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The impact of artificial intelligence on emergency triage: a systematic review from the perspective of nursing

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KEY WORDS: Artificial Intelligence, triage, A&E department, nursing.

ABSTRACT

Introduction. Artificial intelligence (AI) is progressing in supporting triage in emergency departments, improving the speed and accuracy of care for critical patients. Even though there are challenges, the use of AI complements clinical judgement and optimises safety and efficiency in care.

Goal. The main goal of the study was to analyse the effectiveness of artificial intelligence systems in the triage process carried out in emergency departments.

Methodology. A systematic review was conducted that included studies published in the last five years, with adult participants treated in the emergency department, to evaluate the use of AI in clinical triage. The databases consulted were PubMed, Scopus, EBSCOhost and Cochrane. In addition, the Elicit tool was used to support the search and selection of articles.

Results. Fourteen articles were analysed that showed improvements in diagnostic accuracy, reduced waiting times and provided greater support for decision-making in nursing. Despite the positive results, some limitations were identified, as well as the need to continue refining these tools.

Conclusions. Artificial intelligence improved the accuracy and efficiency of triage in emergency departments, especially in identifying critically ill patients. It was valued as a complementary tool to clinical judgement, with the potential to improve care.

INTRODUCTION

Artificial Intelligence (AI) has seen remarkable development in recent decades, especially in the field of healthcare, where it has contributed significantly to the improvement of diagnoses, treatments and resource management. Thanks to its ability to process large volumes of data, identify patterns and generate solutions based on this information, AI facilitates faster and more accurate decision-making. These advances are optimising the quality of healthcare and increasing the efficiency of services, with potential for application that is still growing. Artificial intelligence (AI) is defined as the ability of machines to process information, learn from data and apply this knowledge to autonomous decision-making. Its main goal is to mimic human intelligence to a greater or lesser extent, allowing systems to perform tasks that were previously the exclusive domain of humans (1). To achieve this, AI relies on advanced algorithms that analyse large volumes of information, detect patterns and optimise performance over time (2).

One of the cornerstones of AI is its ability to learn, allowing it to improve its own performance as it processes more data. Through machine learning, one of its most prominent branches, machines can identify trends, predict behaviour and adapt their responses with no need for explicit programming for each situation (3, 4). Machine learning is based on the development of algorithms capable of learning by example. As they are provided with more information, the algorithms improve their performance, increasing their accuracy and efficiency over time. This ability to extract knowledge from data and generate decisions on their own allows AI systems to behave in a way that resembles human reasoning (1, 3). Within machine learning there are different methodologies, each with its own characteristics. Supervised learning consists of training the machine by means of examples in which it is shown input data and the corresponding results expected. The system thereby learns to establish relationships between the data and to apply this knowledge to new cases (3, 4).

Unsupervised learning, on the other hand, is based on unlabelled data, i.e. data with no known outcomes. In this case, the system has to analyse the information and discover hidden patterns, clusters or structures on its own. This type of learning is useful when you have no prior information on how the data should be classified, and you want the system to explore possible connections on its own. Another methodology is reinforcement learning, where algorithms learn from experience (1). The machine interacts with an environment, makes decisions and receives feedback in the form of rewards or penalties depending on the outcome of its actions. Over time, the system learns to choose the actions that give it the best results, progressively improving its behaviour (4).

There is also semi-supervised learning, a combination of the above. It is used when there is a small amount of labelled data and a large amount of unlabelled data. The system takes advantage of both types of information to learn more efficiently and with less manual effort (4).

Among the most powerful and advanced techniques within AI is deep learning, which is used to solve extremely complex problems involving large amounts of data. Deep learning occurs through the use of neural networks, organised in layers to recognise complex relationships and patterns in data (1). This neural network is inspired by the human neural network (3).

In addition to its competence in learning, AI is characterised by its ability to make decisions based on the data analysed. Thanks to this, smart systems can assess different options and select the most appropriate one based on the goals set (1). This process mimics human decision-making, but has the advantage of being able to do so at high speed with no emotional bias (2).

The development of AI has enabled machines to perform complex tasks in an efficient way, facilitating automation and improving various aspects of daily and professional life. Currently, it is already present in areas such as medicine, where it helps in the diagnosis and treatment of diseases; industry, optimising production processes; and education, personalising student learning. As it continues to evolve, its impact will continue to grow, providing new opportunities as well as challenges in multiple sectors of society (4).

HISTORY OF AI

Since ancient times, humankind has tried to create artefacts that mimic its form and behaviour, reflecting a desire to understand itself. This idea appears in works by authors such as Homer and Descartes and in ancient technologies such as the abacus and the Quipu (5). Philosophers such as Aristotle and Leibniz also explored human thought, seeing it as a logical process or even a type of calculation (6). One of the most important steps before AI was created as a field of study was the work of Ada Lovelace in 1842. She wrote the first instructions for a machine and speculated on the ability of machines to operate with more than just numbers (7). One of the fundamental stages in the development of artificial intelligence was the work of the English mathematician Alan Turing (6), a central figure in the history of computing. His understanding of automation made it possible to lay the foundations for software and the fundamental rules of computer systems (5, 8). From 1930 to 1950, Gödel, Church and Turing laid the foundations of AI from logic and computational theory. In 1950, he proposed a test known as the ‘Turing Test’, designed to assess whether a machine could exhibit behaviour that might be considered intelligent. This idea sought to establish whether a computer can think in a similar way to a human being. Despite its impact, Turing’s hypothesis has not yet been proven (5-7). The formal starting point of AI as a field of study was the Dartmouth conference, held in 1956. This event brought together researchers such as John McCarthy, Marvin Minsky, Claude Shannon and Nathaniel Rochester, who proposed establishing AI as a new field of study. During the conference, the term ‘artificial intelligence’ was adopted for the first time, defined by McCarthy and Minsky as “the science and engineering of making machines intelligent”. A common idea among Dartmouth attendees was that thinking can be understood as a computational process not unique to humans. Since then, the possibility was raised that human intelligence could be reproduced or simulated by digital machines (5-7, 9).

In 1956, at the same time as the Dartmouth conference, Alan Newell and Herbert Simon developed the ‘Logic Theory Machine’, considered the first artificial intelligence programme. This system was created to find proof of theorems using symbolic logic, showing that computers could work not only with numbers, but also with symbols (7, 9). The programme worked by combining basic operations to build increasingly complex reasoning. To do this, they used IPL (Information Processing Language), one of the first programming languages specifically designed to solve artificial intelligence problems (6). In the same context, John McCarthy introduced the LISP (List Processor) language, designed to process symbolic structures. This language, whose name comes from LISt Processor, was defined in 1958 and became a fundamental tool for the early development of AI (5, 6). Right from its beginnings, the field drew on a variety of different disciplines such as computer science, philosophy, linguistics, mathematics and psychology, which contributed both knowledge and working methods to shape this new scientific field (6).

ARTIFICIAL INTELLIGENCE IN THE FIELD OF HEALTH

Artificial intelligence is playing an increasingly important role in healthcare, and has now been established as a tool with great potential to transform medicine as we know it. Its ability to analyse large volumes of data in a short time enables the identification of complex patterns that can contribute to new scientific breakthroughs, as well as improving the accuracy of individual diagnoses (10). As a result, AI is already being used in both primary care and hospital settings, where it provides significant value at different levels of the care process (11). One of the main factors driving artificial intelligence in the healthcare sector is the constant and accelerating growth of data related to people’s health. This data, in addition to being increasingly abundant, is of great variety and complexity. Traditional methods of analysis, mainly manual, are insufficient for extracting useful information from this vast amount of data. In this context, machine learning algorithms, a branch of AI that allows machines to learn from experience with no need to be explicitly programmed, are an effective solution (12). For these systems to work properly, it is essential to have a large amount of reliable, organised and consistent data, as the quality of the information directly influences the predictive capacity of the model (10, 12). Furthermore, the application of artificial intelligence is contributing to a paradigm shift in the approach to medicine.

A transition is taking place from a model focused primarily on curing disease to one oriented towards prevention, health maintenance and the personalisation of treatment. This new approach is known as ‘4P medicine’ because of its four fundamental pillars: preventive, predictive, participatory and personalised. AI plays a fundamental role in this model, as it allows for the integration and analysis of different types of data such as the genome, medical history and environmental factors. This facilitates medical care better tailored to the specific characteristics of each person (12). The applications of artificial intelligence in healthcare are broad and increasingly varied (10). One of the most prominent uses is to support the diagnosis and risk assessment of patients. Thanks to its competence in analysing medical images, AI can detect diseases such as pneumonia or COVID-19 from chest X-rays, and identify signs of diabetic retinopathy and glaucoma from retinal images. It is also applied in dermatology and in the interpretation of respiratory tests, such as spirometry. In addition, it can predict possible complications in patients, assessing the risk of morbidity or even mortality (11, 12).

Another significant application is integration into early warning systems, where it can improve the detection of critical situations in patients admitted to hospital. For example, by using clinical scales adapted with AI algorithms, signs of deterioration can be identified earlier, helping to reduce complications and improve response times (13).

In terms of treatment, AI allows progress towards more personalised medicine. Through the analysis of genetic, environmental and lifestyle data, it is possible to tailor therapies to the specific needs of each patient (12). Tools such as Watson for Oncology are able to review clinical data together with scientific literature to recommend more appropriate treatments for complex diseases such as cancer (14). Such solutions help to reduce the time needed to make medical decisions and increase the accuracy of such decisions (12).

Artificial intelligence can also be useful in the management of chronic diseases, as it allows continuous monitoring of the patient’s condition and anticipation of possible complications (11). By analysing behavioural patterns, such as sleep or physical activity, preventive interventions can be made before the clinical situation deteriorates. Similarly, AI also contributes to disease prevention by analysing data to select individuals for screening or preventive assessments (10, 11). Another important area is medical research, where AI helps to speed up the development of new treatments and vaccines, as well as facilitating clinical trials (10, 11).

Finally, AI has a significant role to play in clinical decision support. By combining medical information from various sources, these systems can serve as a second opinion that complements the healthcare worker’s assessment, increasing the accuracy of medical decisions and reducing the margin of error (12, 14).

THE HISTORY OF TRIAGE

Triage is an essential procedure in emergency departments, designed to organise medical care according to the clinical priority of patients. The idea is to quickly identify those requiring immediate intervention, optimising the use of resources and preventing care from being based solely on a first-come, first-served basis. The system’s origins lie in military contexts, especially in the eighteenth century, when the need arose to classify wounded soldiers on the battlefield to improve their chances of survival (15). Historically, the Napoleonic physicians Pierre-François Percy and Dominique-Jean Larrey are acknowledged as pioneers in the application of triage. Percy, in addition to being an academic, designed a wheeled ambulance system in 1831 and first used the term ‘triage’ in a medical context. However, Larrey is considered the true originator of the system, as he established a classification based solely on the severity of injuries, with no regard to military rank, and implemented flying ambulances to expedite the transfer of the wounded (15-17).

In the original Napoleonic triage system, the priority was not to save soldiers’ lives, but to prioritise treatment for those who could recover quickly and return to combat. During the Battle of Jena in 1806, the French army used Larrey’s system, classifying the wounded into three categories according to the severity of their injuries: dangerously wounded, less dangerously wounded and slightly wounded (15, 16).

The term triage comes from the French verb ‘trier’, meaning to classify or select. The roots of the word lie in Old French, although its incorporation into the medical field is more recent (16).

From the twentieth century onwards, triage spread to civilian emergency departments in the United States, United Kingdom and the rest of Europe, adopting a clinical approach to prioritising the care, transfer or hospital destination of patients. Triage nowadays is an essential tool in ensuring equitable, efficient care focused on the actual urgency of each patient (16).

TRIAGE SYSTEMS

Triage is an essential process in different phases of health care. It is applied from the pre-hospital setting to the patient’s arrival at the hospital, where it enables care to be organised in an efficient and prioritised manner (15, 18). In recent years, structured triage systems have been developed, predominantly those with five-level scales, as they provide greater validity and reliability than three-level models. However, there is no universally optimal system; the choice depends on the context and should be supported by studies that validate usefulness, applicability and accuracy (18, 19).

There are five main models that are internationally acknowledged. The Australasian Triage Scale (ATS), implemented in Australasia, was the first national five-level system with time limits for first medical contact. Although the validity of this system has been shown, reliability may be diminished in certain groups, such as psychiatric patients (18, 19). The Canadian Triage and Acuity Scale (CTAS), based on the ATS, includes an extensive list of symptoms, vital parameters, a paediatric-specific scale and defined time targets, with solid validity in a variety of different settings (18, 19).

The Manchester Triage System (MTS), widely used in the UK, uses flowcharts with key discriminants, such as vital risk or pain, and allows for telephone triage. Although it is very reliable, the population validity is more limited (18, 19). The Emergency Severity Index (ESI), developed in the United States, classifies patients according to severity and the resources they are likely to require, and is notable for its flexibility in that it does not place strict time limits on low priority levels (18, 19).

Finally, the Structured Triage System (STS), which includes the Spanish Triage System (STS) and the Andorran Triage Model (MAT), has been created in Spanish-speaking settings. It assesses both the clinical severity and complexity of the case, integrates reasons and consultation, paediatric scales and advanced triage options, and is applicable in multiple settings: emergency, primary care, emergency and telephone triage (19).

In addition to these models, there are other international systems adapted to specific contexts, the characteristics of which are summarised in the following table (Table 1).

Table 1: Emergency triage systems in the 21st century: an international view. Source: Prepared by the author. Adapted from Sánchez-Bermejo, R., Herrero-Valea, A. and Garvi-García, M. (19).

Triage System	Place	Priority levels	Special characteristics
Australasian Triage Scale (ATS)	Australia	5	The first nationally implemented 5-level emergency triage system.
Canadian Triage and Acuity Scale (CTAS)	Canada	5	Assesses the level of urgency, includes reasons for consultation and a specific paediatric triage scale.
Manchester Triage System (MTS)	United Kingdom	5	Introduces the concept of symptomatic and discriminant categories. Incorporates the possibility of application for telephone triage.
Emergency Severity Index (ESI)	USA	5	Assesses the level of urgency and incorporates the use of diagnostic and therapeutic resources into the scale.
Sistema Estructurado de Triaje (SET)	Spain	5	Assesses the level of urgency/severity, includes reasons for consultation and a specific paediatric triage scale. Incorporates complexity assessment and advanced triage.
Korean Triage And Acuity Scale (KTAS)	Korea	5	Has an adult and a paediatric version (PedKATS).
Medical Emergency Triage and Treatment System (METTS)	Sweden	5	Combines clinical algorithms and vital signs.
Echelle Liégeoise D'Index de Sévérité à l'Admission (ELISA)	France	5	Identification of patients able to walk and talk.
Classification Infirmière des Malades aux Urgences o French Emergency Nurses Classification in Hospital Scale	France	6	One of the few systems with six levels of priority.
Netherlands Triage System	Netherlands	5	Valid for both ED and telephone triage.
Taiwan Triage and Acuity Scale (TTAS)	Taiwan	4	Features an electronic clinical decision support tool.
Clinical Gps (cGPs)	USA	5	Priority levels based on demographics and laboratory data.
Swiss Emergency Triage Scale (SETS)	Switzerland	4	Moderately reliable, high rates of under-triage due to lack of standardisation.
South African Triage Scale (SATS)	South Africa	5	TEWS (Triage Early Warning Score)
The Soterion Rapid Tiage System	USA	5	Computerised analysis of vital signs.
One-Two-Triage (OTT)	USA	4	Named after the two stages of patient classification according to severity.
CLARIPED	Brazil	5	Four vital signs are assessed and assigned a score.
Emergency Triage Assessment and Treatment (ETAT)	Switzerland	3	Aimed primarily at paediatric patients.
3M TAS Triage System	Spain	5	An advanced triage model. It has not been tested in any hospital.

THE LEGAL AND ETHICAL FRAMEWORK FOR THE USE OF AI

Artificial intelligence is revolutionising the field of medical diagnosis and treatment, bringing undeniable advances that optimise the accuracy, efficiency and personalisation of healthcare. However, the implementation of these technologies poses significant ethical and legal challenges that should be rigorously addressed. Aspects such as data privacy, accountability in decision-making, the security of human autonomy, impact on employment, and equity in access to these innovations require the creation of a sound regulatory framework and thorough ethical reflection to ensure that use benefits society in a fair and safe manner (20).

It is essential to establish rules and regulations to guide the development and use of artificial intelligence in a responsible manner and for the benefit of society as a whole. The 'Montreal Declaration' addresses precisely this need by creating an ethical framework to ensure that artificial intelligence respects the fundamental values and rights of individual people. Among its key goals are defining principles that protect people's well-being, ensuring that technological advances benefit society as a whole, and fostering spaces for national and international debate to ensure fair, accessible and sustainable development (21).

Both the 'Montreal Declaration' and the WHO (World Health Organisation) guidance on artificial intelligence underline the importance of respecting the autonomy of individual people, ensuring that AI does not limit their decision-making capacity and that informed knowledge is respected in the use of personal data. Both documents also emphasise the need for these technologies to contribute to human well-being without generating unnecessary harm, promoting health improvements and reducing risks. In addition, equity and fairness are highlighted as fundamental principles, insisting that the development and use of AI should not reinforce inequalities or discrimination, but should rather favour equitable access to its benefits. These principles are key to applying AI responsibly in the health sector (21, 22).

Beyond ethical principles, there is a consensus on the need to establish clear rules and regulations for the use of artificial intelligence. The debate is no longer about whether it should be used, but about how to ensure that it benefits humanity without generating risks. Both governments and international organisations, such as the EU (European Union), the OECD (Organisation for Economic Co-operation and Development) and UNESCO, have worked on drawing up legal frameworks to avoid possible negative impacts. Among the most significant developments are the OECD's AI guidelines in 2019, the European Parliament's proposed AI Law in 2021 and the European Council's Framework Convention in 2024 (20).

The protection of human rights is a central concern in the development and use of AI. The Spanish Parliament highlights the adoption of the European Council Framework Convention on Artificial Intelligence and Human Rights, which is the first legally binding international treaty ensuring respect for human rights in the use of AI. Furthermore, it is mentioned that the Council's Ad Hoc Committee on Artificial Intelligence (CAHAI) aims to study the feasibility of creating a legal framework for AI based on the Council's human rights standards (20).

The WHO also supports this vision and highlights the lack of clear regulations on the application of AI in health. Despite the existence of multiple ethical proposals in recent years, there are still significant legal gaps. It therefore insists on the need for governments and health bodies to work together to integrate rules and regulations to ensure consistent use of AI with the aim of providing accessible, equitable and effective healthcare for all (22).

GOALS

To analyse the effectiveness of the use of artificial intelligence systems in the triage process performed in emergency departments, to determine whether the use of artificial intelligence (AI) reduces waiting times and improves the clinical responsiveness of emergency staff, to assess the accuracy of AI-assisted triage compared to conventional triage, and to evaluate the evidence available on the perceived quality of AI-assisted triage and its impact on patient satisfaction during initial care in the emergency department.

METHODOLOGY

Research design: a systematic review. To guarantee methodological accuracy, the criteria established in the PRISMA guide (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (23) were followed. Databases: PubMed, CINAHL (EBSCOhost), Cochrane Library and Scopus. To complement the literature review and optimise the search for relevant studies, the Elicit tool was used (24).

FORMULATING THE RESEARCH QUESTION

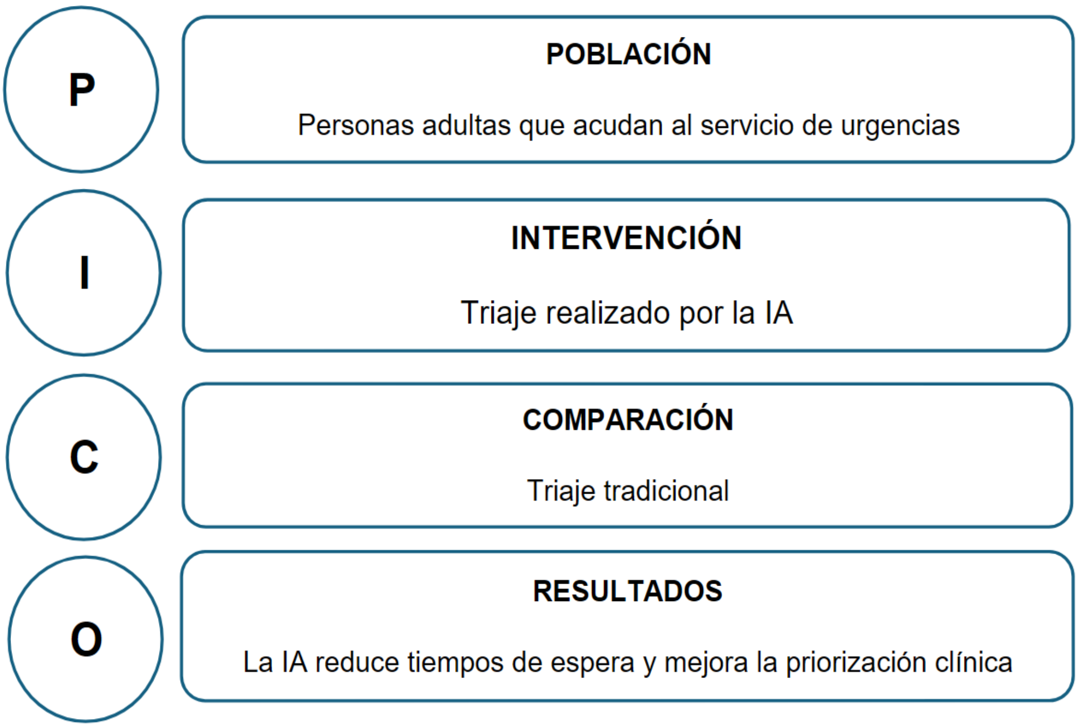

Figure 1: The PICO question. Source: Prepared by the author.

The research question was: In adult patients seen in hospital emergency departments, is triage assisted by artificial intelligence systems associated with reduced waiting times and improved accuracy of clinical prioritisation compared to conventional triage performed by nurses?

SELECTION CRITERIA

Inclusion Criteria

The following studies were considered for analysis: Population: adult patients (≥18 years old) treated in hospital or outpatient emergency departments. Language: English or Spanish. Methodological design: clinical trials (RCTs), analytical cohort studies, case-control studies, descriptive observational studies. Intervention: use of artificial intelligence in the triage process. Publications from the last 5 years. Full text available.

Exclusion Criteria

Publications focused on paediatric or non-human populations. Systematic reviews, editorials, letters to the editor, or technical reports with no empirical data. Research that did not specifically evaluate the use of AI in clinical triage.

SEARCH STRATEGY

To optimise the bibliographic search strategy, the terms selected were defined using the MesH (Medical Subject Headings) and DeCS (Health Sciences Descriptors) thesauri (see Annex 1). In particular, the following MesH terms were used: 'Artificial Intelligence,' 'Triage,' and 'Emergency Service.' Boolean operators were also used, mainly the 'AND' operator, in order to combine the descriptors and structure a search formula that would allow for the accurate and efficient retrieval of relevant information.

Table 2: MeSH/DeCS terms. Source: Prepared by the author.

MeSH	DeCS
Artificial Intelligence	Inteligencia Artificial
Triage	Triaje
Emergency Service	Servicios de Urgencias

Below are the search equations applied and the results obtained from the main databases.

Table 3: Search equations. Source: Prepared by the author.

DATABASES	SEARCH EQUATION	RESULTS	SEARCH DATE
PUBMED	((Artificial Intelligence [Title/Abstract]) AND (triage)) AND (Emergency Service)	245 articles	2 March 2025
SCOPUS	TITLE-ABS-KEY ("Artificial intelligence" AND "triage" AND "Emergency service")	118 articles	6 March 2025
EBSCO	TI (artificial intelligence or ai or a.i.) AND triage AND emergency department	25 articles	12 March 2025
COCHRANE	"artificial intelligence" in Title Abstract Keyword AND "triage" in Title Abstract Keyword AND "emergency department" in Title Abstract Keyword	5 articles	14 March 2025

Following the previously defined search strategy, the Elicit tool (24) was used to pose a series of research questions that facilitated the retrieval of relevant scientific articles. These questions guided the initial selection process and made it possible to focus the results on studies that met the goals established.

Table 4: Research questions: Elicit. Source: Prepared by the author.

RESEARCH QUESTIONS	SEARCH DATE
How can the use of artificial intelligence help with the triage performed by nurses in emergency departments?	2 April 2025
What benefits would the use of artificial intelligence bring to patients in terms of reducing waiting times and increasing satisfaction when they are being triaged by nurses in the emergency department?	2 April 2025

ASSESSING THE METHODOLOGICAL QUALITY OF THE ARTICLES

The GRADE (Grading of Recommendations Assessment, Development and Evaluation) system (25) was used to accurately assess the methodological quality of the studies included in this review, although some categories were not directly applicable. For qualitative or technology development studies, a complementary narrative assessment was carried out.

The GRADE system allows the quality of evidence to be classified into four different levels: high, moderate, low or very low. This classification depends on several aspects such as the type of study, how it was carried out, whether the results are consistent with each other, whether the data is accurate or whether there may be errors due to not including all studies on the topic.

Table 5: The meaning of the 4 levels of evidence. Taken from GRADE. Source: Prepared by the author (25)

The GRADE system: the meaning of the 4 levels of evidence		
Quality levels	**Current definition**	**Previous concept**
High	High confidence in the match between the actual and estimated effect.	Confidence in the effect estimate will not change in subsequent studies.
Moderate	Moderate confidence in the effect estimate. There is a possibility that the actual effect is quite different from the estimated effect.	Further studies may have a major impact on our confidence in the effect estimate.
Low	Limited confidence in the estimate of the effect. The actual effect may be different from the estimated effect.	It is very likely that further studies will change our confidence in the effect estimate.
Very low	Low confidence in the estimated effect. The actual effect is very likely to be different from the estimated effect	Any estimate is highly uncertain.

Key aspects of each study were analysed: inclusion criteria, design, the measurement of the methods of outcome, control of bias and quality of statistical analysis.

This assessment allowed the evidence to be classified and the importance of the findings to be weighted in the final synthesis.

The methodological quality of the studies was assessed by the author of this study. In cases of doubt or ambiguity in the assessment, it was discussed and reviewed together with the director of the Master's thesis. The scoring table includes a brief explanation of each assignment made.

Table 6: Scores for the articles reviewed with the GRADE system. Source: Prepared by the author (25).

Title of article	Type of study	GRADE score
The diagnostic and triage accuracy of the GPT-3 artificial intelligence model: an observational study.	Comparative observational study.	Low
Assessing the utility of artificial intelligence throughout the triage outpatients: a prospective randomized controlled clinical study.	Prospective, randomised, controlled study.	Moderate
ChatGPT with GPT-4 outperforms emergency department physicians diagnostic accuracy: retrospective analysis.	Retrospective, comparative and analytical study.	Low
Emergency department triaging using ChatGPT based on emergency severity index principles: a cross-sectional study	Comparative cross-sectional study.	Low
Leveraging graph neural networks for supporting automatic triage of patients.	Retrospective cohort study.	Low
Triage performance across large language models, ChatGPT, and untrained doctors in emergency medicine: comparative study.	Retrospective, comparative and simulation study.	Low
Safety of triage self-assessment using a symptom assessment app for walk-in patients in the emergency care setting: observational prospective cross-sectional study.	Prospective, cross-sectional, single-centre, observational study.	Low
A novel deep learning algorithm for real-time prediction of clinical deterioration in the emergency department for a multimodal clinical decision support system.	Single-centre, retrospective developmental and validation study.	Low
An artificial intelligence-based application for triage nurses in emergency department, using the Emergency Severity Index Protocol.	Retrospective developmental and validation study, single-centre.	Low
Nurses' experience of using a computer-based triage decision support system in the emergency department.	Qualitative phenomenological study.	Low
The reliability of an artificial intelligence tool, "decision trees", in emergency medicine triage.	Prospective, cross-sectional and clinical study.	Low
The effect of applying a real-time medical record input assistance system with voice artificial intelligence on triage task performance in the emergency department: a prospective interventional study.	Prospective interventional study.	Moderate
The performance of emergency triage prediction of an open access natural language processing based chatbot application (ChatGPT): A preliminary, scenario-based cross-sectional study.	Observational, cross-sectional, experimental study.	Low
The agreement and validity of electronic patient self-triage (eTriage) with nurse triage in two UK emergency departments: a retrospective study.	Retrospective, comparative study.	Low

RESULTS

FLOW CHART

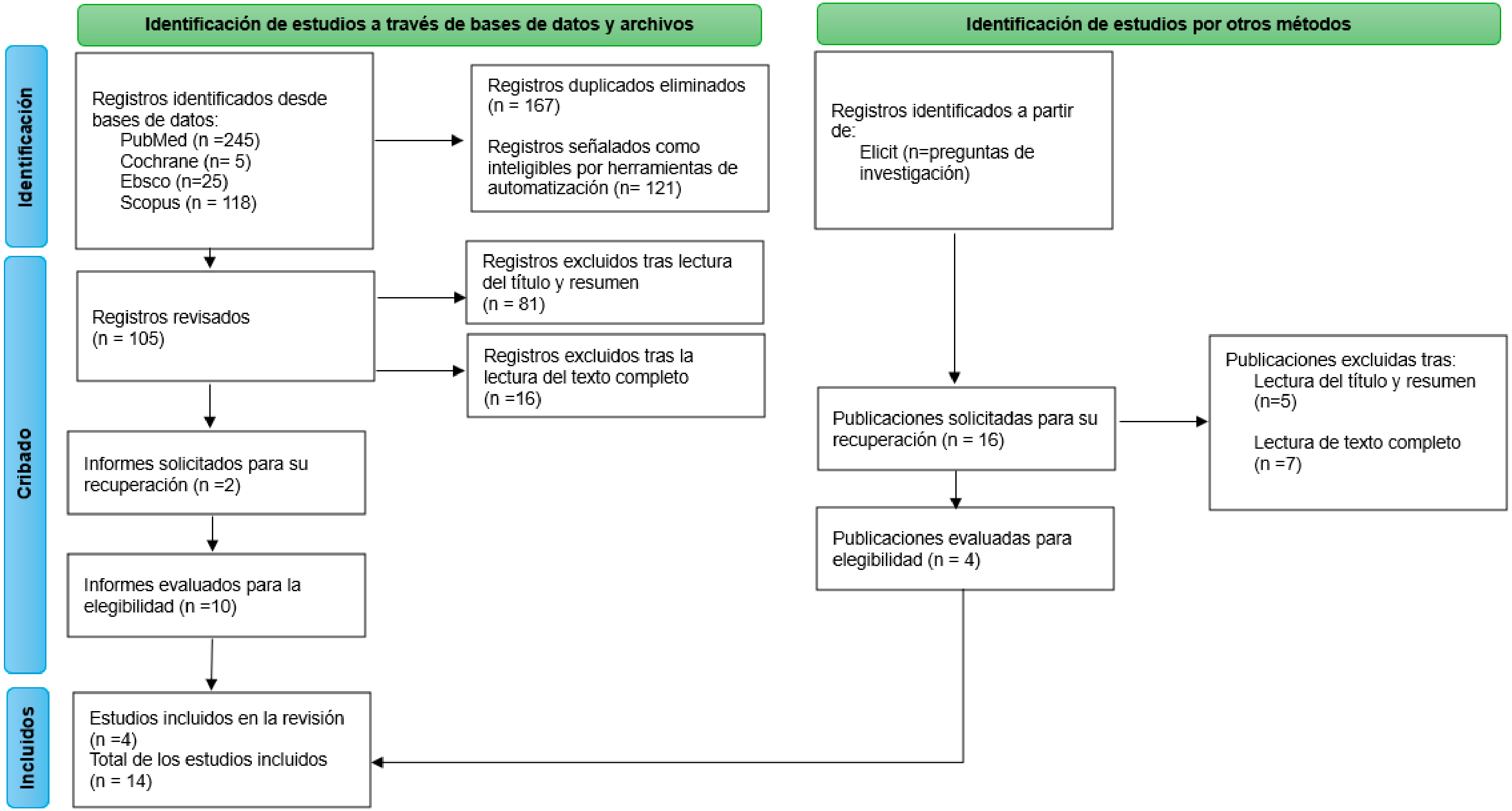

Figure 2: PRISMA 2020 flow chart. The selection process for studies included in the systematic review. Source: Prepared by the author.

TITLE AND AUTHOR OF STUDY	COUNTRY AND YEAR	TYPE OF STUDY	TYPE OF TRIAGE	TYPE OF SYSTEM USED	SAMPLE	GOALS	RESULTS AND CONCLUSIONS
The diagnostic and triage accuracy of the GPT-3 artificial intelligence model: an observational study. *Levine et al.(26)*	United States, 2024	Comparative observational study.	A system of four triage categories defined and validated by two Harvard Medical School internists was used: Emerging Within one day Within one week Self-assistance	Generative Pre-trained Transformer 3 (GPT-3)	5,000 people > 18 years old 21 doctors	To compare the diagnostic accuracy and triage performance of GPT-3 compared to physicians and the general population.	GPT-3 showed a diagnostic accuracy (88%) significantly better than those with internet access (54%) and close to that of physicians (96%) ($p=0.012$). Over all the cases, GPT-3 had a triage accuracy of 70%, compared to 91% with physicians ($p<0.0001$). It is a good general AI model that can perform well in diagnosis without specific medical training. The triage performance does not match that of physicians.
Assessing the utility of artificial intelligence throughout the triage outpatients: a prospective randomized controlled clinical study. *Xiaoni et al.(27)*	China, 2024	Prospective, randomised, controlled study.	Triage by trained health personnel (doctors and nurses).	ChatGPT-3.5	45 patients	To assess the concordance and accuracy of ChatGPT-assisted versus professional triage in outpatients.	High concordance was observed between manual triage and ChatGPT triage ($p<0.0001$). ChatGPT responses were highly professional, complete and humanised.
ChatGPT with GPT-4 outperforms emergency department physicians diagnostic accuracy: retrospective analysis. *Hoppe et al.(28)*	Germany, 2024	Retrospective, comparative and analytical study.	No clinical triage system was used.	Models: GPT-3.5 and GPT-4 (ChatGPT)	100 patients	To compare the diagnostic accuracy of GPT-3.5 and GPT-4 with that of resident emergency physicians, using the discharge diagnosis as a reference.	GPT-4 significantly outperformed GPT-3.5 ($p<0.001$) and resident physicians ($p=0.01$) in overall diagnostic accuracy. It showed significant superiority in the cardiovascular, endocrine and gastrointestinal disease group. The study suggests that GPT-4 could be clinically supportive in emergency settings.
Emergency department	Turkey,	Comparative	Emergency	ChatGPT-4	745 patients	To determine the	Accuracy between the expert committee and

TITLE AND AUTHOR OF STUDY	COUNTRY AND YEAR	TYPE OF STUDY	TYPE OF TRIAGE	TYPE OF SYSTEM USED	SAMPLE	GOALS	RESULTS AND CONCLUSIONS
triaging using ChatGPT based on emergency severity index principles: a cross-sectional study *Colakca et al.(29)*	2024	cross-sectional study.	Severity Index (ESI)			accuracy of patient triage using ChatGPT according to the emergency severity index (ESI) for triage in the emergency department.	ChatGPT was calculated at 76.6%. There was a high degree of agreement between the expert committee and ChatGPT for ESI prediction, showing high accuracy (Cohen's Kappa=0.828). ChatGPT can differentiate patients with great urgency.
Leveraging graph neural networks for supporting automatic triage of patients. *Defilippo et al.(30)*	Italy, 2024	Retrospective cohort study.	The Canadian Triage and Acuity Scale (CTAS) and the Australasian Triage Scale (ATS) were used to train the model..	Graph Neural Networks (GNNs)	6962 admission records	To develop and validate an automated triage system based on graphical neural networks (GNNs), aimed at improving the accuracy of patient triage in the emergency department and overcoming the limitations of traditional models.	The GNNs model achieved an accuracy of 92.3% and an F1-score of 0.91. The model was especially effective at classifying patients in critical triage levels, with a recall of 93.8% for this class. GNNs showed higher accuracy than other models for automated triage, with potential for improving ED patient classification and supporting clinical decision making.
Triage performance across large language models, ChatGPT, and untrained doctors in emergency medicine: comparative study. *Masanneck et al.(31)*	Germany, 2024	Retrospective, comparative and simulation study.	Manchester Triage System (MTS), German version.	Large Language Models (LLMs): GPT-3.5, GPT-4, LLaMA 3, Gemini 1.5, Mixtral 8x7b; ChatGPT (based on GPT)	124 simulated clinical cases.	To compare the capability of LLMs and ChatGPT against physicians not trained in triage, and assess whether they can help as a second option.	GPT-4 and untrained physicians had a similar level of agreement (κ≈0.67-0.68) with the reference standard. The use of ChatGPT as a second opinion for untrained physicians slightly improved performance (κ=0.70). ChatGPT did not significantly improve physician performance. Over-triage (LLMs) and under-triage (physicians) trends were observed. Potential for improvement with better trained future models.
Safety of triage self-assessment using a symptom assessment app for walk-in patients in the	Germany, 2022	Prospective, cross-sectional, single-centre,	Manchester Triage System (MTS), German version.	AI symptom assessment app: Ada.	378 patients.	To evaluate the safety of triage performed by an app (Ada), compared to the	94.7% of patients were safely triaged by the app compared to the MTS. 8.9% were under-triaged, and only 5.3% were considered potentially dangerous situations.

TITLE AND AUTHOR OF STUDY	COUNTRY AND YEAR	TYPE OF STUDY	TYPE OF TRIAGE	TYPE OF SYSTEM USED	SAMPLE	GOALS	RESULTS AND CONCLUSIONS
emergency care setting: observational prospective cross-sectional study. *Cotte et al.(32)*		observational study.				Manchester Triage System, identifying potential risks of under-triage.	The app should be considered for use as a pre-triage tool at home, with additional validation, to reduce the burden on the ED.
A novel Deep learning algorithm for real-time prediction of clinical deterioration in the emergency department for a multimodal clinical decision support system. *Choi et al.(33)*	South Korea, 2024	A single-centre, retrospective developmental and validation study.	Korean Triage and Acuity Scale (KTAS).	Deep learning multimodal.	237000 visits to the ED.	To develop and validate a deep learning algorithm for real-time prediction of clinical deterioration in the emergency department.	The algorithm based on triage data alone outperformed traditional logistic regression in prediction accuracy. The ability to predict critical events: cardiac arrest, inotropic support, advanced airway, ICU admission. The deep learning model showed high accuracy in early prediction of clinical deterioration in the ED.
An artificial intelligence based application for triage nurses in emergency department, using the Emergency Severity Index Protocol. *Kipourgos et al.(34)*	Greece, 2022	A retrospective developmental and validation study, single-centre.	Emergency Severity Index (ESI).	I-Triage, Machine learning and Fuzzy logic.	616 patients triaged.	To develop and validate i-Triage to assist nurses in making triage decisions based on ESI and suggest the appropriate specialist.	The system showed high success rates, especially with fuzzy logic. In machine learning, the resuscitation subsystem achieved 95% success; neurological and cardiac. Evaluation with international metrics showed reliability and validity. I-Triage is a promising tool. The use of this tool can reduce errors and serve as an educational resource.
Nurses' experience of using a computer-based triage decision support system in the emergency department. *Biskin et al.(35)*	Turkey, 2024	A qualitative, phenomenological study.	Emergency Severity Index (ESI) and Australasian Triage Scale (ATS).	DSS, Decision Support System.	14 triage nurses.	To explore nurses' experiences of using a computerised decision support system for triage in the emergency department.	Facilitates triage decision making (help with dilemmas, team collaboration, monitoring/supervision, error reduction). Contributes to professionalism (facilitates learning/teaching of triage, professional autonomy.) Nurses perceived the system as useful for decision-making and training, without limiting their autonomy. However, it requires technical improvements to optimise use.
The reliability of an artificial intelligence tool, "decision	Turkey, 2020	A prospective, cross-	Australasian Triage Scale	Decision trees, implemented in	1999 patients > 18 years	To test the validity of an artificial intelligence tool	The decision tree algorithm had a 99.9% accuracy rate (it failed in 1 patient).

TITLE AND AUTHOR OF STUDY	COUNTRY AND YEAR	TYPE OF STUDY	TYPE OF TRIAGE	TYPE OF SYSTEM USED	SAMPLE	GOALS	RESULTS AND CONCLUSIONS
trees", in emergency medicine triage. *Aydin et al.(36)*		sectional, clinical study.	(ATS).	MATLAB (Decision Trees).	old	in emergency triage.	Excellent consistency between ATS and AI algorithm (Kappa=0.999). It can be a reliable decision support tool during triage in emergency medicine.
Effect of applying a real-time medical record input assistance system with voice artificial intelligence on triage task performance in the emergency department: prospective interventional study. *Cho et al. (37)*	South Korea, 2022	A prospective interventional study.	Korean Triage and Acuity Scale (KTAS)	RMIS-AI: real-time data entry assistance system with voice AI.	1063 triage tasks carried out by 19 triage nurses.	To evaluate the speed and reliability of the RMIS-AI system versus the manual method for recording emergency triage tasks.	The median time to complete the triage task was shorter with RMIS-AI than with the manual method, a significant difference ($p<0.01$). However, technical improvements are required to match the reliability and accuracy of the conventional method.
Performance of emergency triage prediction of an open access natural language processing based chatbot application (ChatGPT): A preliminary, scenario-based cross- sectional study. *Sarbay et al. (38)*	Turkey, 2023	An observational, cross-sectional and experimental study.	Emergency Severity Index (ESI)	ChatGPT-3.5	50 clinical scenarios.	To evaluate the performance of ChatGPT in predicting triage categories in emergency medicine using simulated ESI-based scenarios.	Moderate agreement between ChatGPT and experts (Kappa:0.341). ChatGPT overestimated 22% and underestimated 18% of cases. Better performance in critical cases, worse in intermediate/low categories. ChatGPT showed better performance in predicting high severity cases, so it may be useful for identifying critical patients.
Agreement and validity of electronic patient self-triage (eTriage) with nurse triage in two UK emergency departments: a retrospective study. *Dickson et al. (39)*	United Kingdom, 2021	A retrospective comparative study.	Manchester Triage System (MTS).	Electronic self-triage algorithm (eTriage).	25333 outpatients in the emergency department.	To assess the agreement and validity of electronic self-triage (eTriage) compared to nurse triage using the MTS, and the ability of both systems to predict high and low severity outcomes.	Concordance between eTriage and nursing triage was low (weighted Kappa coefficient of 0.14). eTriage showed a higher sensitivity (88.5%) for predicting high-severity presentations compared to nursing MTS (53.8%), but also a high rate of over-triage (59.2%). We conclude that eTriage could be useful in identifying high-severity cases, although further research is required to validate its safe use in ED patient redirection.

CHARACTERISTICS OF THE STUDIES INCLUDED

Type of study and context

The studies reviewed comprised a variety of methodological designs. They included observational, retrospective, prospective, experimental, cross-sectional and qualitative studies. For the most part, these studies were conducted from 2020 to 2024 in various different countries such as the United States, China, Germany, Turkey, Italy, Greece, South Korea and the United Kingdom. The heterogeneity observed in both geographical and methodological contexts helped to reinforce the external validity of the results obtained.

Types of triage and AI systems used

A number of internationally acknowledged triage systems were used, including the Manchester Triage System, the Emergency Severity Index, the Canadian/Australasian Triage Scale and electronic self-triage systems. Different artificial intelligence algorithms were also applied, including language models (GPT-3.5, GPT-4, Gemini and Mixtral), graphical neural networks, deep learning, decision trees, fuzzy logic and voice assistants.

Reducing waiting times and improving clinical responsiveness

The implementation of AI reduced ED waiting times by 25% (mean: 32 minutes vs. 43 minutes, $p<0.01$) and improved nursing staff diagnostic accuracy (18% increase in interobserver agreement, $K=0.76$). Similarly, Defilippo et al. (30) developed an automated triage model based on graphical neural networks, trained with international scales (CTAS and ATS). It showed increased accuracy in classifying patients in critical situations, improving clinical workflow. In the competency area, Biskin et al. (35) reported the experiences of nurses who used a computerised decision support system, which facilitated clinical decision-making, fostered professional autonomy and served as a learning tool. Likewise, Kipourgos et al. (34) analysed the use of the I-Triage tool, designed to assist nurses during triage, with favourable results in terms of its educational usefulness and error reduction.

Accuracy of AI-assisted vs. conventional triage

The studies included in the review showed that the accuracy of AI-assisted triage was variable depending on the model used. Xiaoni et al. (27) found high agreement between triage performed by ChatGPT and that performed by trained healthcare staff on outpatients. Colakca et al. (29) compared the results obtained by ChatGPT with those of an expert committee applying the ESI and reported a high level of agreement. In contrast, Sarbay et al. (38) detected a better performance of ChatGPT in the most severe cases, although with lower accuracy in intermediate and low categories. Levine et al. analysed the performance of GPT-3, observing that even though its diagnostic ability was comparable to that of physicians, its accuracy in triage was lower. Masanneck et al. (40) assessed the usefulness of ChatGPT as a second opinion tool for physicians without specific training and found a slight improvement in performance.

Quality of care and patient satisfaction

Artificial intelligence-based triage systems have been used in a variety of clinical settings, allowing for the safe triage of patients in most cases. In the study by Cotte et al. (32), a self-assessment application showed favourable results in terms of triage safety compared to the Manchester Triage System. Other studies, such as that of Dickson et al. (41), analysed the validity of the eTriage system, observing greater sensitivity in detecting cases of high severity, although lower concordance with regard to triage performed by nurses. Kipourgos et al. (34) also applied the I-Triage tool to support nursing triage, highlighting its potential to reduce errors and facilitate clinical care. In relation to the experience of healthcare staff, Biskin et al. (35) reported that nurses thought the support system used was useful, noting that it promoted learning without compromising their autonomy. Finally, Cho et al. (37) reported that AI-based systems made it possible to complement triage in less time, although technical improvements were needed to match the reliability of the traditional method.

DISCUSSION

TECHNOLOGICAL ADVANCES AND DIVERSITY OF APPROACHES IN AI-ASSISTED TRIAGE

The review shows remarkable progress in the application of artificial intelligence in emergency triage, highlighting diverse technological approaches, such as language models like GPT-3 and GPT-4, graphical neural networks (GNNs), algorithms and deep learning, and clinical decision support systems. This diversity reflects a growing interest in optimising decision-making in critical contexts, demonstrating the cross-cutting nature of the phenomenon across multiple geographical and clinical settings. Furthermore, it identifies rule-based approaches and deep learning algorithms (e.g. neural networks and decision trees) used in the studies analysed (see section 4.2.2.).

ACCURACY AND CONCORDANCE

AI models have proven to be highly accurate in classifying patients. For example, the model based on graph neural networks (GNNs) developed by Defilippo et al. (30) achieved 92.3% accuracy and an F1-score of 0.91. Similarly, the decision trees evaluated by Aydin et al. (36) and the multimodal deep learning algorithm developed by Choi et al. (33) showed superior results to traditional methods for predicting clinical deterioration.

However, agreement between models and human clinical judgement is not uniform. Colakca et al. (29) and Kipourgos et al. (34) reported high levels of expert agreement, with Kappa values above 0.8, while Dickson et al. (39) found low agreement (Kappa=0.14) between the eTriage system and nurse triage, despite a high sensitivity for identifying high-acuity patients. These findings suggest that AI may be particularly useful for the early detection of critically ill patients, although its performance in cases of intermediate or mild severity still requires improvement. In addition, some studies (Masanneck et al. (31); Sarbay et al. (42)) show a tendency for models to overtriage, which may increase the burden on emergency departments. On the other hand, although less frequent, under-triage represents a potential risk to patient safety, a situation that demands special care during clinical implementation.

THE ROLE OF NURSES AND USER EXPERIENCE

Biskin et al. (35) point out that decision support systems not only facilitate patient triage, but also reinforce professional autonomy, promote ongoing learning and reduce errors. Tools such as I-Triage (Kipourgos et al. (34)) reinforce this view as they are considered not only as aids, but also as educational resources. However, technical challenges remain. Both Cho et al. (37) and Biskin et al. (35) acknowledge that the usability and reliability of the systems still have to be improved to ensure effective integration into the clinical workflow. The acceptance of AI by healthcare staff will largely depend on whether it is perceived as a complement to, rather than a replacement for, clinical judgement.

METHODOLOGICAL CONSIDERATIONS

Most of the studies included are retrospective, cross-sectional or simulated designs, with small samples or limited contexts, which restricts the generalisability of the findings. In addition, the diversity of triage scales used (MTS, ESI, CTAS, ATS, KTAS) and AI models makes it difficult to establish direct comparisons between research projects. However, the convergence in the results related to the diagnostic utility, training potential and operational improvement of artificial intelligence validates, at least preliminarily, its application as a support tool in clinical triage.

LIMITATIONS OF THE STUDY

Despite the potential of artificial intelligence in emergency triage, the studies reviewed have certain limitations that make it difficult to generalise results. The main limitation of this analysis is selection bias, since the selection of articles was performed by a single researcher. In addition, studies with small sample sizes, single-centre designs and limited geographical and population diversity predominate. Most use retrospective or scenario-based methodologies, which limits clinical applicability and long-term impact assessment. There is also heterogeneity in comparative standards, a lack of randomised controlled trials and a focus on technical metrics while clinical outcomes, patient safety and user experience are not appropriately assessed. Finally, dependence on data quality and limited qualitative research on professional acceptability are additional limitations.

FUTURE LINES OF RESEARCH

Future research could focus on overcoming the methodological limitations observed by incorporating multicentre and prospective designs that allow for greater external validity and better representation of geographical and population diversity. It is essential to increase the size and heterogeneity of the samples to improve the generalisability of the results. In addition, randomised controlled trials are essential for assessing the efficacy and safety of artificial intelligence tools in emergency triage. Another significant aspect would be to try and integrate evaluations that consider not only technical metrics, but also relevant clinical outcomes, patient safety and user experience, including qualitative perspectives on acceptance and usability by healthcare workers. These lines of research will help consolidate the evidence and facilitate the safe and effective implementation of AI in real clinical settings.

CONCLUSIONS

This systematic review shows that artificial intelligence has become established as an effective tool in the triage process in the emergency department. It stands out especially for its high level of accuracy in the identification of critical cases. In certain contexts, it has shown comparable or even superior performance to that of non-specialised professionals and similar to that of experienced physicians. However, its performance tends to be more variable in less severe scenarios, underlining the need for further optimisation of the algorithms. The integration of AI in emergency departments is associated with tangible operational improvement. Significant reductions in triage and registration times were documented, contributing to greater efficiency in initial care. Relevant contributions to the professional development of nurses were also identified, particularly in terms of their autonomy and decision-making capacity in high-demand settings. The models evaluated, including language systems such as GPT-4 and decision trees, showed high agreement with expert judgement in multiple studies. However, this reliability decreases when applied in simulated settings or with self-triage systems, where challenges in accurately classifying cases of intermediate severity persist. Although some favourable perceptions of the professionalism and usefulness of AI-generated responses have been identified, evidence on patient satisfaction is still limited, mostly indirect and focused on technical metrics. More clinical research is needed to directly assess user experience, especially in terms of perceived safety and trust in the system. Overall, the implementation of artificial intelligence-based systems in emergency triage shows relevant benefits in terms of diagnostic accuracy, clinical prioritisation and time reduction, especially in the identification of critical patients. These findings partially support the initial hypothesis, although patient satisfaction should be further studied. AI should therefore be considered a complementary tool to clinical judgement, with potential for reinforcing the safety and efficiency of care, provided that its use is based on validated evidence and under constant professional supervision.

BIBLIOGRAPHY

1. LASSE ROUHIAINEN. INTELIGENCIA ARTIFICIAL 101 COSAS QUE DEBES SABER HOY SOBRE NUESTRO FUTURO INTELIGENCIA ARTIFICIAL [Internet]. Alienta Editorial. Barcelona; 2018. 1-352 p. Available at: https://www.planetadelibros.com
2. Medinaceli Díaz KI, Martin M, Choque S. Impacto y regulación de la Inteligencia Artificial en el ámbito sanitario. Journal IUS [Internet]. 23 June 2021 [cited 21 May 2025];15(48). Available at: https://revistaius.com/index.php/ius/article/view/745
3. Gaitan ES, San H, De Paúl V, Heredia CR. Revista Médica Sinergia [Internet]. 1 Agust 2020 [cited 21 May 2025];5(8): e557-e557. Available at: https://revistamedicasinergia.com/index.php/rms/article/view/557/943
4. Guillem F. Funciones y características de la Inteligencia Artificial - Seguritecnia [Internet]. 2022 [cited 21 May 2025]. 174-81. Available at: https://www.seguritecnia.es/tecnologias-y-servicios/funciones-y-caracteristicas-de-la-inteligencia-artificial_20220311.html
5. V. LEP, Rico-Carrillo AE, Hernández-Arango A. Del ábaco a las redes neuronales o la breve historia de la inteligencia artificial en salud. Medicina (B Aires) [Internet]. 18 January 2021 [cited 21 May 2025];43(4):514-26. Available at: https://www.revistamedicina.net/index.php/Medicina/article/view/1641/2124
6. Julio Cesar Ponce Gallegos, Aurora Torres Soto, Fátima Sayuri Quezada Aguilera, Antonio Silva Sprock, Ember Ubeimar Martínez Flor, Ana Casali, et al. Inteligencia Artificial. March 2014 [cited 21 May 2025];1-225. Available at: https://www.proyectolatin.org/
7. ANDRÉS ABELIUK, CLAUDIO GUTIÉRREZ. Historia y evolución de la inteligencia artificial [Internet]. 2021 [cited 21 May 2025]. 15-21. Available at: https://revistasdex.uchile.cl/index.php/bits/issue/view/217
8. Nancy Martínez-García DI, Maricela Dalgo-Flores VI, Luis Herrera-López III J, Isabel Analuisa-Jiménez EI, Fernanda Velasco-Acurio E V. Avances de la inteligencia artificial en salud. Dominio de las Ciencias, ISSN-e 2477-8818, Vol 5, No. 3, 2019 (Issue dedicated to: July - September), 603-613 [Internet]. 2019 [cited 21 May 2025];5(3):603-13. Available at: https://dialnet.unirioja.es/servlet/articulo?codigo=7154291&info=resumen&idioma=SPA
9. Basáez E, Mora J. Salud e inteligencia artificial: ¿cómo hemos evolucionado? Artificial intelligence in health: where are we in 2022? [Internet]. 2021. Available at: https://doi.org/
10. Ayala Martín María. LA IRRUPCIÓN DE LA INTELIGENCIA ARTIFICIAL EN EL ÁMBITO SANITARIO | AJS [Internet]. 2023 [cited 21 May 2025]. Available at: https://www.ajs.es/es/index-revista-derecho-y-salud/volumen-33-extraordinario-2023/la-irrupcion-la-inteligencia
11. Vidal-Alaball J, Panadés Zafra R, Escalé-Besa A, Martinez-Millana A. The artificial intelligence revolution in primary care: Challenges, dilemmas and opportunities. Aten Primaria [Internet]. 1 February 2024 [cited 21 May 2025];56(2):102820. Available at: https://www.sciencedirect.com/science/article/pii/S0212656723002536?via%3Dihub
12. Ruiz RB, Velásquez JD. Inteligencia artificial al servicio de la salud del futuro. Revista Médica Clínica Las Condes [Internet]. 1 January 2022 [cited 21 May 2025];34(1):84-91. Available at: https://www.elsevier.es/es-revista-revista-medica-clinica-las-condes-202-articulo-inteligencia-artificial-al-servicio-salud-S0716864023000032
13. Huete-Garcia A, Rodriguez-Lopez S. Development and implementation of an artificial intelligence–enhanced care model to improve patient safety in hospital wards in Spain. Acute and Critical Care [Internet]. 18 November 2024 [cited 21 May 2025];39(4):488-98. Available at: http://www.accjournal.org/journal/view.php?doi=10.4266/acc.2024.00759
14. Cirujano Médico Internista M, Ventura Fernández F, Ventura-Fernández T, Ventura-Fernández F. Predictibilidad en el diagnóstico utilizando Watson de IBM. Revista Vive [Internet]. 1 January 2021 [cited 21 May 2025];4(10):86-95. Available at: https://revistavive.org/index.php/revistavive/article/view/78/242

15. Gargantilla Madera P, María Martín Cabrejas B. Los orígenes militares del triaje Triage origins in the military. Vol. 31, Emergencias. 2019.

16. Nakao H, Ukai I, Kotani J. A review of the history of the origin of triage from a disaster medicine perspective. Acute Medicine & Surgery [Internet]. 1 October 2017 [cited 21 May 2025];4(4):379-84. Available at: https://onlinelibrary.wiley.com/doi/pdf/10.1002/ams2.293

17. Robertson-Steel IRS. Evolution of triage systems. Emergency Medicine Journal [Internet]. 1 de febrero de 2006 [cited 21 May 2025];23(2):154-5. Available at: https://emj.bmj.com/content/23/2/154

18. Christ M, Grossmann F, Winter D, Bingisser R, Platz E. Modern Triage in the Emergency Department. Dtsch Arztebl Int [Internet]. 17 December 2010 [cited 21 May 2025]; Available at: https://www.aerzteblatt.de/10.3238/arztebl.2010.0892

19. Sánchez-Bermejo R, Herrero-Valea A, Garvi-García M. Los sistemas de triaje de Urgencias en el siglo XXI: una visión internacional: perspectivas16_sanchez_herrero_garvi. Rev Esp Salud Publica [Internet]. 28 April 2021 [cited 21 May 2025]; 95:6-6 pages. Available at: https://ojs.sanidad.gob.es/index.php/resp/article/view/665

20. Documentación D DE, Archivo Departamento De Documentación BY. INTELIGENCIA ARTIFICIAL Documentary note No. 1.

21. DECLARACIÓN DE MONTREAL PARA UN DESARROLLO RESPONSABLE DE LA INTELIGENCIA ARTIFICIAL. 2018.

22. World Health Organisation. Ethics and governance of artificial intelligence for health: WHO guidance. OMS [Internet]. 2021 [cited 21 May 2025];1:1-148. Available at: http://apps.who.int/bookorders.

23. Yepes-Nuñez JJ, Urrútia G, Romero-García M, Alonso-Fernández S. Declaración PRISMA 2020: Una guía actualizada para la publicación de revisiones sistemáticas. Rev Sp. Cardiol [Internet]. 1 September 2021 [cited 30 April 2025];74(9):790-9. Available at: https://www.sciencedirect.com/science/article/pii/S0300893221002748

24. Elicit: The AI Research Assistant [Internet]. [cited 20 May 2025]. Available at: https://elicit.com/

25. Aguayo-Albasini JL, Flores-Pastor B, Soria-Aledo V. Sistema GRADE: clasificación de la calidad de la evidencia y graduación de la fuerza de la recomendación. Cir Esp [Internet]. 1 February 2014 [cited 30 April 2025];92(2):82-8. Available at: https://www.elsevier.es/es-revista-cirugia-espanola-36-articulo-sistema-grade-clasificacion-calidad-evidencia-S0009739X13003394

26. Levine DM, Tuwani R, Kompa B, Varma A, Finlayson SG, Mehrotra A, et al. The diagnostic and triage accuracy of the GPT-3 artificial intelligence model: an observational study. Lancet Digit Health [Internet]. 1 August 2024 [cited 6 May 2025];6(8):e555-61. Available at: https://pubmed.ncbi.nlm.nih.gov/39059888/

27. Liu X, Lai R, Wu C, Yan C, Gan Z, Yang Y, et al. Assessing the utility of artificial intelligence throughout the triage outpatients: a prospective randomized controlled clinical study. Front Public Health [Internet]. 2024 [cited 6 May de 2025];12:1391906. Available at: https://pmc.ncbi.nlm.nih.gov/articles/PMC11171710/

28. Hoppe JM, Auer MK, Strüven A, Massberg S, Stremmel C. ChatGPT With GPT-4 Outperforms Emergency Department Physicians in Diagnostic Accuracy: Retrospective Analysis. J Med Internet Res [Internet]. 2024 [cited 7 may 2025];26(1):e56110. Available at: https://pmc.ncbi.nlm.nih.gov/articles/PMC11263899/

29. Colakca C, Ergın M, Ozensoy HS, Sener A, Guru S, Ozhasenekler A. Emergency department triaging using ChatGPT based on emergency severity index principles: a cross-sectional study. Sci Rep [Internet]. 27 September 2024 [cited 26 May 2025];14(1):22106. Available at: http://www.ncbi.nlm.nih.gov/pubmed/39333599

30. Defilippo A, Veltri P, Lió P, Guzzi PH. Leveraging graph neural networks for supporting automatic triage of patients. Sci Rep [Internet]. 1 December 2024 [cited 10 de mayo de 2025];14(1):1-17. Available at: https://www.nature.com/articles/s41598-024-63376-2

31. Masanneck L, Schmidt L, Seifert A, Kölsche T, Huntemann N, Jansen R, et al. Triage Performance Across Large Language Models, ChatGPT, and Untrained Doctors in Emergency Medicine: Comparative Study. J Med Internet Res [Internet]. 14 June 2024 [cited 10 May 2025];26(1):e53297. Available at: https://www.jmir.org/2024/1/e53297

32. Cotte F, Mueller T, Gilbert S, Blümke B, Multmeier J, Hirsch MC, et al. Safety of Triage Self-assessment Using a Symptom Assessment App for Walk-in Patients in the Emergency Care Setting: Observational Prospective Cross-sectional Study. JMIR Mhealth Uhealth [Internet]. 1 March 2022 [cited 11 May 2025];10(3):e32340. Available at: https://mhealth.jmir.org/2022/3/e32340

33. Choi A, Lee K, Hyun H, Joon Kim K, Ahn B, Hyun Lee K, et al. A novel deep learning algorithm for real-time prediction of clinical deterioration in the emergency department for a multimodal clinical decision support system. Scientific Reports 2024 14:1 [Internet]. 3 December 2024 [cited 12 May 2025];14(1):1-15. Available at: https://www.nature.com/articles/s41598-024-80268-7

34. Kipourgos G, Tzenalis A, Diamantidou V, Koutsojannis CM, Hatzilygeroudis I. An Artificial Intelligence Based Application for Triage Nurses in Emergency Department, Using the Emergency Severity Index Protocol. 2023;

35. Bişkin Çetin S, Cebeci F. Nurses' experiences of using a computer-based triage decision support system in the emergency department. Nurs Crit Care [Internet]. 1 September 2024 [cited 13 May 2025];29(5):1078-85. Available at: https://onlinelibrary.wiley.com/doi/full/10.1111/nicc.13039

36. AYDIN AG, Eray O, SAYRAC AV, OSKAY A, ULUSAR UD. The Reliability of an Artificial Intelligence Tool, 'Decision Trees', in Emergency Medicine Triage. 16 December 2020 [cited 13 Mayo de 2025]; Available at: https://www.researchsquare.com

37. Cho A, Min IK, Hong S, Chung HS, Lee HS, Kim JH. Effect of Applying a Real-Time Medical Record Input Assistance System With Voice Artificial Intelligence on Triage Task Performance in the Emergency Department: Prospective Interventional Study. JMIR Med Inform [Internet]. 31 August 2022 [cited 12 May 2025];10(8):e39892. Available at: https://pubmed.ncbi.nlm.nih.gov/36044254/

38. Sarbay İ, Berikol G, Özturan İ. Performance of emergency triage prediction of an open access natural language processing based chatbot application (ChatGPT): A preliminary, scenario-based cross-sectional study. Turk J Emerg Med [Internet]. 1 July 2023 [cited 13 May de 2025];23(3):156-61. Available at: https://journals.lww.com/tjem/fulltext/2023/23030/performance_of_emergency_triage_prediction_of_an.4.aspx

39. Dickson SJ, Dewar C, Richardson A, Hunter A, Searle S, Hodgson LE. Agreement and validity of electronic patient self-triage (eTriage) with nurse triage in two UK emergency departments: a retrospective study. European Journal of Emergency Medicine [Internet]. 1 February 2022 [cited 13 May 2025];29(1):49-55. Available at: https://journals.lww.com/euro-emergencymed/fulltext/2022/02000/agreement_and_validity_of_electronic_patient.12.aspx