Research Article

Pamukkale Medical Journal 2026;19(4):812-822
https://doi.org/10.31362/patd.2024046

The reliability of an artificial intelligence tool, 'Decision Trees', in emergency medicine triage

Acil tıp triyajında yapay zeka aracı olarak 'Karar Ağaçları'nın güvenilirliği

Alp Giray Aydın, Oktay Eray, Ali Vefa Sayraç, Alten Oskay, Ümit Deniz Uluşar

Received:24.08.2026 Accepted:09.09.2026

Abstract

Purpose: Emergency department (ED) overcrowding is a significant challenge worldwide. Triage systems categorize patients according to the urgency of their clinical conditions to ensure patient safety and minimize the risk of clinical errors. The aim of this study was to evaluate the utility of decision trees, an artificial intelligence-based model, in emergency medicine triage.

Materials and methods: This prospective, cross-sectional study was conducted in the ED of a tertiary care hospital. A total of 1,999 patients aged >17 years were included. Prior to the study, triage staff received training on the Australasian Triage Scale (ATS). Two independent observers assessed the final triage category of each patient. A new triage algorithm was developed using a decision tree model.

Results: Mean age of the study population was 41.1±17.2 years, and 49.1% (n=981) were male. A total of 867 patients (43.3%) were assigned to triage category 5, whereas 14 patients (0.7%) were assigned to category 1. The most common clinical descriptors were minimal pain with no high-risk features (n=409, 20.5%) and minor symptoms of low-risk conditions (n=362, 18.1%). There was excellent agreement between the independent observers (κ=0.997). The decision tree algorithm incorrectly classified only one patient, yielding an accuracy rate of 99.9%. Agreement between the ATS and the decision tree algorithm was also excellent (κ=0.999). Agreement between physicians and paramedics was moderate (κ=0.541).

Conclusion: Decision tree models may be used to develop practical triage algorithms as decision-support tools in ED triage. Artificial intelligence-based decision trees have the potential to support triage practices.

Keywords: Artificial intelligence, decision trees, emergency department, triage.

Aydin AG, Eray O, Sayrac AV, Oskay A, Ulusar UD. The reliability of an artificial intelligence tool, 'Decision Trees', in emergency medicine triage. Pam Med J 2026;19:812-822.

Öz

Amaç: Acil servis (AS) kalabalıklığı dünya çapında önemli bir sağlık hizmeti sorunudur. Triyaj sistemleri, hasta güvenliğini sağlamak ve klinik hata riskini en aza indirmek amacıyla hastaları klinik durumlarının aciliyetine göre sınıflandırmaktadır. Bu çalışmanın amacı, yapay zeka tabanlı bir model olan Karar Ağaçlarının acil tıp triyajındaki kullanımını değerlendirmektir.

Gereç ve yöntem: Bu prospektif, kesitsel çalışma, üçüncü basamak bir hastanenin acil servisinde gerçekleştirilmiştir. Çalışmaya 17 yaşından büyük toplam 1.999 hasta dahil edilmiştir. Çalışma öncesinde triyaj personeline, Avustralasya Triyaj Ölçeği (ATS) konusunda eğitim verilmiştir. İki bağımsız gözlemci, her hastanın nihai triyaj kategorisini değerlendirmiştir. Karar Ağacı modeli kullanılarrk yeni bir triyaj algoritması oluşturulmuştur.

Bulgular: Çalışma popülasyonunun yaş ortalaması 41,1±17,2 yıl olup, hastaların %49,1'i (n=981) erkekti. Toplam 867 hasta (%43,3) triyaj kategorisi 5'e, 14 hasta (%0,7) ise kategori 1'e atanmıştır. En sık karşılaşılan klinik tanımlayıcılar, yüksek riskli özellikler bulunmaksızın minimal ağrı (n=409, %20,5) ve düşük riskli durumlara ait minör semptomlar (n=362, %18,1) olmuştur. İki bağımsız gözlemci arasındaki uyum mükemmel düzeyde bulunmuştur (κ=0,997). 'Karar Ağacı' algoritması yalnızca bir hastayı yanlış sınıflandırmış ve %99,9 doğruluk oranına ulaşmıştır. ATS ile 'Karar Ağacı' algoristması arasındaki uyum da mükemmel düzeyde bulunmuştur (κ=0,999). Buna karşılık, hekimler ve paramedikler arasındaki uyum orta düzeydeydi (κ=0,541).

Sonuç: Yapay zeka modeli olarak "Karar Ağaçları", acil servis triyajında karar destek aracı olarak kullanılabilecek pratik triyaj algoritmalarının geliştirilmesinde kullanılabilir. Bu bulgular, yapay zekâ tabanlı karar ağaçlarının acil sağlık hizmetlerinde standartlaştırılmış ve doğru triyaj uygulamalarını destekleme potansiyeline sahip olduğunu göstermektedir.

Alp Giray Aydın, M.D. Department of Emergency Medicine, Sisli Hamidiye Etfal Training and Research Hospital, Istanbul, Türkiye, e-mail: dralp07@gmail.com (https://orcid.org/0000-0002-3093-6120)

Oktay Eray, M.D., Professor. Department of Emergency Medicine, School of Medicine, Bandirma Onyedi Eylul University, Balikesir, Türkiye, e-mail: oeray@bandirma.edu.tr (https://orcid.org/0000-0002-1643-6007)

Ali Vefa Sayraç, M.D. Governorship of Antalya, Provincial Health Directorate, Antalya, Türkiye, e-mail: dr.vefa@yahoo.com (https://orcid.org/0000-0002-7781-5027)

Alten Oskay, M.D., Associate Professor. Department of Emergency Medicine, School of Medicine, Pamukkale University, Denizli, Türkiye, e-mail: oskayten@gmail.com (https://orcid.org/0000-0003-4373-6280) (Corresponding Author)

Ümit Deniz Uluşar, Professor. Department of Computer Engineering, Faculty of Engineering, Akdeniz University, Antalya, Türkiye, e-mail: umitulusar@akdeniz.edu.tr (https://orcid.org/0000-0003-2356-5824)

Pamukkale Medical Journal is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License (CC BY-NC 4.0).

Anahtar kelimeler: Yapay zeka, karar ağaçları, acil servis, triyaj.

Aydın AG, Eray O, Sayraç AV, Oskay A, Uluşar ÜD. Acil tıp triyajında yapay zeka aracı olarak 'Karar Ağaçları'nın güvenilirliği. Pam Tıp Derg 2026;19:812-822.

Introduction

Overcrowding has become one of the most critical challenges facing emergency departments (EDs) in recent years. Increasing patient volume and overcrowding can lead to delays in patient evaluation and treatment, adversely affecting patient satisfaction and the quality of care [1, 2]. The need for triage systems emerged from the necessity to prioritize patients according to the urgency of their clinical conditions and ensure timely access to appropriate care.

In recent years, standardized triage systems have been widely implemented worldwide. These scales, administered by trained healthcare professionals, stratify patients according to their presenting symptoms, clinical findings, and other relevant parameters to determine the urgency of care [3].

Artificial intelligence (AI), which aims to replicate aspects of human cognitive processes, has been applied in various fields of medicine since the late 1960s, with promising results [4]. Numerous AI techniques have been developed to address complex clinical problems, making their application in medicine both rational and potentially valuable for improving clinical decision-making.

The present study aimed to evaluate the validity of ‘Decision Trees’, an artificial intelligence-based method, for the triage of patients presenting to the ED.

Materials and methods

Participants and study setting

This prospective cross-sectional study was conducted over a 10-day period in the ED of a tertiary care hospital with an annual patient volume of approximately 73,000 visits. Ethical approval was obtained from the Akdeniz University Faculty of Medicine Clinical Research Ethics Committee. This study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki.

Patients aged >17 years who were presented to the ED with any chief complaint were eligible for inclusion in the study. Patients who declined to provide informed consent were excluded. Written informed consent was obtained from all participants. For patients who were unable to provide informed consent because of their clinical condition, consent was obtained from a first-degree relative or an accompanying person.

Triage training

Before the initiation of the study, eight paramedics and one nurse assigned to the triage area underwent standardized training in the use of the Australasian Triage Scale (ATS) [Supplement]. The training program consisted of three sequential stages: (1) an introduction to the definitions and clinical criteria of each ATS category; (2) discussion and analysis of representative clinical scenarios; and (3) supervised practical application of the ATS to 100 patients in the triage setting.

ATS triage scale categories

Patients were assigned to one of five ATS categories according to the urgency of their clinical condition and the maximum recommended time to medical assessment:

Category 1: Patients requiring immediate resuscitation were assigned directly to the resuscitation area.

Category 2: Patients with potentially life-threating conditions or conditions threatening limb viability were required to receive medical assessment and treatment in the resuscitation or telemetry area within 10 minutes.

Category 3: Patients with conditions that had the potential to progress to a life-threatening state or require urgent intervention were required to receive medical assessment within 30 minutes.

Category 4: Patients with conditions that could reasonably be managed within 1-2 hours were required to receive medical assessment within 60 minutes.

Category 5: Patients presenting with non-urgent conditions were required to receive medical assessment within 120 minutes.

A reference chart summarizing the ATS categories and corresponding maximum recommended waiting times was prominently displayed prominently in the triage area and was available to all staff throughout the study. Patients awaiting medical assessment in the ED were re-triaged at 30-minute intervals to identify any changes in their clinical status or ATS category.

At the end of the study, two independent senior emergency medicine residents independently reviewed the clinical information for each patient and determined the final ATS triage category. In cases of disagreement between the two observers, an emergency medicine associate professor independently reviewed the case and made the final determination.

Study data

Data were prospectively recorded on a standardized study form. The following variables were collected: age, sex, presenting symptoms, comorbidities, blood pressure, body temperature, peripheral oxygen saturation, heart rate, respiratory rate, Glasgow Coma Scale (GCS) score, verbal pain score, and ATS triage category. Pain severity was categorized as severe, moderate, mild, or absent according to the patient's verbal pain score.

Blood pressure, peripheral oxygen saturation and heart rate were measured using a multiparameter patient monitor. Body temperature was measured at the temporal artery using the Exergen Temporal Artery Thermometry® system.

Statistical analysis

A decision tree model, an AI-based machine learning method, was used to evaluate the relationship between routinely collected clinical variables and ATS triage categories. Decision tree analysis was performed using the 'MATLAB classregtree method'. This decision tree algorithm begins at a root node and recursively partitions the dataset into increasingly homogeneous subgroups. At each branching point-decision node, the algorithm evaluates the available predictor variables and identifies the variable and corresponding threshold that provide the greatest improvement in node purity. In the present study, the Gini diversity index was used as the splitting criterion.

At each split, observations were assigned to the left or right branch according to the selected predictor and threshold value. In general, observations with values below the specified threshold were assigned to the left branch, whereas those above the threshold were assigned to the right branch. This recursive partitioning process continued until the predefined stopping criteria were reached. The minimum number of observations required to form a terminal node was set at 1.

All other statistical analyses were performed using MedCalc® Statistical Software. Continuous variables were expressed as mean ± standard deviation or median with interquartile range [IQR] and/or minimum-maximum values, as appropriate. Categorical variables were summarized as frequencies and percentages. Agreement among the decision tree model, paramedics, and physicians in assigning ATS triage categories was assessed using the kappa (κ) statistic.

Results

A total of 2000 patients who provided informed consent were enrolled in the study. One patient was excluded because of missing data on the study form, resulting in 1,999 patients being included in the final analysis.

The mean age of the study population was 41.1±17.2 years, and 49.0% (n=981) of the patients were male. The mean systolic and diastolic blood pressures were 126±23 mmHg and 72±13 mmHg, respectively. The median respiratory rate was 18 breaths/min (IQR:14-20), and the median heart rate was 85 beats/min (IQR:75-97). The mean peripheral oxygen saturation was 96±8%. The most common comorbidities were hypertension (n=347, 17.4%) and diabetes mellitus (n=215, 10.8%) (Table 1).

Table 1. Demographics of study patients

Variable	N=1.999
Age, mean±SD	41.1±17.2
Gender, male, n (%)	981 (49.1)
Systolic blood pressure, mmHg, mean±SD	126.4±22.8
Diastolic blood pressure, mmHg, mean±SD	72.2±12.9
Body temperature, ºC, mean±SD	36.3±1.5
Pulse rate, beats/min, median (IQR)	85 (75-97)
Fingertip oxygen saturation, %, mean±SD	96.5±7.9
Respiration rate, breaths/min, median (IQR)	18 (14-20)
Hypertension, n (%)	347 (17.4)
Diabetes Mellitus, n (%)	215 (10.8)
Coronary artery disease, n (%)	122 (6.1)
Cardiac failure, n (%)	89 (4.5)
Malignancy, n (%)	93 (4.7)
Others, n (%)	87 (4.4)
GCS score, median (min-max)	15 (3-15)
Verbal Pain Score, n (%)	
Severe	49 (2.5)
Moderate	342 (17.1)
Mild pain	974 (48.7)
No pain	578 (28.9)
Not evaluated	56 (2.8)

SD: standard deviation; IQR: interquartile range; min-max: minimum-maximum, GCS: Glasgow Coma Scale

Of the study population, 867 patients (43.3%) were ultimately assigned to ATS Category 5, whereas 14 patients (0.7%) were assigned to ATS Category 1 (Figure 1). Regarding pain severity, 49 patients (2.5%) reported severe pain, 342 (17.1%) reported moderate pain, 974 (48.7%) reported mild pain, and 578 (28.9%) reported no pain.

The median GCS score was 15 (IQR:15-15, min-max:3-15). The demographic and clinical characteristics of the study patients are presented in Table 1. The most frequently observed clinical criteria according to the ATS were minimal pain without high-risk features (n=409, 20.5%), minor symptoms with a stable clinical condition (n=362, 18.1%), moderate pain with a potentially risky condition (n=168, 8.4%), and diarrhea and vomiting without dehydration (n=158, 7.9%).

During the study period, eight patients (0.4%) presented with cardiac arrest, one patient (0.1%) with respiratory arrest and four patients (0.2%) with a GCS score below 9. The distribution of clinical criteria according to the ATS is presented in Figure 2 and Table 2.

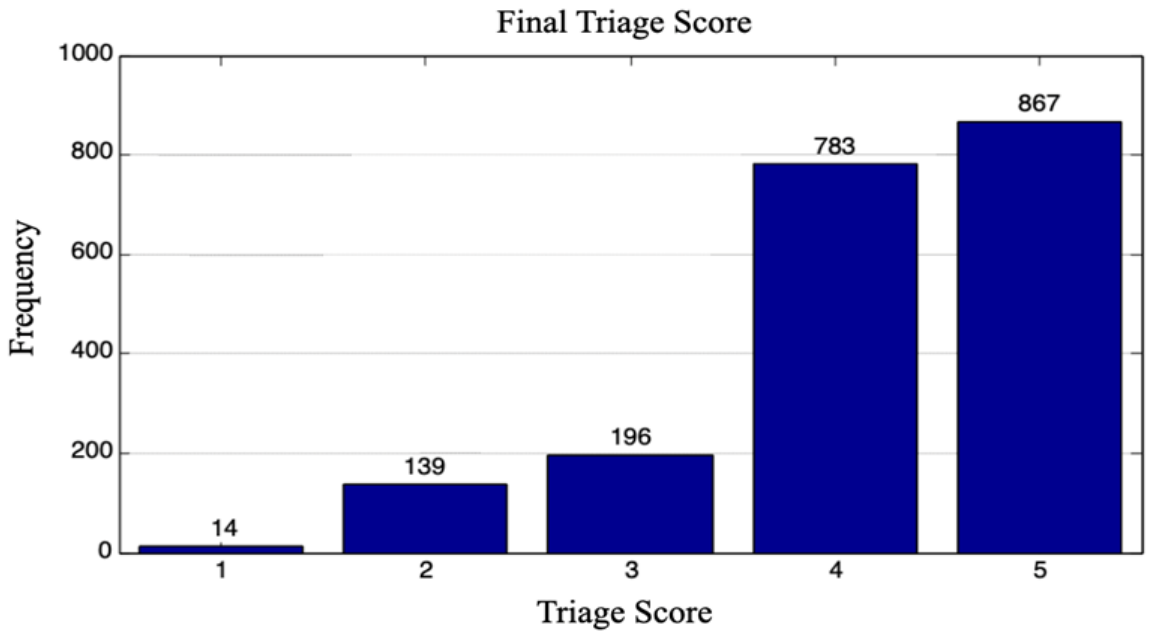

Figure 1. Final triage scores of study patients

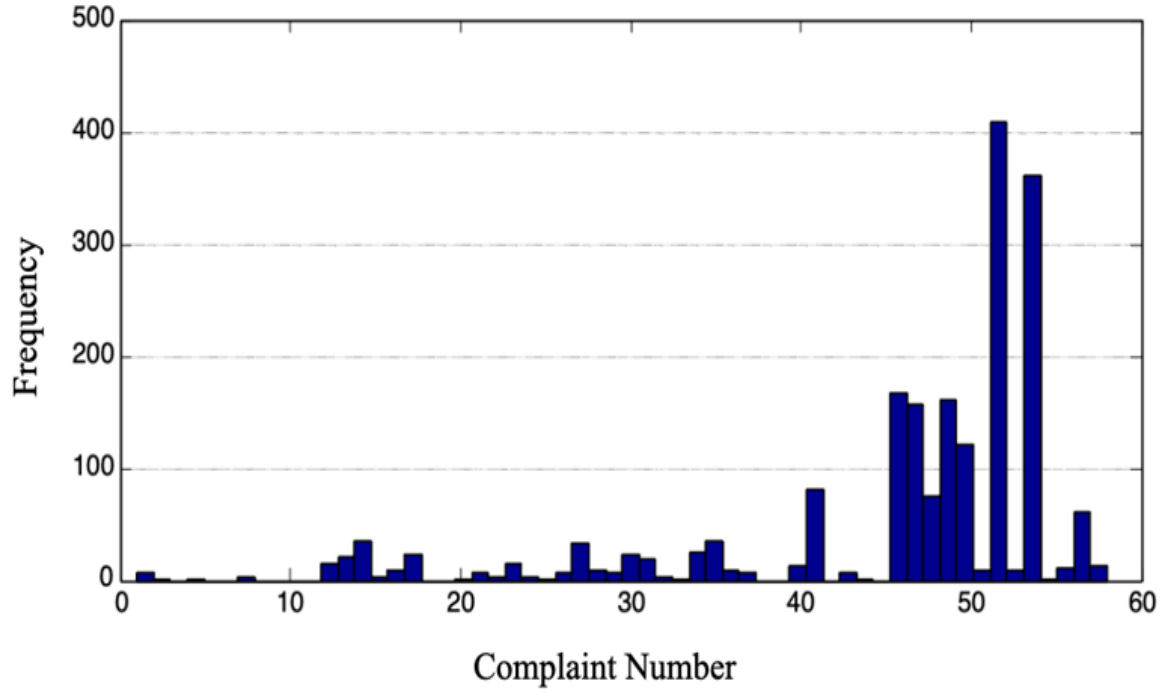

Figure 2. The frequencies of clinical criteria in Australasian Triage Scale

Table 2. Clinical descriptors determined according to Australasian Triage Scale**.** The identifier numbers in parentheses next to clinical descriptors refers to the specified numbers in 'Decision Trees' algorithm

Chief Complaint	N	%
Cardiac arrest (1)	8	0.4
Respiratory arrest (2)	1	0.1
Respiratory rate <10 /min (4)	1	0.1
Unresponsive or responds to pain only (GCS <9) (7)	4	0.2
Extreme respiratory distress (12)	16	0.8
Circulatory compromise (13) clammy or mottled skin, poor perfusion heart rate <50 bpm or >150 bpm hypotension with hemodynamic effects severe blood loss	21	1.1
Chest pain of likely cardiac nature (14)	35	1.8
Very severe pain- any cause (15)	3	0.2
Drowsy, decreased responsiveness any cause (GCS <13) (16)	9	0.5
Acute hemiparesis/dysphasia (17)	24	1.2
Acid or alkali splash to eye- requiring irrigation (20)	1	0.1
Major multi trauma (21)	8	0.4
Severe localized trauma- major fracture, amputation (22)	3	0.2
High-risk history (23) significant sedative or other toxic ingestion severe pain suggesting PE, AAA, ectopic pregnancy	16	0.8
Behavioral/Psychiatric (24) violent or aggressive immediate threat to self or others severe agitation or aggression	3	0.2
Severe hypertension (25)	2	0.1
Moderately severe blood loss- any cause (26)	7	0.4
Moderate shortness of breath (27)	33	1.2
SaO_2 90-95% (28)	9	0.5
Seizure (now alert) (29)	7	0.4
Any fever of immunosuppressed patients (eg. oncology patient, on steroids) (30)	24	1.2
Persistent vomiting (31)	20	1
Dehydration (32)	3	0.2
Head injury with short LOC (now alert) (33)	1	0.1

Table 2. Clinical descriptors determined according to Australasian Triage Scale**.** The identifier numbers in parentheses next to clinical descriptors refers to the specified numbers in 'Decision Trees' algorithm (continued)

Chief Complaint	N	%
Moderately severe pain-any cause-requiring analgesia (34)	25	1.3
Chest pain likely non-cardiac and abdominal pain without high-risk features (severe or patient age >65) (35)	35	1.8
Moderate limb injury- deformity, severe laceration, crush (36)	9	0.5
Limb- altered sensation, acutely absent pulse and trauma- high-risk history with no other risk features (37)	7	0.4
Behavioral/Psychiatric (40) very distressed, risk of self-harm acutely psychotic or thought disordered situational crisis, deliberate self-harm agitated/ withdrawn potentially aggressive	13	0.7
Mild hemorrhage (41)	81	4.1
Chest injury without rib pain or respiratory distress (43)	7	0.4
Difficulty in swallowing, no respiratory distress (44)	2	0.1
Moderate pain, some risk features (46)	168	8.4
Vomiting or diarrhea without dehydration (47)	158	7.9
Eye inflammation or foreign body- normal vision (48)	75	3.8
Minor limb trauma- sprained ankle, possible fracture, uncomplicated laceration requiring investigation or intervention- Normal vital signs, mild/moderate pain (49)	162	8.1
Nonspecific abdominal pain (50)	121	6.1
Behavioral/Psychiatric (51) semi-urgent mental health problem under observation and/or no immediate risk to self or others	10	0.5
Minimal pain with no high-risk features (52)	409	20.5
Low risk history and now asymptomatic (53)	9	0.5
Stable minor symptoms (54)	362	18.1
Minor symptoms of existing stable illness (55)	1	0.1
Minor symptoms of low-risk conditions (56)	11	0.6
Minor wounds-small abrasions, minor lacerations (not requiring sutures) (57)	62	3.1
Behavioral/Psychiatric (58) known patient with chronic symptoms social crisis, clinically well patient	13	0.7

Bpm: beats per minute, LOC: Loss of consciousness, SaO_2: Figertip oxygen saturation, GCS: Glasgow Coma Scale; PE: Pulmonary embolism AAA: Abdominal aortic aneurism

There was excellent interobserver egreement between the two independent observers, with a kappa (κ) value of 0.997. The triage categories assigned by two observers differed in only five patients (0.2%).

A novel triage algorithm was developed using a decision tree model (Figure 3). The decision tree algorithm incorrectly classified only one patient, yielding an overall accuracy of 99.9%. Agreement between the ATS and the 'Decision Tree algorithm" was excellent, with a kappa (κ) value of 0.999. In contrast, moderate agreement was observed between physicians and paramedics, with a kappa (κ) value of 0.541 (Figure 4).

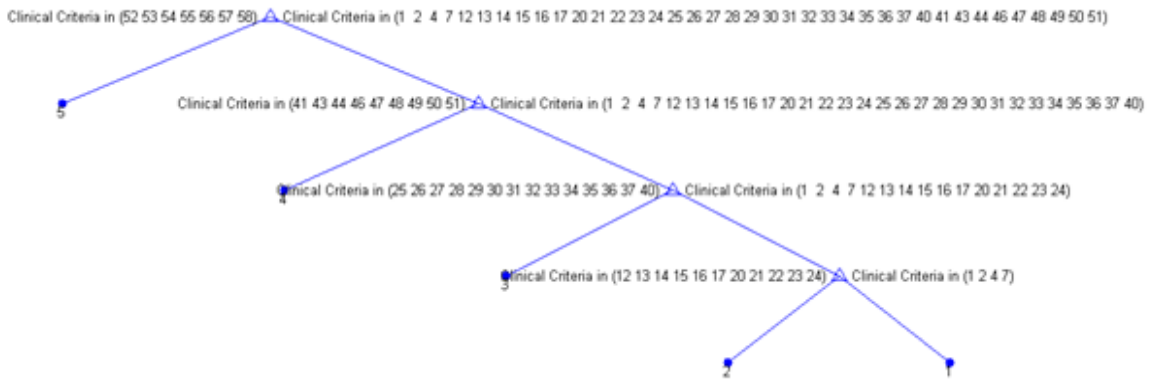

Figure 3. The algorithm of 'Decision Trees'

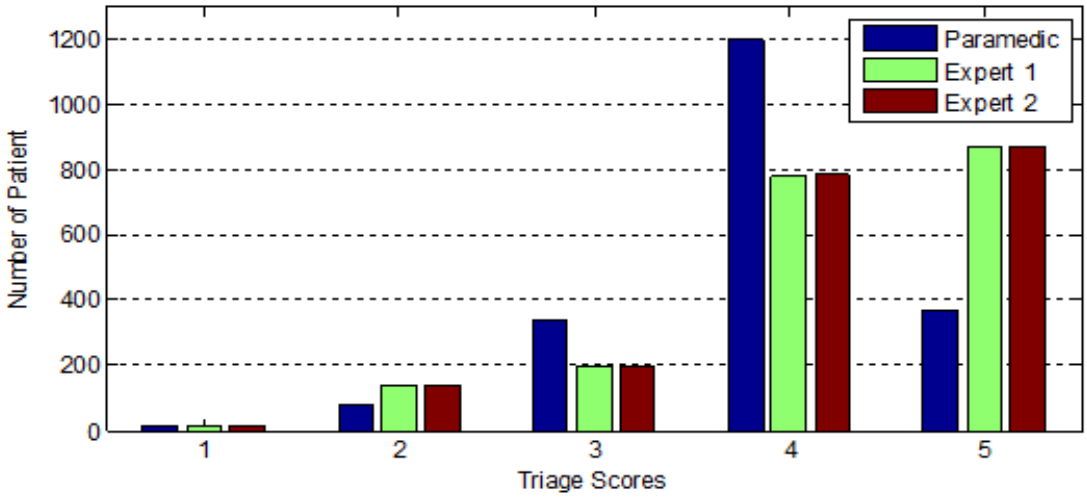

Figure 4. Consistency between physicians and paramedics

Discussion

The term "artificial intelligence" was first defined by John McCarthy [5] as the science and engineering of producing clever machines, particularly clever computer software. AI refers to the ability of machines to perform tasks that would be considered intelligent if performed by humans. It encompasses a broad range of computational methods designed to emulate aspects of human cognition, including learning, reasoning, pattern recognition, and decision-making.

The ability of AI models to identify complex relationships and patterns within large datasets has led to their increasing use in predicting diagnosis, treatment responses, and clinical outcomes across a wide range of medical scenarios [6]. Numerous AI techniques have been developed to address different clinical problems, and their potential to improve disease detection, treatment selection, and clinical decision-making is increasingly recognized.

'Decision Trees' is one of the AI models that is used as a decision support system. Decision Trees construct a prediction model between a patient and disease with the parameters that we determine. Information is presented as a tree composed of distinct steps: the decision step, the probability step, and the conclusion step.

Decision trees are among the AI-based methods that can be used as clinical decision-support tools. A decision tree generates a predictive model by establishing relationships between patient characteristics and clinical outcomes based on predefined variables. The information is represented in a hierarchical tree structure consisting of a series of decision nodes, branches, and terminal nodes, allowing complex clinical data to be transformed into an interpretable decision-making process.

The fundamentals of AI in medicine can be traced back to the mid-1960s, while the introduction of fuzzy set theory and its potential applications in medicine in 1969 stimulated further research in the field. Early successful applications in cardiology were subsequently followed by studies in radiology and other medical specialties [6-11]. Today, AI-based systems are increasingly utilized across a broad range of medical disciplines, with applications ranging from diagnosis and risk stratification to treatment planning and prognostic assessment [6,12-15].

In addition to its widespread applications in other areas of medicine, AI has also been increasingly investigated in emergency medicine. Artificial neural network (ANN), a class of AI methods, have been evaluated for predicting acute coronary syndromes in emergency department patients and demonstrated promising diagnostic performance, with area under the curve (AUC) values of 0.97, 0.93 and 0.95 across different hospitals [16]. Similarly, Bektas et al. [17] developed an ANN to predict craniocervical junction injuries in trauma patients and reported the AUC of 0.912. These findings suggest that AI-based models may have considerable potential as clinical decision-support tools in emergency medicine, particularly in settings where rapid and accurate risk stratification is essential.

In a study by Azeez et al. [18], the validity of AI–based approaches for triage was evaluated by developing prediction models from retrospective chart data using an ANN and a neuro-fuzzy system. The authors reported test-set accuracies of 96.7% for the ANN and 94.0% for the neuro-fuzzy system. Although both methods demonstrated specificities exceeding 90% for the accurate prediction of triage categories, their sensitivities were comparatively lower, particularly for the neuro-fuzzy models, with the exception of one prediction model for each method.

The findings of the present study suggest that decision tree models may be used to develop highly predictive and practical algorithms for emergency department triage. In our study, the decision tree model incorrectly classified only one of the 2,000 patients, corresponding to an overall accuracy of 99.9%. An important advantage of decision tree models is their flexibility and interpretability. These algorithms can be readily adapted and retrained using different combinations of variables selected by the investigator, allowing the model to be tailored to specific clinical settings and patient populations. Although an overall accuracy of 99.9% represents an excellent level of performance, the clinical significance of the misclassified cases should not be overlooked. In particular, identifying which patients are incorrectly classified and understanding the factors underlying these misclassifications may become increasingly important when the model is applied to larger and more heterogeneous patient populations. Future studies should therefore focus not only on overall model accuracy but also on characteriizing the patients who are misclassified and exploring the clinical and patient-related factors that contribute to these errors. Such analyses may help identify potential limitations of decision tree-based triage algorithms and guide their further refinement and validation before implementation in routine clinical practice.

Another emerging area of interest in ED triage is the use of Large Language Models (LLMs). Williams et al. [19] reported an accuracy score of 0.89 for their primary LLM and 0.84 for the comparator LLM in accurately classifying 10,000 pairs of ED patients according to the Emergency Severity Index. In a direct comparison between human and AI-based triage, Arslan et al. [20] reported similar overall triage accuracy rates for nurses and ChatGPT (65.2% and 66.5%, respectively). In contrast, Zaboli et al. [21] found that human triage outperformed ChatGPT-4.0, with AUROC values of 0.88 and 0.70, respectively.

Despite the growing number of studies evaluating AI–based approaches and conventional triage scales, no single model has yet demonstrated consistently superior performance across different clinical settings. The heterogeneity of patient populations, regional healthcare systems, outcome measures, triage personnel, and individual levels of clinical experience may limit the generalizability of existing models. These challenges highlight the need for further research to develop robust and generalizable triage models that can accommodate these variations and be reliably implemented across diverse emergency care settings [22].

The present study has several limitations. First, the study was conducted over a relatively short period of 10 days, which may limit the representativeness of the study population and the generalizability of the findings. Second, only patients who provided informed consent were included. Finally, the relatively small number of participating physicians and paramedics may have limited the generalizability of our findings. Future multicenter studies involving larger and more diverse patient populations and healthcare professionals are warranted to externally validate the decision tree model and further assess the generalizability of our findings.

In conclusion, the findings of our study do not suggest that AI should replace human triage personnel. Rather, AI-based decision tree models should be considered decision-support tools that can assist healthcare professionals, particularly less experienced staff and those working in high-volume clinical settings where rapid, accurate, and consistent patient assessment is essential.

As a future direction, decision tree models should be further developed and validated as practical, user-friendly algorithms that can be integrated into ED triage systems and used as decision-support tools to enhance the accuracy, consistency, and efficiency of the triage process.

Declaration of Conflicting Interests and Ethics: No conflict of interest was declared by the authors. Ethical approval was obtained from the Akdeniz University Faculty of Medicine Clinical Research Ethics Committee (approval date: 30.05.2011 and approval no: B.30.2.A KD.0.20.05.05/2011-193).

Funding: None.

Artificial Intelligence (AI) Disclosure: The conceptualization, research design, methodology, and structural development of this study were strictly executed by the human author(s). All final content was thoroughly reviewed, verified, and approved by the authors, who assume full responsibility for the accuracy and scientific integrity of the manuscript. An artificial intelligence–based language assistant was used to provide limited language support and improve the language quality of the translated manuscript. The author takes full responsibility for accuracy and final content of the translation.

Contribution of Authors: A.G.A. and O.E. constructed the main idea and hypothesis of the study. A.G.A., A.V.S., A.O. and U.D.U. developed the theory and arranged/edited the material and method section. A.G.A., O.E. U.D.U. and A.O. have evaluation the data in the Results section. The Discussion section of the article was written by A.G.A and A.V.S. A.G.A., O.E., A.V.S., A.O and U.D.U. reviewed, corrected, and approved. In addition, all authors discussed the entire study and approved the final version.

References

1. Shiber, J. R., Longley, M. B., & Brewer, K. L. (2009). Hyper-use of the ED. *World journal of emergency medicine, 27*(5), *588-594.* https://doi.org/10.1016/j.ajem.2008.05.006
2. Pines, J. M., Prabhu, A., McCusker, C. M., & Hollander, J. E. (2010). The effect of ED crowding on education. *The American journal of emergency medicine, 28*(2), 217-220. https://doi.org/10.1016/j.ajem.2008.10.030
3. Dikme, O., Atilla, R., Colak, Oray, N., Saracoglu, G., Girgin, M., & Akyol, P. Y. (2019). Dokuz Eylul Triage System: A five category triage algorithm, reliability and validity study. *Anatolian journal of emergency medicine,, 2*(3)*,* 1-7.
4. Morey, J. R., Zhang, X., Yaeger, K. A., Fiano, E., Marayati, N. F., & Kellner, C. P., (2021). Real-world experience with artificial intelligence-based triage in transferred large vessel occlusion stroke patients. *Cerebrovascular diseases (Basel, Switzerland), 50*(4)*,* 450-455. https://doi.org/10.1159/000515320

5. McCarthy, J. What is artificial intelligence? Computer Science Department, Stanford University. Available at: https://www-formal.stanford.edu/jmc/whatisai.pdf. Accessed December 31, 2025.
6. Fahim, Y. A., Hasani, I. W., Kabba, S., & Ragab, W. M. (2025). Artificial intelligence in healthcare and medicine: clinical applications, therapeutic advances, and future perspectives. *European journal of medical research, 30*(1)*,* 848. https://doi.org/10.1186/s40001-025-03196-w
7. Zadeh, L.A. (1969). *Biological Applications of the Theory of Fuzzy Set and Systems*, In: Proctor, L. D., editors. The Proceedings of an International Symposium on Biocybernetics of the Central Nervous System, Little, Brown and Company, Boston; p. 199-206.
8. Kalmanson, D., & Stegall, H. F. (1975). Cardiovascular investigations and fuzzy sets theory. *The American journal of cardiology, 35*(1)*,* 80-84. https://doi.org/10.1016/0002-9149(75)90562-7
9. Jain, R., Mazumdar, J., & Moran, W. (1998). Application of fuzzy classifier system to coronary artery disease and breast cancer. *Australasian physical & engineering sciences in medicine, 21*(3), 141-147.
10. Güler, I., Hardalaç, F., & Barişçi, N. (2002). Application of FFT analyzed cardiac Doppler signals to fuzzy algorithm. *Computers in biology and medicine, 32*(6)*,* 435-444. https://doi.org/10.1016/s0010-4825(02)00021-5
11. Guler, D., Hardalac, F., Ergu, U., & Barisci, N. (2004). Classification of Aorta Doppler signals using variable coded-hierarchical genetic fuzzy system. *Expert systems with applications, 26*(3)*,* 321-333. https://doi.org/10.1016/j.eswa.2003.09.004
12. Gulkesen, K. H., Koksal, I. T., Ozdem, S., & Saka, O. (2010). Prediction of prostate cancer using decision tree algorithm. *Turkish journal of medical sciences, 40*(5), 681-686. https://doi.org/10.3906/sag-0906-47
13. Eken, C., Bilge, U., Kartal, M., & Eray, O. (2009). Artificial neural network, genetic algorithm, and logistic regression applications for predicting renal colic in emergency settings. *International journal of emergency medicine, 2*(2)*,* 99-105. https://doi.org/10.1007/s12245-009-0103-1
14. Liu, Y., Wei, L. Q., Li, G. Q., Lv, F. Y., Wang, H., & Zhang, Y. H., & Cao, W. L. (2010). A decision-tree model for predicting extubation outcome in elderly patients after a successful spontaneous breathing trial. *Anesthesia and analgesia, 111*(5)*,* 1211-1218. https://doi.org/10.1213/ANE.0b013e3181f4e82e
15. Genişol, İ., & Bakırarar, B. (2025). Application of machine learning techniques for survival prediction in pediatric malignant non-seminomatous germ cell testicular tumors: a SEER database study. *Pamukkale Medical Journal, 18*(2)*,* 358-367. https://doi.org/10.31362/patd.1528303
16. Harrison, R. F. & Kennedy, R. L. (2005). Artificial neural network models for prediction of acute coronary syndromes using clinical data from the time of presentation. *Annals of emergency medicine, 46*(5), 431-439. https://doi.org/10.1016/j.annemergmed.2004.09.012
17. Bektaş, F., Eken, C., Soyuncu, S., Kilicaslan, I., & Cete, Y. (2008). Artificial neural network in predicting craniocervical junction injury: an alternative approach to trauma patients. *European journal of emergency medicine : official journal of the European Society for Emergency Medicine, 15*(6)*,* 318-323. https://doi.org/10.1097/MEJ.0b013e3282fce7af
18. Azeez, D., Ali, M. A., Gan, K. B., & Saiboon, I. (2023). Comparison of adaptive neuro-fuzzy inference system and artificial neutral networks model to categorize patients in the emergency department. *SpringerPlus, 2,* 416. https://doi.org/10.1186/2193-1801-2-416
19. Williams, C. Y. K., Zack, T., Miao, B. Y., Sushil, M., Wang, M., & Kornblith, A. E., (2024) Use of a large language model to assess clinical acuity of adults in the emergency department. *JAMA network open, 7*(5)*,* e248895. https://doi.org/10.1001/jamanetworkopen.2024.8895
20. Arslan, B., Nuhoglu, C., Satici, M. O., & Altinbilek, E. (2025). Evaluating LLM-based generative AI tools in emergency triage: A comparative study of ChatGPT Plus, Copilot Pro, and triage nurses. *The American journal of emergency medicine, 89,* 174-181. https://doi.org/10.1016/j.ajem.2024.12.024
21. Zaboli, A., Brigo, F., Brigiari, G., Massar, M., Parodi, M., & Pfeifer, N., (2025). Chat-GPT in triage: Still far from surpassing human expertise - An observational study. *The American journal of emergency medicine, 92,* 165-171. https://doi.org/10.1016/j.ajem.2025.03.028
22. Porto, B. M. (2024). Improving triage performance in emergency departments using machine learning and natural language processing: a systematic review. *BMC emergency medicine, 24*(1)*,* 219. https://doi.org/10.1186/s12873-024-01135-2