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FUZZY MULTI-CRITERIA EVALUATION OF RESEARCH MATERIALS BASED ON LEARNING STYLE

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ABSTRACT

Current Research Materials (RM), obtained through internet search, is not in accordance with students' Learning Styles (LS). This study aims to evaluate and rank RM based on students' LS. A fuzzy evaluation method is proposed to evaluate and rank research material based on learning style. This method is able to deal with multiple critical factors, in order to evaluate RM. The fuzzification scale of linguistic variables is designed based on the expression method of fuzzy variables by students with specific learning styles. The proposed method was used to rank 10 obtained RM, in a particular research topic, for various LS. The ranking results were compared with the order of RM in a current search engine. The results of this comparison illustrate the applicability and efficiency of the method to arrange RM based on LS.

Keywords: learning styles, fuzzy MCDM, research materials, evaluation, ranking.

INTRODUCTION

Research Materials (RM) are information resulting from search through internet search engines. Students are the most common users of scholarly research materials. Scholarly RM, like scientific and technical RM, contain text, Tables, pictures, flow-charts, drawings, maps, Figures, and mathematical expressions (Alesandrini, 1984). Since students have different Learning Styles (LS), they should obtain different orders of RM to address their information requirements. The objective of this study is to evaluate and rank RM based on students' LS.

Information processing represents LS models that have an intellectual approach to assimilate information. These models, such as Honey and Mumford (Mumford and Honey, 1992), Gardner Multiple Intelligence (Gardner, 1993), and VARK model (Fleming and Mills, 1992), focus on the processes by which information is obtained, sorted, stored, and utilized. Among these models, the VARK model is most preferable, since it uses sensory modality. Sensory modality is a combination of perception and memory i.e., how the mind receives and stores information. Sensory modality is one of the more practical and recently popular ways to define and assess LS that one prefers when learning (Dobson, 2009). This model was tested and validated empirically by Leite (2009).

VARK consists of four LS, namely Visual, Audio, Read/write, and Kinaesthetic (Fleming & Baume, 2006). The Audio LS is not considered to be the same as Reading; however, Visual, Read/write, and Kinesthetic are three types of LS that are related to research materials. LS can be identified by multiple factors; therefore, evaluation of RM is in accordance with the weight and measure of these factors, and can be formulated as a Multi-Criteria Decision Making (MCDM) problem. Within this evaluation, there are quantitative and qualitative factors. Classic MCDM methods do not address the uncertainty of qualitative factors.

In this study, we integrated a fuzzy set theory (Zadeh, 1965) with MCDM methods, in order to measure qualitative factors accurately. The Fuzzy pairwise comparison used, which was inspired by the AHP method (Saaty, 1980), was employed to weight and evaluate criteria and RM based on the weighted criteria used.

Finally, we applied the proposed method to rank a set of RM in a particular research topic for all three LS. The accuracy of results were then evaluated based on student's and expert's opinions.

METHOD

The proposed method (as shown in Figure-1) was used for the multiple criteria evaluation of RM. The proposed method employs two phases to evaluate and rank RM. The first phase relates to the weighting of factors. During this phase, the input data (which is collected from humans) is fuzzy. The Eigenvector method was employed to weight factors. During the second phase, which relates to the evaluation of RM, the input data is collected from the content of RM.

Critical evaluation factors were determined during the first phase. Critical factors can be used to identify student's learning styles. The importance of each identifier factor in different learning styles is determined by analysis of students' opinions with different LS. Students' opinions were the main source used for the evaluation of identifier factors. For the evaluation and weighting of factors, students expressed their opinions in terms of pairwise comparisons between factors and using linguistic variables. Linguistic variables are variables that have linguistic term values. The concept of a linguistic variable is extremely useful in dealing with situations that are too complex (or too ill-defined) to be reasonably described in conventional quantitative expressions (Chen, 2000; Zadeh, 1965).

The linguistic value could be used for approximate reasoning, within the framework of a fuzzy set theory (Zadeh, 1965), to effectively handle the ambiguity involved in data evaluation and the vague property of linguistic expression. Normal trapezoid or

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triangular fuzzy numbers were used to characterize the fuzzy values of the quantitative data and linguistic terms used in approximate reasoning. The fuzzification of variables converts the linguistic variables to crisp numbers and increase the accuracy of analysis.

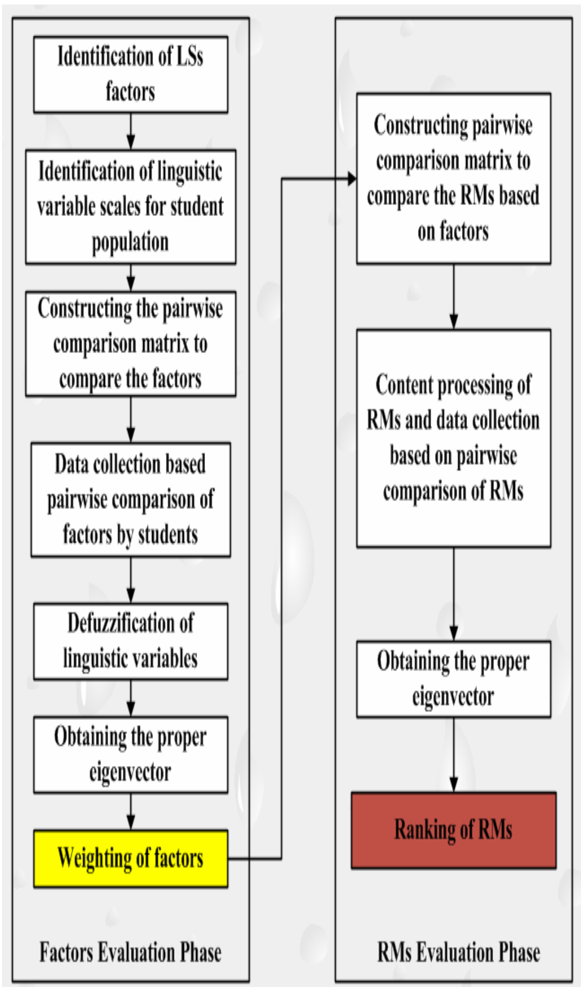

Figure-1. Flowchart of the proposed method for the evaluation and ranking of RM.

The fuzzy set theory was an extension of the classical set theory proposed by Prof. Zade, which is used to defuzzify and computerize linguistic or fuzzy variables (Zadeh, 1965). In a classical set, an element can only have two possible states i.e., it is either a member or it is not a member. However, in a fuzzy set, each element has a degree of membership that it presents by fuzzy numbers. Triangular Fuzzy Numbers (TFN) use three numbers to defuzzify linguistic variables. Therefore, by applying TFN, it is easy to convert fuzzy numbers to crisp numbers. A TFN $\tilde{a}$ defines through a trio (l, m, u) (as shown in Figure-2). The membership function $\mu_{\tilde{a}}(x)$ is defined to represent the ambiguity of the linguistic variables. (Amin and Razmi, 2009; Buckley, 1985; Chang and Wang, 2009; Dagdeviren and Yueksel, 2008; Ertugrul and Karakasoglu, 2009; Oenuet, Efendigil, and Kara, 2010; van Laarhoven and Pedrycz, 1983; Zimmermann, 2001)

Let $\tilde{a}_1$ be a TFN defined through the trio (l, m, u). Next, we convert the considered fuzzy number to the crisp value using the following centroid fuzzification formula:

$$a = (l + m + u) / 3 \qquad (1)$$

Where the variable 'a' consists of the crisp value of $\tilde{a}_1$ fuzzy value.

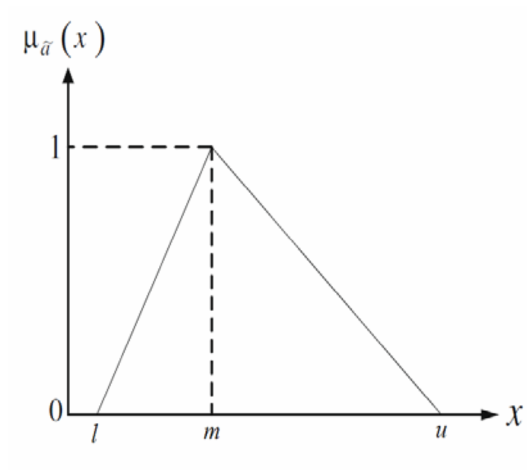

Figure-2. TFN $\tilde{a}$.

In this study, the descriptive words expressed by the students were analysed. Proper linguistic variable scales were determined to represent the linguistic variables. We determined that their related Triangular Fuzzy Number (TFN) should be replaced by the linguistic variables expressed by the students (see Table-1).

Table-1. The student's linguistic variable scales and their related fuzzy numbers.

Linguistic variables	Related TFN
Very important	(7, 9, 10)
Fairly important	(5, 7, 9)
Important	(3, 5, 7)
Preferred	(1, 3, 5)
Considerable	(1, 1, 3)
Equal	(1, 1, 1)

We applied pairwise comparisons in order to consider the different learning style factors. The relative importance of one criterion over another criterion for ranking is expressed by the considered scales. These comparisons were used to construct a pairwise comparison matrix of criteria. The criteria were compared pairwise according to their levels of influence; based on the

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students' opinions. The linguistic variables of the comparison matrix were replaced with fuzzy numbers.

During the RM evaluation phase, we constructed a pairwise comparison matrix to compare the RM based on factors. Within this comparison, the RMs were compared within each learning style factor. This comparison was not based on human ideas; but on the content of the RM. This content was processed and the number and percentage of each factor was determined. The obtained data was imported into the pairwise comparison matrices. We applied squaring, summarization and normalization operations on pairwise comparison matrix to obtain the eigenvector. The proper eigenvector is the priority vector that shows the weight of RMs. According the obtained weights the RMs are ranked.

FINDINGS

The proposed method receives the RM and produces a ranking of the RM's Visual LS. We examined the applicability of that by ranking five RMs for visual LSs. We then asked students to rank the RM. The order of the Google (as the most popular search engine) RM results were compared with the order of the RM results according to the student's ranking.

The four popular factors determined for the Visual learning style were PT (picture), FC (flowchart), MP (Map), and DR (drawing). We asked the students to express their ideas and compare the considered factors by designing a linguistic variable scale (see Table-1). A pairwise comparison matrix was determined for comparison.

We employed the pairwise comparison and the eigenvector method to obtain the weight of the determining factors for the Visual learning style (see Table-2).

Table-2. Rank of visual learning style factors.

Factors	Weight	Rank
PT[1]	0.92678	1
FC[2]	0.88761	2
MP[3]	0.64095	3
DR[4]	0.48316	4

RM ranking was achieved using the following three steps for each LS:

Step 1. Construct a fuzzy performance rating matrix and set an appropriate TFN; which was obtained by adapting Table-1 to convert experts' opinions (see Table-3).

Table-3. Fuzzy performance rating matrix for visual LS.

	PT	FC	MP	DR
RM1	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(7, 9, 10)
RM2	(1, 3, 5)	(3, 4, 5)	(7, 9, 10)	(5, 7, 9)
RM3	(7, 9, 10)	(1, 1, 3)	(5, 7, 9)	(1, 1, 1)
RM4	(1, 1, 1)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)
RM5	(1, 3, 5)	(3, 4, 5)	(1, 1, 3)	(3, 5, 7)

Step 2. Construct a weighted normalized fuzzy decision matrix (see Table-4).

Table-4. Weighted fuzzy performance matrix.

	PT	FC	MP	DR
RM1	(2.00, 2.50, 3.00)	(1.50, 1.80, 2.10)	(0.36, 0.48, 0.60)	(0.56, 0.64, 0.72)
RM2	(1.50, 2.00, 2.50)	(1.20, 1.50, 1.80)	(0.72, 0.84, 0.96)	(0.40, 0.48, 0.56)
RM3	(4.00, 4.50, 5.00)	(0.30, 0.60, 0.90)	(0.60, 0.72, 0.84)	(0.08, 0.08, 0.08)
RM4	(0.50, 0.50, 0.50)	(1.80, 2.10, 2.40)	(0.48, 0.60, 0.72)	(0.48, 0.56, 0.64)
RM5	(0.50, 1.00, 1.50)	(0.90, 1.20, 1.50)	(0.12, 0.24, 0.36)	(0.32, 0.40, 0.48)

Step 3. RM ranking (see Table-5).

Table-5. Results of RM evaluation.

RMs	Weight of RMs	Final ranking
RM3	0.71483	1
RM1	0.65740	2
RM2	0.61984	3
RM4	0.40789	4
RM5	0.30089	5

CONCLUSIONS

In this study, a fuzzy evaluation method was proposed to evaluate and rank RM based on learning style. This method is able to deal with multiple critical factors for the evaluation of RM. A fuzzification scale of linguistic variables was designed based on the method of expression of fuzzy variables by students with specific learning styles. The proposed method was applied to rank five obtained RM in a particular research topic for various LS.

From the results, PT, FC, MP, and DR were determined to be the most popular factors for the Visual LS. We also concluded that the most important criteria used for evaluation and ranking of research materials by students with a Visual learning style was “picture (PT).” Meanwhile, the least important criteria was “drawing (DR).” Furthermore, the ranking of research materials was achieved using the proposed method.

The model was tested by ranking five research materials, using ten students with a Visual LS. Comparison of the results against students’ opinions showed a high efficiency of the proposed method for ranking research materials based on student’s learning style.

The contributions of this study are as follows:

- Defining the important factors of student’s learning styles
- Weighting the factors to determine the rate of importance of the factors in learning styles
- Implementation of a new method to evaluate and rank research material based on student learning styles
- Evaluation of the proposed method.

It is suggested that for future work, this method’s result’s accuracy could be improved by extending the evaluation range from five to a larger RM set.

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