Artificial Intelligence in Triage

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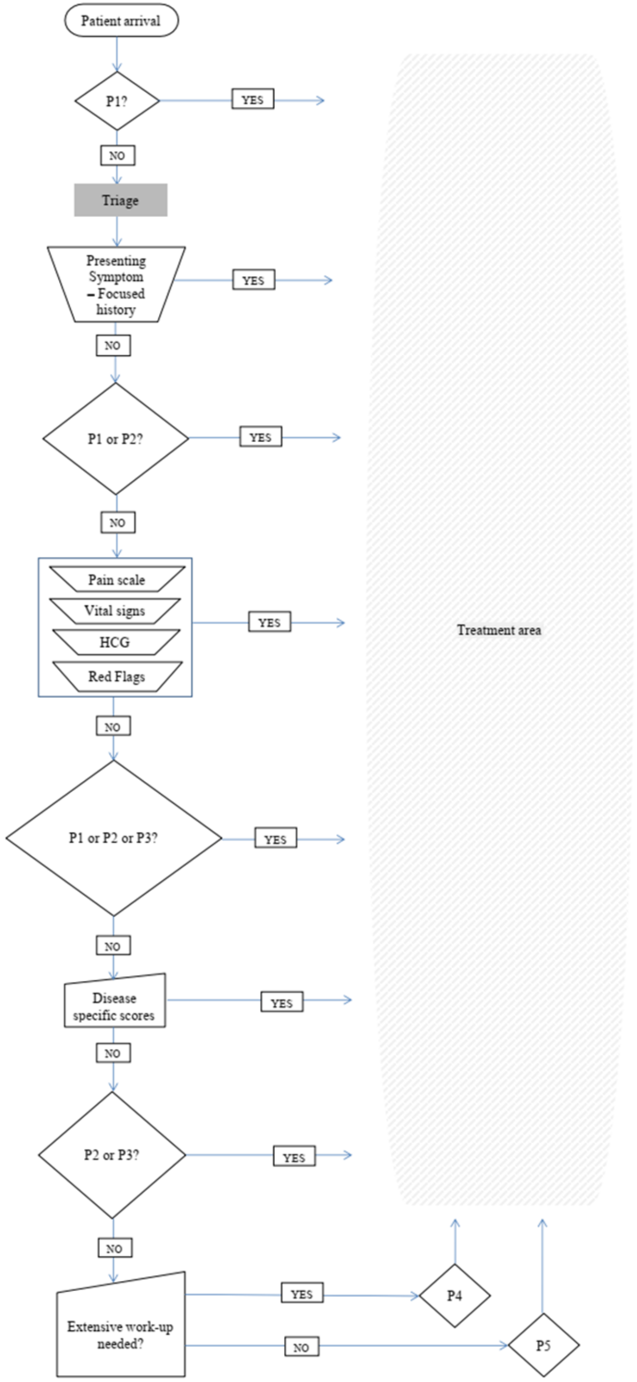
TİKA

Disclosures

Head of CarePOI Triage R&D

Triage



Patient arrival
P1?
YES
NO
Triage
Presenting Symptom – Focused history
YES
NO
P1 or P2?
YES
NO
Pain scale
Vital signs
HCG
Red Flags
YES
NO
P1 or P2 or P3?
YES
NO
Disease specific scores
YES
NO
P2 or P3?
YES
NO
Extensive work-up needed?
YES
NO
P4
P5
Treatment area

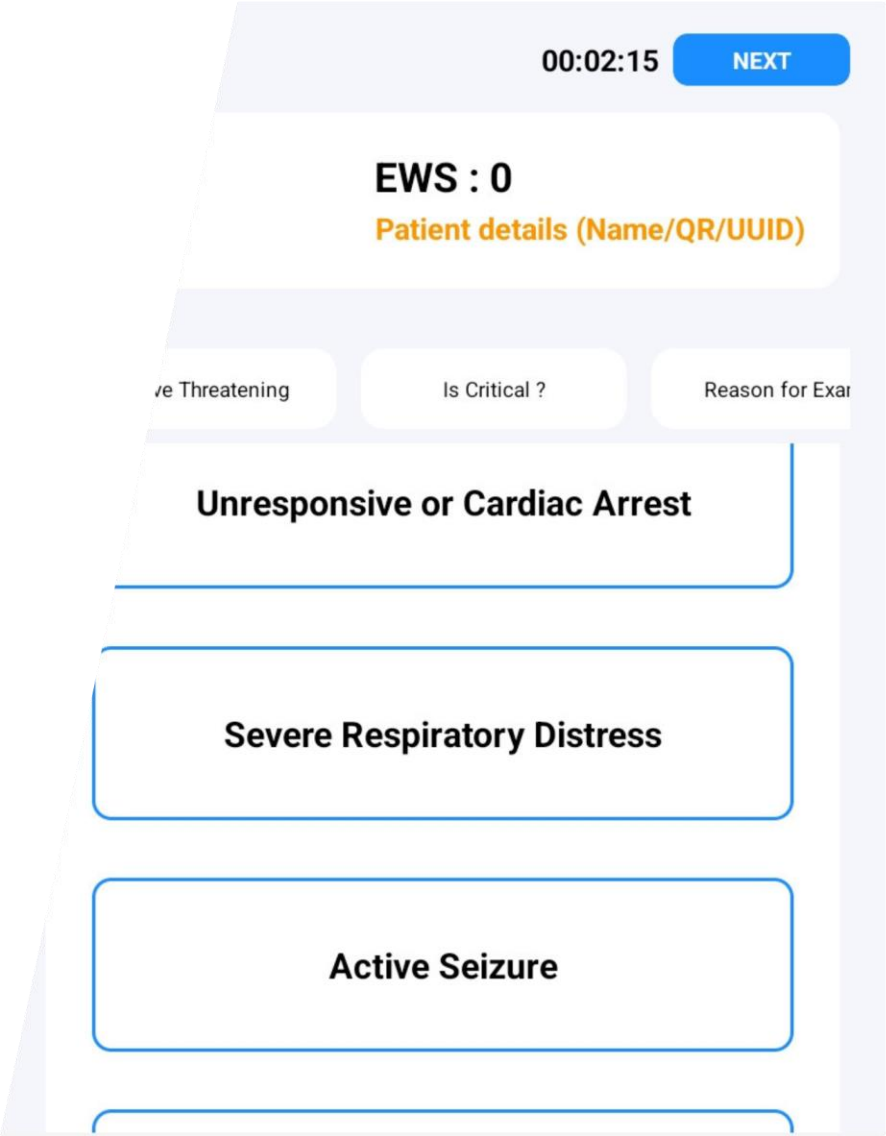
Triage

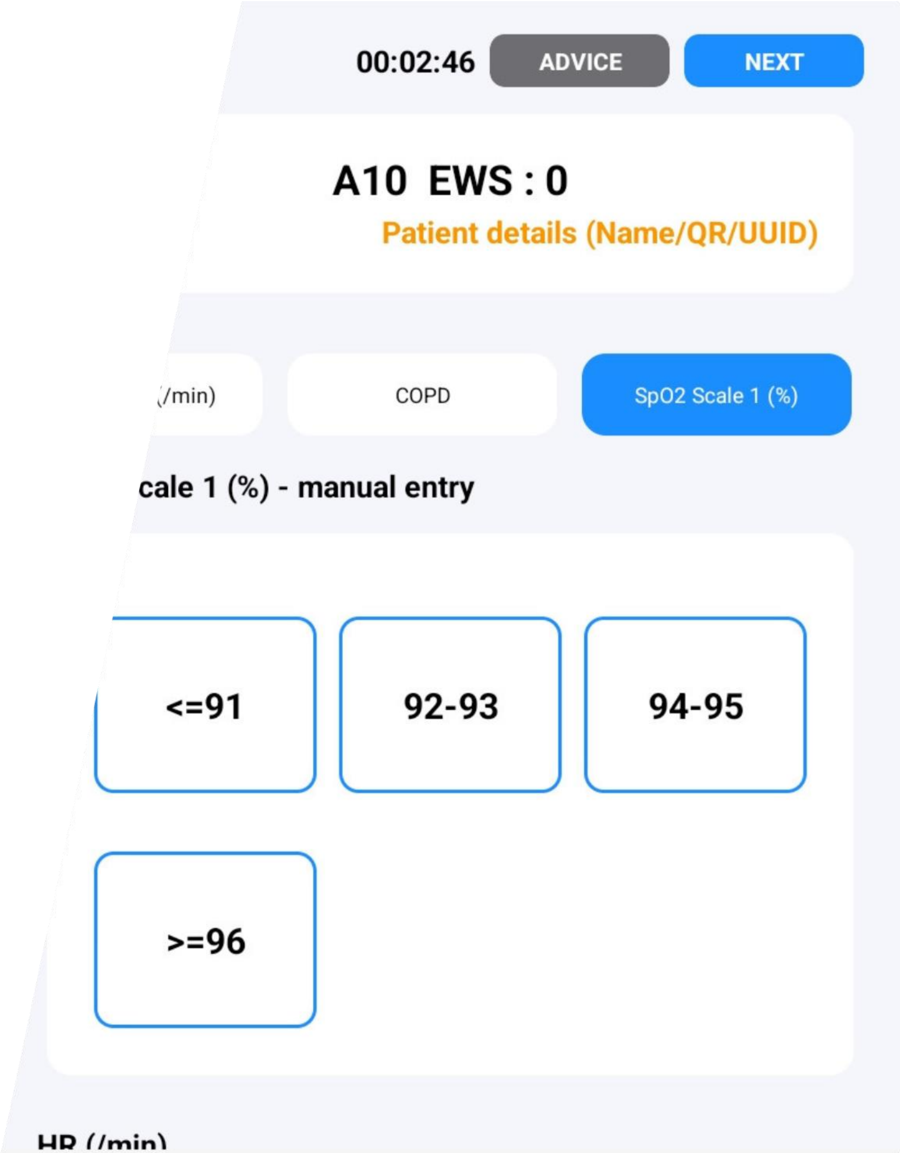
Physiological parameter	Score 3	2	1	0	1	2	3
Respiration rate (per minute)	≤8		9–11	12–20		21–24	≥25
SpO_2 Scale 1 (%)	≤91	92–93	94–95	≥96			
SpO_2 Scale 2 (%)	≤83	84–85	86–87	88–92 ≥93 on air	93–94 on oxygen	95–96 on oxygen	≥97 on oxygen
Air or oxygen?		Oxygen		Air			
Systolic blood pressure (mmHg)	≤90	91–100	101–110	111–219			≥220
Pulse (per minute)	≤40		41–50	51–90	91–110	111–130	≥131
Consciousness				Alert			CVPU
Temperature (°C)	≤35.0		35.1–36.0	36.1–38.0	38.1–39.0	≥39.1	

NEW score	Clinical risk	Response
Aggregate score 0–4	Low	Ward-based response
Red score Score of 3 in any individual parameter	Low–medium	Urgent ward-based response*
Aggregate score 5–6	Medium	Key threshold for urgent response*
Aggregate score 7 or more	High	Urgent or emergency response**

* Response by a clinician or team with competence in the assessment and treatment of acutely ill patients and in recognising when the escalation of care to a critical care team is appropriate.

**The response team must also include staff with critical care skills, including airway management.


00:02:15
NEXT
EWS : 0
Patient details (Name/QR/UUID)
ve Threatening
Is Critical ?
Reason for Exar
Unresponsive or Cardiac Arrest
Severe Respiratory Distress
Active Seizure


00:02:46
ADVICE
NEXT
A10 EWS : 0
Patient details (Name/QR/UUID)
(/min)
COPD
SpO2 Scale 1 (%)
cale 1 (%) - manual entry
<=91
92-93
94-95
>=96

This is 1st Generation AI

- A rule-based system to simulate a human's decision making
- Can not handle ambiguity
- Can not adapt to solve complex problems

JAMA Network Open

Original Investigation | Health Informatics

Early Warning Scores With and Without Artificial Intelligence

Dana P. Edelson, MD, MS; Matthew M. Churpek, MD, MPH, PhD; Kyle A. Carey, MPH; Zhenqiu Lin, PhD; Chenxi Huang, PhD; Jonathan M. Siner, MD; Jennifer Johnson, MSN, APRN; Harlan M. Krumholz, MD, SM; Deborah J. Rhodes, MD

JAMA Network Open. 2024;7(10):e2438986.

Corrected on November 7, 2024. doi:10.1001/jamanetworkopen.2024.38986

CONCLUSIONS AND RELEVANCE In this cohort study of inpatient encounters, eCART outperformed the other AI and non-AI scores, identifying more deteriorating patients with fewer false alarms and sufficient time to intervene. NEWS, a non-AI, publicly available early warning score,

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Next Generation AI

Piliuk K. Artificial intelligence in emergency medicine. A systematic literature review. Int J Med Inform. 2023 Dec;180:105274. doi: 10.1016/j.ijmedinf.2023.105274. Epub 2023 Oct 31. PMID: 37944275

Table 4
Summary of mortality prediction studies.

Reference	Main data input	Method
[1]	TRISS and ASCOT components	Logistic regression
[2]	Multiple triage scores components	Logistic regression
[3]	Multimodal input	Random forest
[78]	vital signs, heart rate variability	Support vector machine
[79]	Vital signs	Random forest
[80]	National Early Warning Score components, blood glucose	Random forest
[81]	ECG data	Logistic regression
[82]	Emergency calls	Gradient boosting, CNN, TabNet
[83]	Trauma description	Bagging classifier
[84]	Multimodal input	FCNN
[85]	Clinical measurements	FCNN, CNN
[86]	Vital signs	Prompt CNN
[87]	Vital signs	Logistic regression
[88]	Multimodal input	Multiple ML/DL methods
[89]	Ordinal features for the severity of injuries	Multiple ML/DL methods
[90]	Heart rhythm	Logistic regression, Random forest
[91]	Multimodal input	Multiple ML/DL methods
[92]	Multimodal input	Random forest
[93]	Multimodal input	Multiple ML/DL methods
[94]	Multimodal input	Multiple ML/DL methods
[95]	Multimodal input	AutoScore
[96]	Multimodal input	CNN
[97]	Multimodal input	AutoScore
[98]	EtCO2 levels	Multiple ML/DL methods
[99]	OMICS data	Multiple ML/DL methods
[100]	Data on accident	Decision tree
[101]	Vital signs	Decision tree
[102]	Admission notes	Word2Vec
[103]	Multimodal input	Multiple ML/DL methods
[104]	Intracranial/cerebral perfusion pressure	Logistic regression

Table 5
Summary of outcome prediction studies.

Reference	Main data input	Method
[106]	Clinical measurements	Ensemble of ML classifiers
[107]	First 24h ED measurements	Multiple ML/DL methods
[108]	Clinical measurements	Logistic regression
[110]	Clinical measurements, Biomarkers, Peptides	FCNN
[111]	Multimodal input	Bayesian additive regression trees
[109]	Prehospital on-scene factors (initial rhythm, witnessed arrest, etc.)	Decision tree
[112]	Data on resuscitation actions	FCNN
[113]	Multimodal input	FCNN
[114]	Lipidomic signatures	Linear regression, LASSO, SVM

The diagnostic and triage accuracy of the GPT-3 artificial intelligence model: an observational study

David M Levine*, Rudraksh Tuwani*, Benjamin Kompa, Amita Varma, Samuel G Finlayson, Ateev Mehrotra, Andrew Beam

Lancet Digit Health 2024; 6: e555–61

Interpretation A general-purpose AI language model without any content-specific training could perform diagnosis at levels close to, but below, physicians and better than lay individuals. We found that GPT-3's performance was inferior to physicians for triage, sometimes by a large margin, and its performance was closer to that of lay individuals. Although the diagnostic performance of GPT-3 was comparable to physicians, it was significantly better than a typical person using a search engine.

Review article

Artificial intelligence in emergency medicine. A systematic literature review

International Journal of Medical Informatics 180 (2023) 105274
https://doi.org/10.1016/j.ijmedinf.2023.105274

Konstantin Piliuk *, Sven Tomforde

- Common issues that are typical for the majority of the contributions
  - High specialization and lack of generalization
    - Among the 116 selected studies only 16 are not focusing on a specific disease, and only one of them is devoted to the diagnosis prediction
  - Universal benchmarks and data privacy issues
    - Both general and specific quantitative solutions suffer from the lack of commonly accepted data benchmarks, which can be used to consistently evaluate the performance of different algorithms
  - Data quality
    - Through data heterogeneity, we understand a variety of patient-specific information that can be used for modeling purposes.
  - Preference for ML methods

The architecture is composed of the following steps:

- Data Layer (Input Sources)
- Preprocessing & Feature Engineering
- Training and Validation
- Classification
- Integration layer
- Compliance and Security

Theoretical Background of ER-TRIAGE

Journal of Biomedical Informatics 41 (2008) 217–223

Tracing and cataloguing knowledge in an e-health cardiology environment

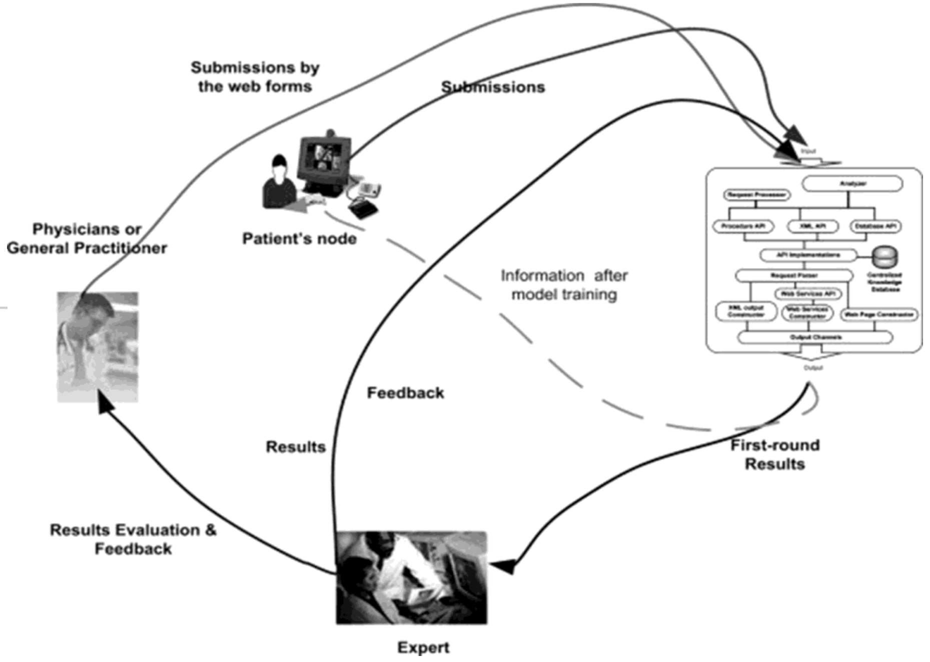
L.G. Gortzis *, G. Nikiforidis

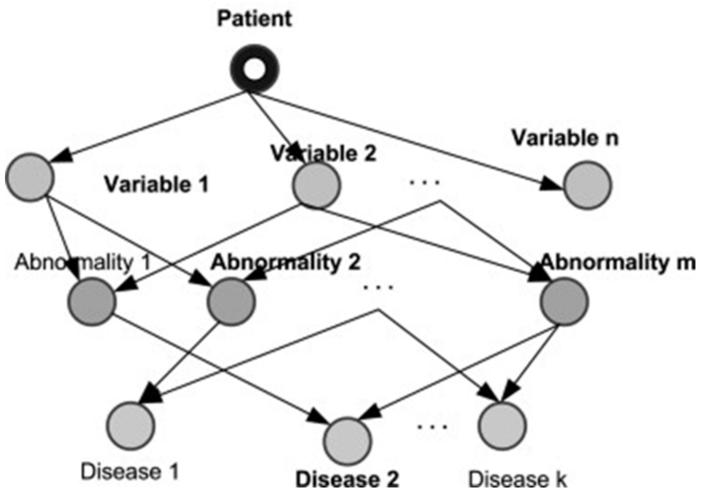
BMC Health Services Research

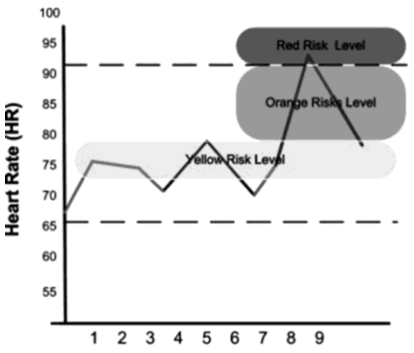
Research article

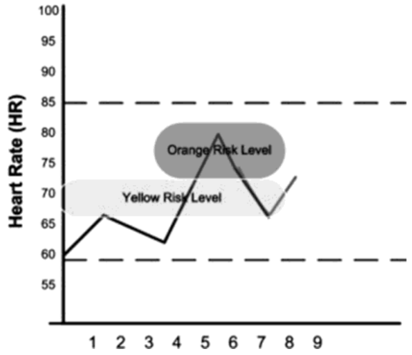
Predicting ICU survival: A meta-level approach

Lefteris G Gortzis*[1], Filippos Sakellaropoulos[1], Ioannis Ilias[2], Konstantinos Stamoulis[3] and Ioanna Dimopoulou[3]









Types of ML algorithms

- Deep Learning algorithms
  - Automatically learn feature hierarchies
  - Require a large amount of data to make predictions
  - Take significantly more time to train than traditional ML algorithms.
- In supervised learning, a decision tree is a method of classification and regression structured like a flowchart.
  - It recursively partitions the data into subsets based on the feature value that minimizes the impurity of the resulting subsets.
  - Ensemble learning is an ML method that combines multiple algorithms to increase accuracy and decrease variance

Open Access Review Article

DOI: 10.7759/cureus.59906

Cureus 16(5): e59906. DOI 10.7759/cureus.59906

Use of Artificial Intelligence in Triage in Hospital Emergency Departments: A Scoping Review

Samantha Tyler [1], Matthew Olis [1], Nicole Aust [1], Love Patel [1], Leah Simon [1], Catherine Triantafyllidis [1], Vijay Patel [1], Dong Won Lee [1], Brendan Ginsberg [1], Hiba Ahmad [1], Robin J. Jacobs [1]

- Limitations of the articles in the review
  - The limited scope of the data may not fully capture the variability and complexity of patient populations and clinical practices in different healthcare environments.
  - The exclusion of ED visits with missing data during the preprocessing stage was noted as a significant limitation by researchers
  - This exclusion of a large amount of data could have potentially affected the generalizability of the model.
  - Numerous datasets were derived from a single teaching hospital, also raising concerns about the generalizability of the prediction model to other hospital settings
  - All the authors of the articles in this review acknowledged that their study was based on retrospective data.
  - This absence of prospective validation is noteworthy since it may impact the applicability of the model to real-time clinical settings.
  - There are limitations to the potential influence of the ML models on physicians’ behavior in a real-world scenario.
  - When comparing the performance of ML models to that of healthcare professionals, no account for individual nurse demographics such as years of nursing and triage experience.
- Implications for future research
  - Future research could explore the long-term impact of AI on patient outcomes
  - The acceptance of AI among healthcare professionals
  - The development of standardized guidelines for AI implementation in emergency care settings

For our model

- We started from zero
- Two centers with different characteristics
  - Urban – Rural
  - High volume – medium volume
- Prospective data input
- Concise flow chart
- Multiple established parameters
- Pre-defined training program for triage personnel
- Triage personnel are “blind” to the AI processes running in the background
- No time pressure

Data Layer

- Clinical Input
  - Patient demographics: age, gender
  - Vital signs: NEWS 2
  - Symptoms: ICPC2, HEART, ROSIER
  - History: OPQRST, SAMPLE
- Structured Input
  - User-friendly interface
  - HL7/FHIR compatible data feeds
  - Triage assessment
- Sensors / Diagnostic equipment Integration

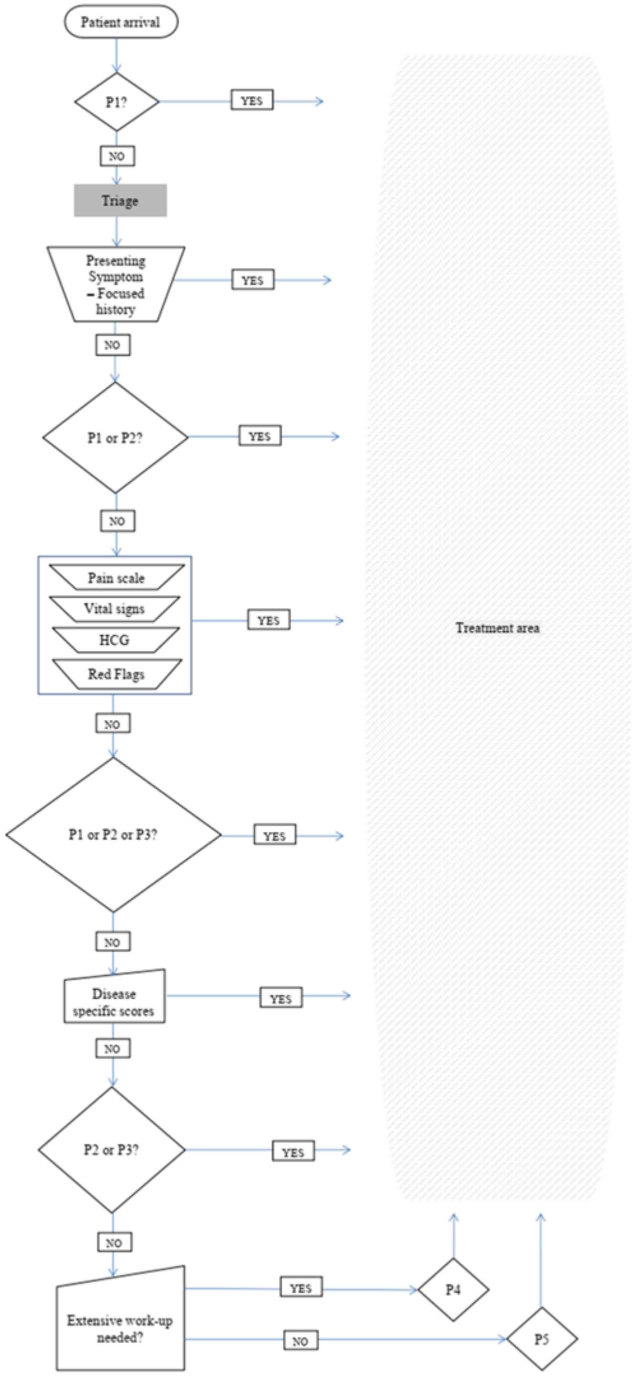
healthcare

MDPI

Review

Adult triage in the Emergency Department. Introducing a multi-layer triage system

Dimitrios Tsiftsis [1,*], Andreas Tasioulis [2] and Dimitrios Bampalis [3]



Clear end points

- From the ED
  - Triage personnel Priority level assignment
  - ED outcome
    - Death
    - Admission
    - Discharge
  - From admissions
    - Working diagnosis on admission
    - Final diagnosis on discharge
    - Days in hospital
    - In hospital deaths

7 Steps to More Effective Parenting

- Catch Kids Being Good
- Set Limits and Be Consistent
- Make Time for Your Kids
- Be a Good Role Model
- Make Communication a Priority
- Be Flexible and Willing to Adjust Your Parenting Style
- Know Your Own Needs and Limitations as a Parent

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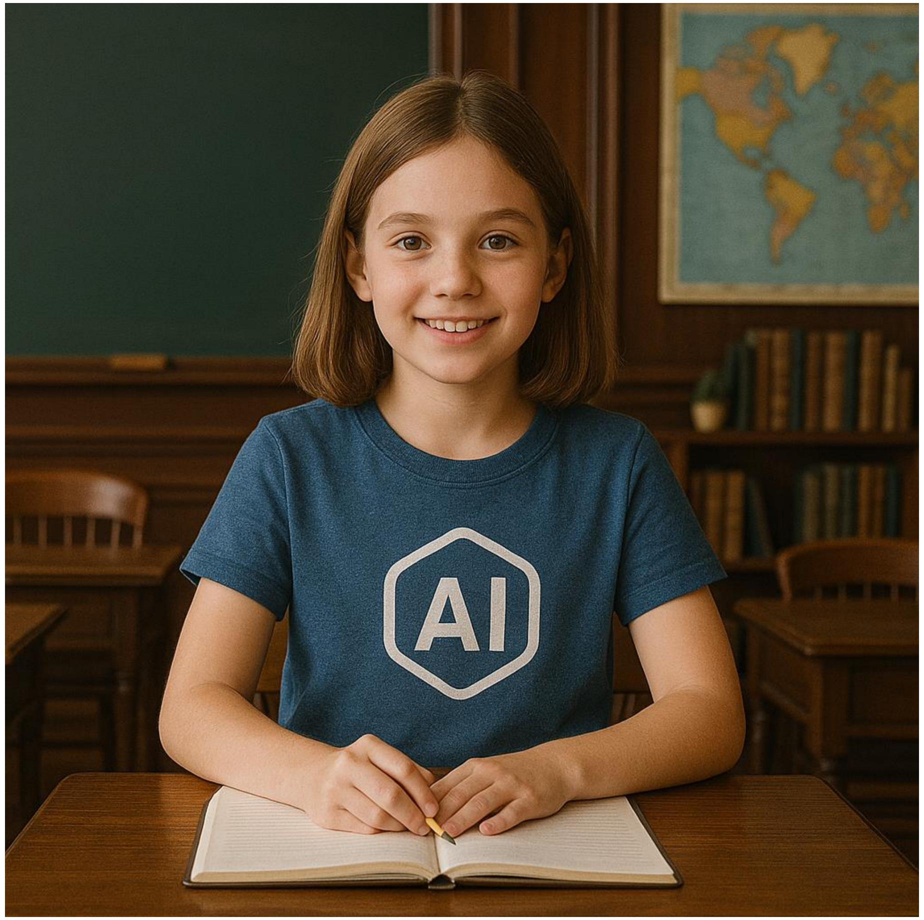

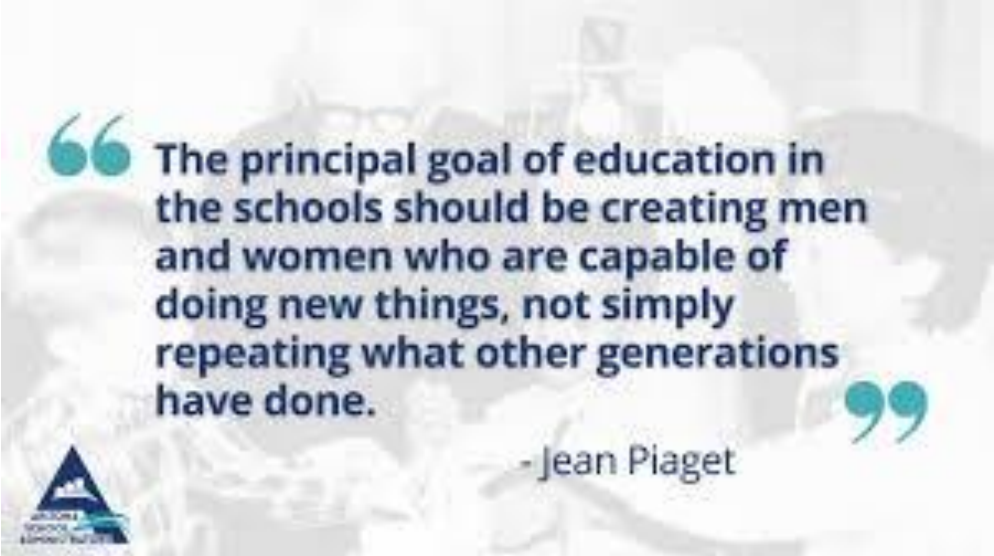

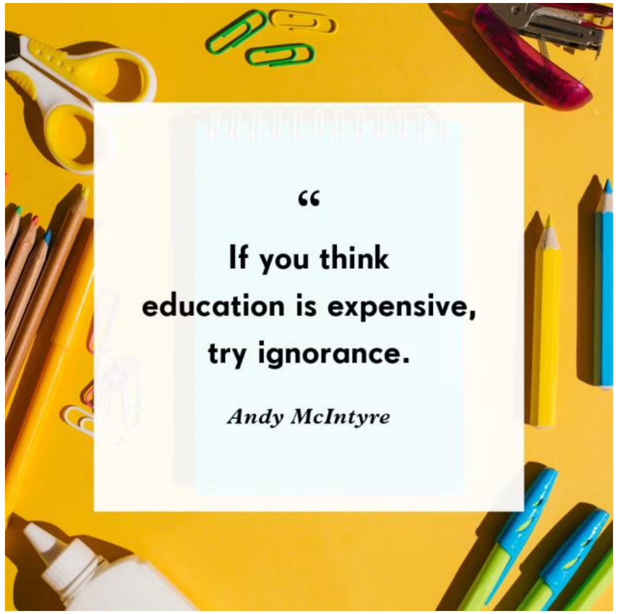

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Today

- We have the algorithm
- The system has been debugged
- We have the hardware
- We have trained our personnel on the triage process
- We have a friendly user interface
- We have a rule-based system in place
- We have run simulated triage scenarios with our triage staff

Next steps

- Run simulated scenarios with and without the system
- Partial real-life implementation
- Full real-life implementation

For questions and collaboration

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WACEM World Academic Council of Emergency Medicine

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