Artificial intelligence-assisted triage in the emergency department: Current status and future perspectives

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Artificial intelligence in emergency service

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Abstract
This review article examines triage with artificial intelligence in emergency departments and its future role. Currently, the increasing number of patients, limited resources, and challenges experienced in emergency departments make effective triage indispensable. The increasing use of technology in every field is parallel to the increasing use of technology in health services. This paper discusses AI-assisted triage systems, their advantages and challenges. It emphasizes that AI-assisted triage can further improve patient assessment speed, balance resource utilization, and provide consistent triage decisions. However, data privacy, algorithmic biases and healthcare professionals' adoption of these systems remain significant challenges. In conclusion, AI-assisted triage systems have the potential to improve emergency department efficiency and patient care quality when used in combination with traditional methods.

Keywords
Intelligence, Emergency, Triage

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Introduction

Emergency departments are one of the most critical and complex components of healthcare systems because population growth, aging of populations and the increase in chronic diseases are increasing the need for emergency services [1]. This, combined with limited resources and personnel, makes effective patient management difficult [2]. Triage provides the most appropriate use of available resources by accurately classifying patients in a busy emergency department [3].

Traditional triage methods are based on clinical assessments by experienced healthcare personnel. However, inconsistencies due to human factors, errors stemming from fatigue, and increased workloads can limit the effectiveness of these methods [4]. From this perspective, artificial intelligence technologies are promising to support and improve triage [5].

In recent years, artificial intelligence has proven its effectiveness in various areas of healthcare, including image analysis, diagnostic support and personalized treatment planning, and now it has significant potential for use in emergency room triage [6]. Thanks to the algorithms and natural language processing techniques that come with artificial intelligence, triage decisions are supported to be made more accurately and quickly by analyzing large amounts of data quickly and accurately [7].

This review article considers the current status and benefits of AI-assisted triage systems in emergency departments, as well as the challenges faced. It discusses the future progression of AI-assisted triage technologies and their potential impact on clinical practice. It will also presents healthcare professionals and researchers the capabilities and future potential of AI-assisted triage systems [8].

Triage In Emergency Services

Triage is a critical component of emergency services, used to assess and prioritize the medical urgency of patients [9]. It ensures the most effective use of available resources and aims to quickly recognize and intervene in patients at risk of death [10].

Traditional Triage Methods

Several triage systems widely used in emergency departments. The most commonly used are five-level triage systems:

1. Emergency Severity Index (ESI)
2. Manchester Triage System (MTS)
3. Canadian Triage and Acuity Scale (CTAS)
4. Australian Triage Scale (ATS)

These systems assess patients' current clinical status and place them into one of five urgency categories [11]. Triage-trained personnel make the appropriate classification by assessing the patient's vitals, presenting complaints, and current condition [12].

Challenges and Limitations of Triage

Traditional triage methods are effective in managing patient flow in emergency departments, but they face several challenges.

1. Human Factors: Triage can depend on the experience, knowledge and condition of healthcare personnel at the time. This can lead to inconsistent decisions in triage [13].
2. Workload and Time Pressure: It is very difficult to allocate enough time to patients in busy emergency rooms. As a result, inaccurate assessments and consequently inaccurate triage categorization may occur [14].
3. Complex Cases: Atypical symptoms and patients with multiple medical problems pose difficulties in triage categorization [15].
4. Dynamic Changes: A patient's condition can change rapidly, whereas traditional triage systems are almost entirely static and therefore may not capture changes in a timely manner [16].
5. Cultural and Linguistic Barriers: Culture differences or language barriers can make communication with patients and thus the triage process difficult [17].
6. Limited Resources: Triage systems may not be able to provide optimal operation during extremely busy times [18].

New approaches are needed to improve and support the triage process. Artificial intelligence technologies are promising in overcoming these challenges [19].

Artificial Intelligence and Triage

Artificial intelligence (AI) technologies are being used in more and more branches of healthcare as in many other fields. Particularly in emergency services, AI's ability to stabilize patient flow and support clinical decision-making processes increases interest in its potential. AI seems to be very effective in overcoming the challenges faced by traditional methods in triage and in patient assessment [20].

With the ability to process large amounts of data quickly and accurately, AI-assisted triage analyzes the patients' vitals, complaints, history, and other clinical data and can predict the level of urgency. Thanks to AI learning algorithms, it also has the ability to increase accuracy and consistency by learning from the patients' past data [21].

Various machine learning techniques, such as artificial neural networks, support vector machines, and decision trees have shown successful results in predicting important clinical outcomes such as the risk of mortality, the need for intensive care, or the likelihood of hospitalization when patients present to the emergency department. For example, a machine learning-based triage model predicted patient outcomes more accurately than the traditional Emergency Severity Index (ESI) [22].

Natural language processing (NLP) techniques, a key component of AI-enabled triage systems, can reveal important clinical information by analyzing patients' complaints and medical records. This can reduce the workload of triage staff while increasing the scope and accuracy of patient assessments. NLP technologies can also facilitate communication with patients who speak different languages [23].

AI-enabled triage systems are dynamic and capable of continuous learning. These systems constantly updated with new patient data and clinical outcomes and can adapt to emergency department variability. This improves the accuracy of triage decisions [24].

Image processing and computerized imaging technologies are also used in AI-supported triage systems. They can be used to analyze the patient's condition, skin lesions or to quickly interpret radiological examinations. For example, machine learning models can quickly detect emergencies such as pneumonia from chest X-rays [25].

Another advantage of AI-assisted triage is its potential to optimize resource allocation. By instantly analyzing patient volume and emergency room resources, it can reduce waiting times and thus improve patient care. AI models can also predict subsequent admissions, which can help in staff planning and resource management [26].

There are also challenges and ethical concerns in the implementation of AI triage systems. Issues such as data confidentiality, security, algorithm transparency, adoption by healthcare personnel and legal liability of AI decisions must therefore be addressed. In addition, AI models should be developed for specific populations, validated in health systems and frequently calibrated [27].

Artificial Intelligence-Supported Triage Systems

Existing Artificial Intelligence Triage Systems and Models

AI-supported triage systems and models have been developed in recent years to improve patient analysis and optimization in emergency departments. They are used as complementary or alternative options to traditional triage methods [28].

eTriageTool, one of the AI triage systems, uses machine learning algorithms. This system determines the level of urgency by analyzing patients' vital signs, medical history and background. Compared to the traditional Canadian Triage and Acuity Scale (CTAS), it can make more consistent and accurate triage decisions [29].

Deep Learning Emergency Triage (DIET), another important model, analyzes patients' clinical data and predicts the level of urgency. It has been shown to be superior to traditional triage methods, paticularly in complex cases and patients with atypical symptoms [30].

qER is another AI-supported triage system. It uses natural language processing techniques and analyzes patient complaints, and as a result, estimates the level of Emergency Severity Index (ESI) [31].

Case Studies and Pilot Applications

Many healthcare organizations are conducting pilots and case studies to evaluate the effectiveness of AI-supported triage systems. These studies reveal potential benefits and implementation challenges.

In a study conducted at Johns Hopkins Hospital, a machine learning-based electronic triage system was tested. It was found to be more successful than traditional ESI in predicting the likelihood of hospitalization and transfer to the intensive care unit (ICU) [32].

In the UK, NHS Digitali, an AI-powered triage chatbot, was used in an online application. by analyzing the symptoms of patients, it enabled to reduce unnecessary admissions to emergency departments in the COVID-19 pandemic [33].

APOLLO, an AI triage system implemented at Changi Hospital in Singapore, was successful in reducing patient waiting times and improving resource allocation. It instantly analyzed patient volume and improved emergency department performance [34].

In a multicenter study conducted in France, AI-Triage, an AI-powered triage system, was tested. It successfully predicted 30-day mortality risk by analyzing patients' data. Its performance was comparable to that of experienced physicians in identifying high-risk patients [35].

These studies and pilots demonstrate the potential of AI triage systems to improve patient care and allocate resources correctly. However, further research and validation are needed for large-scale implementation [36].

Advantages of Artificial Intelligence Assisted Triage

AI triage systems provide significant advantages in patient assessment and management processes. They contribute to speed, efficiency, accuracy and consistency improvements, and resource allocation.

One of the most significant advantages of AI triage is that it accelerates the patient assessment process and increases efficiency. It can process and analyze large amounts of data much faster than traditional triage methods [37]. This increases speed reduces waiting times in busy emergency departments and positively affects patient flow. A study revealed that the AI triage system reduced the triage time by 27% [38]. Thanks to the increased efficiency, the workload of healthcare personnel is also reduced with time savings. As a result, healthcare professionals can focus on more complex cases and their care [39].

Being accurate and consistent is another advantage of AI-supported triage systems. Machine learning algorithms minimize errors caused by human factors by learning from large datasets. It can make more objective and consistent triage classifications by extensively analyzing patients' data, vitals, and medical histories [40]. Studies also show that higher accuracy rates are achieved compared to traditional methods. For example, an AI-based triage model ranked patient urgency with over 90% accuracy [41]. This increased accuracy and consistent results allow for faster referral of patients for appropriate care, which in turn has the potential to improve clinical outcomes [42].

Another advantage of AI-supported triage systems is their contribution to resource allocation. They provide more efficient use of resources by analyzing in real-time [43]. By evaluating historical data and current conditions, AI algorithms can predict future patient demands and help staff planning accordingly. When an AI-supported resource management system was used, average waiting times in the emergency department decreased by 30% and patient satisfaction increased [44]. It also identifies high-risk patients more effectively, allowing critical resources to be allocated to prioritized cases. This allows potentially life-saving interventions to be delivered in a timely manner [45].

Challenges and Ethical Issues

Despite the potential benefits of artificial intelligence (AI)-assisted triage systems, challenges such as data privacy, security, algorithm bias, and the role and acceptance of healthcare professionals arise during the implementation and dissemination of this technology.

Data privacy and security are among the most critical challenges in implementation. These systems analyze large amounts of sensitive patient data. Patient data protection and privacy is both a legal and ethical obligations [46]. Data leaks or unauthorized access can undermine trust and lead to serious legal consequences. In addition, data sharing and integration across different healthcare organizations and data standardization are among the major challenges [47]. Therefore, strong data protection measures and regular security audits are required during the development and use of these systems [48].

Algorithmic bias is another important issue. This can lead to discrimination against certain patient groups or incorrect triage decisions [49]. For example, one study showed that the AI algorithm showed racial bias and incorrectly assessed the health needs of patients belonging to certain ethnic groups [50]. To prevent these, diverse and representative data should be used during the development process with continuous performance monitoring and frequent algorithm audits [51].

AI systems are designed to support and reduce the workload of healthcare professionals rather than replace them. However, the use of this technology may lead to changes in the traditional roles of healthcare staff [52]. Some healthcare professionals may have difficulty trusting the systems or may be concerned about their own clinical judgment. One study found that healthcare professionals' attitudes toward AI-enabled systems were mixed and acceptance may take time [53]. Therefore, for successful implementation, comprehensive training programs must be organized and the clarity of the systems needs to be increased, and the feedback of healthcare professionals needs to be continuously evaluated [54].

Future Perspectives

The future role of AI-enabled triage systems is continues to evolve with rapidly advancing technologies and new approaches. In parallel with these developments, their use in emergency medicine and wider healthcare is expanding.

Emerging Technologies and Approaches

The future of AI-assisted triage is increasing the ability of triage systems to analyze and process more complex patient data with numerous technological advances such as deep learning and natural language processing [55]. For example, multimodal AI systems have the power to make large-scale assessments by analyzing a patient's voice, facial expressions and body language [56].

Internet of Things (IoT) technologies and wearable devices provide new gains to triage. By instantly analyzing vital signs and health status of patients, triage systems are provided with continuous data flow [57]. In this way, instant changes in patients can be detected immediately and triage decisions can be updated without delay.

Federated learning AI is promising in addressing data privacy and security concerns. This AI makes it possible to learn from larger and more diverse datasets by allowing AI models to be trained by keeping data from different healthcare organizations separate and not aggregating them [58].

Advances in Explainable AI are improving the clarity and understandability of triage decisions. This technology can solve the trust problem of healthcare professionals and patients in these systems [59].

Potential Application Areas

The use of AI-assisted triage systems is not limited to emergency services; it is gradually spreading throughout healthcare. Telehealth and remote triage applications have gained importance, especially after the COVID-19 pandemic. It can reduce unnecessary hospital admissions by allowing patients to be evaluated remotely from their homes, while also improving the efficiency of healthcare resource allocation[60].

Disaster management and triage in mass incidents is another serious application area of AI systems. By providing fast and accurate triage in large-scale emergencies, it enables the most effective allocation of limited resources [61].

In chronic disease management, AI-assisted triage can be used for early detection and treatment of changes in patients. It is especially important for the aging population and increasing number of patients with chronic diseases [62].

In the field of mental health, AI-assisted triage can be used to analyze the mental health of patients and determine emergency intervention if necessary. Natural language processing and sentiment analysis technologies can help identify patients' mental health risks from their written or verbal expressions [63].

In conclusion, the future of AI-supported triage systems is changing in a way that is dependent on technological advances and new application areas. Continuous research, development studies and ethical evaluations should be carried out on these systems [64].

Conclusion

Summary of Findings and Main Points

Artificial intelligence (AI)-assisted triage systems offer significant potential for patient analysis and management. The main advantages of these systems are accelerated triage, more accurate and consistent results, and appropriate allocation of healthcare resources [65]. AI-assisted triage can produce faster and more consistent results than traditional methods. It can make a significant difference especially in busy emergency departments [66].

However, data privacy and security, algorithmic bias, and adoption of systems by healthcare professionals are important issues that must be addressed [67]. The clarity and explainability of AI systems are critical for gaining the trust of healthcare professionals and for ethical and legal processes [68].

A multidisciplinary approach is required for the successful implementation of AI-supported triage systems. A broad collaboration ranging from clinicians to data scientists and ethical experts is indisputable in the development and implementation of these systems [69]. In addition, continuous improvement, compliance with changing health needs and technological developments are important.

Thoughts on the Future of Artificial Intelligence Assisted Triage

The future of AI-enabled triage systems holds challenges but strong promise. Emerging technologies are continuously enhancing the capacity and applicability of these systems. Advances in machine learning and natural language processing are particularly increasing the capacity of triage systems to evaluate and interpret more complex patient data [70].

In the future, AI-supported triage systems are expected to gain significance not only in emergency services but also across various areas of healthcare. These systems have the potential to play a significant role in telehealth applications, chronic disease management and even home care services [71]. The integration of wearable technologies and Internet of Things (IoT) devices has great potential for continuous patient monitoring and early warning systems [72]. In addition, the future of AI-supported triage systems depends on their development and implementation in an ethical and seriously responsible manner. Making algorithms fairness, ensuring data confidentiality and structuring AI systems as human-machine collaboration should be the center of future research and development efforts [73].

In conclusion, it is clear that AI-supported triage systems will play a crucial role in the future of healthcare. In addition to technological advancements, ethical, legal and social factors will need to be addressed for success. Considering the potential to improve the quality and efficiency of healthcare services, the development and implementation of AI-assisted triage systems will rely on continuous research and investment [74].

Scientific Responsibility Statement

The authors declare that they are responsible for the article's scientific content including study design, data collection, analysis and interpretation, writing, some of the main line, or all of the preparation and scientific review of the contents and approval of the final version of the article.

Animal and Human Rights Statement

All procedures performed in this study were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or compareable ethical standards.

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Conflict of Interest

The authors declare that there is no conflict of interest.

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