Special Communication

Revolutionizing Emergency Medicine and Triage Systems through Artificial Intelligence

Hazqeel Afyq Athaillah Kamarul Aryffin,[1] Mohd Halim Mohd Noor,[1] Kamarul Imran Musa,[2,3] Kamarul Aryffin Baharuddin [4]

[1] School of Computer Sciences, Universiti Sains Malaysia, 11800 Minden, Penang
[2] Department of Community Medicine, School of Medical Sciences, Universiti Sains Malaysia, 16150 Kubang Kerian, Kelantan
[3] Digital Health Sciences Unit, School of Medical Sciences, Universiti Sains Malaysia, 16150 Kubang Kerian, Kelantan
[4] Department of Emergency Medicine, School of Medical Sciences, Universiti Sains Malaysia, 16150 Kubang Kerian, Kelantan

Abstract

Artificial intelligence (AI) is increasingly recognized for its potential in emergency medicine. AI applications in this field encompass a broad spectrum, including predictive modeling, patient monitoring, and optimization of emergency department operations. The integration of AI into triage processes is particularly notable, where machine learning algorithms assist in prioritizing patient care based on urgency and predicted outcomes. By analyzing extensive and heterogeneous clinical data, AI enhances the accuracy and efficiency of triage decisions, potentially reducing waiting times and most importantly, improving patient outcomes. This potential of AI to significantly enhance patient care underscores the importance of its integration into emergency medicine. Despite its promise, the integration of AI in emergency medicine faces significant challenges, primarily related to the quality and quantity of the input data. The principle of "garbage in, garbage out" (GIGO) also underscores the importance of high-quality data for AI performance. Poor-quality, incomplete, or imprecise data can lead to erroneous predictions and suboptimal patient care. Understanding and addressing data bias is essential for developing accurate AI systems. Therefore, effective AI models must be trained on comprehensive datasets that accurately represent patient populations and clinical scenarios. Current comparisons between AI-assigned and nurse-assigned triage scores indicate that while AI shows potential, further refinement is needed to match the reliability of human triage. The urgency and importance of continued research and development in this field cannot be overstated, as they are essential to overcome these barriers and fully integrate AI into emergency medical practice.

Keywords: *artificial intelligence, emergency medicine, triage systems*

INTRODUCTION

Artificial intelligence (AI) to some clinicians is synonymous with computer science, leading them to believe that proficiency in computer science equates to proficiency in AI. This perception is similar to viewing medicine as equivalent to health sciences. In reality, health sciences encompass a wide range of disciplines, with medicine being just one branch. Other branches include dentistry, pharmacy, biomedicine, nutrition, medical radiation, audiology, psychology, speech science, nursing, and sport sciences. Similarly, AI is a specialized branch of computer science and is regarded as one of the challenging subjects within the field.[1]

Recently, AI has become a significant focus among clinicians, aiming to develop intelligent computer systems that replicate human cognitive processes, such as learning and decision-making. In healthcare, AI refers to the utilization of machines to review, analyse, interpret, and propose solutions to complex medical issues based on entered medical data.[2] This approach is akin to having a tireless, error-free assistant, provided that the system's training is accurate. The most common AI technique is machine learning, which involves training models with data using statistical methods.[2] For instance, support vector machine, a type of machine learning algorithm, is widely used to predict diseases or treatment outcomes based on structured data from patient attributes.

Artificial Intelligence in Medicine

Historically, the usage of computer as a decision support system in healthcare services was introduced in 1959 based on logic and probabilistic reasoning.[3] However, since the 1970s, AI approaches have been utilised by the medical expert systems for diagnostic processes based on pattern recognition or heuristic methods.[4] Glaucoma and certain infectious diseases were among the earliest diseases diagnosed by AI.[4]

Currently, the utilisation of AI in the medical field covers every aspect of healthcare services, ranging from drug development to health monitoring, the online scheduling of appointments, the digitization of medical records, digital consultation, disease diagnostics, personalised treatment, medical treatment and surgical treatment.[5] The increasing availability of healthcare data and the ability to unlock obscure clinically relevant information in the massive amount of data has made applications of AI more important.[6] AI also covers five areas of health profession education: student learning experience, assessment, healthcare, faculty development and research.[7]

Among medical specialties, radiology is the most advanced in the use of AI.[8] Given the extensive use of computers in radiology for image acquisition and storage, AI offers substantial assistance in labelling abnormal and negative exams.[5] Screening mammography has shown the most robust outcomes, with computer-assisted interpretation significantly aiding in diagnosis through improved positive predictive values, sensitivity, and specificity.[8] Large technology companies such as Samsung, Apple, Google, and Microsoft have been investing in AI-assisted medical imaging. This investment is expected to expedite scan times, enhance diagnostic accuracy, and reduce the workload of radiologists.[9]

AI techniques have also been applied in cardiovascular medicine for diagnosis, precision medicine, prediction and improvement of patient care.[10] Revolution in the field of surgery was also made possible with AI, such as the Da Vinci robotic surgical system with robotic arms, which has better precision and magnification options that allow the surgeon to perform minute incisions.[5] Over time, AI has enabled marked improvements in accuracy, productivity and patient care for high-performance medicine.[11]

The application of AI in medicine has evolved considerably worldwide, with extensive research and development occurring predominantly in high-income countries.[12] In early 2020, the European Commission published a white paper on AI, identifying health as a crucial application area.[13] The African continent has initiated several significant pilot projects, including human resource planning, optimizing the scheduling of community health workers, and detecting diabetic retinopathy and pulmonary tuberculosis.[14] Singapore, our neighboring country, has also gained substantial experience with promising AI trials across a wide range of diseases.[15] Notably, healthcare services are one of the five major new national projects in Singapore under the 'National AI Strategy'.[16]

In Malaysia, a number of AI projects have taken place, for example an AI model to predict dengue outbreaks.[17] This model utilizes a Bayesian network based on predictor variables derived from 15 years of data provided by the Institute for Medical Research, Malaysia, and the Ministry of Health. Another example is a study that investigated the readiness of medical students to integrate AI applications in medicine, revealing their extensive interest and deep engagement with AI topics.[18]

Challenges of Artificial Intelligence in Medicine

AI lacks the inherent common knowledge that humans possess, necessitating that it be meticulously taught.[19] The quality and quantity of the input data is crucial in determining the validity and accuracy of the AI output. The phrase "Garbage In, Garbage Out" (GIGO), coined in the late 1950s, emphasizes that a computer can only process what it is given.[20] This means that poor quality input will inevitably lead to poor quality output. Missing values, incomplete and imprecise data can be detrimental to training AI, as they may lead to conclusions that do not accurately represent the target population.[19]

Supervision and proper data handling, such as ensuring data integrity and thorough cleaning, are essential in machine learning to ensure accurate application in research.[21] The relevance of GIGO in AI research is critical and should be a guiding principle in AI implementation. Factors contributing to "garbage" input include incomplete, inaccurate, biased, misleading, and poorly structured data. Conversely, factors leading to "garbage" output include poor model design, algorithmic bias, inadequate training, hardware limitations, poor data integration, and lack of regular updates. Ensuring high-quality data and robust model design is paramount for effective AI performance.[22]

Other challenges are understanding and addressing bias. While many biases are related to computational factors, it's crucial to recognize that non-computational factors such as human, institutional, and societal factors also play a significant role. Examples of computational factors include bias in data and design, bias in AI model design, and bias in deployment.[23] Ethical considerations are also critical, as the complexity of AI may surpass an emergency physician's capacity to provide patients with informed consent regarding its decision-making process and recommendations. Patients may prefer human interaction over algorithms in managing their conditions and have the right to refuse its application in their care.[24]

Artificial Intelligence in Emergency Medicine

Emergency medicine is unique because it represents the initial contact of acute patients with hospital services. These patients are undifferentiated and provide extensive and heterogeneous data, which traditional biostatistical methods are inadequate to handle.[25] When designed with clinical workflow considerations, AI in emergency medicine can enhance clinical decision-making, improve care, reduce errors, and increase efficiency.[26] However, this complexity remains a challenge for AI, as accurate data extraction is essential for the success of AI tools.[27]

The use of AI in emergency medicine can be categorized into three primary domains: AI in disease outcome and severity prediction, AI in patient monitoring, and AI in emergency department operations.[25] Its application can also extend to prehospital emergency services, such as predicting the need for critical care services and differentiating ischemic from hemorrhagic stroke using AI-microwave-based imaging helmets.[28,29] Current AI applications potentially involve various aspects of a patient's journey through the emergency department, including triage, point-of-care tests, automated documentation, and monitoring vital signs, to predict future complications such as sepsis or cardiac arrest.[30] AI in emergency departments is also utilized for diagnosing pulmonary embolism, risk stratification, and predictions related to unscheduled visits, hospital admissions, clinical deterioration, and triage.[31] Given the current and foreseeable applications of AI in emergency medicine, it has the potential for comprehensive integration, beginning from self-triage and prehospital care to ambulance services, reducing waiting times, improving emergency department care, and managing discharge processes and hospitalizations.[23]

According to a recent Delphi study, with most experts from North America being emergency physicians, a consensus has been reached on the desired clinical applications of AI in emergency medicine. These applications include using AI to interpret imaging studies, guide medication prescribing for pregnant and lactating patients, inform antibiotic choice, assist with language translation, conduct real-time analysis of cardiac monitoring, guide differential diagnoses, and predict high-risk discharges.[32]

Artificial Intelligence in Triage System

Triage is a process of sorting and prioritizing patients based on the severity of the condition. Those who are critical will be triaged to the red zone where the doctors will see them within minutes. Those who are semi critical will be triaged to the yellow zone and will be seen by the doctors within 30 minutes. Those who are not critical will be triaged to the green zone and will be seen by doctors within 2 hours.[33]

Triage involves the process of identifying the primary presenting complaint and rapidly recognizing patients with evident or potential life-threatening or limb/organ-threatening injuries or illnesses, as well as those with high-risk medical profiles. Objective vital signs, such as blood pressure, pulse rate, respiratory rate, temperature, and pain score, were assessed. Patients are subsequently triaged according to the Malaysian Triage System, categorizing them into red, yellow, or green classifications.[34,35] This system is also utilized to manage the flow of incoming patients, which can sometimes be overwhelming.

The primary objective of triage is to quickly identify patients in critical and time-sensitive condition and to prioritize their care over those who can wait. Under-triage, or the failure to recognize and differentiate patients with severe acute illnesses (e.g., myocardial ischaemia, sepsis) from those with less urgent needs (e.g., indigestion, minor infections), leads to delays in time-sensitive interventions and can result in avoidable clinical deterioration, morbidity, and mortality. This issue is a significant threat to patient safety and quality of care worldwide. Therefore, accurate and reliable emergency department triage is essential.[36]

According to the American College of Surgeons Committee on Trauma (ACSCOT), the acceptable under-triage rate is less than 5%. However, a systematic review of 21 trauma studies revealed a wide discrepancy in under-triage rates, ranging from 1% to 71.9%, due to variations in definitions.[35] Certain patient characteristics, such as advanced age, asthma, and higher Glasgow Coma Scale scores, are associated with a greater likelihood of under-triage.[35,37] Under-triage is also a significant factor affecting the number of transfers between the emergency department and the intensive care unit.[38] Based on our experience, under-triage is a substantial contributing factor to the morbidity and mortality audits.

In Malaysia, triage is performed by the registered nurses or medical assistants who have received specific training for this task. However, there are varying levels of expertise among triagers that can influence decision-making.[39] Additionally, the human capacity for multitasking and rapid information synthesis is limited, making triagers prone to errors. AI and machine learning tools are essential for assisting triagers to enhance their decision-making processes.[25] AI is increasingly applicable in healthcare, with a growing number of tasks where algorithms have matched or even surpassed physician performance.[29]

Research has demonstrated that the application of AI in triaging patients with acute abdominal pain can achieve an acceptable level of accuracy.[40] Zmiri et al. implemented various data mining methods, including the naïve Bayes and C4.5 algorithms, to triage emergency department patients by assessing their severity grades. Their findings were promising, indicating that it is feasible to automatically learn physicians' methods for ranking patient cases by severity using existing triage data. This approach enables the development of a severity ranking classifier using data mining algorithms.[41]

According to a recent scoping review of triage in hospitals, 29 studies have demonstrated that AI with machine learning exhibits superior discrimination abilities compared to conventional systems by using triagers.[42] The integration of AI into the triage process has significantly enhanced predictive accuracy, disease identification, and risk assessment. However, the review encompasses AI applications aimed not only at improving triage efficiency but also at predictive modelling for disease identification, predicting hospital admissions, and optimizing resource allocation. Of the 29 studies, only two studies specifically focused on reducing the incidence of under-triage or over-triage, thereby decreasing errors in triage rates.[43,44]

One study highlighted that a machine-learning triage algorithm reduced the mis-triage rate from 1.2% to 0.9% by employing the CatBoost Python package (an open-source tool from Russia) as the training model for predicting mis-triage.[43] Even though the percentage may look small, any study related to triage depends on the denominators. The Ministry of Health, Malaysia has set a standard of less than 0.5% for the mis-triage rate.[35] Another study aimed at reducing under-triage and over-triage among pediatric patients utilized four machine learning prediction models: (1) logistic regression with lasso regularization (LASSO regression), (2) random forest, (3) gradient-boosted decision tree, and (4) deep neural network.[44]

The study design for integrating AI into triage involves several systematic phases or stages, such as mapping, measuring, and managing.[31] The initial phase included data collection with a predetermined sample size, capturing objective vital signs such as blood pressure, pulse rate, respiratory rate, temperature, pain score, chief complaint, and the patient's triage category. Following data collection, data cleaning and integration are performed. Textual data are then encoded into numerical vectors using text representation techniques (Figure 1).

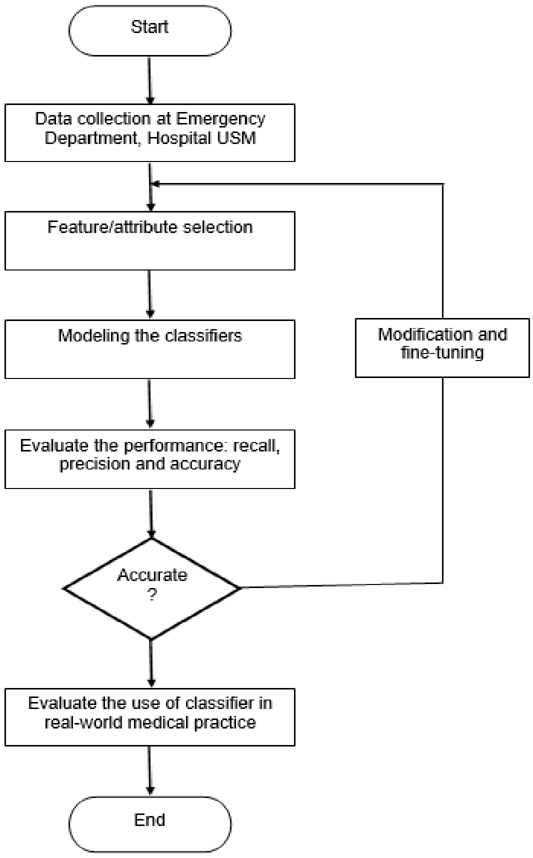

Figure 1: Developing an AI-based patient triage system for an emergency department

Patient parameters (attributes) are critical for triage classification. Therefore, in the next phase, all attributes are incorporated in building predictive models. Both discriminative and generative classification algorithms, including decision trees, naïve Bayes, and support vector machines, are examined. Additionally, ensemble learning techniques are utilized in the experiments to enhance model performance. The parameters of the classification algorithms are fine-tuned to obtain the most optimized models. In ensemble machine learning, the fundamental principle is that a diverse group of models can often outperform any single model by leveraging their collective strengths and mitigating individual weaknesses. Common ensemble methods include bagging (e.g., Random Forests), boosting (e.g., XGBoost, AdaBoost), and stacking. These techniques work best when the individual models are diverse in their errors, allowing the ensemble to capture a broader range of patterns in the data. One of the key advantages of ensemble methods is their ability to reduce overfitting, as they typically have lower variance than individual models. This characteristic, combined with the integration of multiple perspectives, often leads to improved accuracy and generalization in real-world applications.

The final phase involves testing and validation to assess the performance and viability of the proposed models in predicting patient triage categories (model's performance and generalizability). Validation involves using a separate dataset (validation set) during training to tune hyperparameters and prevent overfitting. It helps assess how well the model performs on unseen data. Testing refers to the final evaluation of a trained model using a completely separate dataset (test set) that was not used during training or validation. This provides an unbiased estimate of the model's performance on new, unseen data. The evaluation is conducted using both qualitative and quantitative methods. The proposed algorithm is tested with collected data, and performance metrics such as recall, precision, and F-score are utilized for the evaluation. Although these phases are feasible, a recent comparison between AI-assigned and nurse-assigned triage scores revealed poor to fair reliability among the groups.[45] The use of AI with machine learning algorithms still requires refinement to become a reliable triage tool.[46]

CONCLUSIONS

The future of AI in emergency medicine is promising and has the potential to fundamentally reshape the field. Comprehensive integration of AI, spanning prehospital care to patient disposition, can significantly enhance emergency medical services. However, for AI to have a meaningful impact, ongoing refinement, high-volume and high-quality input are required to avoid the pitfalls of GIGO. Ensuring the reliability and accuracy of input data is crucial for optimizing AI performance and achieving its full potential for improving patient outcomes and operational efficiency, especially in triaging patients at the emergency medicine department in Malaysia.

ACKNOWLEDGEMENTS

We gratefully acknowledge the financial support from the Research University (Individual), Universiti Sains Malaysia Grant, with reference/grant code: #2020/0311/UO1994. Their support has been invaluable in funding the on-going research, entitled ‘Use of Artificial of Artificial Intelligence to Improve Accuracy in Triage System in Emergency Department’.

CORRESPONDENCE

Professor Dr Kamarul Aryffin BAHARUDDIN
MD, MMed (Emergency Medicine), OHD (Niosh), FADUSM, PGCertLIM (Harvard)
Department of Emergency Medicine
School of Medical Sciences
Universiti Sains Malaysia
16150 Kubang Kerian, Kelantan
Malaysia
Email: amararyff@usm.my

REFERENCES

1. Cook K. Top 6 Most Popular Hardest Subjects In Computer Science To Learn First [Internet]. [cited 2020 Sep 4]. Available from: https://www.houseofbots.com/news-detail/4219-1-top-6-most-popular-hardest-subjects-in-computer-science-to-learn-first
2. Chan EW. AI in healthcare: Applications and challenges. International E-Journal of Science, Medicine and Education. 2021; 15(3): 1-4
3. Ledley RS, Lusted LB. Reasoning foundations of medical diagnosis. MD computing: computers in medical practice. 1991;8(5):300-15.
4. Vihinen M, Samarghitean C. Medical expert systems. Current Bioinformatics. 2008;3(1):56-65.
5. Malik P, Pathania M, Rathaur VK. Overview of artificial intelligence in medicine. Journal of family medicine and primary care. 2019;8(7):2328-31.
6. Jiang F, Jiang Y, Zhi H, Dong Y, Li H, Ma S, Wang Y, Dong Q, Shen H, Wang Y. Artificial intelligence in healthcare: past, present and future. Stroke and vascular neurology. 2017;2(4).
7. Mitra NK, Chitra E, Wong PS, Sow CF, Binti Abd Razak SS, Er HM, Nadarajah VD. Artificial Intelligence: Opportunities and Challenges in Health Professions Education. International E-Journal of Science, Medicine & Education. 2023; 17(3): 2-8
8. Mayo RC, Leung J. Artificial intelligence and deep learning–radiology's next frontier?. Clinical imaging. 2018;49:87-8.

9. Alexander A, Jiang A, Ferreira C, Zurkiya D. An intelligent future for medical imaging: a market outlook on artificial intelligence for medical imaging. Journal of the American College of Radiology. 2020;17(1):165-70.
10. Krittanawong C, Zhang H, Wang Z, Aydar M, Kitai T. Artificial intelligence in precision cardiovascular medicine. Journal of the American College of Cardiology. 2017;69(21):2657-64.
11. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nature medicine. 2019;25(1):44-56.
12. Wahl B, Cossy-Gantner A, Germann S, Schwalbe NR. Artificial intelligence (AI) and global health: how can AI contribute to health in resource-poor settings?. BMJ global health. 2018;3(4):e000798.
13. Cohen IG, Evgeniou T, Gerke S, Minssen T. The European artificial intelligence strategy: implications and challenges for digital health. The Lancet Digital Health. 2020 Jul 1;2(7):e376-9.
14. Owoyemi A, Owoyemi J, Osiyemi A, Boyd A. Artificial intelligence for healthcare in Africa. Frontiers in Digital Health. 2020;2:6.
15. Tan EC, Hons B(. Artificial Intelligence and Medical Innovation [Internet]. 2020 [cited 2020 Sep 17]. Available from: https://med.stanford.edu/content/dam/sm/sm-news/
16. Singapore Taking Major Steps with Artificial Intelligence – OpenGov [Internet]. [cited 2020 Sep 17]. Available from: https://opengovasia.com/singapore-taking-major-steps-with-artificial-intelligence/
17. Raja DB, Mallol R, Ting CY, Kamaludin F, Ahmad R, Ismail S, Jayaraj VJ, Sundram BM. Artificial intelligence model as predictor for dengue outbreaks. Malaysian Journal of Public Health Medicine. 2019;19(2):103-8.
18. Xuan PY, Fahumida F, Ismath M, Al Nazir Hussain MI, Jayathilake NT, Khobragade S, Soe HH, Moe S, Htay N, Nu M. Readiness Towards Artificial Intelligence Among Undergraduate Medical Students in Malaysia. Education in Medicine Journal. 2023;15(2).
19. Kuismin-Raerinne A, Nieminen L. Garbage in, Garbage out. University of Helsinki, Faculty of Law, Master of Laws Master's Thesis. 2022
20. Roden B, Lusher D, Spurling TH, Simpson GW, Klein T, Brailly J, Hogan B. Avoiding GIGO: Learnings from data collection in innovation research. Social Networks. 2022;69:3-13.
21. Hyde SJ, Bachura E, Harrison JS. Garbage in, garbage out: A theory-driven approach to improve data handling in supervised machine learning. InMethods to Improve Our Field 2023 Jan 18 (pp. 101-132). Emerald Publishing Limited.
22. Oksana Zdrok. Why Garbage In, Garbage Out Should be the new mantra for AI implementation. [Internet] [cited June 16,2024]. Available from: https://shelf.io/blog/garbage-in-garbage-out-ai-implementation/
23. Chenais G, Lagarde E, Gil-Jardiné C. Artificial intelligence in emergency medicine: viewpoint of current applications and foreseeable opportunities and challenges. Journal of Medical Internet Research. 2023;25:e40031.
24. Iserson KV. Informed consent for artificial intelligence in emergency medicine: A practical guide. The American Journal of Emergency Medicine. 2024;76:225-30.\
25. Liu N, Zhang Z, Ho AF, Ong ME. Artificial intelligence in emergency medicine. Journal of Emergency and Critical Care Medicine. 2018;2.
26. Raita Y, Goto T, Faridi MK, Brown DF, Camargo CA, Hasegawa K. Emergency department triage prediction of clinical outcomes using machine learning models. Critical care. 2019;23:1-3.
27. Hazel Tang. Complex emergency department data still a challenge for AI – AIMed [Internet]. [cited 2020 Sep 18]. Available from: https://ai-med.io/ai-med-news/complex-emergency-department-data-still-a-challenge-for-ai/
28. Kang DY, Cho KJ, Kwon O, Kwon JM, Jeon KH, Park H, Lee Y, Park J, Oh BH. Artificial intelligence algorithm to predict the need for critical care in prehospital emergency medical services. Scandinavian journal of trauma, resuscitation and emergency medicine. 2020;28(1):17.
29. Stewart J, Sprivulis P, Dwivedi G. Artificial intelligence and machine learning in emergency medicine. Emergency Medicine Australasia. 2018;30(6):870-4.
30. Grant K, McParland A, Mehta S, Ackery AD. Artificial intelligence in emergency medicine: surmountable barriers with revolutionary potential. Annals of emergency medicine. 2020;75(6):721-6.
31. Petrella RJ. The AI future of emergency medicine. Annals of Emergency Medicine. 2024

32. Li H, Hayward J, Aguilar LS, Franc JM. Desired clinical applications of artificial intelligence in emergency medicine: A Delphi study. The American journal of emergency medicine. 2024;79:217-20.
33. Ministry of Health Malaysia. Emergency Medicine and Trauma Services Policy. 2012.
34. Min NS, Tharaneetharan H, Li L, Benjamin J, Amira N, Azmi B. Knowledge Towards Emergency Triage System in Malaysia Among Undergraduate Medical Students of a Private Medical College. International Journal of Nursing and Health Science. 2019;6(3):37–43.
35. Abd Halim Q, Yaacob N, Ismail MM, Fauzi MH, Baharuddin KA, Sjahid AS, Bakar MA. An analysis of Undertriage at Hospital Sultan Abdul Halim, Sungai Petani, Kedah, Malaysia. Malaysian Journal of Public Health Medicine. 2023;23(1):182-90.
36. Hinson JS, Martinez DA, Schmitz PS, Toerper M, Radu D, Scheulen J, Stewart de Ramirez SA, Levin S. Accuracy of emergency department triage using the Emergency Severity Index and independent predictors of under-triage and over-triage in Brazil: a retrospective cohort analysis. International journal of emergency medicine. 2018;11:1-10.
37. Grossmann FF, Zumbrunn T, Ciprian S, Stephan FP, Woy N, Bingisser R, Nickel CH. Undertriage in older emergency department patients–tilting against windmills?. PloS one. 2014;9(8):e106203.
38. Yurkova I, Wolf L. Under-triage as a significant factor affecting transfer time between the emergency department and the intensive care unit. Journal of Emergency Nursing. 2011;37(5):491-6.
39. Hitchcock M, Gillespie B, Crilly J, Chaboyer W. Triage: an investigation of the process and potential vulnerabilities. Journal of advanced nursing. 2014;70(7):1532-41.
40. Farahmand S, Shabestari O, Pakrah M, Hossein-Nejad H, Arbab M, Bagheri-Hariri S. Artificial intelligence-based triage for patients with acute abdominal pain in emergency department; a diagnostic accuracy study. Advanced Journal of Emergency Medicine. 2017;1(1).
41. Zmiri D, Shahar Y, Taieb-Maimon M. Classification of patients by severity grades during triage in the emergency department using data mining methods. Journal of evaluation in clinical practice. 2012;18(2):378-88.
42. Tyler S, Olis M, Aust N, Patel L, Simon L, Triantafyllidis C, Patel V, Lee DW, Ginsberg B, Ahmad H, Jacobs RJ. Use of Artificial Intelligence in Triage in Hospital Emergency Departments: A Scoping Review. Cureus. 2024;16(5)
43. Liu Y, Gao J, Liu J, Walline JH, Liu X, Zhang T, Wu Y, Wu J, Zhu H, Zhu W. Development and validation of a practical machine-learning triage algorithm for the detection of patients in need of critical care in the emergency department. Scientific reports. 2021;11(1):24044.
44. Goto T, Camargo CA, Faridi MK, Freishtat RJ, Hasegawa K. Machine learning–based prediction of clinical outcomes for children during emergency department triage. JAMA network open. 2019;2(1):e186937-.
45. Nasser L, McLeod SL, Hall JN. Evaluating the Reliability of a Remote Acuity Prediction Tool in a Canadian Academic Emergency Department. Annals of Emergency Medicine. 2024.
46. Lebold KM, Preiksaitis C. Is Artificial Intelligence Ready to Take Over Triage?. Annals of Emergency Medicine. 2024;83(5):500-2.