Capítulo 02

Artificial Intelligence in Emergency Medicine: From Automated Triage to Real-Time Support

ANA LUIZA DIAS DA SILVA CAVALINI [1]
SAMARA OFNI PEREIRA [2]
LETÍCIA JERONIMO IZABEL [3]
NICOLAS LAUXEN KONRAD [4]
LAYNARA VIVIAN LOPES DA SILVA [2]
ELAINE GUIMARÃES MARZOLLA [5]
ALICE NEVES[6]
PAULA ALICIA
MARTINS NASCIMENTO[7]

[1] Discente - Medicina na Universidade Santo Amaro (UNISA)
[2] Discente - Medicina na Universidad Nacional de Rosario (UNR)
[3] Discente - Medicina na Faculdade de Medicina de Petrópolis (FMP)
[4] Discente - Medicina na Universidade do Vale do Taquari (UNIVATES)
[5] Discente - Medicina na Universidade das Américas (CAM/FAM)
[6] Discente - Medicina na Universidade Estácio de Sá (IDOMED)
[7] Discente - Medicina na Universidade de Buenos Aires (UBA)

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INTRODUCTION

Emergency departments (EDs) are highly challenging environments, characterized by overcrowding, limited resources, and a wide range of clinical severity among patients. In this context, triage becomes a fundamental step to establish priorities based on medical urgency, ensuring that the most severe cases receive timely care (TAHERNEJAD et al., 2024).

Traditionally, triage systems use tags or color-coded cards to classify patients according to the severity of their clinical condition. Although these methods are well-established, they have significant limitations, such as limited space to record vital signs, difficulty in locating patients in high-demand settings, and a lack of accuracy in representing the patient's real clinical status (TAHERNEJAD et al., 2024). Moreover, there is considerable reliance on the experience of the healthcare professional conducting the triage, which can introduce subjectivity and inconsistencies (DA'COSTA et al., 2025).

In this scenario, artificial intelligence (AI) emerges as a strategic tool to transform triage processes. The integration of techniques such as machine learning (ML), deep neural networks (DNNs), and natural language processing (NLP) contributes to the standardization, accuracy, and efficiency of triage in EDs (DA'COSTA et al., 2025). AI-based solutions can operate in an automated and integrated manner, from collecting and analyzing clinical data to providing real-time feedback, supporting clinical decision-making through robust algorithms.

Recent studies also highlight the emerging role of AI-assisted virtual triage. This approach involves the use of remote electronic tools in which patients themselves enter their symptoms into automated platforms, which then assess the severity of the cases and guide the type of care needed (NASSER et al., 2025). Virtual triage has proven to be viable and promising, especially in high-demand scenarios such as during the COVID-19 pandemic, reducing individual biases and improving the accuracy of clinical recommendations.

During this critical period, a behavioral AI-based technology — Behavioral Artificial Intelligence Technology (BAIT) — was tested in the Netherlands to support triage decisions in Intensive Care Units (ICUs). The model proved effective by making explicit the implicit criteria adopted by intensivists to determine the eligibility of COVID-19 patients for ICU admission, making the process more transparent and reproducible (DE METZ et al., 2021).

In addition, AI applications have also shown a direct impact on emergency neurological diagnoses. A study conducted in the United States analyzed the use of AI to detect large vessel occlusions (LVO) in patients with acute stroke through imaging exams. The use of algorithms significantly increased the speed and accuracy in identifying these lesions, allowing earlier and more assertive interventions, with the potential to alter clinical outcomes (Forghani & Gupta, 2023).

Given these advancements, this chapter aims to explore the theme *"Artificial Intelligence in Emergency Medicine: From Automated Triage to Real-Time Clinical Support"* in a narrative way, discussing its foundations, practical applications, and ethical implications. The proposed approach seeks to consolidate the most current knowledge on the use of AI in emergency triage, based solely on the scientific evidence available in the studies selected for this review.

Automated Smart Triage

The use of artificial intelligence to support the interpretation of radiological exams has proven particularly valuable in high-demand scenarios, such as intensive care units. In these settings, routine chest X-rays are frequently performed to monitor patients with cardiopulmonary diseases, generating a massive volume of images that require serial analysis—a process demanding a high level of expertise and contributing to professional overload (YUN et al., 2023). To mitigate this issue, Yun et al. (2023) developed a deep learning algorithm based on chest records and image subtraction to automatically identify relevant clinical changes over time. With an area under the curve (AUC) of up to 0.80, the model demonstrated satisfactory ability to differentiate images with and without changes, even in complex clinical contexts such as emergency departments and intensive care units.

Nonetheless, challenges remain. Variability in factors such as patient positioning, level of inspiration, and the presence of medical devices can hinder image standardization and limit algorithm performance (Yun et al., 2023). This technical limitation underscores the importance of incorporating more robust normalization and calibration methods, as well as expanding validation studies across multiple clinical centers.

Another important advancement involves remote triage. AI-based digital tools have been implemented to allow patients themselves to input symptoms and receive an automated assessment of severity, guiding them to the appropriate level of care (NASSER et al., 2025). While results are promising—especially in reducing emergency department overcrowding and improving access—barriers such as low digital literacy among older adults, with 38.2% needing assistance to use these platforms, still hinder full effectiveness (NASSER et al., 2025).

In prehospital and disaster contexts, machine learning algorithms have been applied to expedite victim classification in the field. Technologies embedded in mobile sensors and wearable devices can now analyze vital signs in real time, stratify risk, and prioritize care, increasing agility and reducing stress on health-care providers (ALRAWASHDEH et al., 2024). Additionally, automatic speech recognition systems have been successfully tested to speed up the identification of cardiac arrests in emergency calls, outperforming human operators in detection speed (BIESHEUVEL et al., 2024).

Despite these advances, consolidating automated smart triage still requires addressing structural challenges. Issues such as algorithmic bias, heterogeneity in input data, and a lack of external validation need to be resolved to ensure these technologies truly optimize care without compromising equity (COCCA et al., 2024). The successful integration of these tools into clinical practice demands an interdisciplinary effort focused on standardization, safety, transparency, and acceptance by healthcare professionals.

AI in Dynamic Monitoring and Predictive Alarms

The progress of artificial intelligence in emergency medicine has moved beyond static triage models, gaining ground in more sophisticated applications, such as continuous monitoring of physiological data and the triggering of predictive alarms. These dynamic approaches enable early detection of clinical deterioration, aiding healthcare teams in making critical decisions in real time.

In trauma care, the early detection of hidden hemorrhages is crucial for reducing morbidity and mortality. The APPRAISE–Hemorrhage Risk Index (HRI) algorithm exemplifies AI's potential in this setting. Developed from more than 500 hours of continuous vital sign data from 1,659 patients, the model evaluates heart rate and systolic/diastolic blood pressure to stratify hemorrhage risk into three levels (low, medium, high). The results were consistent, with a significantly higher hemorrhage risk index in the HRI III group (likelihood ratio of 5.75), and the model maintained predictive stability even amidst physiological variations in prehospital environments.

Similarly, Abe et al. (2022) used the XGBoost algorithm to develop a triage model for traumatic intracranial hemorrhage based on simple clinical information collected on-site, such as GCS eye score, scalp wounds, and pupillary abnormalities. Although the initial focus was on triage, the study also evaluated the potential of adapting the model for continuous data monitoring, suggesting that incremental learning could allow updates to predictions as new information becomes available, including evolving clinical signs during transport to the hospital.

The role of smart alarms expands even further in war or disaster contexts. In addition to risk classification, the APPRAISE-HRI also issues minute-by-minute alerts as data are collected, identifying patients in urgent need of intervention. This ability to generate real-time alerts based on changes in vital signs is essential for optimizing decisions about aeromedical evacuation, blood preparation, or activation of emergency surgical teams.

However, not all AI models developed for dynamic support are mature enough. One example is VTriage, applied in hospital settings. This algorithm estimates severity scores based on chief complaint, age, sex, and pain but showed low agreement with nurse-conducted triage (kappa between 0.17 and 0.37) and high rates of overtriage. Its limited interpretation of complex clinical contexts and lack of dynamic physiological data reduced its accuracy and compromised its reliability as a predictive tool.

Another critical point is the need to ensure that algorithms embedded in predictive alarm systems are trained with high-quality, clinically diverse data. Challenges such as algorithmic bias, lack of transparency in alert activation criteria, and possible alert fatigue must be addressed with rigorous methodology and strict ethical governance.

The future trend points toward models based on continuous learning (online learning), which re-evaluate patient risk as new data are recorded—whether through wearable sensors, hospital monitors, or electronic records. These adaptive systems, by integrating dynamic monitoring and smart alarms, may offer proactive and individualized clinical support, transforming the emergency response paradigm.

AI in Real-Time Therapeutic Decision Support

Therapeutic decision support in emergency and urgent care settings demands speed, diagnostic accuracy, and integration of multiple clinical variables. In this context, artificial intelligence (AI) has emerged as a promising tool to assist healthcare professionals, especially during critical moments when time is crucial for patient survival and recovery.

In emergency ophthalmology, the DOTS (DemDx Ophthalmic Triage System) was developed as an AI-based platform to classify eye complaints based on reported symptoms. By assigning urgency levels using color codes, the system aided in the initial triage of adult patients in urgent care, enhancing efficiency and safety. In a recent prospective study, over 90% of participating healthcare professionals found the tool useful and safe, highlighting its impact on reducing misclassification and ensuring appropriate case referral (JINDAL et al., 2023).

In emergency neurology, AI has been used for automated analysis of imaging exams to enable early detection of large vessel occlusions (LVO) in stroke patients. The tool assessed by Forghani & Gupta (2023) showed relevant accuracy in interpreting CT and brain perfusion scans, offering real-time diagnostic support. This approach directly contributes to reducing the "door-to-needle" time, allowing more effective and timely interventions such as thrombolysis or thrombectomy.

Beyond these applied clinical examples, other AI tools have focused on predicting critical clinical outcomes, such as the need for hospital admission, based on initial admission data. In a study by Patel et al. (2018), machine learning algorithms were able to predict admission needs based on parameters like vital signs, chief complaints, and initial lab tests, supporting immediate decisions about referral, support, and resource allocation.

AI capabilities are further expanding with the concept of continuous learning (online learning), where models can update their predictions based on real-time data input. This feature is especially useful in dynamic clinical environments like emergency departments, where patient conditions can evolve rapidly. Abe et al. (2022) noted that XGBoost-based incremental learning systems, when applied to detecting traumatic intracranial hemorrhages, have the potential to refine decisions as clinical monitoring progresses.

Despite these advances, the use of AI in clinical decision support still faces ethical, regulatory, and technical challenges. The so-called "algorithmic black box" — i.e., the opacity of automated decision-making processes—makes traceability difficult and raises concerns about medical accountability. Grant et al. (2020) argue that the lack of transparency in deep learning models can hinder clinical acceptance and advocate for frameworks such as “segmentation and classification networks” to make processes more understandable. Additionally, ongoing debates concern data privacy, legal responsibility, and multicenter algorithm validation.

Ultimately, it is essential to understand that although AI presents itself as a powerful ally in therapeutic decision-making, its safe implementtation depends on rigorous clinical validation processes, efficient integration into workflows, and an ethical balance between medical autonomy and technological delegation.

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