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# Decision support system for triage management: A hybrid approach using rule-based reasoning and fuzzy logic

Mahsa Dehghani Soufi[a], Taha Samad-Soltani[a], Samad Shams Vahdati[b], Peyman Rezaei-Hachesu[a,c,*]

[a] Department of Health Information Technology, School of Management and Medical Informatics, Tabriz University of Medical Sciences, Tabriz, Iran
[b] Road Traffic Injury Research Center, Department of Emergency Medicine, Tabriz University of Medical Sciences, Tabriz, Iran
[c] Iranian Center of Excellence in Health Management, Tabriz University of Medical Sciences, Tabriz, Iran

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ABSTRACT

*Objectives:* Fast and accurate patient triage for the response process is a critical first step in emergency situations. This process is often performed using a paper-based mode, which intensifies workload and difficulty, wastes time, and is at risk of human errors. This study aims to design and evaluate a decision support system (DSS) to determine the triage level.
*Methods:* A combination of the Rule-Based Reasoning (RBR) and Fuzzy Logic Classifier (FLC) approaches were used to predict the triage level of patients according to the triage specialist's opinions and Emergency Severity Index (ESI) guidelines. RBR was applied for modeling the first to fourth decision points of the ESI algorithm. The data relating to vital signs were used as input variables and modeled using fuzzy logic. Narrative knowledge was converted to If-Then rules using XML. The extracted rules were then used to create the rule-based engine and predict the triage levels.
*Results:* Fourteen RBR and 27 fuzzy rules were extracted and used in the rule-based engine. The performance of the system was evaluated using three methods with real triage data. The accuracy of the clinical decision support systems (CDSSs; in the test data) was 99.44%. The evaluation of the error rate revealed that, when using the traditional method, 13.4% of the patients were miss-triaged, which is statically significant. The completeness of the documentation also improved from 76.72% to 98.5%.
*Conclusions:* Designed system was effective in determining the triage level of patients and it proved helpful for nurses as they made decisions, generated nursing diagnoses based on triage guidelines. The hybrid approach can reduce triage misdiagnosis in a highly accurate manner and improve the triage outcomes.

## 1. Introduction

Hospital emergency departments (EDs) attempt to provide a timely service for clients who do not plan ahead. Compared with other health centers, the ED is a unique environment with limited resources and a wide range of patients in need of care [1]; it is considered one of the most important departments among all health care systems. However, as overcrowding in EDs threatens the health of patients, triage is performed as an effective solution to tackle this problem [2].

The triage process is the first critical step in giving care to the clients of EDs by prioritizing patients at different triage levels based on the severity of their clinical conditions. Triage servers prioritize patients for urgent care based on a short initial clinical assessment usually performed by emergency nurses. In some hospitals, in addition to treatment priority, triage determines the visiting location of patients; for example, interior room, trauma room, cardio-pulmonary resuscitation room, or an outpatient room [3,4]. In emergency situations, fast and accurate patient triage for the response process is critical in the coordination of medical services with hospital sources since there is a high mortality rate. In many hospitals, the triage process is often performed using a paper-based mode; however, this method intensifies workload and difficulty, wastes time, and is open to human errors [5,6].

Triage decision-making is an important task that should be conducted for each patient referring to the ED. However, the characteristics of the triage server, such as his or her evaluation and experience, the patient's clinical history, and the availability of necessary resources all contribute to the complexity of the triage process. The most important task to accomplish in the ED is enabling the available physician to quickly and accurately recognize the patient's medical needs to avoid costs of unnecessary surgeries and other medical treatments [7]. For

* Corresponding author.
*E-mail address:* rezaeip@tbzmed.ac.ir (P. Rezaei-Hachesu).

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more accurate recognition, some standardized classification systems were developed for the triage process. For example, the Emergency Severity Index (ESI) is a standard instrument for classifying patients based on the estimated acuity and resource consumption [2]. Research findings have shown that the ESI triage method is regarded as one of the best ways to prioritize patients in many countries, including Iran, and that this method is considered a valid and accurate system for improving the access to medical care that is used in the ED of Iranian hospitals [2].

Levels 1 and 2 of the ESI have been respectively assigned for emergency and urgent situations requiring the immediate assessment and intervention by service providers to prevent death. Clients at triage levels 3, 4, and 5 are less urgent, and they are classified based on the prediction of required resources. Version 4 of the ESI triage system, which has been approved by the Agency for Healthcare Research and Quality (AHRQ), is derived from evidence-based research [8,9].

Nurses routinely perform the triage process since they have received extensive practical and academic training on the employment of the ESI rules and the assessment of patient acuity. In such situations, the occurrence of miss-triage arises in the form of under-triage or over-triage, which might result in negative outcomes for patients waiting to receive care [10].

However, the challenge of increased demand against the reduced quality of the emergency care system has led hospital administrators to attempt to devise an efficient solution for offering timely and high quality services. In the healthcare sector, the use of information systems is undeniably necessary to ensure an efficient, effective, and quality service and employee and client satisfaction. Today, most countries have implemented modern and emerging technologies in hospital EDs. Clinical decision support systems(CDSSs) can provide a suitable solution to the aforementioned challenges [11,12]. CDSSs can also assist with information management to support clinicians' decision-making abilities, reduce workload, and improve clinical workflows. When they are well designed and implemented, CDSSs have the potential to improve health care quality, increase efficiency, and reduce health care costs [13].

The correct realization of emergency patients' triage level is considered a serious decision-making challenge in the conduct of the triage process. In this regard, a high number of studies undertaken in this domain have reiterated the positive impact of CDSSs because error minimization is among the main advantages of this system [14,15]. However, in practice, CDSSs are not adequately used in clinical centers and very few successful uses of this system have been reported [16]. Nevertheless, it is difficult for a researcher or expert in this area to convince medical practitioners to bridge the gap between physicians and the CDSS. In an evidence-based mode, experts should make physicians aware of the suitability and effectiveness of this powerful tool for improving the care-giving services and patient conditions, and reducing costs [17].

Clinical triage practices and guidelines have suggested criteria for the correct diagnosis of the triage levels. These systems are accurate tools and approaches for implementing the guidelines and can boost compliance with clinical practices [18]. Hence, CDSSs are implemented mostly based on clinical solutions and the expert opinion of those integrating these solutions. Although clinical solutions are beneficial for healthcare provision and health outcomes, they suffer from pitfalls such as vagueness and ambiguity. Fuzzy logic can obviate such ambiguity and vagueness in DSSs [15]. The main advantage of a fuzzy logic rule-based classifier is its effectiveness in its predictive power of diagnostic accuracy [19].

Another advantage of data management and DSSs is their ability to improve the quality of the documentation of medical records, which is a legal and professional requirement. In addition to the certainty about the care given to patients and facilitating the exchange of patient information for healthcare team members, quality of documentation measure can be used for research, qualitative assessments, and forensic purposes. However, the status and quality of the documentation have not currently reached desirable levels in Iran's hospital EDs [20]. Because employing computer systems increases the quality of documentation, allows access to up-to-date information, enhances completeness, and diminishes workload [21], assessing the quality of the information being entered into electronic systems is of paramount importance.

Accordingly, this study aims to design and assess a DSS that not only determines patients' triage levels but can also be used as a patient data management system and provide a diagnosis module, which employs combined decision methods. We also assess the accuracy of the diagnoses and the error reduction rate.

## 2. Methods

Using a hybrid approach, we developed a CDSS based on the ESI triage guidelines. To achieve this, we first observed the triage workflow in some EDs. We administered surveys and conducted interviews with four clinicians (emergency medicine experts and triage nurses) and three technical experts who were members of the CDSS team and were responsible for implementing the system on embedding ESI rules in a clinical environment. To examine the current efficiency of paper-based triage, team experts carried out a focus group discussion that was facilitated by a health information technology expert. Unstructured interviews were held with the participants to determine the major weak and strong points of the existing system and to survey the flow of triage and the available strategies and guidelines. The participants were asked about their perceptions, opinions, beliefs, and attitudes toward the shortcomings of paper-based triage. The potential strong points of implementing a triage DSS were explained to them. To use the ESI, a nurse starts at the top of the algorithm process (Fig. 1), which encompasses four decision points (A, B, C, and D) on assigning patients to one of five triage levels. Fig. 1 shows the four key questions for this task. For ESI 1 and 2, the nurse considers only a patient's acuity in accomplishing an ESI assignment. If the answer to these initial questions is "no," then the nurse proceeds down the algorithm process to the questions regarding resources and moves on to decision point C. In this decision point, emergency department nurses are required to clearly understand that available resources should be estimated before a patient is assigned to ESI level 3. The nurse then needs to look at the patient's vital signs. If the vital signs exceed acceptable parameters, the triage nurse should consider upgrading the triage level to ESI 2. The triage nurse is responsible for determining whether a patient should be upgraded to this level on the basis of vital sign abnormalities. Patients classified under ESI level 4 are predicted to require one resource, and patients assigned to ESI level 5 are predicted to require no resources [22,23]. In the implementation phase of the hybrid triage DSS, nurses in the emergency department periodically completed paper-based documentation in different work shifts as a routine task. In the same shift, two triage nurses were randomly selected to use the triage DSS independently. No differences existed between the nurses' seniority levels in both groups, thus reducing the Hawthorne effect. The ethics committee of Tabriz University of Medical Sciences approved the procedures of the study.

We used a combination of the Rule-Based Reasoning (RBR) and Fuzzy Logic Classifier (FLC) approaches to predict the triage level of patients based on the triage specialists 'opinions and ESI guidelines. In the proposed method, the RBR method was applied to model the first to fourth decision points of the ESI algorithm. Table 1 shows a summary of the triage levels based on the ESI algorithm. With this triage algorithm, patients are assigned an ESI level ranging from 1 (most urgent) to 5 (least urgent), considering the patients' acuity, pain, and resource needs. Finally, the data regarding the vital signs (heart rate, SPO2 [Saturation of Peripheral Oxygen], respiratory rate, and triage level as an output) were used as input variables in specific conditions and modeled using the FLC.

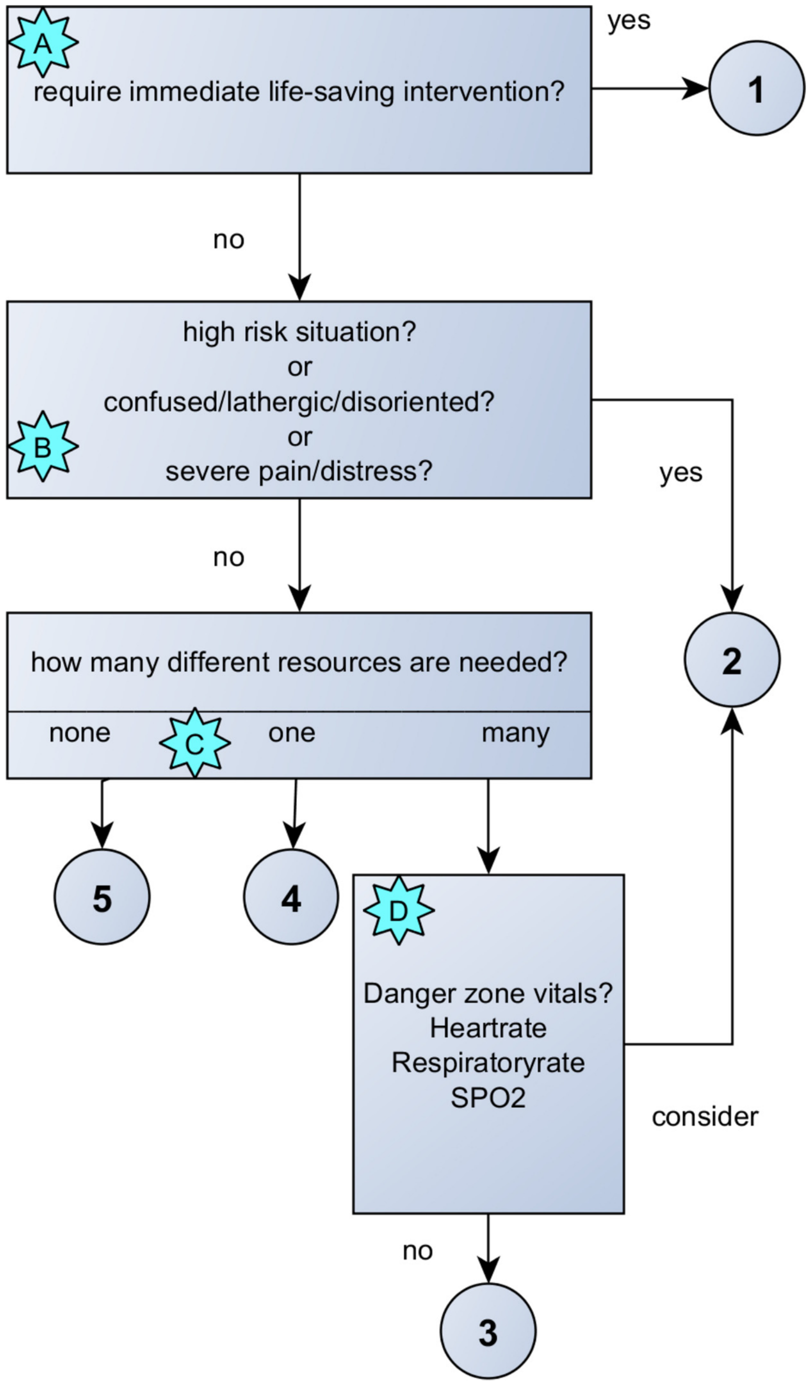


**Fig. 1.** Emergency severity index, version four.

**Table 1**
Linguistic description of Emergency Severity Index, fourth edition.

| ESI level | Linguistic terms of triage level | Description | Resource needs | Color |
|---|---|---|---|---|
| 1 | Critical | Requires immediate life-saving intervention? | – | Red |
| 2 | Emergent | High risk situation? | – | Orange |
| 3 | Urgent | 2 or many different resources are needed? | x > = 2 | Yellow |
| 4 | Out Patient with producer | One resource is needed? | 1 | Green |
| 5 | Out Patient without producer | No resource | 0 | Blue |

**Table 2**
Selected features of designed hybrid triage decision support system.

| Feature | Selected item |
|---|---|
| Controller | Mamdani(m-input, single output) |
| Linguistic terms | Triangle, Trapezoid |
| Activation method | General |
| Conjunction and Implication(T-norms) | Minimum |
| Disjunction and Aggregation(S-norm) | Maximum |
| Defuzzifier | Centroid of area |

**Table 3**
parameters of linguistic terms of triage FIS.

| Variables | Terms | Shape | Values | | | |
|---|---|---|---|---|---|---|
| | | | $a_1$ | $a_2$ | $a_3$ | $a_4$ |
| Heart rate | Bradycardia | Triangle | 0.00 | 30.00 | 60.00 | |
| | Normal | Triangle | 50.00 | 80.00 | 110.00 | |
| | Tachycardia | Trapezoid | 100.00 | 130.00 | 200.00 | 240.00 |
| Respiratory rate | Hypoventilation | Triangle | 0.00 | 6.00 | 12.50 | |
| | Normal | Triangle | 11.50 | 13.00 | 16.50 | |
| | Hyperventilation | Trapezoid | 15.00 | 17.00 | 55.00 | 61.00 |
| SPO2 | Severe hypoxia | Triangle | 50.00 | 80.00 | 92.00 | |
| | Moderate hypoxia | Triangle | 91.00 | 93.00 | 94.50 | |
| | Normal | Triangle | 94.00 | 97.00 | 100 | |
| Triage level | Level2 | Triangle | 0.00 | 0.33 | 0.66 | |
| | Level3 | Triangle | 0.33 | 0.75 | 1.00 | |

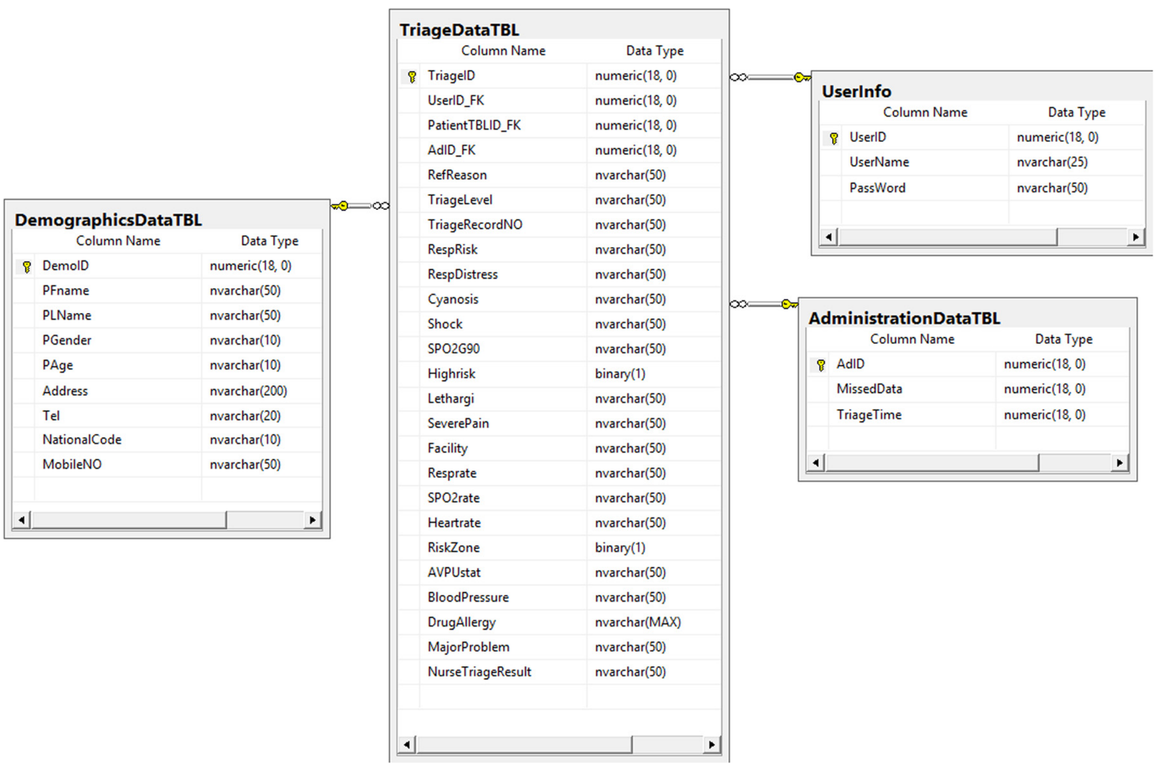


**Fig. 2.** Entity relationship diagram of hybrid triage decision support system.

### 2.1. RBR module

The most common expert systems are currently based on the conventional RBR, which comprises a knowledge base (rules) and an inference engine (routing mechanism) that analyzes fact patterns and matches applicable rules. In this study, RBR covers ESI decision points, such as A, B, and C, because the existing knowledge related to these points are simple, short rules that constitute the major section of our decision tree.

### 2.2. FLC

An FLC facilitates the process of vagueness treatment in a DSS by generating fuzzy rules instead of conventional rules to the model decision boundaries in a more flexible way. As its name suggests, a Fuzzy Inference System (FIS) uses fuzzy rules and fuzzy reasoning to perform its functions [24,25]. FLC covers decision point D, wherein vital signs are assessed by the system. In this research, ambiguity in the boundaries of the vital sign variables prompted the development of a fuzzy logic classifier. On the basis of the nature of rules and decision points, compatible algorithms were selected at different points of the ESI decision tree. Ambiguity is mapped to the keyword "fuzzy logic" and it is defined as the concepts without borders. Although there are some borderline properties overlapping these phenomena; it is possible to make some key distinctions that separate one of the others. The main feature of a vague word is that it denotes boundaryless concepts; in this study heart rate is a good example. In heart rate status; the fuzzy sets of tachycardia; normal and bradycardia; can be obtained. A person who has tachycardia is a member of the normal set with a degree of membership of 0.1; and at the same time; he is also a member of the tachycardia set with a degree of 0.4.

The present study used Madman's inference system to predict the triage levels. Its base structure includes four main components: a fuzzifier, which translates a crisp input (classical numbers) into fuzzy values; an inference engine, which applies a fuzzy reasoning mechanism to obtain a fuzzy output (in the case of Madman's inference); a knowledge base, which contains a set of fuzzy rules and a set of membership functions representing the fuzzy sets of linguistic variables;

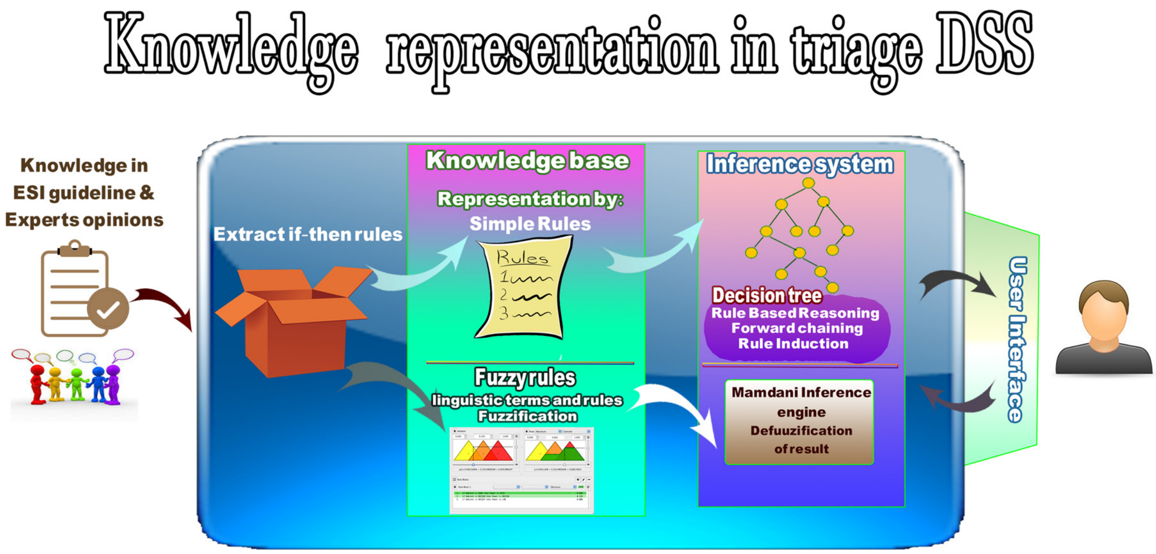


**Fig. 3.** Knowledge representation in hybrid triage decision support system.

**Table 4**
A comprehensive view of hybrid system rules.

| RBR results | | | | Fuzzy rules results | |
|---|---|---|---|---|---|
| level of consciousness[1] | Immediate intervention | High risk situation | Resources | Danger zone vitals?[2] | Triage level |
| A | YES | YES | 0 | YES | 1 |
| A | NO | YES | 0 | YES | 2 |
| A | NO | NO | 0 | YES | 5 |
| A | NO | NO | 1 | YES | 4 |
| A | NO | NO | X > = 2 | YES(L2) | 2 |
| A | NO | NO | X > = 2 | NO(L3) | 3 |
| V | YES | YES | 0 | YES | 1 |
| V | NO | YES | 0 | YES | 2 |
| V | NO | NO | 0 | YES | 5 |
| V | NO | NO | 1 | YES | 4 |
| V | NO | NO | X > = 2 | YES(L2) | 2 |
| V | NO | NO | X > = 2 | NO(L3) | 3 |
| P | YES | YES | 0 | YES | 1 |
| U | YES | YES | 1 | YES | 1 |

[1] "AVPU" is a criterion to assess the patient's level of consciousness using the following terms: **A**: Alert **V**: Responsive to Verbal stimulus **P**: Responsive to Pain **U**: Unresponsive.
[2] This column shows the results of fuzzy inference (decision is taken by the fuzzy system according to the guidelines).

and a defuzzifier, which translates the fuzzy output into crisp values.

Triangular and trapezoid membership functions and Madman's fuzzy inference system were applied for simplicity and flexibility. Fig. 1 and Tables 2–4 provide a more detailed description of the input variables, the linguistic terms, fuzzy set variables, and the membership functions of three inputs and the output variable "triage level. Table 2 shows the comprehensive features of the proposed FIS, which was designed according to the recommendations of Bouchon-Meunier et al. [26]. Table 3 presents the parameterization of linguistic terms in the designed CDSS. A Mamdani inference engine with a centroid defuzzification strategy was applied because fuzzy rules represent expert knowledge in Mamdani and because these are the most commonly used methods in clinical fuzzy systems [27]. A Mamdani inference system is also the most widely accepted defuzzification technique for computing the centroid of an output area [28]. To illustrate the system database, an entity relationship diagram (ERD) of the system is displayed in Fig. 2. More information is provided in the data source and data collection section.

### 2.3. Knowledge representation

A very popular method for the representation of knowledge is the use of production rules of the form '*IF conditions, THEN conclusion.*' In this study, the conditions specify level of consciousness (AVPU), patient acuity and required resources (using the RBR method), parameters of vital signs (using a fuzzy logic classifier), and the outcome state, which consists of triage levels as the final suggestion of a triage nurse. All guideline recommendations (ESI) and specialists' opinions in decision points A, B, and C should be expressed in the if–then format, which makes up a decision tree, with all parameters strictly defined using routinely collected triage data. In the system, variables regarding a patient's vital signs (decision point C) are fuzzified as linguistic variables, and other decision points are modeled in the form of qualitative rules. Fig. 3 shows the process of knowledge representation from guideline recommendation to decision making. This figure explains knowledge extraction, representation, and application in the hybrid triage DSS.

### 2.4. User interface

The user interface was designed using Visual Studio 2012 software and C# programming language in bilingual form (Persian and English).

### 2.5. Data source and data collection

All the data were triage records of patients who had visited the ED of Imam Reza Hospital (Tabriz-Iran) between June 2016 and December 2017. The triage data were recorded simultaneously by the nurses on the paper-based triage form and by the system user on the DSS. The intelligent triage system was evaluated based on the final collected dataset, which included 537 cases. Fig. 2 displays the ERD of the current DSS, which was designed in an SQL server database management system to store and retrieve data effectively. The database consists of four tables that contain demographic, triage, user, and administrative data. A total of 40 data elements are stored in the database.

### 2.6. Evaluation parameters

In predictive analytics, a confusion matrix is a table with rows and columns that list the number of true or false diagnoses. This matrix is often used to describe the performance of a classification model (or "classifier") on a set of test data for which true values are known. A

**Table 5**
Extracted fuzzy rules of triage decision support based on vital signs input variables.

| | |
|---|---|
| Rule1 | "IF (RESPRate IS HYPO) AND (SPO2 IS SE) AND (HeartRate IS BC) THEN TriageLevel IS L2" |
| Rule2 | "IF (RESPRate IS HYPO) AND (SPO2 IS M) AND (HeartRate IS BC) THEN TriageLevel IS L2" |
| Rule3 | "IF (RESPRate IS HYPO) AND (SPO2 IS N) AND (HeartRate IS BC) THEN TriageLevel IS L2" |
| Rule4 | "IF (RESPRate IS N) AND (SPO2 IS SE) AND (HeartRate IS BC) THEN TriageLevel IS L2" |
| Rule5 | "IF (RESPRate IS N) AND (SPO2 IS M) AND (HeartRate IS BC) THEN TriageLevel IS L2" |
| Rule6 | "IF (RESPRate IS N) AND (SPO2 IS N) AND (HeartRate IS BC) THEN TriageLevel IS L3" |
| Rule7 | "IF (RESPRate IS HYPR) AND (SPO2 IS SE) AND (HeartRate IS BC) THEN TriageLevel IS L2" |
| Rule8 | "IF (RESPRate IS HYPR) AND (SPO2 IS M) AND (HeartRate IS BC) THEN TriageLevel IS L2" |
| Rule9 | "IF (RESPRate IS HYPR) AND (SPO2 IS N) AND (HeartRate IS BC) THEN TriageLevel IS L3" |
| Rule10 | "IF (RESPRate IS HYPO) AND (SPO2 IS SE) AND (HeartRate IS N) THEN TriageLevel IS L2" |
| Rule11 | "IF (RESPRate IS HYPO) AND (SPO2 IS M) AND (HeartRate IS N) THEN TriageLevel IS L2" |
| Rule12 | "IF (RESPRate IS HYPO) AND (SPO2 IS N) AND (HeartRate IS N) THEN TriageLevel IS L3" |
| Rule13 | "IF (RESPRate IS N) AND (SPO2 IS SE) AND (HeartRate IS N) THEN TriageLevel IS L2" |
| Rule14 | "IF (RESPRate IS N) AND (SPO2 IS M) AND (HeartRate IS N) THEN TriageLevel IS L2" |
| Rule15 | "IF (RESPRate IS N) AND (SPO2 IS N) AND (HeartRate IS N) THEN TriageLevel IS L3" |
| Rule16 | "IF (RESPRate IS HYPR) AND (SPO2 IS SE) AND (HeartRate IS N) THEN TriageLevel IS L2" |
| Rule17 | "IF (RESPRate IS HYPR) AND (SPO2 IS M) AND (HeartRate IS N) THEN TriageLevel IS L2" |
| Rule18 | "IF (RESPRate IS HYPR) AND (SPO2 IS N) AND (HeartRate IS N) THEN TriageLevel IS L3" |
| Rule19 | "IF (RESPRate IS HYPO) AND (SPO2 IS SE) AND (HeartRate IS TC) THEN TriageLevel IS L2" |
| Rule20 | "IF (RESPRate IS HYPO) AND (SPO2 IS M) AND (HeartRate IS TC) THEN TriageLevel IS L2" |
| Rule21 | "IF (RESPRate IS HYPO) AND (SPO2 IS N) AND (HeartRate IS TC) THEN TriageLevel IS L3" |
| Rule22 | "IF (RESPRate IS N) AND (SPO2 IS SE) AND (HeartRate IS TC) THEN TriageLevel IS L2" |
| Rule23 | "IF (RESPRate IS N) AND (SPO2 IS M) AND (HeartRate IS TC) THEN TriageLevel IS L2" |
| Rule24 | "IF (RESPRate IS N) AND (SPO2 IS N) AND (HeartRate IS TC) THEN TriageLevel IS L3" |
| Rule25 | "IF (RESPRate IS HYPR) AND (SPO2 IS SE) AND (HeartRate IS TC) THEN TriageLevel IS L2" |
| Rule26 | "IF (RESPRate IS HYPR) AND (SPO2 IS M) AND (HeartRate IS TC) THEN TriageLevel IS L2" |
| Rule27 | "IF (RESPRate IS HYPR) AND (SPO2 IS N) AND (HeartRate IS TC) THEN TriageLevel IS L3" |

**Table 6**
The linguistic variables in fuzzy system and their related fuzzy terms.

| Fuzzy variable | Linguistic terms | | |
|---|---|---|---|
| SPO2 | Severe hypoxia | Moderate hypoxia | Normal |
| Respiratory Rate | hypo ventilation | Normal | Hyper ventilation |
| Heart rate | Bradycardia | Normal | Tachycardia |

confusion matrix was used to measure the accurate prediction of the classification model (how often the classifier performs correctly) and the error rate of triage nurses in using the paper-based method (how often the classifier commits errors). The measurement was aimed at determining accuracy, as indicated in the following equations: [29,30]

$$Accuracy = \frac{TP + TN}{Totall}(\%),$$

$$Error \;\; rate = \frac{FP + FN}{Totall}(\%),$$

Where TP denotes a true positive rate, TN is a true negative rate, FP is a false positive rate, and FN is a false negative rate.

#### 2.6.1. Completeness

Two assessors reviewed the paper forms and evaluated the number and distribution of the completeness or incompleteness of the records. One technical assessor (query) did the same for the cases registered in the system. Incompleteness means a record has one or more missing items of data in every form. To calculate the record completeness measure, the following equations were used:

$$Completeness = \left(\frac{Total \;\; complete \;\; records}{Total \;\; records}\right)\%,$$

$$Incompleteness = ((1 - completeness) \times 100)\%.$$

## 3. Results

### 3.1. Descriptive data analysis

The triage input data consist of categorical, free text, and continuous data. The triage output has five categories, as shown in Table 1. The median age of the patients was 56 years old (19–94). Among the 537 patients evaluated in the study, 341(63.5%) were male and 196(36.49%) were female. ESI–3 s and ESI–4 s were the most commonly categorized ESI patient types. Table 5 (confusion matrix) shows the number of patients for each ESI level.

### 3.2. RBR and fuzzy rules result

The extracted rules, including 14 RBR and 27 fuzzy rules, were created in the rule-based engine and used to predict the triage levels. To design the rule-based engine, the results of the RBR and fuzzy rules extracted in first step of the study were displayed as a comprehensive table. Table 4 shows the rules list and a combination of the rules to achieve the triage level.

Table 5 indicates the complete list of extracted fuzzy rules used to categorize the patients' triage levels. An output of Level 2 in the fuzzy rules displays that the patient is requires urgent care. Level 3 displays a safer state. We used the ESI guidelines to define the linguistic term and fuzzy set variable of the vital signs. To differentiate between levels 2 and 3, three variables play a critical role: SPO2, respiratory rate, and heart rate. Table 6 explains the results of the fuzzification method. A comprehensive computational view of the hybrid triage DSS and the system's decision support process are displayed in Fig. 3.

Fig. 4 presents a section of the designed graphic user interface of the system for decision point D, in which fuzzy decision support is received. To ease the required training, we mirrored the existing paper layout and content but implemented optimization for device size. Some fields such as drug allergies and pregnant were stored in database because of local paper-based form has similar fields.

Fig. 5 shows how fuzzy logic intersects with RBR algorithms. This model provides a detailed representation of the decision support process from a computational viewpoint.

System evaluation is crucial for the development of a reliable DSS to drive improvements. The performance of the system was evaluated using three methods with real triage data. The methods are the accuracy rate (calculated based on the confusion matrix by applying the accuracy formula), the error rate of triage nurses (calculated based on FN and FP values), and the quality of the documentation (calculated

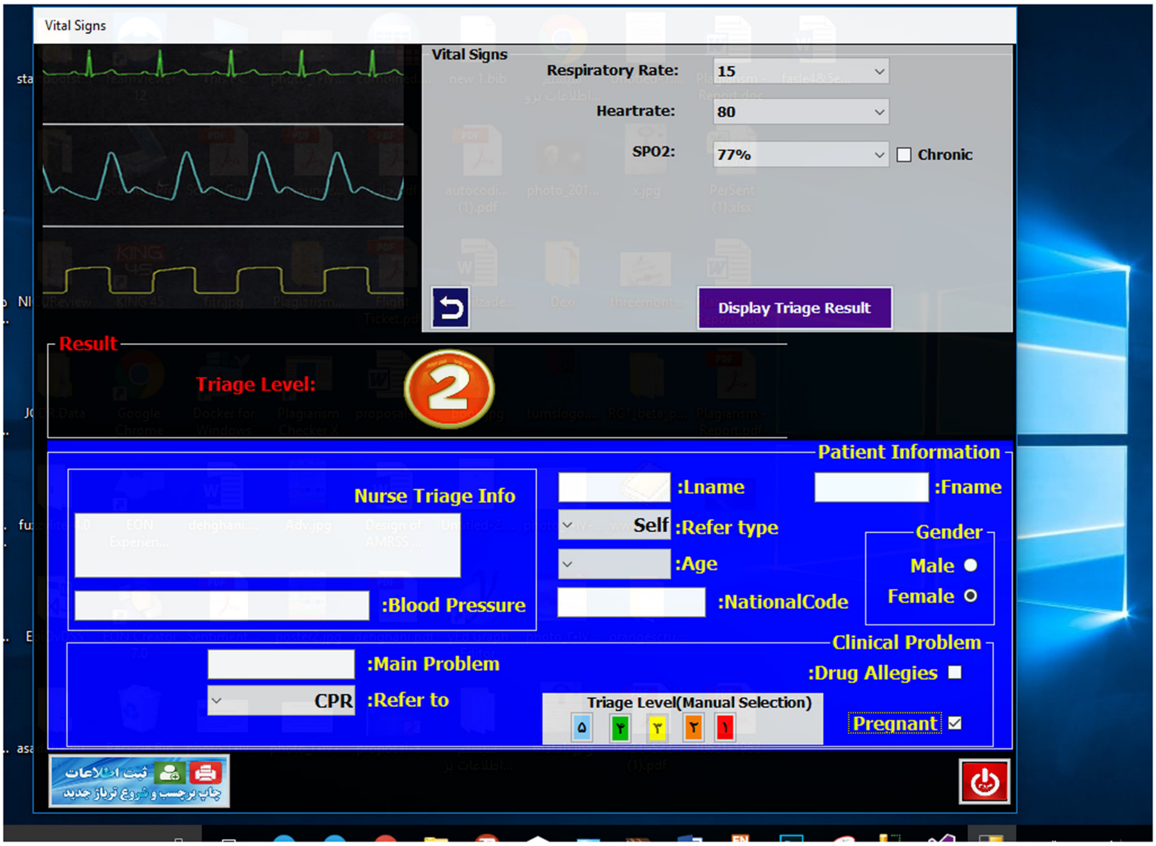


**Fig. 4.** User interface of decision point D in the hybrid triage decision support system.

using statistical methods). As shown in Table 7, the accuracy of the CDSS (in the test data) was 99.44%. The error rate of the triage nurses was also calculated; the evaluation revealed that with the traditional method, 13.4% of the patients were miss-triaged, which is statistically significant ($p < .05$).

Elements of designed system match those of the normal triage form. A comparison of the system-based and paper-based documentation achieved the following results.

In the triage system, five nurses (consultants and trainees in triage) created 537 triage records. Among 529 (98.5%) triage records, all mandatory forms were completed and only eight (1.5%) records were incomplete. In five (62.5%) of the uncompleted records, the nurse failed to complete the referral procedure at the end of triage, and in three (37.5%) cases, technical problems (network and hardware failure) led to incompleteness.

In the paper-based method, five different nurses completed the same 537records, simultaneously. In 412(76.72%) of those records, all mandatory forms were completed, and in 125 records, one or more items of missing data were identified. Some demographic data were missing in 101 records and in other records, the missing data included AVPU (13[54.1%]), vital signs (31[24.8%]), and the date and time (77[61.1%]). Of the incomplete records, 74 (59.2%) had more than three missing fields.

## 4. Discussion

To improve the efficiency and quality of patient care in EDs, hospitals are increasingly relying on computer technology to improve the efficiency and accuracy in determining the triage level. We have thus developed a CDSS for predicting triage output. We applied a hybrid approach for this prediction. The results show that the hybrid approach achieved the highest prediction accuracy. This approach is therefore considered an acceptable model for developing the CDSS. This triage CDSS was designed to support the entire process of triage because many studies have found that it is important to use CDSS to improve adherence to the ESI guidelines [31]. A hybrid approach is preferred because it (1) provides the ability to model fuzzy variables, which enables the uncertainty to be appropriately modeled, and (2) reduces the error rate of triage nurses by estimating and predicting the triage level.

To evaluate the quality of data, i.e., its completeness, we performed a comparison between paper-based and electronic records, and evaluated the content in terms of missing data. The results indicated that the quality of documentation improved by approximately 22%.

Completeness was the most commonly assessed dimension of data quality and was an area of focus in 61 (64%) of the articles [32]. The statistics community has focused extensively on determining in what manner data are missing. Specifically, data may be considered to be missing at random, missing completely at random, or missing not at random [32].

The potential benefits of electronic records in healthcare, such as increased communication between users, reduced paperwork, fewer medical errors, and cost savings have been widely discussed. Electronic records allow for "just in time "access and have led to faster data searches and increased physician efficiency [33]. Behind the scenes of designed CDSSs, an electronic data management system for storage and retrieval of patient's information was developed. Some basic reports were designed to allow users to query on a database and achieve aggregated information. Unlike the paper-based process, the current system enables patient's information to be accessed in real-time. The proposed system covered important advantages of Information Technology (IT) in ED such as error reduction, documentation quality (e.g., data completeness), and improved accessibility.

Although no other studies relate to developing a hybrid method using RBR and FLC for predicting the triage levels, researchers have successfully designed the electronic triage system (ETS) to be used in EDs in hospitals [34]. Their ETS automatically determines the triage

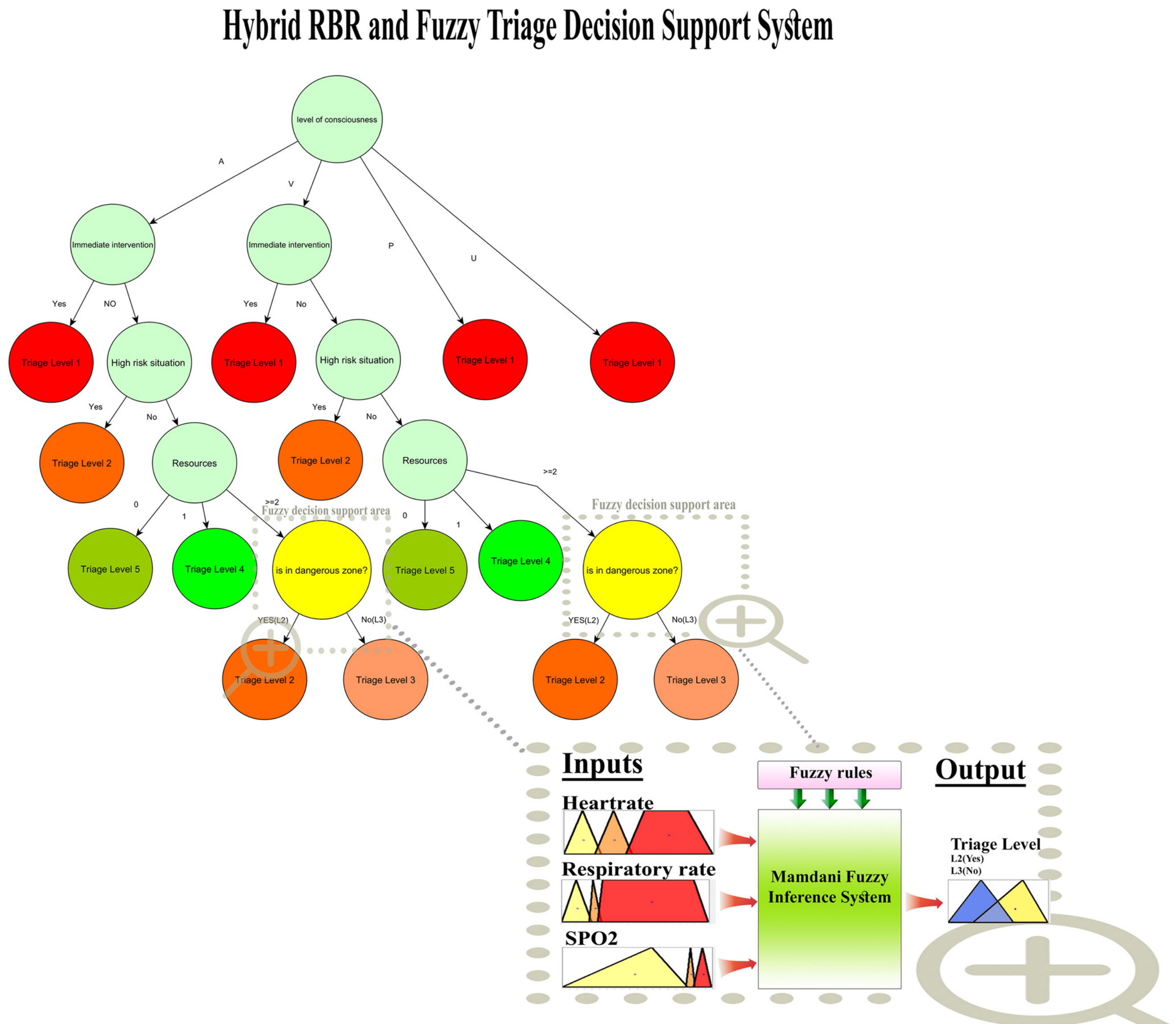


**Fig. 5.** The comprehensive view of computational aspect of hybrid triage decision support system.

**Table 7**
Confusion matrix for triage model using RBR and fuzzy system.

| Predicted condition(System) | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | TL1[a] | TL2 | TL3 | TL4 | TL5 | Sum |
| True condition(Expert) | TL1 | 15 | 0 | 0 | 0 | 0 | 15 |
| | TL2 | 0 | 15 | 0 | 0 | 0 | 15 |
| | TL3 | 0 | 2 | 240 | 1 | 0 | 243 |
| | TL4 | 0 | 0 | 0 | 103 | 0 | 103 |
| | TL5 | 0 | 0 | 0 | 0 | 25 | 25 |
| | Sum | 15 | 17 | 240 | 104 | 25 | 537 |

[a] Triage Level.

level and treatment room based on input data [3]. Most studies focusing on ETSs have compared the performance of different methods; for example, a study conducted by Seifu et al. compared the capabilities of predicting the ESI level using ordinal logistic regression (OLR), artificial neural networks (NNs), and naïve Bayesian networks (NBNs). Their study revealed that all models were > 60% accurate using the entire dataset for training [10]. Azeez and colleagues designed a primary triage model using two different models(ANN architecture and ANFIS model). The results showed that the accuracy, which was evaluated by measuring specificity and sensitivity for binary classification of the training data, was99% for the ANN model and 96% for ANFIS model. The ANN model performed better for both training and unseen data than the ANFIS model in terms of generalization, and in terms of model accuracy, the ANN model was found to work better than the ANFIS model in triage prediction. The ANN model was therefore chosen as the technique to use for developing the triage prediction model [7]. Owing to the nature of the ESI guideline, which uses a rule-based approach for classifying patients, our study applied knowledge-based methods rather than machine learning (ML) algorithms. The RBR and fuzzy approaches are two popular knowledge-based methods used for designing expert systems and DSSs. The results obtained in some studies show higher accuracy compared with the ML methods, near to 100%. The current study proposes that, in evidence-based diagnosis and guideline-based medicine, domain knowledge should be made available to developers because knowledge-based methods are more efficient to design and clearer for stakeholders to understand. Some ML algorithms such as ANN behave as a black box and the inference process is not clear for interpretation by experts [35]. However, a knowledge-based algorithm performs like a white box. In many health challenges, it is important to analyze the problem-solving pathway. Owing to the uncertainty of medicine, knowledge-based methods, especially fuzzy logic, help to analyze the relations between rules and outcomes.

A prototype version of our triage CDSS was tested during a six-month pilot study conducted at Imam Reza hospital. During this pilot study, the system was quickly accepted by its users and could be easily integrated into the ED working processes.

While our experiences are limited to the triage CDSS with RBR and FLC, our objectives and general approaches might be applicable to other ED settings; however, other EDs could benefit from similar methods or architecture to predict the patients' triage levels.

To benefit from the technological advances in EDs, this study implemented a triage CDSS to improve the triage process, which could predict the triage level, prioritize treatment, and determine a suitable treatment room. Previous studies have shown the benefits of such systems in EDs of U.S. hospitals [36].

This research study developed an expert system to predict the triage level using a novel hybridization method designed with RBR and FLC. The diagnosis performances of the proposed system demonstrate the advantages of this system: it is rapid, easy to operate, and inexpensive, and it has a flexible architecture with a clear white box structure and real-time accessibility. We have shown that systems with flexible architectures that can support large domains are very much needed and are more useful than systems that are domain specific. The system's modular design makes it easy to modify its clinical functionality or expand its scope by adding new clinical modules.

## 5. Conclusions

Nurses often encounter problems in triage-level decision making on diagnosis. The use of a CDSS is a well-recognized solution to increasing the quality and efficiency of care. The correspondence between CDSS design and guidelines and clinicians' opinions is of utmost importance because this reduces over-triage and under-triage cases and improves safety. Conducting interviews with users and clinicians early in the development process informs the identification of design requirements and provides a context for how a CDSS will be most useful to providers. Insight into end-users' cognitive processes can facilitate the design of CDSS systems with promising usability. Analyzing CDSSs before deploying these systems for real-world application potentially saves money, time, and effort during implementation. Tool developers are responsible for ensuring the safety, usability, and usefulness of such systems.

The essence of this study lies in its combination of FLC and RBR, which can improve the triage outcomes and will be useful in medical areas. The hybrid approach can reduce triage misdiagnosis in a highly accurate manner. We expect the use of this method to minimize the design iterations of the developed CDSS, which combines two or more methodologies. The measurements obtained in this work are consistent with those reported in other related studies. The developed system proved helpful for nurses as they made decisions, generated nursing diagnoses based on triage guidelines, and improved the quality measures for accuracy and documentation in the triage process. We designed and evaluated the CDSS on the basis of ESI triage guidelines and found that the designed system effectively determines the triage level required for patients. The methods put forward in this work can be applied to other clinical decision support systems and settings, and we hope that further exploration of the system will provide improved results.

## Clinical relevance statement

Current study improved clinical outcomes in ED.

## Conflict of interests

There is no conflict of interest.

Summary table

**What was already known on this topic?**

- Clinical triage practices and guidelines have suggested criteria for the correct diagnosis of the triage levels; But they were not implemented effectively in clinical environment.
- CDSS is an effective tool to implement and apply clinical guideline.
- Triage classification is a complex, fuzzy and algorithmic process that needs to a hybrid approach.

**What this study added to our knowledge?**

- In our study a hybrid algorithmic approach was proposed to handle triage process.
- This CDSS improved documentation quality as well as reduced mistriaged.

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## References

[1] J.E. Hurwitz, J.A. Lee, K.K. Lopiano, S.A. McKinley, J. Keesling, J.A. Tyndall, A flexible simulation platform to quantify and manage emergency department crowding, BMC Med. Inform. Decis. Mak. 14 (2014) 50.
[2] M. Maleki, R. Fallah, L. Riahi, S. Delavari, S. Rezaei, Effectiveness of five-level Emergency Severity Index triage system compared with three-level spot check: an Iranian experience, Arch. Trauma Res. 4 (2015).
[3] F. Pourasghar, A. Daemi, J.S. Tabrizi, A. Ala, Inter-rater reliability of triages performed by the electronic triage system, Bull. Emerg. Trauma 3 (2015) 134.
[4] S.L. Dong, M.J. Bullard, D.P. Meurer, I. Colman, S. Blitz, B.R. Holroyd, B.H. Rowe, Emergency triage: comparing a novel computer triage program with standard triage, Acad. Emerg. Med. 12 (2005) 502–507.
[5] T. Gao, D. White, A next generation electronic triage to aid mass casualty emergency medical response, AMIA Symposium Proceedings, Citeseer, 2006, pp. 6501–6504.
[6] A. Wright, S. Phansalkar, M. Bloomrosen, R.A. Jenders, A.M. Bobb, J.D. Halamka, G. Kuperman, T.H. Payne, S. Teasdale, A.J. Vaida, Best practices in clinical decision support: the case of preventive care reminders, Appl. Clin. Inf. 1 (2010) 331–345.
[7] D. Azeez, M.A.M. Ali, K.B. Gan, I. Saiboon, Comparison of adaptive neuro-fuzzy inference system and artificial neutral networks model to categorize patients in the emergency department, SpringerPlus 2 (2013) 416.
[8] P. Dalawari, J. Sanning, D. Pan, J. Storm, Emergency severity index version 4 during the first year of implementation at an academic institution, J. Hosp. Adm. 5 (2015) 35.
[9] S. Mahapatra, C.P. Koelling, L. Patvivatsiri, B. Fraticelli, D. Eitel, L. Grove, Emergency departments II: pairing emergency severity index5-level triage data with computer aided system design to improve emergency department access and throughput, Proceedings of the 35th conference on Winter simulation: driving innovation, Winter Simulation Conference (2003) 1917–1925.
[10] S.J. Chonde, O.M. Ashour, D.A. Nembhard, G.E.O. Kremer, Model comparison in emergency severity index level prediction, Expert Syst. Appl. 40 (2013) 6901–6909.
[11] D. Aronsky, I. Jones, K. Lanaghan, C. Slovis, Supporting patient care in the emergency department with a computerized whiteboard system, J. Am. Med. Inf. Assoc. 15 (2008) 184–194.
[12] J.J. Kelly, E. Thallner, R.I. Broida, D. Cheung, H. Meisl, A.G. Hamedani, S.J. Klauer, C. Beach, Emergency medicine quality improvement and patient safety curriculum, Acad. Emerg. Med. 17 (2010) e110–e129.
[13] E.S. Berner, Clinical Decision Support Systems: State of the Art, AHRQ publication, Rockville, Maryland, 2009.
[14] T. Samad-Soltani, M. Ghanei, M. Langarizadeh, Development of a fuzzy decision support system to determine the severity of obstructive pulmonary in chemical injured victims, Acta Inf. Med. 23 (2015) 138.
[15] H. Wollersheim, J. Burgers, R. Grol, Clinical Guidelines to Improve Patient Care, (2005).
[16] W.C. Kinney, Web-based clinical decision support system for triage of vestibular patients, Otolaryngol.-Head Neck Surg. 128 (2003) 48–53.
[17] D.W. Bates, G.J. Kuperman, S. Wang, T. Gandhi, A. Kittler, L. Volk, C. Spurr,

R. Khorasani, M. Tanasijevic, B. Middleton, Ten commandments for effective clinical decision support: making the practice of evidence-based medicine a reality, J. Am. Med. Inf. Assoc. 10 (2003) 523–530.
[18] R. Goud, A. Hasman, N. Peek, Development of a guideline-based decision support system with explanation facilities for outpatient therapy, Comput. Methods Programs Biomed. 91 (2008) 145–153.
[19] J. Warren, G. Beliakov, B. Van Der Zwaag, Fuzzy logic in clinical practice decision support systems, System Sciences, 2000, Proceedings of the 33rd Annual Hawaii International Conference on, IEEE (2000) (10 pp.).
[20] G. Faridaalaee, B. Boushehri, N. Mohammadi, O. Safari, Evaluating the quality of multiple trauma patient records in the emergency department of Imam Khomeini hospital in Urmia, Iran. J. Emerg. Med. 2 (2015) 88–92.
[21] K. Häyrinen, K. Saranto, P. Nykänen, Definition, structure, content, use and impacts of electronic health records: a review of the research literature, Int. J. Med. Inf. 77 (2008) 291–304.
[22] P. Tanabe, N. Gilboy, D.A. Travers, Emergency severity index version 4: clarifying common questions, J. Emerg. Nurs. 33 (2016) 182–185.
[23] N. Gilboy, U.S.A.f.H. Research, Quality, Emergency Severity Index: Implementation Handbook. Version 4, Agency for Healthcare Research and Quality, 2012.
[24] M. Abbasi, S. Kashiyarndi, Clinical Decision Support Systems: A discussion on different methodologies used in Health Care, Marlaedalen University, Sweden, 2006.
[25] M. Nilashi, O. Ibrahim, A. Ahani, Accuracy improvement for predicting Parkinson's disease progression, Sci. Rep. 6 (2016).
[26] B. Bouchon-Meunier, M. Dotoli, B. Maione, On the Choice of Membership Functions in a Mamdani-type Fuzzy Controller, (1996).
[27] H. Cherifi, J.M., Zain, E. El-Qawasmeh, Digital Information and Communication Technology and Its Applications: International Conference, DICTAP 2011, Dijon, France, June 21–23, 2011. Proceedings, Springer Berlin Heidelberg2011.
[28] A. Ginart, G. Sanchez, I. Links, G. Back, Fast defuzzification method based on centroid estimation, Appl. Modell. Simul. 58 (2002) 20–25.
[29] M.R. Mohebian, H.R. Marateb, M. Mansourian, M.A. Mañanas, F. Mokarian, A hybrid computer-aided-diagnosis system for prediction of breast cancer recurrence (HPBCR) using optimized ensemble learning, Comput. Struct. Biotechnol. J. 15 (2017) 75–85.
[30] P.R. Hachesu, M. Ahmadi, S. Alizadeh, F. Sadoughi, Use of data mining techniques to determine and predict length of stay of cardiac patients, Healthc. Inf. Res. 19 (2013) 121–129.
[31] K. Kawamoto, C.A. Houlihan, E.A. Balas, D.F. Lobach, Improving clinical practice using clinical decision support systems: a systematic review of trials to identify features critical to success, BMJ 330 (2005) 765.
[32] N.G. Weiskopf, G. Hripcsak, S. Swaminathan, C. Weng, Defining and measuring completeness of electronic health records for secondary use, J. Biomed. Inf. 46 (2013) 830–836.
[33] J. Tsai, G. Bond, A comparison of electronic records to paper records in mental health centers, Int. J. Qual. Health Care 20 (2008) 136–143.
[34] M. Kim, J. Shapiro, N. Genes, M. Aguilar, D. Mohrer, K. Baumlin, J. Belden, A pilot study on usability analysis of emergency department information system by nurses, Appl. Clin. Inf. 3 (2012) 135–153.
[35] A. Nabaei, M. Hamian, M.R. Parsaei, R. Safdari, T. Samad-Soltani, H. Zarrabi, A. Ghassemi, Topologies and performance of intelligent algorithms: a comprehensive review, Artif. Intell. Rev. (2016) 1–25.
[36] A.B. Landman, S.L. Bernstein, A.L. Hsiao, R.A. Desai, Emergency department information system adoption in the United States, Acad. Emerg. Med. 17 (2010) 536–544.