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Developing a fuzzy expert system to determine the levels of students' eHealth literacy

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Abstract

The concept of eHealth literacy refers to the ability of a person to access electronic health information, evaluate the information, and apply the resulting knowledge to address or solve a health problem. Considering the uncertainties and the subjective nature of e-health literacy, determining the levels of students' e-health literacy is a complex problem. The aim of this research is to develop and implement a fuzzy expert system to determine the level of eHealth literacy anytime and anywhere without accessing the experts personally. Thus, after studying the different methods of measuring people's literacy level, the Digital Health Literacy Instrument was chosen for developing the system. Its reliability and validity were evaluated based on the experts' judgment and by asking for the participation of 50 university students. The implementation of the fuzzy expert system showed that the proposed system succeeded in 88% of analyzed cases. Moreover, to decrease the number of rules systematically to help with expert fatigue while responding to surveys, the fuzzy expert system was modified based on rough set theory, which caused a reduction in the number of rules from 432 to 200. The comparison between the two fuzzy expert systems demonstrated that no significant difference was detected and the modified system.

Keywords: eHealth literacy; Fuzzy expert system; eHealth Literacy Scale; eHEALS; Digital Health Literacy Instrument; DHLI.

1. Introduction

The growing use of applications and Internet-based services makes rapid changes in the health care system. Nowadays, electronic health care services such as patient forums, health information pages, electronic patient records, or self-tracking systems that can be used along with fitness wristbands or smartwatches build up the people's confidence and develop their ability for participating in health management actively (Griebel, et al. 2017). Along with these changes, the eHealth literacy becomes more important. For the very first time, Norman and Skinner (2006b) introduced electronic health literacy in 2006. According to their definition, e-health literacy is designed for living in a rich information society and refers to the individual's ability to access health information from the Internet, evaluate that information, and apply the resulting knowledge to address or solve a health problem. A person's health and the quality of their health care are influenced by their level of eHealth literacy (Hsu, et al. 2014). In other words, people with low e-health literacy will experience difficulty in accessing electronic health information, and poor e-health literacy is a major obstacle to accessing, evaluating, and using electronic health information (Norman and Skinner, 2006a). Today, e-health literacy is a concept not only in the field of health education but also in many aspects of health promotion (Korda and Itani, 2013). Recent studies show relationships between eHealth literacy and the presence of chronic illness, perceived self-management skills, and better self-perceived understanding of health status, symptoms, and optional treatments (Neter and Brainin, 2012). Promoting and securing community health, which is one of the key pillars of community development can be achieved by improving people's health literacy (Liu, et al. 2018).

One of the critical life stages in terms of the formation and performance of health-promoting behaviors and their impact on the later stages is the university student's life. In addition, attempt to maintain and promote health in educational and research environments, including universities is one of the most important areas for the realization of education and research. Students, with the provision of an individual, social, and environmental health promotion, can maximize their potential in education and training, and, as such, make knowledge development in the country easier. The identification and investigation of the relevant and effective factors for encouraging students to healthier and low-risk behaviors are the utmost importance that e-health literacy is one of those factors. Existing studies have shown that although most of the university students are familiar with the Internet to find health information, many students lacked e-health literacy skills, which may cause overestimating their ability to successfully locate and evaluate eHealth information. Many scholars have suggested that special attention should be paid for improving the students' ability to obtain and evaluate electronic health information (Stellefson, et al. 2011).

There is a need for a valid instrument on eHealth literacy measurement to measure individuals' ability to use the wide spectrum of online information and to observe the results of eHealth accomplishments on an individual and a population level. Additionally, an eHealth service developer who is the creator of a tool that is suitable for people to tailor health information services may require the level of people's e-health literacy (Enwald, 2013). Thus, for presenting relevant content to a user who accesses an online health service for the first time, it is essential to measure their eHealth literacy by a valid and short questionnaire and/or usability tests (Griebel, et al. 2017).

1.1.Related literature

Due to the importance of this area of research, various studies have been undertaken to determine the level of electronic health literacy of people. For this purpose, different methods including quantitative, qualitative, or their combination, were used. Different data collection methods such as questionnaires or interviews were employed to manually investigate and calculate e-health literacy of people by using deterministic and crisp variables (Ivanitskaya 2012; Van Der Vaart, et al. 2013; Chew, 2014; Tang, et al. 2014; Furstrand and Kayser, 2015; Park and Lee, 2015; Lee, et al. 2016). Most studies on eHealth literacy have used the 8-item eHealth Literacy Scale (eHEALS) that is provided by Norman and Skinner (2006a) to measure the individual's literacy level. Since this scale has been the only validated instrument for measuring the individual's literacy level for a long time (Van Der Vaart, et al. 2013), its different translation from English into different languages, such as German (Soellner, et al. 2014), Spanish (Pérez, et al. 2015), and Japanese (Mitsutake, et al. 2011) has been made. Currently, some studies remark problems on the existing concept of eHealth literacy or with measurement methods (Norman, 2011; Van Der Vaart, et al. 2011; Ashurst, et al. 2012; Kayser, et al. 2015; Norgaard, et al. 2015). Hargittai (2005) mentioned problems of validity in measurements based on self-assessment. Cameron Norman (2011) considered the dynamic environment of the eHealth services while the original eHealth literacy concept had been developed for the first generation of eHealth services and consequently did not include social media. Van Der Vaart et al. (2013) showed a weak correlation between eHealth literacy measured by eHEALS and the Internet use of a person while it was high when eHEALS was developed. Although there are no changes in the skillset that eHEALS should measure, the online environment has become more dynamic due to the invention of mobile health and social media (Griebel, et al. 2017). Recently, Van Der Vaart and Drossaert (2017) contributed to the Digital Health Literacy Instrument (DHLI), which can incorporate the diversity of skills to use both the use of health information that is available on the Internet and the use of interactive technologies, which support people to communicate about their health (with peers and with health care professionals), to self-monitor their health, and even to receive treatment via the Internet.

The competency of the e-health literacy of a person can be at different levels. Operational and navigational skills are required for the lower level, and the higher-level needs the ability to choose and critically evaluate available information (Griebel, et al. 2017). The higher the level of e-health literacy, the more intention to use eHealth services (Noblin, et al. 2012). Determining the level of eHealth literacy may help individuals to access high-quality eHealth resources that are suitable for them (Chesser, et al. 2016). Using deterministic methods and crisp variables for measuring the different aspects of topics such as e-health literacy, which is expressed mentally, qualitatively, and by linguistic variables, has the following drawbacks:

(1) The ambiguity associated with the judgments of experts and the changes in their value by turning into quantitative data is ignored (Norman and Skinner, 2006b).

(2) Mental judgment, selection, and prioritization of experts have a great influence on the results of methods using crisp variables (Lin, et al. 2006).

(3) While there is a non-linear relationship between variables of e-health literacy, the most quantitative statistical analysis in the literature assumed a linear relationship between variables that cause errors in their models (Lin, et al. 2006).

(4) Some of the criteria for determining the level of e-health literacy are expressed by linguistic variables that, contrary to the quantitative variables, are inaccurate and vague. These variables make the determination of the level of e-health more difficult, and the modeling process more complicated (Norman and Skinner, 2006a; 2006b).

In most studies, e-health literacy is determined manually based on the quantitative Norman and Skinner model using questionnaires for collecting data (Brown and Dickson, 2010; Britt and Hatten, 2013; Hsu, et al. 2014; Robb and Shellenbarger, 2014; Tang, et al. 2014; Park and Lee, 2015; Pérez, et al. 2015; Lee, et al. 2016) Using this method ignores the ambiguity associated with the judgments of experts and the changes in the value as a result of converting verbal information to quantitative data. Also, the subjective concept of the e-health literacy, the multitude of effective qualitative factors on students' eHealth literacy, and the unknown effective variables make it difficult to provide a structured model for determining the level of students' e-health literacy (Norman and Skinner, 2006a; 2006b).

1.2.Objective

Rule-based fuzzy expert systems are useful tools for dealing with issues that are vague and obscure. Fuzzy expert systems are a developed form of expert systems that use fuzzy logic for processing. In these systems, a set of membership functions and fuzzy rules are used instead of crisp and binary variables for receiving inputs and inference. Fuzzy expert systems make it possible not only to convert linguistic variables to quantitative data, which is more suitable for analyses but also to consider non-linear relationships between criteria and inputs. These systems are used when there is a knowledge base gathered from previous studies or expert judgments to relate outputs to inputs. Moreover, a fuzzy expert system will be appropriate when there is not sufficient data for modeling. Fuzzy concepts help evaluators to use standard language for expressing linguistic variables, and linking these phrases to appropriate membership functions performs more relevant and more accurate analyzes. In quantitative studies, the required information is expressed numerical, but when the research is carried out in a qualitative field, and knowledge is ambiguous, information cannot be expressed as numbers or crisp variables. So that in most researches, it is stated that most people cannot give a precise number for expressing their opinion, therefore they evaluate verbally instead of numerically; thus, the use of verbal information rather than numbers for making a realistic model can be useful. In conclusion, developing a simple fuzzy logic model for dealing with the ambiguities in measuring methods seems necessary (Lin, et al. 2006).

This research aims to develop and implement a fuzzy expert system to determine the level of eHealth literacy to overcome the mentioned drawbacks. The main advantage of creating an expert system is to use the expertise of experts anytime and anywhere without accessing them personally. Also, developing this new fuzzy expert system has the advantages of eliminating the possible contradiction between experts' judgments because it is using an inference engine (a component of the expert system). In expert systems, the aggregation of different opinions and viewpoints will be well integrated to reach the optimum result. Furthermore, since there is a non-linear relationship between variables (each item in the questionnaire) of e-health literacy, using the expert system allows experts to consider a weighed-scale for each item to measure the overall eHealth literacy rather than the traditional or manual way of adding up the points of questionnaires. After validating the system by asking students of Mashhad University of Medical Sciences to participate in the study, the fuzzy expert system is ready for evaluation of the levels of students' e-health literacy. The weakness of students' e-health literacy can be identified and based on the results; it would be possible to suggest intervention programs to help the responsible organizations such as the Ministry of Health or the university to improve students' e-health literacy.

The remainder of the paper is organized as follows. The second section presents the research methodology and different steps of developing a fuzzy expert system. Section 3 reports the results of the proposed system implementation. The discussion about outputs and conclusions are presented in the two last sections.

2. Methods

In this study, a fuzzy rule-based expert system was developed and implemented through three main steps (Figure 1). The first step was the selection of the proper measures for the determination of eHealth literacy level. Different eHealth literacy measurement approaches were extracted from the literature, and the most appropriate instrument was selected. Next, a fuzzy expert system was designed to determine the level of e-health literacy. Generally, there are six steps for computing the output of the fuzzy expert system using the Mamdani fuzzy model:

(1) Determining a set of fuzzy rules
(2) Fuzzifying the inputs using the input membership functions
(3) Combining the fuzzified inputs according to the fuzzy rules to establish a rule strength (Fuzzy Operations)
(4) Finding the consequence of the rule by combining the rule strength and the output membership function (implication)
(5) Combining the consequences to get an output distribution (aggregation)
(6) Defuzzifying the output distribution

In the last step, we tried to reduce the number of rules systematically using rough set theory since the increasing number of rules may cause receiving perfunctory answers due to the respondents’ fatigue which results in deterioration. Expert’s answers are then inputted into a new expert system to develop another eHealth literacy inference engine. The comparison between the outputs of the two expert systems illustrates the possibility of reducing the rules without weakening the expert system.

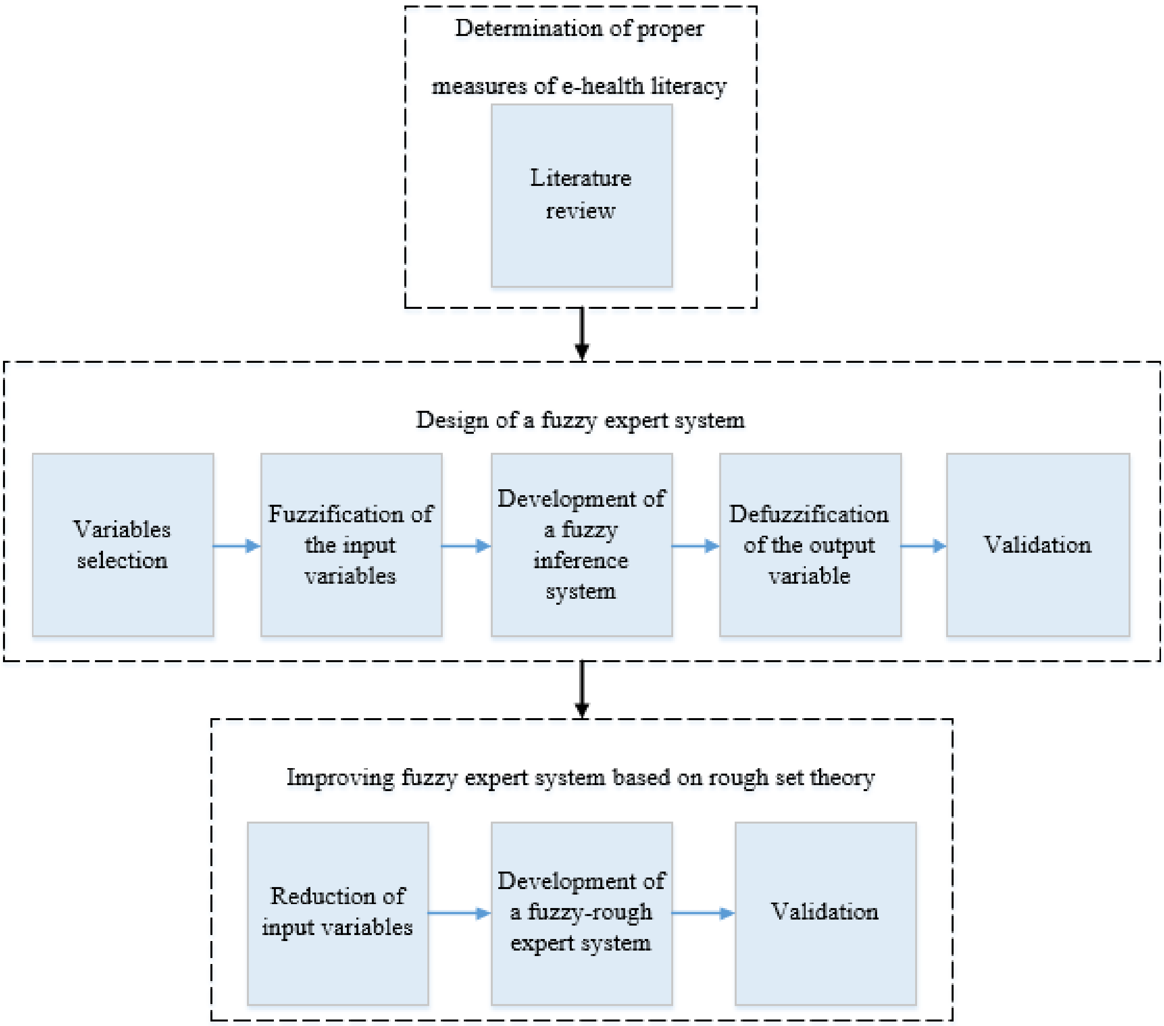

Figure 1. Overview of the research methodology

2.1.Determination of proper measures of e-health literacy

As it was mentioned, a list of different ways of determining the level of eHealth literacy was drawn up by reviewing the literature. Subsequently, different instruments consists of the eHealth Literacy Scale (eHEALS), the eHealth Literacy Assessment Toolkit (eHLA), the instrument to measure patient's readiness to engage in health information technology (PRE-HIT), the eHealth literacy measurement (e-HLS), the Health Research Readiness Self-Assessment (Health-RRSA), the different recent revisions of eHEALS, the Research Readiness Self-Assessment (RRSA-h) instrument, the Patient eHealth Readiness Scale (PERQ), and the

Digital Health Literacy Instrument (DHLI) were investigated. According to the expert panel comments, which was consisted of five experts who had more than ten years' experience in health literacy as well as holding the PhD degree related to the research topic, and the investigation of different criticism in recent articles, the Digital Health Literacy Instrument was selected as the most proper and comprehensive tool, which can take Health 1.0 (information gathering) and Health 2.0 (interactivity on the Web) aspects into account.

The DHLI considers seven separate skills to discover and evaluate online health data, to employ apps for interacting with peer patients, to retrieve disease-related information by utilizing a personal electronic medical record for monitoring their health (Van Der Vaart and Drossaert, 2017). To determine the seven skills, there are 21 self-report items (Table 1) that people rate the difficulty of understanding specific tasks and how often they experience certain problems on the Internet.

Table 1. The Digital Health Literacy Instrument (DHLI) (Van Der Vaart and Drossaert, 2017)

Item	Skill
How easy or difficult is it for you to…	
1. Use the keyboard of a computer (e.g., to type words)?	Operational skills
2. Use the mouse (e.g., to put the cursor in the right field or to click)?	
3. Use the buttons or links and hyperlinks on websites?	
When you search the Internet for information on health, how easy or difficult is it for you to…	
4. Choose from all the information you find?	Information searching
5. Use the proper words or search query to find the information you are looking for?	
6. Find the exact information you are looking for?	
7. Decide whether the information is reliable or not?	Evaluating reliability
8. Decide whether the information is written with commercial interests (e.g., by people trying to sell a product)?	
9. Check different websites to see whether they provide the same information?	
10. Decide if the information you found applies to you?	Determining relevance
11. Apply the information you found in your daily life?	

12. Use the information you found to make decisions about your health (e.g., on nutrition, medication, or to decide whether to ask a doctor's opinion)?	
When you search the Internet for health information, how often does it happen that…	
13. You lose track of where you are on a website or the Internet?	Navigation skills
14. You do not know how to return to a previous page?	
15. You click on something and get to see something different than you expected?	
When typing a message (e.g., to your doctor, on a forum, or social media such as Facebook or Twitter) how easy or difficult is it for you to…	
16. Clearly formulate your question or health-related worry?	Adding self-generated content
17. Express your opinion, thoughts, or feelings in writing?	
18. Write your message as such, for people to understand exactly what you mean?	
When you post a message on a public forum or social media, how often…	
19. Do you find it difficult to judge who can read along?	Protecting privacy
20 Do you (intentionally or unintentionally) share your private information (e.g., name or address)?	
21. Do you (intentionally or unintentionally) share some else's private information?	

2.2.Design of a fuzzy expert system

As it is illustrated in Figure 1, designing a fuzzy rule-based system consists of five principal steps, namely variables selection, development of the variables' architecture, development of a fuzzy inference system, defuzzification of the output variable, and model validation.

Variables selection

The first step in designing a fuzzy expert system is to determine the input and output variables. In this study, the DHLI skills were used as the input parameters (Table 2). On the other hand, the goal of designing this expert system is to identify the levels of eHealth literacy with the highest degree of agility and accuracy, so the output variable of the fuzzy inference engine is a crisp variable between 0 to 100 (as the percentage) that indicates the levels of electronic health literacy (Table 3).

Development of the variables' architecture

The next step is to analyze and review the input variables to determine and allocate different linguistic label to each of the variables. For this purpose, the same expert panel as who were employed for the determination of proper e-health literacy instrument was asked to comment on the determined linguistic value of input variables. They considered not only the number of input variables but also the application and the role of the variables in the fuzzy expert system of identification of eHealth literacy. For determining the linguistic labels of each skill and the output, the experts were invited to specify the required labels on a five-point Likert scale (very low, low, moderate, high, and very high).

Table 2. Fuzzy variables of inputs

Input variables	Linguistic label	Membership function	Fuzzy number
Operational skills	Low	Trapezoidal	(0, 0, 1, 4)
	Medium		(1, 4, 5, 8)
	High		(5, 8, 9, 9)
Information searching	Low	Trapezoidal	(0, 0, 1, 4)
	Medium		(1, 4, 5, 8)
	High		(5, 8, 9, 9)
Evaluation reliability	Low	Trapezoidal	(0, 0, 1, 4)
	Medium		(1, 4, 5, 8)
	High		(5, 8, 9, 9)
Determining relevance	Low	Trapezoidal	(0, 0, 1, 8)
	High		(1, 8, 9, 9)
Navigation skills	Low	Trapezoidal	(0, 0, 1, 8)
	High		(1, 8, 9, 9)
Adding self-generated content	Low	Trapezoidal	(0, 0, 1, 8)
	High		(1, 8, 9, 9)
Protecting privacy	Low	Trapezoidal	(0, 0, 1, 8)
	High		(1, 8, 9, 9)

In this study, each self-report item was rated on a four-point scale, ranging from "very easy" to "very difficult" and from "never" to "often" equal to 0 to 3, respectively, to determine each skill level. A higher score of each skill demonstrates a higher skill level. Thus, the input of every skill is a crisp number between 0 to 9. The process of changing a real scalar value into a fuzzy value is called fuzzification. This can be achieved with the different types of fuzzifiers (membership functions). For all the linguistic variables, according to the experts' opinion and the concept of each indicator, the fuzzy trapezoidal membership function was defined (Table 2). The output of the fuzzy expert system is stated after defuzzification by a crisp value between 0 to 100 as the level of eHealth literacy to make it possible to compare the level of eHealth literacy of different students. For each of the input variables (Table 2) and also the output variable (Table 3), sets of linguistic labels, which are varied from two to five terms were defined according to the same experts.

The determination of these linguistic labels was carried out carefully considering their application and role in the system. Due to a large number of variables, the attempt to eliminate the terms that do not affect the determination of eHealth literacy was taken. For example, there were only two linguistic labels of "low" and "high" for the determination of “protecting privacy." According to the experts’ opinion, the word "moderate" was ineffective and had little effect on identifying the levels of e-health literacy. In other words, although the term "moderate" indicates a level of the ability of a person to protect privacy, this level has little effect on the result of the system (compared with the other two labels of "low" and "high") and can be neglected. Therefore, at this stage, it was tried to determine the terms that not only can express and observe the experts’ judgment effectively but also would not impose excess rules on the system.

Table 3. Fuzzy variables of output

Output variable	Linguistic label	Membership function	Fuzzy number
Level of eHealth literacy	Very low	Trapezoidal	(-20, -5, 5, 20)
	Low		(5, 20, 30, 45)
	Medium		(30, 45, 55, 70)
	High		(55, 70, 80, 95)
	Very high		(80, 95, 105, 120)

Development of a fuzzy inference system

The knowledge base is one of the most important parts of the fuzzy rule-based expert system, as is called the heart of the system. The rule base and the database are jointly referred to as the knowledge base. The most important element in the development of an expert system is knowledge acquisition (Niwa, et al. 1984). It consists of formulating the fuzzy rules which are defined with the support of the experts. A well-defined fuzzy rule base, which contains several fuzzy *if-then rules*, should be complete, consistent, and continuous. If there is at least one active rule for each value from the input space, the knowledge base is complete, that is $\exists_{i=1,2,\ldots,I}\ \mu_{A^{(i)}}(x) \neq 0$. The consistency of the knowledge base means no rules with the same antecedent but different consequents. And if there are no neighboring rules, for which the result of the intersection of fuzzy sets in their consequents is an empty set, the knowledge base is continuous (Czabanski, et al. 2017). Knowledge could be obtained by interviewing experts and/or finding out by experience (Niwa, et al. 1984).

The number of rules and how the inputs and outputs are related are very important for the good performance of the fuzzy inference system (Abraham, 2005). Due to the number of input variables (main skills), the combinations of all possible permutation of the seven input variables with their fuzzy sets were considered, and 432 rules were set for the fuzzy inference system.

For knowledge acquisition, a questionnaire was designed and distributed among the experts. Through the questionnaire, experts were asked to determine the level of eHealth literacy of each statement according to the specified linguistic value for each of seven skills. Then the questionnaire was distributed among 60 experts of health literacy, who were selected based on their resume and capabilities. All of the chosen experts hold an academic degree related to the research topic (e.g. health education, health promotion, epidemiology, medical epidemiology, medical librarianship and information science), have teaching experience in topics related to health literacy or information literacy, and have research experience in the field of health literacy, information literacy, health information literacy and electronic health literacy. It should be noted that these experts are the same experts who were usually surveyed for determining eHealth literacy of individuals when the research was conducted in the traditional/manual method, in most research studies previously done in Iran. The questionnaire was sent through the e-mail, and 43 responses (72%) were received (Table 4). They determined the level of eHealth literacy of each statement from their point of view. Cronbach's alpha (Eq. 1) was calculated as 0.849, which means the questionnaire had internal consistency and reliability.

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{K} \sigma_{Y_i}^2}{\sigma_X^2}\right) \qquad (1)$$

Where $X = \sum_{i=1}^{K} Y_i$, which is a quantity sum of K components, σ_X^2 is the variance of the observed total test scores, and $\sigma_{Y_i}^2$ is the variance of component i for the current sample of persons.

Table 4. Demography of the respondents

Gender	Frequency	Percentages of respondents (%)
Male	37	86
Female	6	14
Educational background		
B.Sc.	3	7
M.Sc.	26	60
PhD	14	33
Work experience in health literacy		
Less than 3 years	4	9
3 to 5 years	12	8
5 to 10 years	8	19
More than 10 years	19	44

In this study, Mamdani fuzzy system (Mamdani and Assilian, 1975) as the individual rule-based inference was selected because it is based on the conjunctive interpretation of fuzzy rules. In addition, the inference is based on separate rules that are used for aggregation, so each rule plays an effective role in determining the output before integrating into other rules; the rules are local; using Mamdani minimum operator is conservative; and the minimum and maximum are used for t-norm and t-conorm operators respectively (Figure 2). Therefore, the inference engine of the fuzzy system of this study is:

$$\mu_{\acute{B}}(y) = \vee_{i=1}^{I}\left[\mu_{A_1^{(i)}}(x_{01}) \wedge \mu_{A_2^{(i)}}(x_{02}) \wedge \ldots \wedge \mu_{A_N^{(i)}}(x_{0N}) \wedge \mu_{B^{(i)}}(y)\right] \qquad (2)$$

Where the conjunctive "and" of a rule antecedent is defined with the t-norm minimum (∧), and the inference results from individual rules are aggregated by applying the t-conorm maximum (∨).

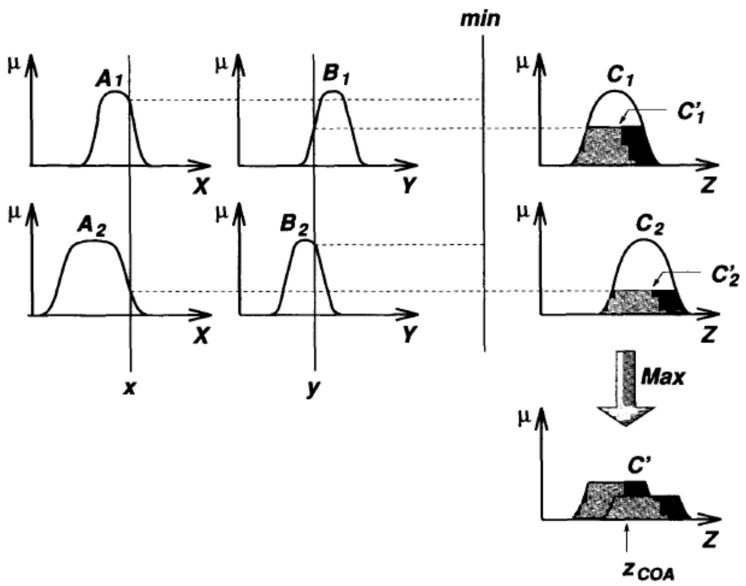

Figure 2. Mamdani fuzzy inference system using min and max for t-norm and t-conorm operators (Abraham, 2005)

As a result, for the linguistic variables modeling the type Mamdani fuzzy rule-based was used, which are articulated in the way: IF variable 1 is … AND variable 2 is …THEN the level of e-health literacy is …. For instance, the inference rule No. 1 was:

IF the operational skills are high

AND the ability for information searching is high

AND the ability to evaluate reliability is high

AND the ability for determining relevance is high

AND the navigation skills are high

AND the ability to add self-generated content is high

AND the ability to protect privacy is high

THEN the level of eHealth literacy is very high

Defuzzification of the output variable

The result of the reasoning is a fuzzy set, which can be associated with a specific linguistic label. However, for further calculation and discussion, a crisp numerical inference outcome is required. The process of calculating a representative numerical output $y_0 \epsilon Y$ from the outcome fuzzy set $B(\acute{y})$ on Y is called defuzzification. Defuzzification is a mapping of a multitude of fuzzy sets defined on the space Y to a single numerical value from Y (Czabanski, et al. 2017). One of the most popular defuzzification procedure, which was used in this study is a center of gravity method (COG). This method specifies the result as a center of the area under the membership function $\mu_{\acute{B}}(y)$:

$$y_0 = \frac{\int_Y \; y\mu_{\acute{B}}(y)dy}{\int_Y \; \mu_{\acute{B}}(y)dy} \qquad (3)$$

Where y_0 is the output of the fuzzy expert system as the level of eHealth literacy.

For example, to determine the level of eHealth literacy, the fuzzy inference mechanism is as follows. For a person, the seven items of operational skills, information searching, evaluating reliability, determining relevance, navigation skills, adding self-generated content, and protecting privacy are rated as 6, 9, 9, 9, 9, 9, and 9, respectively. According to the number of input variables, the system goes to rules number 1 and 4. The linguistic level of eHealth literacy of the person is determined by using the Mamdani fuzzy inference system using min and max for t-norm and t-conorm operators, which is shown in Figure 2. The crisp level of eHealth literacy is 84.21 after defuzzification. The procedure for determining the level of eHealth literacy of a person with the proposed fuzzy expert system is shown in Figure 3.

Figure 3. Sample procedure for determining the level of eHealth literacy of a person with the proposed fuzzy expert system

Validation

In this section, the expert system is validated by comparing the experts' judgment with the system output (Figure 4). For this purpose, a list of records was gathered and used as input variables of the expert system. Then the output of the system, which is determined for each record was compared to the experts' judgment.

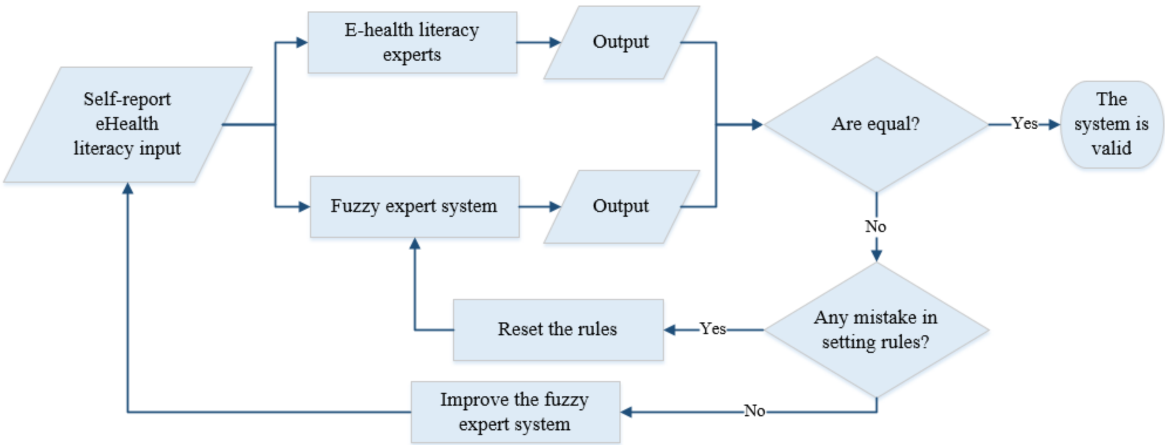

Figure 4. The expert system validation procedure

To validate the developed fuzzy expert system, 50 students of Mashhad University of Medical Sciences were asked to participate in determining their level of eHealth literacy. As it was depicted in Figure 4, the results of the fuzzy expert system were compared to the experts' judgment, because an expert system tries to simulate the way that an expert makes a decision.

2.3.Improving the fuzzy expert system based on rough set theory

As it was stated, it is very important to develop an expert system that determines the levels of e-health literacy with the highest degree of agility and accuracy. One of the most important parts of an expert system is its knowledge base. In this study, the experts should evaluate a lengthy list of statements, which is called rules to acquire experts' knowledge for developing an expert system. The questionnaire of experts' knowledge acquisition was drawn up with the combinations of all possible permutation of the seven input variables (432 rules). According to the fact that the increasing number of rules may cause receiving perfunctory answers due to the respondents' fatigue which results in deterioration, we tried to reduce the number of rules systematically to help with expert fatigue while responding to surveys. The rough set theory was used to reduce the number of rules and eliminate redundant input variables (resulting in

200 rules). The expert's answers were then inputted into a new expert system to develop an eHealth literacy inference engine.

Reduction of input variables using rough set theory

In this step, ineffective and redundant self-report items were identified and eliminated using fuzzy-rough set feature selection algorithm for the real cases of electronic health. Thus, the number of input variables of the system and the number of rules decreased; as a result, the time of the determination of the levels of the eHealth literacy was reduced. In this regard, the fuzzy-rough set algorithm was used to identify the input variables that have the greatest impact on the output of the developed fuzzy expert system, and the rules of the system were defined on these inputs.

The algorithm of the fuzzy-rough set theory was implemented using 60 samples of the real cases in the e-health literacy field, which more than half of them were collected from Iranian universities' students and the rest was extracted from the literature in the field of the students of other countries eHealth literacy. The Weka software was used to consider and analyze the values of all seven skills.

Development of a fuzzy-rough expert system

The fuzzy-rough expert system was developed based on the main steps that were explained before. It should be noted that, except the input variables and knowledge base, all components of the fuzzy-rough expert system, such as the output variable, membership functions, fuzzification, defuzzification, and fuzzy inference engine were quite similar to the fuzzy expert system.

Validation

As the final step, the fuzzy-rough expert system was tested on statistical samples, and its results were compared with the results of the fuzzy system outputs. The comparison between the results of the two systems was used for its validation.

3. Results

The output of the fuzzy expert system is stated in a range from zero to one hundred; the closer the number to 100, the upper level of the eHealth literacy. By contrasting the two results, 44 out of 50 results succeeded in the determination of the level students' eHealth literacy, therefore 6 errors resulted. In Table 5, only a fraction of the tests that were carried out can be seen. By calculating the confidence indicator (Eq. 4), it was observed that the fuzzy expert system succeeded in the 88% analyzed cases. According to the confidence result, the developed system can work as a disseminator of the level of students' eHealth literacy.

$$Confidence\ indicator = \left(\frac{Success\ number \times 100}{Total\ of\ tests}\right) \tag{4}$$

As it was stated, the agility and accuracy of an expert system are very important. The developed fuzzy expert system contains 432 rules and 21 input indicators. To reduce the number of rules, and thus the knowledge acquisition biases, the developed fuzzy expert system was improved by identifying and eliminating redundant input variables using rough set theory. After executing the Algorithm, not only the number of effective criteria reduced from seven to six skills (the ability to protect privacy was omitted) but also sixteen ineffective and redundant rules were identified and eliminated using fuzzy-rough set feature selection algorithm; consequently, the number of rules decreased from 432 to 200 *if-then rules*.

The developed fuzzy-rough expert system was tested using the result of the fuzzy expert system. The comparison between the two systems showed that the fuzzy-rough expert system could determine the level of students' eHealth literacy as precision as the fuzzy expert system. The confidence result of the fuzzy-rough expert system was 90%, which reveals that the system can work properly.

Table 5. Fraction of tests with the e-health literacy level determiner fuzzy inference system

Test	Operational skills	The ability for information searching	The ability to evaluate reliability	The ability for determining relevance	Navigation skills	The ability to add self-generated content	The ability to protect privacy	eHealth literacy level	Success

1	9	9	9	9	9	9	9	100	Yes
2	8	8	9	9	9	9	9	100	Yes
3	8	9	6	8	8	8	9	84.21	Yes
4	6	9	9	9	9	9	9	84.21	Yes
5	5	4	5	5	4	4	3	15.09	No
6	1	0	1	1	1	0	0	0	Yes
7	4	5	5	4	4	3	1	37.12	Yes
8	1	4	3	1	2	1	1	16.46	Yes
9	8	6	9	8	8	9	9	84.21	Yes
10	7	7	8	7	6	8	8	71.16	Yes

4. Discussion

The development and use of the fuzzy expert system in some cases, such as the level of eHealth literacy that is qualitatively evaluated, can reduce the controversy among experts. Also, by eliminating the expert panel, the level of e-health literacy is determined faster anytime and anywhere without accessing them personally. This fuzzy expert system can even be helpful in places where there is a lack of expert since the system contains nearly all information, knowledge, and expertise of experts in e-health literacy. Hence, it is a useful training tool for new students who want to become an expert. Additionally, the implementation of a fuzzy expert system needs only a computer and software of commercial use. Therefore, it can be used anywhere with a very low cost.

Furthermore, the results of this study verified that rough set theory is a suitable method to decrease the number of rules and input variables to reduce biases without weakening the expert system. In other words, with the least set of rules, it is possible to get the same result when surveying the experts with the questionnaire for any future research within similar topics.

5. Conclusion

In this paper, the stages of designing, implementing, and evaluating a fuzzy expert system (which uses a collection of fuzzy logic and *if-then rules*) for determining the level of electronic health literacy were described. This fuzzy expert system was developed using the Mamdani fuzzy model. The effective indicators of determining eHealth literacy were extracted, and the Digital Health Literacy Instrument was used for developing a fuzzy rule-based expert system.

The developed system was tested using 50 university students' records that showed the confidence rate of 88%. To decrease the number of rules and input variables to reduce biases without weakening the expert system, the rough set theory was used to decrease the input variables and rules, which caused a reduction in the number of rules from 432 to 200. The results of testing the fuzzy-rough expert system showed that the system has a precision of 90%. Through using the proposed expert system, the level of eHealth literacy can be determined considering different aspects of this issue and uncertainties by using linguistic values for items evaluation that leads to more accurate judgment. Besides, the results of this study just verified that rough set theory is a suitable method to decrease the number of rules and input variables to reduce biases without weakening the expert system.

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References

Abraham, Ajith. 2005. "Rule-based Expert Systems." In *Handbook of Measuring System Design*, 909-919. Stillwater, OK, USA: John Wiley & Sons, Ltd. doi:10.1002/0471497398.mm422.

Ashurst, Emily J., Ray B. Jones, Graham R. Williamson, Tobit Emmens, and Jon Perry. 2012. "Collaborative learning about e-health for mental health professionals and service users in a structured anonymous online short course: pilot study." *BMC Medical Education* 12 (37). doi:10.1186/1472-6920-12-37.

Britt, Rebecca K. , and Kristen Nicole Hatten. 2013. "Need for Cognition and Electronic Health Literacy and Subsequent Information Seeking Behaviors Among University Undergraduate Students." *SAGE Open* 3 (4): 1-10. doi:10.1177/2158244013508957.

Brown, Cary A., and Rumona Dickson. 2010. "Healthcare Students' e-Literacy Skills." *Journal of Allied Health* 39 (3): 179-184.

Chesser, Amy, Anne Bruke, Jared Reyes, and Tessa Rohberg. 2016. "Navigating the digital divide: A systematic review of eHealth literacy in underserved populations in the United States." *Informatics for Health and Social Care* 41 (1): 1-19. doi:10.3109/17538157.2014.948171.

Chew, F. 2014. "Developing a new scale to measure e-health literacy." *Medicine 2.0 Conference.* Toronto. http://www.medicine20congress.com/ocs/index.php/med/med2014/paper/view/2886.

Czabanski, Robert, Michal Jezewski, and Jacek Leski. 2017. "Introduction to Fuzzy Systems." In *Theory and Applications of Ordered Fuzzy Numbers*, 23-43. Springer, Cham. doi:10.1007/978-3-319-59614-3_2.

Enwald, Heidi. 2013. Tailoring health communication. The perspective of information users´ health information behaviour in relation to their physical health status. University of Oulu, ACTA Universitatis Ouluensis.

Furstrand, Dorthe, and Lars Kayser. 2015. "Development of the eHealth Literacy Assessment Toolkit, eHLA." *Studies in health technology and informatics* 971. doi:10.3233/978-1-61499-564-7-971.

Griebel, Lena, Heidi Enwald, Heidi Gilstad, Anna-Lena Poh, Julia Moreland, and Martin Sedlmayr. 2017. "eHealth literacy research—Quo vadis?" *Informatics for Health and Social Care* 43 (4): 427-442. doi:10.1080/17538157.2017.1364247.

Hargittai, Eszter. 2005. "Survey Measures of Web-Oriented Digital Literacy." *Social Science Computer Review* 23 (3): 371-379. doi:10.1177/0894439305275911.

Hsu, WanChen, ChiaHsun Chiang, and ShuChing Yang. 2014. "The Effect of Individual Factors on Health Behaviors Among College Students: The Mediating Effects of eHealth Literacy." *Journal of Medical Internet Research* 16 (12). doi:10.2196/jmir.3542.

Ivanitskaya, L. 2012. "An Adaptive EHealth Information Literacy Assessment for Pre-Professional Health Students." *Medicine 2.0 Conference.* Toronto. http://www.medicine20congress.com/ocs/index.php/med/med2012/paper/view/798.

Kayser, Lars, Andre Kushniruk, and Paul Turner. 2015. "Enhancing the Effectiveness of Consumer-Focused Health Information Technology Systems Through eHealth Literacy: A Framework for Understanding Users' Needs." *JMIR Human Factors* 2 (1). doi:10.2196/humanfactors.3696.

Korda, Holly, and Zena Itani. 2013. "Harnessing Social Media for Health Promotion and Behavior Change." *Health Promotion Practice* 14 (1): 15-23. doi:10.1177/1524839911405850.

Lee, Jaesub, Soojun Kim, Hojoon Choi, and Zhiwen Xiao. 2016. "General Self-Efficacy, eHealth Literacy, and Health Literacy Among College Students: Measurements and Relationships." *Proceedings of the 2016 Kentucky Conference on Health Communication.* Lexington. http://healthdocbox.com/Psychology_and_Psychiatry/68600636-Proceedings-of-the-2016-kentucky-conference-on-health-communication.html.

Lin, Ching-Torng, Hero Chiu, and Po-Young Chu. 2006. "Agility index in the supply chain." *International Journal of Production Economics* 100 (2): 285-299. doi:10.1016/j.ijpe.2004.11.013.

Liu, Hongyan, Huan Zeng, Yang Shen, Fan Zhang, Manoj Sharma, Weiyun Lai, Yu Zhao, Genhui Tao, Jun Yuan, and Yong Zhao. 2018. "Assessment Tools for Health Literacy among the General Population: A Systematic Review." *International Journal of Environment Research and Public Health* 15 (8): 1-16. doi:10.3390/ijerph15081711.

Mamdani, E. H., and S. Assilian. 1975. "An experiment in linguistic synthesis with a fuzzy logic controller." *International Journal of Man-Machine Studies* 7 (1): 1-13. doi:10.1016/S0020-7373(75)80002-2.

Mitsutake, Seigo, Ai Shibata, Kaori Ishii, Kanzo Okazaki, and Koichiro Oka. 2011. "[Developing Japanese version of the eHealth Literacy Scale (eHEALS)]." *[Nihon Koshu Eisei Zasshi] Japanese Journal of Public Health* 58 (5): 361-371.

Neter, Efrat, and Esther Brainin. 2012. "eHealth Literacy: Extending the Digital Divide to the Realm of Health Information." *Journal of Medical Internet Research* 14 (1). doi:10.2196/jmir.1619.

Niwa, Kiyoshi, Koji Sasaki, and Hirokazu Ihara. 1984. “An Experimental Comparison of Knowledge Representation Schemes.” *AI Magazine* 5 (2): 29-36. doi:10.1609/aimag.v5i2.435.

Noblin, Alice M., Thomas T. H. Wan, and Myron Fottler. 2012. “The Impact of Health Literacy on a Patient's Decision to Adopt a Personal Health Record.” *Perspectives in Health Information Management* 9 (Fall).

Norgaard, Ole, Dorthe Furstrand, Louise Klokker, Astrid Karnoe, Roy Batterham, Lars Kayser, and Richard H. Osborne. 2015. “The e-health literacy framework: A conceptual framework for characterizing e-health users and their interaction with e-health systems.” *Knowledge Manage and E-Learning* 7 (4): 522-540.

Norman, Cameron D., and Harvey A. Skinner. 2006a. “eHEALS: The eHealth Literacy Scale.” *Journal of Medical Internet Research* 8 (4). doi:10.2196/jmir.8.4.e27.

Norman, Cameron D., and Harvey A. Skinner. 2006b. “eHealth Literacy: Essential Skills for Consumer Health in a Networked World.” *Journal of Medical Internet Research* 8 (2). doi:10.2196/jmir.8.2.e9.

Norman, Cameron. 2011. “eHealth Literacy 2.0: Problems and Opportunities With an Evolving Concept.” *Journal of Medical Internet Research* 13 (4). doi:10.2196/jmir.2035.

Park, Hyejin, and Eunjoo Lee. 2015. “Self-reported eHealth literacy among undergraduate nursing students in South Korea: A pilot study.” *Nurse Education Today* 35 (2): 408-413. doi:10.1016/j.nedt.2014.10.022.

Pérez, Gema Paramio, Bartolomé J. Almagro, Ángel Hernando Gómez, and Ignacio Aguaded. 2015. “Validation of the eHealth Literacy Scale (eHEALS) in Spanish University Students.” *Revista Espanola de Salud Publica* 89 (3): 329-338. doi:10.4321/S1135-57272015000300010.

Robb, M., and T. Shellenbarger. 2014. “Influential Factors and Perceptions of eHealth Literacy among Undergraduate College Students.” *On - Line Journal of Nursing Informatics: OJNI* 18 (3).

https://search.proquest.com/openview/3a6da179fefd2df4ce098cda64c0a0bf/1?pq-origsite=gscholar&cbl=2034896.

Soellner, Renate, Stefan Huber, and Maren Reder. 2014. “The Concept of eHealth Literacy and Its Measurement.” *Journal of Media Psychology* 26 (1): 29-38. doi:10.1027/1864-1105/a000104.

Stellefson, Michael, Bruce Hanik, and Enmanuel Antonio Chavarria. 2011. “eHealth Literacy Among College Students: A Systematic Review With Implications for eHealth Education.” *Journal of Medical Internet Research* 13 (4). doi:10.2196/jmir.1703.

Tang, Zeng, Fan Wang, and Hua Fu. 2014. “Development and assessment on the eHealth Literacy Scale for college students.” *Chinese Journal of Health Education* 1. http://en.cnki.com.cn/Article_en/CJFDTOTAL-ZGJK201401010.htm.

Van Der Vaart, Rosalie, Alexander JAM Van Deursen, and Mart AFJ Van De Laar. 2011. “Does the eHealth Literacy Scale (eHEALS) Measure What it Intends to Measure? Validation of a Dutch Version of the eHEALS in Two Adult Populations.” *Journal of Medical Internet research* 13 (4). doi:10.2196/jmir.1840.

Van Der Vaart, Rosalie, and Constance Drossaert. 2017. “Development of the Digital Health Literacy Instrument: Measuring a Broad Spectrum of Health 1.0 and Health 2.0 Skills.” *Journal of Medical Internet Research* 19 (1). doi:10.2196/jmir.6709.

Van Der Vaart, Rosalie, Constance HC Drossaert, and Mart AFJ Van De Laar. 2013. “Measuring Actual eHealth Literacy Among Patients With Rheumatic Diseases: a Qualitative Analysis of Problems Encountered Using Health 1.0 and Health 2.0 Applications.” *Journal of Medical Internet Research* 15 (2). doi:10.2196/jmir.2428.