Autonomous Emergency Triage Support System

Short Paper — CSCI-RTHI

Ol'Tunde Ashaolu[†]*, William Lyons[‡]*, Ioannis Stefanakos[‡], Radu Calinescu[‡], Ibrahim Habli[‡], Victoria Hodge[‡], Chiara Picardi[‡], Katherine Plant[§], Beverley Townsend[‡]

[†]York and Scarborough Teaching Hospitals, NHS Foundation Trust / Hull-York Medical School, York, UK
[‡]Department of Computer Science, University of York, York, UK
[§]Faculty of Engineering and Physical Sciences, University of Southampton, Southampton, UK

tunde.ashaolu@nhs.net, {billy.lyons,ioannis.stefanakos,radu.calinescu,ibrahim.habli,victoria.hodge,chiara.picardi}@york.ac.uk, k.plant@soton.ac.uk, bev.townsend@york.ac.uk

*The first two authors contributed equally to the research presented in this paper.

***Abstract*—Medical staff shortages and growing healthcare demands due to an ageing population mean that many patients face delays in receiving critical care in the emergency departments (EDs) of hospitals worldwide. As such, the use of autonomous, robotics and AI technologies to help streamline the triage of ED patients is of utmost importance. In this paper, we present our ongoing work to develop an *autonomous emergency triage support system* intended to alleviate the current pressures faced by hospital emergency departments. By employing a combination of robotic and AI techniques, our solution aims to speed up the initial stages of ED triage. Its preliminary evaluation using synthetic patient datasets generated with ED medic input suggests that our solution has the potential to improve the ED triage process, supporting the timely and accurate delivery of patient care in emergency settings.**

***Index Terms*—autonomous systems, AI, healthcare, emergency triage, emergency care**

I. Introduction

Healthcare systems around the world were facing staff shortages and other challenges [1], [2] even before encountering the added complexities of the COVID-19 pandemic. The pandemic then amplified these difficulties and greatly increased the emotional stress and infection risk for healthcare professionals [3]. As such, it is imperative to leverage new and emerging technologies in order to alleviate the growing pressures on medical personnel, supporting and enabling them to utilize their limited time with increased efficacy.

The emergency department (ED) in hospitals is a prime area where high demand and staff shortages can easily lead to unacceptably long waiting times, with a significant negative impact on the emergency care received by patients. Long wait times adversely impact patient satisfaction, and heighten the risk of both administrative and medical errors, associated with adverse outcomes and a rise in patient mortality [4]. Prolonged ED waiting times also correlate with extended inpatient stays [4], [5], exacerbating the pressures on an already short-staffed system. This initial point of interaction in hospitals presents an opportunity to exploit new technologies with the potential to enhance patient experience and well-being.

Emergency triage [6] is a process used in medical settings, particularly ED, to rapidly assess and prioritise patients based on the severity of their condition. The aim is to ensure that those with the most serious or life-threatening injuries or illnesses are treated first, while those with less severe conditions are attended to with lower priority. The improvement of the triage process, also affected by the aforementioned issues, has already been targeted by several approaches using artificial intelligence [7], [8] and autonomous (robotic) systems [9]. However, the lack of a singular standard for categorising patient severity in these approaches limits their wide application and adaptation within the triage process.

In this paper, we present a robot-assisted emergency triage solution that is easily adaptable and can: (i) recommend a course of action to be escalated to the doctor; and (ii) automate several triage tasks, reducing the workload of ED nurses and doctors. The rest of the paper is organised as follows. Section II defines a five-stage ED triage process based on existing literature and our conversations with emergency clinicians. Section III presents our autonomous emergency triage support system, and Section IV provides a preliminary evaluation of this solution. Section V compares our overall approach with existing work. Finally, Section VI provides a summary of the research, and presents our directions for future work.

II. Emergency triage process

Fig. 1 depicts the five key stages of the ED triage process, which we identified through integrating the results of established studies of the ED triage activities [10], [11] and the findings from our dedicated conversations with ED clinicians from our project partner York and Scarborough Teaching Hospitals NHS Foundation Trust, UK. This diagram summarises the main objectives and potential enhancements for each phase. We note that, as with any high-level representation of a complex process, this diagram cannot capture all details and specific clinical requirements of each phase. Furthermore,

This work received funding from the UKRI Trustworthy Autonomous Systems Hub, UKRI project EP/V026747/1 'Trustworthy Autonomous Systems Node in Resilience', and the Assuring Autonomy International Programme.

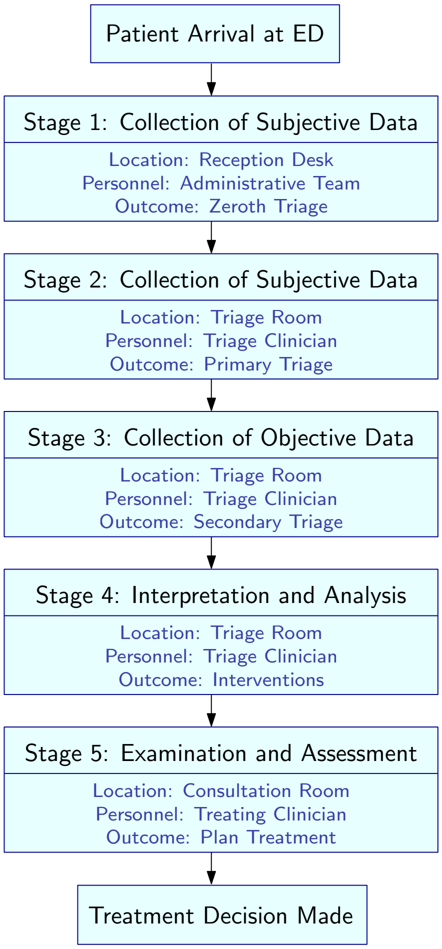

Fig. 1. The five stages of the emergency triage process.

the execution of the activities within subsequent five stages may overlap, in particular because the process needs to be tailored to each patient's unique circumstances. Nevertheless, summarising the ED triage process in this way remains a very useful means of capturing its main stages and activities, which are briefly described below.

Stage 1: When patients first arrive at the ED on their own (i.e., as opposed to being brought to the hospital by an ambulance), they approach a reception desk. Here, administrative healthcare personnel gather preliminary information based on what the patient describes. This team, through a visual assessment and listening to the patient's description, conducts an initial (or "zeroth level") triage. If a case appears severe, it can be escalated immediately. However, most cases proceed to the following stage.

Stage 2: In this stage, a trained clinician continues to gather detailed information from the patient. They delve deeper into the patient's initial account, asking more specific questions about the patient's symptoms. This helps to form a clearer clinical picture. While critical situations can be escalated as in Stage 1, most cases move to the next step.

Stage 3: This stage typically overlaps with Stage 2. The clinician uses devices to monitor and measure vital parameters like blood pressure, oxygen levels, and temperature. These objective data offer a concrete perspective into the patient's health, aiding in triage. Given the availability of these data, it is common for cases to be escalated (if needed) at this stage.

Stage 4: Here, the triage clinician assesses all collected data to judge the severity of the illness, finalize the triage category, and pinpoint potential diagnoses. Depending on the analysis, several actions can be taken. The possible outcomes of this stage include escalating the case, moving the patient to a treatment area, sending the patient back to the waiting room, or directing the patient to other hospital departments.

Stage 5: At this point, the treating clinician reviews all the gathered data. They then physically examine the patient, aiming to solidify or adjust the initial diagnosis. After this, the clinician decides on a management strategy in coordination with the rest of the healthcare team. The outcomes of the stage vary from completing treatment and discharging the patient, to referring them for in-depth investigations or sending them to another hospital facility.

The prototype autonomous emergency triage support system presented in this paper covers a subset of activities spanning Stages 2 through 5. To that end, our system gathers the patient information from Stages 2 and 3, and then proposes assessment results and suggestions, and recommends further investigations and preliminary low-level treatments corresponding to several of the activities from Stages 4 and 5. Notably, even though our system's data collection covers Stages 2 and 3 of the ED triage process, it coincides temporally with Stage 1 of the conventional triage process, in the sense that it takes place without a medical expert's oversight.

III. Technical Solution

Our proposed technical solution, called 'Diagnostic AI SYstem for robot-assisted ED triage' or 'DAISY' for short, is a semi-autonomous, socio-technical AI-supported system designed to guide ED patients through the triage process. This system captures both objective and subjective data. Patients are facilitated to provide personal information about their health conditions, and DAISY assists them in using wirelessly connected medical devices to obtain vital signs measurements like blood pressure, heart rate, temperature, and respiratory rate. At its core, DAISY employs a rule-based Diagnostic Algorithm for Intelligent Clinical Intervention (`dAvInci`) designed by an ED medical expert (see Section III-C). This algorithm maps the patients' demographics, characteristics, symptoms, and vital signs to potential health conditions, and evaluates the urgency of the medical interventions required.

Example 1. Consider the representation of a rule for an assessment of potential meningitis[1] as depicted in Fig. 2. This rule indicates that for a patient to potentially suffer from meningitis she or he can have any demographic information, should be experiencing symptoms in either the head or neck,

[1]Meningitis is an infection of the protective membranes that surround the brain and spinal cord (meninges).

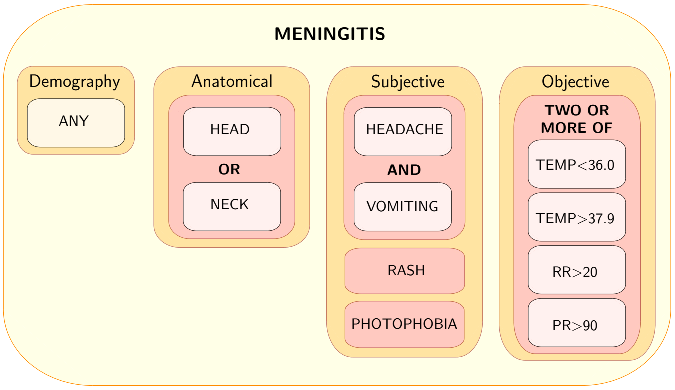

Fig. 2. Rule for an assessment of potential meningitis. TEMP refers to temperature, RR is respiratory rate, and PR is pulse rate.

should have either a rash or photophobia, or headache and vomiting together, and any two or more of the objective signs listed in the rightmost area (labelled 'Objective') from Fig. 2.

DAISY's strength lies in its ability to detect potential health challenges, recommend further diagnostic tests, and suggest relevant specialist consultations. The system is able to analyse four classes of patient data – demographic, anatomic, subjective, and objective – together, making the identification of potential maladies more efficient. The algorithm then produces a comprehensive preliminary report of potential early diagnoses and additional tests based on the gathered data.

These initial insights undergo a validation process, in which medical practitioners can approve, modify, or discard them, aiding the preliminary ED triage phases.

A. *Automated triage workflow*

We identify two primary users of the DAISY system, i.e. patients and clinicians, each accessing the system in ways that are distinct from one another, and distinct from the typical patient-clinician interaction scenarios. Fig. 3 depicts the workflow of the DAISY process. Upon arrival at the ED, patients will be presented with two options: proceed with the standard triage process or opt for DAISY.

Patients using DAISY will attend a prearranged triage location which will contain equipment suitable for collecting objective signs (blood pressure, temperature, respiratory rate, pulse rate, and blood oxygen saturation). An autonomous agent (i.e., a social robot) will guide the patient through a series of surveys designed by the clinical members of the team to collect pertinent information for the `dAvInci` algorithm, and will subsequently assist the patient through the use of the medical equipment to collect their vital signs measurements. The agent will then guide the patient to the waiting room, and a member of the clinical staff will be available for healthcare provision and/or additional investigations.

Clinicians receiving the DAISY output, will obtain the reported symptoms per anatomical area, relevant demographic information, objective signs, as well as a series of potential assessment outcomes and investigations that the system suggests alongside low-level treatment interventions like painkillers and antibiotics. The clinicians receiving this information can make their own assessments in conjunction with the system's assessments and investigations, confirming, adding, or removing the system suggestions as and where they deem it appropriate. The ongoing plan decided by the treating clinician can then be enacted by clinical staff to confirm potential diagnoses, or the treating clinician can attend the patient directly to confirm and refer the patient to an appropriate healthcare setting.

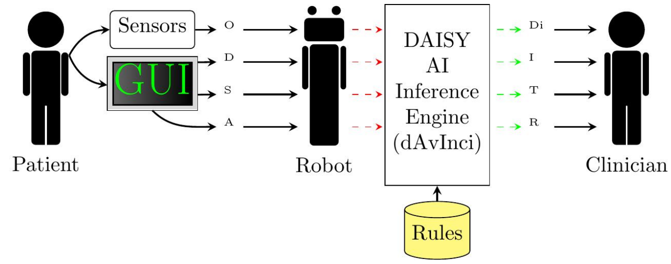

Fig. 3. DAISY workflow: Guided by an autonomous robot, the patient uses a graphical user interface (GUI) running on a tablet computer and a series of sensors to provide Demographic (D), Subjective (S), Objective (O) and Anatomic (A) data inputs, which the robot computer then processes to produce a report comprising Diagnostic (Di), Investigation (I), Treatment (T) and Referral (R) suggestions for an ED clinician to consider.

More information about the system and a demonstration that illustrates its intended use are available on our project's website at https://www.cs.york.ac.uk/research/projects/daisy-project/.

B. *Architecture*

We outline the architecture and components of the DAISY system using the C4 modelling approach (https://c4model.com/) for visualising software architectures due to its clarity for abstracting software, particularly useful across multidisciplinary teams. The context of the DAISY system has two main use cases. The primary use case is a loop, starting with the patient interacting with the robot to provide medically relevant information that is then supplied to the `dAvInci` algorithm for processing. The outcome of this process is compiled into a standardised form, and sent to a printer for use by a member of the emergency department's medical team. As can be seen in Fig. 4, the secondary use case requires minimal interaction with the other elements of the DAISY context, and consists solely of the healthcare expert interacting with the knowledge base of rules for either adding new rules or updating the existing rules.

The interface for the primary use case is the touchscreen of the robot, or alternatively a touchscreen tablet as shown in Fig. 5. This option was selected due to the necessity to develop a tool that could be used across various platforms. As such, the decision was made to opt for a web application.

The front-end of the web application captures the demographics, the symptoms and the vital metrics of the patient using a patient form. Upon submission of the form, the data provided is sent via the local network to the back-end, where it is then passed through the `dAvInci` inference engine. The inference engine operates on the obtained patient data to generate potential assessment results and suggested

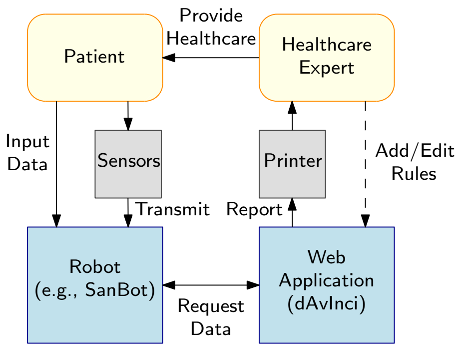

Fig. 4. Context of the DAISY system with the two use cases. The primary use case (solid arrows), and the secondary use case (dashed arrow).

investigations, treatments and referrals for the patient. This is then subsequently sent to a report constructor to generate a report of the form outlined by our clinical investigator, which in a clinical setting would be de-anonymised and printed for the healthcare expert to review and act on.

C. Triage algorithm

The conceptualisation of the `dAvInci` algorithm evolved around a formulaic methodology for questions to ask, and triggers for potential diagnoses and investigations common to the ED triage domain. These were distilled both from NHS guidelines and practices, as well as the extensive experience of our NHS consultant. Specifically, we observed that each parameter which defines a patient can be described by decomposition of one of four medically distinct datatypes, i.e. *Demographic, Anatomic, Subjective,* and *Objective*.

Given (i) the sets of all possible objective, demographic, subjective and anatomic property names $All\_DemProps$, $All\_AnatProps$, $All\_SubjProps$ and $All\_ObjProps$, respectively, (ii) a function $range$ that takes one of these property names and returns the set of possible values for that property, and (iii) the patient datasets

$$\begin{aligned} D &= \{(dProp, val) \mid dProp \in All\_DemProps \wedge \\ &\quad val \in range(dProp)\} \\ A &= \{(aProp, val) \mid aProp \in All\_AnatProps \wedge \\ &\quad val \in range(aProp)\} \\ S &= \{(sProp, val) \mid sProp \in All\_SubjProps \wedge \\ &\quad val \in range(sProp)\} \\ O &= \{(oProp, val) \mid oProp \in All\_ObjProps \wedge \\ &\quad val \in range(oProp)\} \end{aligned}$$

the algorithm computes the set of assessments to recommend as:

$$\begin{aligned} Assessments(D, A, S, O) = \{a : All\_Assessments \mid \\ dem(a, D) \wedge anat(a, A) \\ subj(a, S) \wedge obj(a, O)\}. \end{aligned} \tag{1}$$

In this equation, $obj(a, O) = boolExpr_a(BO_a)$, ..., where $boolExpr_a$ is a boolean expression with operators AND, OR, NOT over the atomic propositions from

$$BO_a = \{\text{`}val \in target\_val_a(oProp)\text{'} \mid (oProp, val) \in O\},$$

and $target\_val_a(oProp) \subseteq range(oProp)$ is a set of values that property $oProp$ may take and that are of relevance to assessment (i.e., "malady") a; and each of functions $dem(a, D)$, $anat(a, A)$ and $subj(a, S)$ are defined in an analogous manner for the other three types of patient data.

Each potential assessment outcome of the patient, suggested investigations, treatments, and referrals are defined by relationships of these parameters both within their datatype, as well as extrinsic to their own datatype.

Example 2. Consider again the example of Fig. 2. Given this rule format, we can formalise the four functions from (1) as follows:

$$\begin{aligned} dem(\text{meningitis}, D) &= \mathsf{true} \\ anat(\text{meningitis}, A) &= \text{head} \vee \text{neck} \\ subj(\text{meningitis}, S) &= (\text{headache} \wedge \text{vomiting}) \vee \text{rash} \\ &\qquad \vee \text{photophobia} \\ obj(\text{meningitis}, O) &= (T > 37.9 \vee T < 36) \wedge PR > 90 \\ &\quad \vee (T > 37.9 \vee T < 36) \wedge RR > 20 \\ &\quad \vee (PR > 90 \wedge RR > 20) \end{aligned}$$

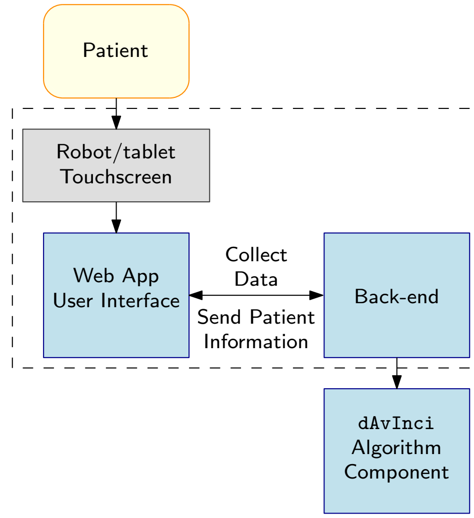

Fig. 5. The web application component.

D. Implementation

The implementation of the DAISY system is divided into two containers. The first pertains to the robotic elements of the solution, such as navigation, avoidance, and human-robot interaction, as seen in Fig. 6. The second focuses on the technical execution of the `dAvInci` algorithm as a functional program.

As the first part is still in early stages, our primary focus has been the implementation of the `dAvInci` algorithm in order to test the validity of our solution against potential patient datasets. Through the graphical user interface provided by the constructed web application we were able to get clinicians involved into testing DAISY and generating synthetic datasets to be used during the system's preliminary evaluation. A screenshot of the web application's graphical user interface

Fig. 6. A user's interaction with DAISY during vital measurements.

can be seen in Fig. 7. In the depicted scenario, the user has already selected the anatomy related to the experiencing issue, and the system prompts them to indicate a pain score and some additional observations, before generating the final report.

IV. Preliminary Evaluation

Having completed the implementation of our solution, we are now in the early stages of evaluating its correctness and usability. The preliminary results of these evaluations are summarised below.

Correctness evaluation. For our early evaluation of the DAISY correctness, the emergency clinician member of the team assembled a synthetic dataset comprising 6237 patient entries for testing the triage capabilities of our solution. As shown in Table I, these data entries covered a broad range of medical conditions, patient demographics, etc.

Each of the synthetic patient entries were supplied to the deployed DAISY system, which generated triage reports for all entries. Each of these reports was then manually checked by our medical expert, with 81.74% of the reports confirmed as producing correct assessments (16995 out of 20790). We are currently working on fine-tuning the DAISY ruleset to address the issues identified by this preliminary evaluation, with our investigation of these issues indicating that they are due to an incomplete ruleset and ranking system as there are often multiple terms referring to the same or similar illness.

Usability evaluation We additionally assessed the usability of our DAISY solution by inviting 12 participants with a computer science background to experiment using a prototype of the system and provide their thoughts from a user's perspective. The findings of this study are summarised in Table II below, which shows the overall positivity of the users in using DAISY. We are also planning to invite more users in our usability evaluation from more diverse backgrounds.

V. Related Work

The majority of research in the literature focuses on a singular stage of the triage process, with a lower percentage

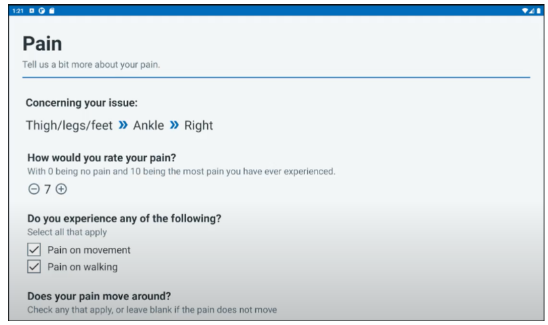

Fig. 7. Screenshot from the web application's graphical user interface.

of the proposed approaches extending beyond a single stage. Specifically, the work in [12] employs a symptom checker used at the ED that offers guidance on the severity of a patient's condition. It also suggests the most appropriate setting for treatment, whether that be in a hospital, primary care facility, or at home. While symptom checkers can aid in ED triage, they're more effective when used before arriving at the ED to reduce unnecessary visits, as highlighted in many studies.

Additionally, the authors in both [8] and [13] propose the use of machine learning techniques to monitor patients' symptoms. The first approach aims at identifying those who should be directed to a "Fast Track" system, and the second those that need to undergo head CT exam, and by that allowing clinicians to attend to them promptly with a faster diagnosis and treatment. An extreme gradient boosting decision tree framework is presented in [14] that is used towards developing a model that predicts re-attendance to the ED by patients who have not been admitted.

An IoT-wearable device that obtains information on heart rate, temperature, oxygen saturation and respiratory rate is introduced in [15], which also monitors the patient and provides alerts in case of a sudden change. While such devices would need thorough validation, significant changes in sensor readings could serve as a sign of deteriorating health, prompting clinical staff to prioritize the patient for monitoring.

Machine learning and clinical natural language processing are employed in [16] to classify patients into an existing triage system. Using medical history, medication data, risk factors, and vital signs, the model produced a triage acuity classification more accurate than that of triage nurses.

The closest comparable to the DAISY methodology is the approach proposed in [17], which uses anchor learning to generate patient phenotypes which provide potential assessments, investigation and treatment plans. However, unlike the previously described approaches, DAISY is the only methodology that covers all five triage stages of the ED triage.

VI. Conclusion and Future Work

The escalating challenges faced by hospital emergency departments worldwide, exacerbated by medical staff shortages and an ageing population, necessitate innovative approaches to patient triage. Our proposed work towards the development of an autonomous emergency triage support system, leveraging robotic and AI technologies, offers a promising

TABLE I
SUMMARY OF THE PATIENT CHARACTERISTICS FROM THE SYNTHETIC DATA ENTRIES.

Category	Patient Characteristics				
Age	18-35 (28.57%)	36-45 (15.87%)	46-55 (15.87%)	56-65 (15.87%)	65+ (23.81%)
Sex	male (55.56%)	female (33.33%)	neutral (11.11%)		
Temperature	<35.5C (9.09%)	35.5C-36.9C (27.27%)	37C-38.4C (27.27%)	>38.4C (36.36%)	
Oxygen Saturation	>95% (100.00%)				
Systolic BP	90-120 mmHg (22.22%)	>120 mmHg (77.78%)			
Diastolic BP	60-80 mmHg (88.89%)	>80 mmHg (11.11%)			
Medical Condition	cardiovascular (33.33%)	injury (11.11%)	respiratory (11.11%)	other (44.55%)	
Medical History	diabetes (11.11%)	learning disability (11.11%)	asthma (11.11%)	mental health (11.11%)	other (11.11%)
Drug History	warfarin (11.11%)	beta blockers (22.22%)	other (11.11%)		
Allergies	penicillin (55.56%)	other (11.11%)			
Family History	diabetes (11.11%)				
COVID-19 Vaccination	yes (77.78%)	no (22.22%)			

TABLE II
DAISY USABILITY EVALUATION QUESTIONS, WHERE 1.STRONGLY DISAGREE, 2.DISAGREE, 3.NEUTRAL, 4.AGREE, 5.STRONGLY AGREE.

Question	Average Score
Evaluating step 1: Inputting information	
I found the DAISY system easy to use	4
I would probably need the support of a technical person to use this DAISY system part	2
I felt confident using the DAISY system	3.67
I thought there was too much inconsistency in the DAISY system	1.92
I felt frustrated using the DAISY system	2.17
I felt satisfied using the DAISY system	4
I felt the mental demand for this activity was reasonable and manageable	3.75
Evaluating step 2: Medical equipment	
I found the medical equipment easy to use	3.33
I would probably need the support of a technical person to use the medical equipment	3.42
I felt confident using the medical equipment	3.33
I thought there was too much inconsistency in the medical equipment	2.08
I felt frustrated using the medical equipment	2.08
I felt satisfied using the medical equipment	3.5
I felt the mental demand for this activity was reasonable and manageable	3.67
I felt the physical demand for this activity was reasonable and manageable	3.83
Thinking about the system overall and its output	
I feel suspicious of the DAISY system	2
I am confident in the DAISY system	3.25
The DAISY system has high integrity	3.5
I can trust the DAISY system	3.42
The DAISY system provides security	3.8
The DAISY system is reliable	3

avenue to address these challenges. Preliminary evaluations using synthetic patient datasets, underpinned by real-world medic insights, attest to the system's potential in enhancing the efficacy of the ED triage process. Such advancements not only have the potential to alleviate existing pressures on emergency healthcare professionals but also pave the way for the consistent, timely, and accurate delivery of critical care, ensuring optimal patient outcomes in emergency scenarios. As future work, we plan to continue improving the algorithm's implementation to achieve results of higher accuracy, and also, test our solution against real patient datasets from hospitals.

REFERENCES

[1] B. Finlayson, J. Dixon, S. Meadows, and G. Blair, "Mind the gap: the extent of the nhs nursing shortage," *BMJ*, vol. 325, pp. 538–541, 2002.

[2] M. Marć, A. Bartosiewicz, J. Burzyńska, Z. Chmiel, and P. Januszewicz, "A nursing shortage–a prospect of global and local policies," *International Nursing Review*, vol. 66, pp. 9–16, 2019.

[3] E. David, J. M. DePierro, D. B. Marin, V. Sharma, D. S. Charney, and C. L. Katz, "Covid-19 pandemic support programs for healthcare workers and implications for occupational mental health: A narrative review," *Psychiatric Quarterly*, vol. 93, pp. 227–247, 2022.

[4] G. Savioli, I. F. Ceresa, N. Gri, G. Bavestrello Piccini, Y. Longhitano, C. Zanza, A. Piccioni, C. Esposito, G. Ricevuti, and M. A. Bressan, "Emergency department overcrowding: Understanding the factors to find corresponding solutions," *Journal of Personalized Medicine*, 2022.

[5] S. Wyatt, R. Joshi, J. M. Mortimore, and M. A. Mohammed, "Relationship between emergency department and inpatient occupancy and the likelihood of an emergency admission: a retrospective hospital database study," *Emergency Medicine Journal*, vol. 39, pp. 174–180, 2022.

[6] K. Mackway-Jones and C. Robertson, *Emergency triage*. BMJ, 1997.

[7] H. Elhaj, N. Achour, M. H. Tania, and K. Aciksari, "A comparative study of supervised machine learning approaches to predict patient triage outcomes in hospital emergency departments," *Array*, vol. 17, 2023.

[8] W. Caicedo-Torres, G. García, and H. Pinzón, "A machine learning model for triage in lean pediatric emergency departments," in *Advances in Artificial Intelligence*, 2016, pp. 212–221.

[9] S. Kotha, H. Viswanath, K. Tiwari, and A. Bera, "Artemis: Ai-driven robotic triage labeling & emergency medical information system," 2023.

[10] A. Kuriyama, S. Urushidani, and T. Nakayama, "Five-level emergency triage systems: variation in assessment of validity," *Emergency Medicine Journal*, vol. 34, pp. 703–710, 2017.

[11] C. M. Fernandes, P. Tanabe, N. Gilboy, L. A. Johnson, R. S. McNair, A. M. Rosenau, P. Sawchuk, D. A. Thompson, D. A. Travers, N. Bonalumi, and R. E. Suter, "Five-Level Triage: A Report from the ACEP/ENA Five-Level Triage Task Force," *Journal of Emergency Nursing*, vol. 31, pp. 39–50, 2005.

[12] F. Chan, S. Lai, M. Pieterman, L. Richardson, A. Singh, J. Peters, A. Toy, C. Piccininni, T. Rouault, K. Wong, J. K. Quong, A. T. Wakabayashi, and A. Pawelec-Brzychczy, "Performance of a new symptom checker in patient triage: Canadian cohort study," *PLOS ONE*, vol. 16, 2021.

[13] E. Klang, Y. Barash, S. Soffer, S. Bechler, Y. S. Resheff, T. Granot, M. Shahar, M. Klug, G. Guralnik, E. Zimlichman, and E. Konen, "Promoting head ct exams in the emergency department triage using a machine learning model," *Neuroradiology*, vol. 62, pp. 153–160, 2019.

[14] F. P. Chmiel, D. K. Burns, M. Azor, F. Borca, M. J. Boniface, Z. D. Zlatev, N. M. White, T. W. V. Daniels, and M. Kiuber, "Using explainable machine learning to identify patients at risk of reattendance at discharge from emergency departments," *Scientific Reports*, 2020.

[15] B. Fyntanidou, M. Zouka, A. Apostolopoulou, P. D. Bamidis, A. Billis, K. Mitsopoulos, P. A. Angelidis, and A. Fourlis, "Iot-based smart triage of covid-19 suspicious cases in the emergency department," *IEEE Globecom Workshops*, pp. 1–6, 2020.

[16] O. Ivanov, L. A. Wolf, D. Brecher, K. Masek, E. Lewis, S. Liu, R. B. Dunne, K. Klauer, K. Montgomery, Y. Andrieiev, M. McLaughlin, and C. Reilly, "Improving emergency department esi acuity assignment using machine learning and clinical natural language processing," *Journal of emergency nursing*, 2021.

[17] Y. Halpern, S. Horng, Y. Choi, and D. Sontag, "Electronic medical record phenotyping using the anchor and learn framework," *Journal of the American Medical Informatics Association*, pp. 731–740, 2016.