanations) is employed to calculate the impact weight of each feature within each generated scenario, ensuring the rationality and diversity of scenario generation. The impact of these features helps in understanding how to allocate rescue resources in different scenarios. The formula for calculating the feature value $S_i$ of the generated scenario is as follows, where $S_i$ represents the weight of each feature in the scenario generation:

$$S_i = \sum_{j=1}^{n} w_j \cdot x_{i,j} \tag{1}$$

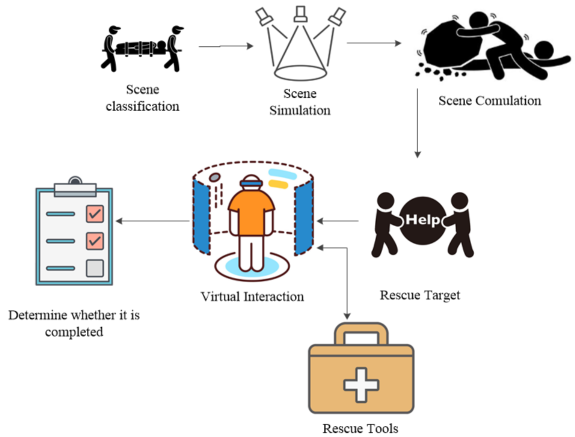


**Fig. 1.** System Architecture Diagram

Here, $w_j$ represents the importance weight of feature $j$, $x_{i,j}$ represents the standardized value of feature, and $n$ is the total number of features.

To help rescue personnel understand how the triage classification system categorizes patients based on symptoms, this system uses LIME (Local Interpretable Model-agnostic Explanations) to explain the triage classification process. Whenever the AI system automatically assigns a patient to a specific level (red, yellow, green, or black), LIME displays key symptom indicators, such as respiratory rate and heart rate, assisting rescue personnel in understanding the reasoning behind the classification decisions. In the system, the priority level $P$ of a patient is a weighted result based on symptom indicators, where the weights of respiratory rate $R$, heart rate $H$, and capillary refill time $T_c$ are $w_1$, $w_2$, and $w_3$, respectively:

$$P = w_1 \cdot R + w_2 \cdot H + w_3 \cdot T_c \tag{2}$$

Based on the explanation results from LIME, users can view the contribution of each symptom indicator to the final triage level, thus gaining a better understanding of the rationality and importance of the classification. XAI technology can also automate the generation of multi-scenario assessments, setting optimal parameters for different situations. Through this technology, the training system can dynamically adjust the rescue priority needed for each scenario. For example, if the damage level in a scenario is high, the system will automatically increase the emphasis on urgency in the triage classification, allowing high-priority patients to be classified earlier.

Assuming the damage index of the scenario is $D$, the adjustment formula for calculating patient priority is as follows:

$$P' = P \times (1 + \alpha \cdot D) \tag{3}$$

In this context, $\alpha$ represents the impact factor of scenario damage. When the $D$ value is high, the system raises the priority classification of patients to meet the urgent demands of the disaster site. The feedback functionality of XAI allows the system to provide tailored recommendations for each trainee, showing the rationale behind each classification decision, thereby enhancing the trainee's understanding of triage principles. Additionally, the system's self-learning capability optimizes parameters for the next round of scenario generation upon receiving new classification data, making the simulations more closely aligned with real disaster scenarios.

### 3.3. Virtual Reality Scenario System

The Scene Simulation Module focuses primarily on scene generation and scene scaling. This module uses the Unity 3D engine to construct an overturned compartment scenario, simulating damaged structures inside the compartment, scattered patients, and broken objects. Unity's terrain generation and physics engine operate within the disaster scenario to provide realistic visual effects and physical behaviors. The scene is scaled based on the size of the scenario and the distribution of patients to ensure the accurate representation of scene details. The calculation formula is as follows:

$$S_C = \frac{R_s}{S_s} \tag{4}$$

Here, $S_C$ represents the scene scaling factor, $R_s$ is the real-world scene length, and $S_s$ is the real-world scene width. By controlling the scaling, the compartment's length and width are adjusted to achieve a realistic simulation effect. This scaling reduces the system resource load, enabling a smoother simulation process.

Patients are classified based on their condition (e.g., breathing, heartbeat, consciousness) into four categories: red, yellow, green, and black. Each color represents a different level of urgency. First, check the patient's breathing status to determine if they are breathing. If there is no breathing, the patient is classified as black, calculated as follows:

$$R = \frac{B_n}{M} \tag{5}$$

Here, $R$ represents the respiration rate, $B_n$ is the number of breaths, and $M$ is the number of minutes. When $R = 0$, the patient is classified as black, indicating no signs of life. If the capillary refill time $(TC)$ exceeds 2 seconds, the patient is assigned a red classification. Based on the patient's heart rate $H$, if $H < 60$ or $H > 120$, the patient is also classified as red. Using these formulas, the system quickly classifies patients and automatically assigns the corresponding color label.

The Interactive Control Module is designed for player movement and interaction control. Using the keyboard (W, A, S, D keys), players can move their character, and a first-person perspective is used to simulate the intensity of the scene. When players approach a patient, symptom information automatically pops up, allowing them to select the appropriate triage level. In the simulation scenario, users can interact with different patients and choose the correct triage level based on symptoms. The system provides various emergency items (such as first aid bandages, pain relievers, etc.), enabling players to select and use resources in the simulation. Players can pick up and use items to respond to specific patient conditions.

The system process is designed as follows:

1. Enter the simulation scenario
   Once the player enters the scene, the system presents a damaged compartment, scattered patients, and emergency supplies. The player can freely explore the scene and search for patients.

2. Triage Operation
When the player approaches a patient, the system automatically displays the patient's basic symptoms (such as breathing status, consciousness, etc.). Based on the observed symptoms, the player determines the triage level (red, yellow, green, or black) and can make a selection using mouse controls.
3. Item Usage
The player selects from available first aid items in the scene and applies them to the patient. Items are automatically matched to symptom needs, assisting the player in performing effective first aid.
4. Result Evaluation
Once triage is completed for all patients, the system automatically generates a score and feedback, evaluating the accuracy and efficiency of the player's classifications and providing suggestions for improvement.

## 4. Experimental Results

This system was developed on the Unity platform using C# as the programming language, simulating a train derailment disaster scenario with the aim of training emergency responders in triage decision-making when faced with a large number of casualties. The experiment included 10 patients with varying symptoms, and 15 participants were invited to test the system to evaluate its effectiveness and the learning outcomes of the participants.

### 4.1. Experimental Design and Procedure

In the experiment, participants were asked to play the role of emergency responders arriving at the scene, required to quickly assess patients' injuries and classify them (red, yellow, green, or black level) to appropriately address varying degrees of injury. After completing the triage for each patient, that patient would disappear from the scene, indicating successful treatment. Patients who were not successfully classified would remain in the scene, and participants would need to re-evaluate them until a correct classification decision was made.

For all 15 participants, the system recorded their accuracy in judgment across different symptoms, average completion time, and response speed. The results showed that the system effectively improved participants' accuracy and speed in triage classification. Specific data are as follows:

1. Accuracy Analysis
In the first attempt, the average triage classification accuracy for the 15 participants was 83%. Most participants were able to correctly distinguish between red and green level patients, but there was some deviation in judging yellow and black levels. After three repeated tests, the participants' average accuracy improved to 94%.
2. Completion Time
In the initial test, participants took an average of 48 seconds to complete the classification for each patient. As they became more familiar with the triage process, the average completion time was reduced to 32 seconds, indicating that practice helped participants respond more quickly.

3. Retest Scores and Error Rate
   For patients initially misclassified, participants were able to correctly classify them in 90% of cases on the second attempt. The most common errors were in distinguishing between black and yellow levels; some participants found it challenging to decide when to classify a patient as black (no signs of life) or yellow (secondary priority).
4. Sense of Achievement and Feedback
   After classifying all patients, the system provided participants with an achievement score based on the number of successfully classified patients. Most participants reported that the achievement score increased their motivation to learn and helped them understand triage standards. They noted that repeated testing on unclassified patients allowed them to clearly understand the reasons for misjudgments and make targeted improvements in future decisions.

### 4.2. Effectiveness Evaluation

The experimental results of this system indicate that conducting triage training in a simulated environment helps improve responders' reaction speed and triage accuracy. Through repeated testing and the system's real-time feedback, participants were able to more effectively grasp classification principles, particularly in making rapid judgments for severely injured patients. Additionally, the achievement system and feedback mechanism motivate learners, allowing them to gain deeper learning experiences from mistakes.

Overall, this system has demonstrated good effectiveness in enhancing triage skills. In the future, the complexity of simulated scenarios could be expanded for field application to further improve training outcomes. Figures 2 to 5 illustrate the system interface during scenario development.

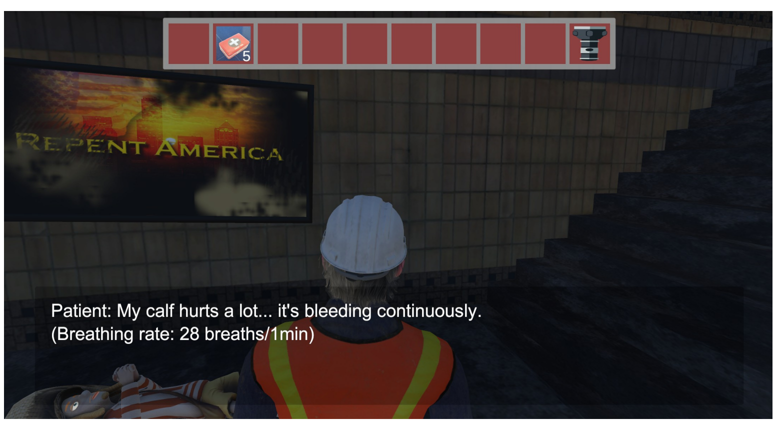


**Fig. 2.** Train Interior Scene


**Fig. 3.** Displaying Symptoms upon Patient Contact


**Fig. 4.** Patient


**Fig. 5.** Triage Classification Options

## 5. Conclusion

This paper leverages digital game simulation technology to create a realistic accident scene training environment, providing emergency responders with an immersive platform for triage training. Using Unity 3D, the system places players in the role of first responders at a disaster site, where they perform triage to enhance their response capabilities and decision-making efficiency in emergencies. Experimental results demonstrate that the system significantly improves the accuracy and speed of patient classification, while also enhancing learners' sense of achievement and engagement. By combining the interactivity of digital games with the realism of 3D simulations, this training model surpasses traditional approaches, offering both emergency personnel and the general public a safe and effective way to experience and learn the importance of triage.

Moreover, the digital game simulation model extends beyond professional responders to serve as a valuable disaster response training tool for the general public. With its user-friendly interface and real-time feedback, the system enables individuals to learn basic triage principles, understand injury classifications, and contribute to casualty reduction during real disasters. This study highlights the significant potential of digital game simulations to revolutionize disaster training, presenting an academically innovative approach that enhances practical emergency response skills. Future research could explore integrating virtual reality technology to further heighten the immersive experience of simulated scenarios. Additionally, expanding the system to address a broader range of disaster contexts would enhance its versatility, establishing it as a widely applicable training platform for achieving more effective rescue outcomes.

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