A NOVEL SYSTEM TO CLASSIFY RISK FACTORS TO PREDICT OUTCOMES AFTER SURGERY USING FUZZY METHODS

Mahyar Taghizadeh Nouei [1,*], Ali Vahidian Kamyad[2] & Somayeh Ghazalbash[3]
[1,2] Department of Applied Mathematics, School of Mathematical Sciences, Ferdowsi University of Mashhad, International Campus, Mashhad, Iran
[3] Cardiac Surgery and Transplantation Research Center (CTRC), Shariati Hospital, Tehran University of Medical Sciences (TUMS), Tehran, Iran.
*Corresponding author: Email: M.nouei@yahoo.ca, Tel: +989121223186, Fax: +9821-88246968

ABSTRACT
The aim of this study is to develop a system to recognize most important risk factors which can help to predict outcomes such as mortality or morbidity before performing the specific surgery by the integration a standard assessment checklist based on theoretical considerations and methodological aspects to evaluate the study quality of each publication, fuzzy analytic hierarchy process (FAHP) to order the risk factors, and fuzzy c-means clustering in order to classification. A fundamental idea of this study for applying FAHP was to consider scoring systems as experts to decision making and use of triangular fuzzy number (TFNs) to represent pairwise comparison of odd ratios in order to capture the vagueness. To illustrate the system implementation, the information of scoring systems developed to predict early mortality after CABG (Coronary artery bypass graft) is considered as input and the reasonable results are concluded. This implementation demonstrates the effectiveness and feasibility of the proposed system.

Keywords: *Fuzzy Analytic Hierarchy Process, Risk Factor, Cardiac Surgery, C-Means Clustering*

1. INTRODUCTION
Risk assessment is increasingly seen as standard practice to monitor and evaluate surgical performance with allowing the physician to define the possibility of adverse outcomes in individuals in a variety of situations by developing risk prediction models for post-operative adverse outcomes. So, Preoperative risk assessment can be an effective method of quality assurance. During the last decades, several risk scoring systems have been developed to predict complications of patient after surgery to aid the surgeon for choosing effective, safe and reliable methods of treatment [1]; [2]. Although several scoring model were developed to predict the outcome after procedures or interventions, no consistent set of significant risk factors have been attained among them. The aim of this study is to develop a system by the integration of fuzzy concept and analytical hierarchy process method in order to recognize most important risk factors which can help to predict mortality or morbidity before performing the specific surgery as well as fuzzy clustering to classify them. In this paper the system is implemented for classifying early mortality risk factors after CABG.
CABG is the most common type of open-heart surgery in the world. It accounts for a significant portion of the total health care expenditure and more resources expended in cardiovascular medicine than any other single procedure [3] ;[4]. Therefore most of the methods developed to stratify cardiac risk were focused on this kind of surgery.
In spite of importance of consistency between significant risk factors, few published studies have been presented to define it for early mortality risk factors after CABG. For example, Jones and associates has categorized 44 clinical variables into 3 level to reflect their relative importance in determining short-term mortality after CABG according to result of two consensus panel meeting [5]. Also, Tu and associates [6] and Hannan and associates [7]compare the importance of the predictors using logistic regression analysis. The result of published studies is based on comprehensive database and they are data-centric. However, present study has been concluded base on the extracted information of scoring systems and the results of them are considered as an input of our system.

2. MATERIALS & METHODS
We developed a system in which extracted information from different scoring system is considered as an input and classification of risk factors as an output. The process unit of this system consists of “Quality Appraisal” module to evaluate the study quality of each publication, “Fuzzy AHP Analysis” module to order the risk factors and “Fuzzy C-means clustering” module in order to classify risk factors. The elements of the system are summarized in the following subsections. Early mortality as an outcome and CABG surgery as a procedure is considered to describe the concepts in detail. Figure 1 shows the system architecture. Entity relationship diagram (ER Diagram) of system is presented in Appendix 1.

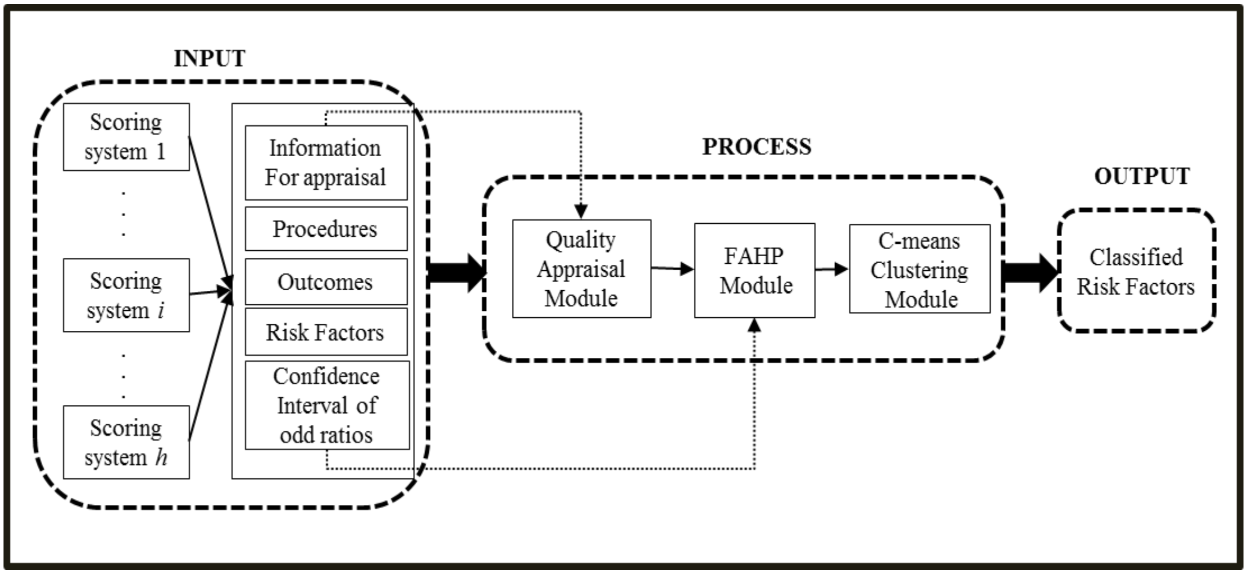


Figure1. The system architecture

2.1. INPUT

A literature search from 1980 to January 2013 is performed using the MEDLINE and Science Direct database because of comprehensive nature of these databases. Language restriction was enforced and non–English-language articles were not translated. For screening the articles some inclusion and exclusion criteria is considered. For this research, it was required that studies reported on risk models to be used for estimating the risk of early mortality for CABG surgery, either with or without concomitant procedure. Moreover, prevalence of patients undergoing isolated CABG had to be reported more than 60 percent. In addition to, we included models exclusively focused on adults and had been presented the association (Odd Ratios with corresponding 95% Confidence Interval (CI)) of predictor factors with the outcome.

Then data of the prognostic studies is extracted including information about scoring systems (study population number and related characteristics, start and end time of data collection, Year of publication), outcome measures, the type of procedure, information for quality appraisal, measure of C-index and multivariate association calculated between predictor factors and outcome in terms of Odds Ratios with 95% CI.

2.2. PROCESS

Firstly, the study quality of the publications which have presented a new scoring model was evaluated using standard assessment checklist. Mentioned checklist developed base on theoretical considerations and methodological aspects, comprises 5 categories, study population, treatment, outcome, prognostic factors and data presentation, and also includes items on validity, precision of method and clinical aspect of study design. Quality appraisal is providing valid assessment of primary studies which is essential process of systematic reviews and meta-analysis in medical research. Authors should include these quality assessments into their synthesis of evidence about prognosis. Therefore, we will benefit of applying this idea to assess the influence degree of scoring models in decision making incorporated in fuzzy AHP modules in our system. The checklist and some additional explanation are provided at [8].

Secondly, AHP and clustering methods are used in fuzzy environment to prioritize and order the risk factors. The Analytic Hierarchy Process, via providing a plausible framework, is a popular decision making technique that has proven to be applicable for complex decisions; when there are many factors for prioritizing among multiple criteria. This methodology has been used in various settings to make decisions [9]. Moreover, AHP has seen widespread applications across numerous fields in health care and medical decision making [10]. Nowhere in the field of biosciences is the need for tools to deal with uncertainty more critical than in medicine and epidemiology [11]. The descriptions of the uncertainties in the risk analysis confirm the suitability of the fuzzy methodologies. There are different applications, where the statistical methods and fuzzy technologies are combined or compared to achieve better results [12]. The use of newer approaches, such as fuzzy logic seems to better address the challenge of increasing complexity predisposing factors linked to the occurrence of mortality events data after open heart surgery. The use of fuzzy sets to describe the risk factors and fuzzy-based decision techniques to help incorporate inherent imprecision, uncertainties and subjectivity of available data, as well as to propagate these attributes

throughout the model, yield more realistic results [9]. So, to deal with vagueness, fuzzy version of AHP should be used in spite of its complexity. In fuzzy AHP, triangular fuzzy numbers are used to represent pairwise comparison of odd ratios and overcome ambiguities involved in the statistical data. A triangular fuzzy number (TFN) is the special class of fuzzy number whose membership is defined by three real numbers, expressed as (l; m; u). A fundamental idea of applying FAHP is to consider scoring systems as experts to decision making and use of triangular fuzzy number (TFNs) to represent pairwise comparison of odd ratios in order to capture the vagueness. In other word, we employ calculated odd ratios in scoring systems as importance degree of risk factors.
As mentioned earlier, in order to attain the priorities of risk factors a fuzzy AHP method is considered to account the uncertainty and vagueness involved in fuzzy decision- making environment. In this work, Chang's extent analysis method [13] is utilized. Taking into consideration the purpose and method of this study, criteria and factors were identified. The risk scoring models were the criteria in this decision model while the significant risk factors of mortality after CABG were the alternatives. Each scoring system provides a different odd ratio for included risk factors according to the determined population. On the other hand, performance measures of these scoring systems describe their precision. TFNs are used to represent pairwise comparison of odd ratios in order to capture the vagueness.

The steps of Chang's extent analysis, [13], can be detailed as follows: Assuming *p* risk factors and *q* scoring models, the pairwise comparison of factor *i* with factor *j* yields a square matrix $A_{(p*p)}$ as follow:

$$\boldsymbol{A^h} = [(\boldsymbol{a_{ij}})]^h = \left(\boldsymbol{l_{ij}}^h, \boldsymbol{m_{ij}}^h, \boldsymbol{u_{ij}}^h\right) \quad , \quad i,j: 1, \dots, p \quad , h: 1, \dots, q \qquad (1)$$

It denotes the comparative importance of risk factor *i* with respect to risk factor *j* for h^{th} model and calculated as follow: Consider two TFNs, $\boldsymbol{a_i}$ and $\boldsymbol{a_j}$ where, $\boldsymbol{a_i} = (\boldsymbol{l_i}, \boldsymbol{m_i}, \boldsymbol{u_i})$ and $\boldsymbol{a_j} = (\boldsymbol{l_j}, \boldsymbol{m_j}, \boldsymbol{u_j})$, So

$$\boldsymbol{a_{ij}} = (\boldsymbol{l_i}/\boldsymbol{u_j}, \boldsymbol{m_i}/\boldsymbol{m_j}, \boldsymbol{u_i}/\boldsymbol{l_j}) \qquad (2)$$

The value of fuzzy synthetic extent with respect to i^{th} risk factor is defined as:

$$\tilde{S}_i = \sum_{j=1}^{p} \tilde{a}_{ij}^{\,h} \otimes \left[\sum_{i=1}^{p} \sum_{j=1}^{p} \tilde{a}_{ij}^{\,h}\right]^{-1}, \quad i = 1, \dots, p \, and \, , h = 1, \dots, q \qquad (3)$$

Where,

$$\left[\sum_{i=1}^{p} \sum_{j=1}^{p} \tilde{a}_{ij}^{\,h}\right]^{-1} = [\left(1/\sum_{i=1}^{p} \sum_{j=1}^{p} u_{ij}\right), \left(1/\sum_{i=1}^{p} \sum_{j=1}^{p} m_{ij}\right), (1/\sum_{i=1}^{p} \sum_{j=1}^{p} l_{ij})] \qquad (4)$$

And,

$$\left[\sum_{j=1}^{p} \tilde{a}_{ij}^{\,h}\right] = \left[\sum_{j=1}^{p} l_{ij}^{\,h}, \sum_{j=1}^{p} m_{ij}^{\,h}, \sum_{j=1}^{p} u_{ij}^{\,h}\right] \qquad (5)$$

The degree of possibility $\tilde{S}_i = (l_i, m_i, u_i) \gg \tilde{S}_j = \left(l_j, m_j, u_j\right)$ is defined as:

$$V\left(\tilde{S}_i \gg \tilde{S}_j\right) = \sup[\min(\mu_{\tilde{S}_i}(x), \mu_{\tilde{S}_j}(y))] \quad , x \gg y \qquad (6)$$

Since $\tilde{S}_i$ and $\tilde{S}_j$ are convex fuzzy numbers, these can equivalently be expressed as follows:

$$V(\tilde{S}_i \gg \tilde{S}_j) = \begin{cases} 1 & if m_i > m_j \\ hgt\left(\tilde{S}_i \cap \tilde{S}_j\right) = \mu_{\tilde{S}_j}(d) & Otherwise \end{cases} \qquad (7)$$

Where *d* is the ordinate of the highest intersection point D between $\mu_{\tilde{S}_j}$, and $\mu_{\tilde{S}_i}$(see figure 2). When $\tilde{S}_i = (l_i, m_i, u_i) and \, \tilde{S}_j = \left(l_j, m_j, u_j\right)$, the ordinate of D is given by Eq. (8).

$$V\left(\tilde{S}_i \gg \tilde{S}_j\right) = hgt\left(\tilde{S}_i \cap \tilde{S}_j\right) = \ (l_i - u_j)/[(m_j - u_j) - (m_i - l_i)] \qquad (8)$$

To compare $\tilde{S}_i$ and $\tilde{S}_j$, we need both the values of $V\left(\tilde{S}_i \gg \tilde{S}_j\right)$ and $V\left(\tilde{S}_j \gg \tilde{S}_i\right)$.

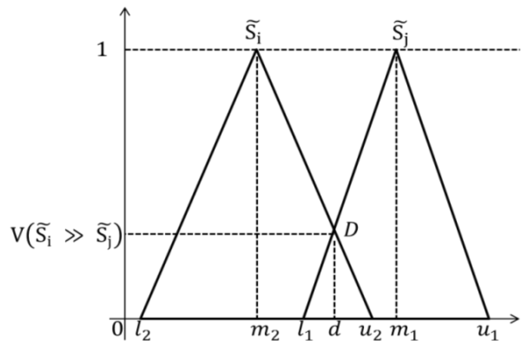


Figure 2.The intersection between $\tilde{S}_i$ and $\tilde{S}_j$.

This step is calculated for each scoring model $(h = 1, \dots, q)$. The degree possibility for a convex fuzzy number to be greater than *k* convex fuzzy numbers can be defined by:

$$(\tilde{S} \gg \tilde{S_1}, \tilde{S_2}, \dots, \tilde{S_k}) = V[(\tilde{S} \gg \tilde{S_1}) and\ (\tilde{S} \gg \tilde{S_2}) and \dots and\ (\tilde{S} \gg \tilde{S_k})]$$

$$= min\, V(\tilde{S} \gg \tilde{S_i}), \quad i = 1,2,\dots,k. \tag{9}$$

Assume that,

$$\acute{d}^h(A_i) = \min V(\tilde{S_i} \gg \tilde{S_k}), for k = 1,2,\dots,p\ ; k \neq i, and, h = 1,\dots,q \tag{10}$$

So, the weight vector of risk factors in h^{th} scoring model matrix is given by:

$$\acute{W}^h = (\acute{d}^h(A_1), \acute{d}^h(A_2), \dots, \acute{d}^h(A_p))^T, h = 1,2,\dots,q \tag{11}$$

Via normalization, we get the normalized weight vector, denoted by:

$$W^h = (d^h(A_1), d^h(A_2), \dots, d^h(A_p))^T, h = 1,2,\dots,q \tag{12}$$

Where, W^h is a non-fuzzy number.

Finally, we compute the overall composite weight of each risk factor based on the weight of each scoring models. The overall weight , P_i, is just normalization of linear combination between the weights derived, $d^h(A_i)$, and the normalized weight of scoring model, K^h, developed based on appraisal results in the third step of model.

$$P_i = \sum_{h=1}^{q} d^h(A_i) * K^h\ , i = 1,2,\dots,p \tag{13}$$

Finally, the results analysed by FAHP method, P_i, classified into 3 levels (core, level 1and level 2) by using Fuzzy C-means clustering method. This algorithm focuses on minimizing the function which is calculated weighted within-group sum of squared errors, J_p, Subject to several constraints as follow:

$$MinJ_E = \sum_{i=1}^{m} \sum_{j=1}^{c} u_{ij}^p \left\| W_i - C_j \right\|^2 \tag{14}$$

$$\text{s.t:} \quad \sum_{j=1}^{c} u_{ij} = 1 \qquad , i = 1,\dots,m \tag{15}$$

$$0 < \sum_{i=1}^{m} u_{ij} < m \qquad ,j = 1, \dots, c \tag{16}$$

where: $$u_{ij} = 1 \Big/ \sum_{k=1}^{c} \left(\|W_i - C_j\| \Big/ \|W_i - C_k\| \right)^{2/m-1} \tag{17}$$

$$C_j = \sum_{i=1}^{m} u_{ij}^{p} . W_i \Big/ \sum_{i=1}^{m} u_{ij}^{p} \tag{18}$$

The complete Fuzzy C-means algorithm is presented in Figure3.

2.3. OUTPUT

Classified risk factors according to the determined outcome (mortality or any kind of morbidity) and procedure are considered as the output in the system. In this work, for describing the system implementation; we presented early mortality as an outcome and CABG surgery as a procedure. The workflow of proposed system depicts in Figure3.

3. RESULTS

The result of identification and screening as well as data preparation steps of the work is described in above section (material & method). The results of the quality assessment are presented in Table1.

Table 1- The results of the quality assessment

Risk Scoring Models	Weight
AusSCORE [14]	92.3%
Amphiascore [15]	76.9%
Carosella et al [16]	76.9%
JACVSD Model [17]	84.6%
NYS II [18]	84.6%
NYS III [19]	92.3%
Pitkanen et al [20]	76.9%
QMMI Model [21]	76.9%
Toronto II [22]	69.2%
THIScore [23]	84.6%
Zheng et al [24]	69.2%

To determine the mortality risk factors weights, Chang's extent analysis methods is used. Pair-wise comparisons are performed using odd ratio's confidence interval of risk factors as triangular fuzzy numbers (TFNs). In this study, 11 risk scoring model as criteria and 45 risk factors as alternatives are considered to construct the fuzzy decision matrix matrix [14-24]. The result of the algorithm for one scoring model, AusSCORE, and one risk factor, Sever Left ventricular Ejection Fraction (Sever LVEF), is summarized in Table 2 to 7.

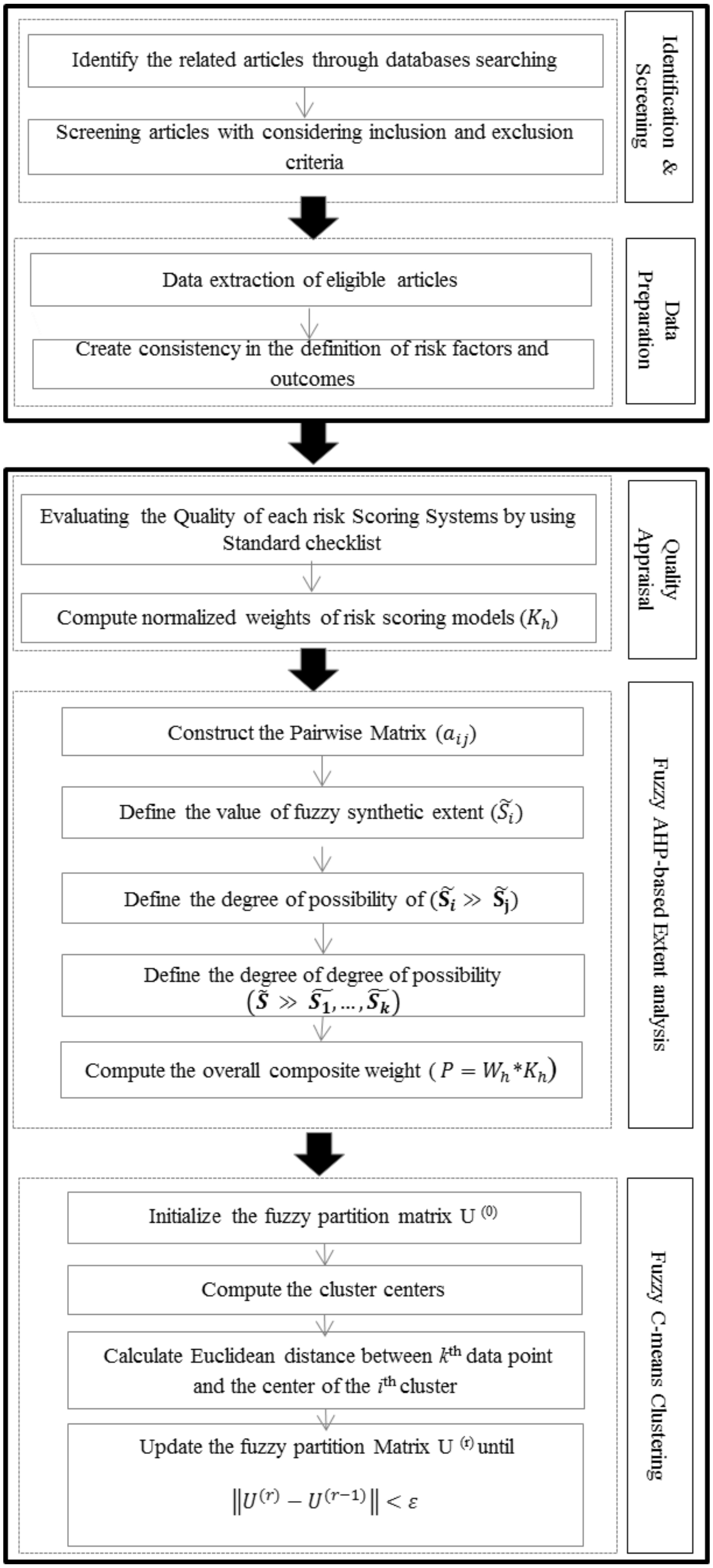


Figure 2- The system workflow

Table 2- Pairwise Matrix for i=1(Sever LVEF) and h=1 (AusSCORE) are calculated by using Equation 2.

Risk Factor i	Risk Factor j	Lower	Middle	Upper
LVEF -sever	Urgent surgery	0.433566434	1.05	4.985075
LVEF -sever	Emergent salvage	0.198294243	0.607229	3.650273
LVEF -sever	Reoperation	0.37804878	1.100437	6.242991
LVEF -sever	Peripheral Vascular Disease	0.525423729	1.194313	5.301587
LVEF -sever	LVEF-moderate	0.488188976	1.155963	5.344
LVEF -sever	LVEF -sever	0.278443114	1	3.591398
LVEF -sever	Age 60-65	0.369781312	1.194313	7.505618
LVEF -sever	Age 65-70	0.369781312	1.194313	7.505618
LVEF -sever	Age 70-75	0.235145386	0.707865	4.175
LVEF -sever	Age 75-80	0.235145386	0.707865	4.175
LVEF -sever	Age 80-85	0.124165554	0.446018	3.13615
LVEF -sever	Age>85	0.124165554	0.446018	3.13615
LVEF -sever	NYHA* class III	0.486910995	1.205742	5.808696
LVEF -sever	NYHA class IV	0.305921053	0.807692	3.690608

*NYHA: New York Heart Association Functional Classification

Table 3- The value of fuzzy synthetic extent for i=1to14 and h=1 (AusSCORE) are calculated by using Equation 3, 4, and 5.

Risk Factor	$\tilde{S}_i$:Middle	$\tilde{S}_i$: Lower	$\tilde{S}_i$: Upper
Urgent surgery	0.055172414	0.003264035	0.860432381
Emergent salvage	0.095402299	0.004457599	1.881318353
Reoperation	0.052643678	0.002606356	0.986789584
Peripheral Vascular Disease	0.048505747	0.003069167	0.71000714
LVEF-moderate	0.050114943	0.003044808	0.764160227
LVEF -sever	0.057931034	0.004530675	1.339787484
Age 60-65	0.048505747	0.002167904	1.008851953
Age 65-70	0.048505747	0.002167904	1.008851953
Age 70-75	0.08183908	0.003897355	1.58648488
Age 75-80	0.08183908	0.003897355	1.58648488
Age 80-85	0.129885057	0.005188353	3.004493489
Age>85	0.129885057	0.005188353	3.004493489
NYHA class III	0.048045977	0.002801224	0.766165896
NYHA class IV	0.071724138	0.004408882	1.219447291

Table 4- Fuzzy synthetic degree values for i=1, j=1 to 14 and h=1 are calculated by using Equation 7 and 8.

Risk Factor i	Risk Factor j	Fuzzy synthetic degree values
LVEF -sever	Emergent salvage	0.972704521
LVEF -sever	Reoperation	1
LVEF -sever	Peripheral Vascular Disease	1
LVEF -sever	LVEF-moderate	1
LVEF -sever	LVEF -sever	1
LVEF -sever	Age 60-65	1
LVEF -sever	Age 65-70	1
LVEF -sever	Age 70-75	0.982417945
LVEF -sever	Age 75-80	0.982417945
LVEF -sever	Age 80-85	0.948843723
LVEF -sever	Age>85	0.948843723
LVEF -sever	NYHA class III	1
LVEF -sever	NYHA class IV	0.989776614

Table 5- Degree of possibility for i=1 and h=1 calculated by using Equation 10 and 11

Risk Factor	Min Fuzzy synthetic degree values	Normalized weight
LVEF -sever	0.948843723	0.071734819

Table 6- Overall composite weight for i=1 and h=1to 11 are calculated by using Equation 12

Scoring Model	Risk Factor	Normalized weight of risk factor	Normalized weight of Scoring
AusSCORE	LVEF -sever	0.071734819	0.10436454
QMMI	LVEF -sever	0.048980181	0.08695161
JACVSD	LVEF -sever	0.042890418	0.09565807
Pitkanen et al	LVEF -sever	0.044178926	0.08695161
Amphiascore	LVEF -sever	0.062680979	0.08695161
Toronto II	LVEF -sever	0.117425719	0.07824514
NYS II	LVEF -sever	0.088623875	0.09565807
Carosella et al.	LVEF -sever	0.04491257	0.08695161
NYS III	LVEF -sever	0.063547092	0.10436454

Table 7- Overall weight of LVEF by using Equation 13

Risk Factor	Overall weight
LVEF -sever	0.053342796

Computations of C-means clustering is done by calling the “Cmeans” function from “e1701-1.6-1” package of R software version (2.15.2) into our system. The values of cluster center, Membership matrix and the value of objective function calculated in different iteration is summarize in Appendix 2.

4. DISCUSSION AND CONCLUSION

The objective of the research was to develop a system to recognize most important risk factors which can help to predict the outcomes such as mortality before performing the specific surgery by the integration of Quality Appraisal, FAHP and fuzzy c-means clustering methods. To illustrate the system implementation, the information of scoring systems developed to predict early mortality after CABG is considered. Although several scoring model were developed to predict mortality after CABG, no consistent sets of significant risk factors have been attained among them. In the other hand, some studies showed that increasing the complexity of the model by using more predictors did not have a major effect on the prediction accuracy. In addition, it is proved that most prognostic information in patients undergoing cardiac surgery can be acquired by a few key variables. Therefore, it may be more preferable to collect essential data attentively rather than to make costly data collection efforts that may include insignificant information.

In spite of potential of this topic to develop comprehensive scoring model for assessing the result of CABG, few published studies has been presented to define and prioritize the importance of related risk factors so far. For example, Jones and associates (The Working Group Panel on the Collaborative CABG Database Project) reported the conclusion of two consensus panel meeting to describe the importance of a set of clinical variables useful for monitoring and improving the short term mortality of patients undergoing CABG and has categorized 44 clinical variables into 7 core, 13 level 1 and 24 level 2 variables, to reflect their relative importance. This group has identified and proposed uniform definitions for a list of 7 core variables (i.e., age, gender, acuity of operation, poor Left Ventricular Ejection Fraction (LVEF), previous operation, left main coronary artery disease and number of diseased coronary arteries) that they consider must be present in any database of patients undergoing CABG [5].

Similarly, Tu and associates [6], using clinical data for all 5,517 patients undergoing isolated CABG in Ontario, developed 12 increasingly comprehensive risk-adjustment models using logistic regression analysis according to 6 of the Panel’s core variables and 6 of the Panel’s level1 variables. They have also suggested a limited set of six core variables (age, gender, emergency operation, previous CABG or redo surgery, LVEF and left main disease) appear to be sufficient for fairly comparing hospital risk-adjusted mortality rates after CABG in Ontario. Hannan and associates [7] compared the ability of a clinical and administrative data base in New York State to predict in-hospital mortality and to assess hospital performance for CABG. The results indicated that the clinical database is substantially better at predicting case-specific mortality than the administrative data base. Also, correlations between hospital mortality rates that are risk-adjusted using the two systems were only moderately high. In addition, they concluded that left ventricular ejection fraction, reoperation, and left main disease have an important impact on hospital risk-adjusted mortality rates and that these factors should be part of any risk adjustment model for assessing the short-term results of CABG.

Aylin and associates [25] used logistic regression to fit three models for CABG, repair of abdominal aortic aneurysm, and colorectal excision for cancer. simple model include year, age, and sex only, the intermediate model include year, age, sex, method of admission, diagnostic, or operation subgroup and a complex model include more appropriate variables such as number of arteries replaced, previous ischemic heart disease, previous myocardial infarction, Reoperation and so on. The power of the complex predictive model according to ROC curve scores was compared in against intermediate and simple model and the values of c-index were computed 0.77, 0.72 and 0.69, respectively which is proved that there was no significant difference between results. Totally, Preoperative risk factors such as advanced age, reoperation, poor LVEF and emergency surgery identified as core risk factor for early mortality as has been reported by our study.

However, Left main coronary artery disease, in this work, was only reported by Torento II scoring model [22] and the evidence on its relative importance remains questionable. In contrast, female gender was presented in several scoring models but the importance of this predictor was lower than another risk factors. Our results proved that Creatinin level unambiguously related to operative mortality, although this predictor is considered as level one variable by Jones and associates. But, Ranucci and associates [26], included serum Creatinine were highly statistically significant predictor of early mortality after CABG for elective patient. Beside, these researchers concluded the model limited to this predictor as well as advanced age and poor LVEF had an accuracy equivalent to or better compared with more complex risk scores. Therefore, the results of our study do not conflict with presented works. In against, there are some differences which will be described.

The first and major difference between presented works and our study is that while prior researches have been mainly data driven, our study tested the feasibility of (and showed promising results for) employing extracted information of scoring models to find important risk factors. In other words, they have concluded according to comprehensive database and they provided methods which operate on data which it may be not available in the most of the hospitals. Because collecting data as well as accuracy in gathering is a challenging task for many hospitals, we believe that our system, or a similar system, could have promising results effortlessly.

Second advantage of using this system is its generalizability. The proposed system can be extended for every outcome or procedure due to the fact that it focused on the extracted information of different scoring model which is available in literature whereas prior researches depend on regional and specific data.

In addition to, we described confidence interval of odd ratio as input of system by using triangular fuzzy number because of fuzzy nature of them. In recent literature, confidence intervals of odd ratios have been reported by adjusted mean as crisp data, to the best of our knowledge. Nevertheless they provide useful information for more accurate analysis and concluding. Finally, it is important to point out that, a system for comparing the importance of predictors of mortality as well as morbidity after surgery with its specific characteristics is the novel contribution and the similar work is not reported in the literature.

The result of this research may be helpful for clinicians to gather important information in order to determine the probability and degree to which a patient may be dead or suffer complication in the future. Besides, it could open new research lines which may allow researcher to keep on with different application. For example, his study could be extended to weight identified risk factors of CABG morbidity or extended length of stay in ICU. Furthermore, predictors of adverse outcome following valve surgery (include aortic, mitral, Tricuspid and multiple valve surgery), Surgery on thoracic aorta, Heart Transplantation or cardiac intervention such as PCI can be prioritized in the same way. Therefore further studies will be required to follow this work.

Our study has some limitations. For testing the system, we omitted some scoring models which did have neither confidence interval of odd ratios, nor its standard deviation to compute it. Also, we were not able to include some related studies in the work because there is no access to the full text of them.

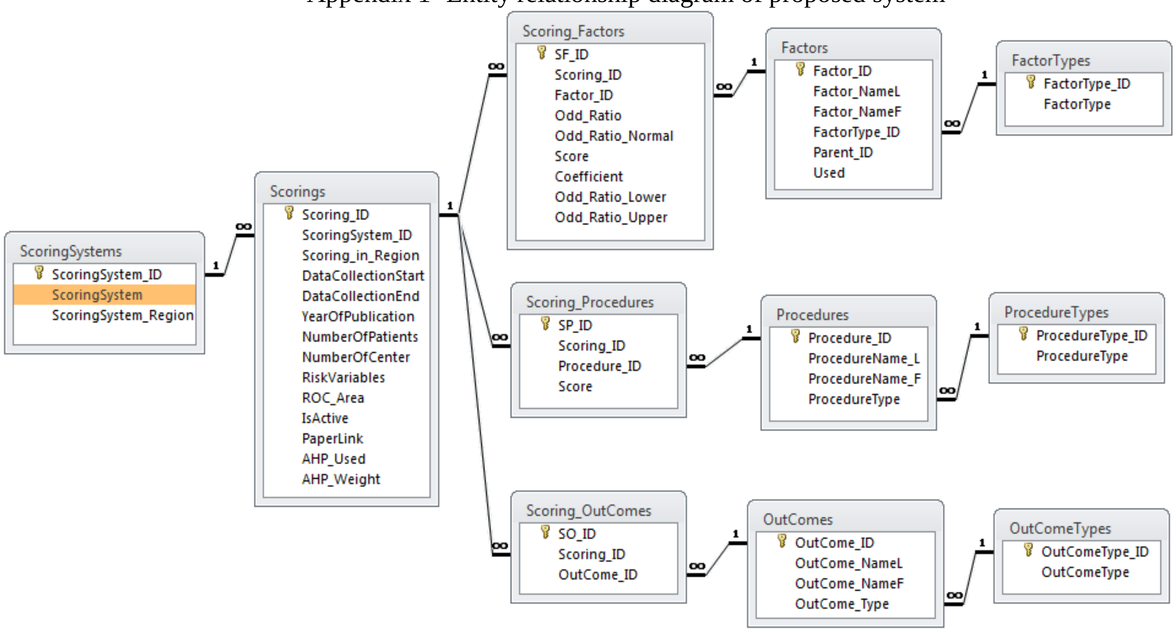
5. ACKNOWLEDGEMENTS
The authors would like to acknowledge Dr. Esfehani F, Epidemiologist Consultant for development research center for providing her suggestions and helps.

6. REFERENCES
[1]. Sadeghi M. M, Arasteh M, Gharipour M, Nilfroush P, Shamsolketabi H, Etesampour A, et al.: Evaluation of accuracy of EuroSCORE risk model in prediction of perioperative mortality after coronary bypass graft surgery in Isfahan. Journal of Research in Medical Sciences, 16(6), 787-792. (2011)
[2]. Nilsson J, Algotsson L, Ho¨Glund P, Lu¨HrsC,Brandt J.: Comparison of 19 pre-operative risk stratification models in open-heart surgery. European Heart Journal, 27(7), 867-874.(2006)
[3]. Eagle K. A, Guyton R. A, Davidoff R, Ewy G. A,Fonger J, Gardner T. J., et al.: ACC/AHA guidelines for coronary artery bypass graft surgery: Executive summary and recommendations: A report of the American college of cardiology/American heart association task force on practice guidelines (committee to revise the 1991 guidelines for coronary artery bypass graft surgery). American Heart Association, 100(13), 1464-1480.(1999)4.
[4]. Magovern J. A, Magovern J. G, Burkholder J. A,Magovern G. J.: A model that predicts morbidity and mortality after coronary artery bypass graft surgery. J Am Coil Cardiol, 28(5), 1147-1153. (1996)
[5]. Jones R. H, Hannan E. L, Hammermeister K. E, Delong E. R, O' Connor G. T, Luepker R. V, et al.: Identification of preoperative variables needed for risk adjustment of short-term mortality after coronary artery bypass graft surgery. Journal of the American College of Cardiology, 28(6), 1478-1487.(1996)
[6]. Tu J. V, Sykora K, Naylor C. D.: Assessing the outcomes of coronary artery bypass graft surgery: How many risk factors are enough? Journal of the American College of Cardiology, 30(5), 1317-1323.(1997)
[7]. Hannan E. L, Kilburn H, Lindsey M. L, Lewis R.: Clinical versus administrative data bases for CABG surgery: Does it matter? Medical Care, 30(10), 892-907.(1992)
[8]. NoueiT. M, Vahidian K. A, Ghazalbash S. : Application of AHP method to identify most important predictors for Early Mortality after Coronary Artery Bypass Graft. Canadian Journal on Computing in Mathematics, Natural Sciences, Engineering and Medicine.(2013)
[9]. Saaty T. L.: Decision making with the analytic hierarchy process. Int. J. Services Sciences, 1(1), 83-98.(2008)
[10]. Liberatore M. J,Nydick R. L.: The analytic hierarchy process in medical and health care decision making: A literature review. European Journal of Operational Research, 189(1), 194-207.(2008)
[11]. Massad E., Ortega N. R. S., Struchiner C. J., Burattini M. N.: Fuzzy epidemics. Artificial Intelligence in Medicine, 29(3), 241-259. (2003)
[12]. TakácsM.: Extended fuzzy methods in risk management, paper presented at the 14th WSEAS International Conference on Applied Mathematics, 300-304.(2009)
[13]. Chang D. Y.: Applications of the extent analysis method on fuzzy AHP. European Journal of Operational Research, 95(3), 649-655.(1996)
[14]. Reid Ch, Billah B, Dinh D, Smith J, Skillington P, Yii M, et al.: An Australian risk prediction model for 30-day mortality after isolated coronary artery bypass: The AusSCORE. Acquired Cardiovascular Disease, 138(4), 904-910.(2009)
[15]. Huijskes R.V.H.P, Rosseel P.M.J,TijssenJ.G.P. : Outcome prediction in coronary artery bypass grafting and valve surgery in the Netherlands: Development of the AmphiaSCORE and its comparison with the EuroSCORE. European Journal of Cardio-thoracic Surgery, 24(5), 741-749.(2003).
[16]. Carosella V. C, Navia J.L, Al-RuzzehSh, Grancelli H, Rodriguezd W, Cardenas C, et al.: The first Latin-American risk stratification system for cardiac surgery: Can be used as a graphic pocket-card score. Interactive Cardiovascular and Thoracic Surgery, 9(2), 203–208.(2009)
[17]. Motomura N, Miyata H, Tsukihara H, Okada M, Takamoto S .: Japan Cardiovascular Surgery Database Organization First report on 30-day and operative mortality in risk model of isolated coronary artery bypass grafting in japan. Ann ThoracSurg, 86(6), 1866-1872. (2008).
[18]. Hannan E. L, Wu C, Bennett E. V, Carlson R. E, Culliford A. T, Gold J. P, et al.: Risk stratification of in-hospital mortality for coronary artery bypass graft surgery. Journal of the American College of Cardiology, 47(3), 661–668.(2006)
[19]. Hannan E. L, Farrell L. S, Wechsler A, Jordan D, Lahey S. J, Culliford A. T, et al.: The new york risk score for in-hospital and 30-day mortality for coronary artery bypass graft surgery. The Annals of Thoracic Surgery, 95(1), 46-52.(2012)
[20]. Pitkaènen O, Niskanen M, Rehnberg S, Hippelaèine M, Hynynen M.: Intra-institutional prediction of outcome after cardiac surgery: Comparison between a locally derived model and the EuroSCORE. European Journal of Cardio-thoracic Surgery, 18(6), 703-710.(2000)

[21]. Fortescue E.B, Kahn K & Bates D. W.: Development and validation of a clinical prediction rule for major adverse outcomes in coronary bypass grafting. American Journal of Cardiology, 88(11), 1251–1258.(2001)
[22]. Ivanov J, Tu J. V,Naylor C. D.: Ready-made, recalibrated, or remodeled? : Issues in the use of risk indexes for assessing mortality after coronary artery bypass graft surgery. American Heart Association, 99(16), 2098-2104.(1999)
[23]. Madan P, Elayda M. A, Lee V, Wilson J. M.: Risk-prediction models for mortality after coronary artery bypass surgery: Application to individual patients. International Journal of Cardiology, 149(2).227-231.(2011)
[24]. Zheng Z, Zhang L, Hu Sh, Li X, Yuan X, GAO H.: Risk factors and in-hospital mortality in Chinese patients undergoing coronary artery bypass grafting: Analysis of a large multi-institutional CHINESE database. Acquired Cardiovascular Disease, 144(2), 355-359.(2012)
[25]. Aylin, P., Bottle, A., Majeed, A.: Use of administrative data or clinical databases as predictors of risk of death in hospital: Comparison of models. BMJ, 19 May 2007(334), 1044-1047.(2007)
[26]. Ranucci M, Castelvecchio S, Menicanti L, Frigiola A, Pelissero G.: Risk of assessing mortality risk in elective cardiac operations: Age, creatinine, ejection fraction, and the law of parsimony. American Heart Association, 119(24), 3053-3061. (2009)

Appendix

Appendix 1- Entity relationship diagram of proposed system



Appendix 2- The values of cluster center, Membership matrix, the value of objective function in C-mean clustering

Membership matrix of c-means clustering algorithm

10	1	2	3		1	2	3
[1,]	6.54E-02	2.68E-02	9.08E-01	[24,]	6.06E-01	3.56E-01	3.78E-02
[2,]	6.54E-02	2.68E-02	9.08E-01	[25,]	4.92E-01	4.71E-01	3.72E-02
[3,]	8.37E-03	2.91E-03	9.89E-01	[26,]	3.21E-01	6.48E-01	3.10E-02
[4,]	7.56E-03	2.62E-03	9.90E-01	[27,]	2.96E-01	6.75E-01	2.95E-02
[5,]	2.34E-03	7.83E-04	9.97E-01	[28,]	2.13E-01	7.63E-01	2.38E-02
[6,]	1.25E-02	3.64E-03	9.84E-01	[29,]	4.87E-02	9.44E-01	7.21E-03
[7,]	1.63E-02	4.68E-03	9.79E-01	[30,]	1.87E-02	9.78E-01	3.04E-03
[8,]	6.80E-02	1.74E-02	9.15E-01	[31,]	5.36E-04	9.99E-01	9.85E-05
[9,]	1.27E-01	2.99E-02	8.43E-01	[32,]	4.80E-04	9.99E-01	9.28E-05
[10,]	1.63E-01	3.65E-02	8.00E-01	[33,]	1.84E-03	9.98E-01	3.65E-04
[11,]	6.50E-01	7.49E-02	2.75E-01	[34,]	2.27E-03	9.97E-01	4.51E-04
[12,]	8.79E-01	4.56E-02	7.53E-02	[35,]	2.97E-03	9.96E-01	5.96E-04
[13,]	9.22E-01	3.32E-02	4.43E-02	[36,]	3.30E-03	9.96E-01	6.66E-04
[14,]	9.25E-01	3.25E-02	4.27E-02	[37,]	3.55E-03	9.96E-01	7.16E-04
[15,]	9.81E-01	9.95E-03	8.67E-03	[38,]	4.36E-03	9.95E-01	8.87E-04
[16,]	9.97E-01	1.92E-03	1.33E-03	[39,]	5.30E-03	9.94E-01	1.09E-03
[17,]	9.98E-01	9.99E-04	6.60E-04	[40,]	6.35E-03	9.92E-01	1.31E-03
[18,]	1.00E+00	2.04E-04	1.26E-04	[41,]	7.62E-03	9.91E-01	1.59E-03
[19,]	9.97E-01	1.84E-03	9.35E-04	[42,]	8.01E-03	9.90E-01	1.68E-03
[20,]	9.82E-01	1.29E-02	5.24E-03	[43,]	1.00E-02	9.88E-01	2.12E-03
[21,]	9.46E-01	4.13E-02	1.30E-02	[44,]	1.22E-02	9.85E-01	2.61E-03
[22,]	9.08E-01	7.33E-02	1.91E-02	[45,]	1.66E-02	9.80E-01	3.64E-03
[23,]	7.79E-01	1.89E-01	3.18E-02				

Custer centroids in c-mean clustering algorithm

[1]	[2]	[3]
0.025254588	0.005680969	0.050758896

Objective function values in c-mean clustering algorithm

Iteration:	Error:	Iteration:	Error:
1,	7.55E-05	8,	1.73E-05
2,	5.09E-05	9,	1.73E-05
3,	2.59E-05	10,	1.73E-05
4,	1.80E-05	11,	1.73E-05
5,	1.74E-05	12,	1.73E-05
6,	1.73E-05	13,	1.73E-05
7,	1.73E-05	14,	1.73E-05