Supporting Web-Based Instructional Design with Fuzzy Approaches for Assessing Attitude Surveys

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Abstract

During the development process of an instructional design, attitude surveys are usually obtained from different groups of evaluators. Since the number of evaluators is small, it is difficult to obtain any significant result by using conventional statistical methods. This study utilizes fuzzy theory to overcome the difficulties caused by the small number of samples. In order to fuzzify the evaluators' response on a certain question, computerized questionnaire design with continuous scales is introduced. Li and Yen's method and Sugeno's measure/integral are applied to investigate the overall quality of an instructional design. To verify the degree of agreement between different groups of evaluators, a method used to measure the degree of agreement is proposed. An example is given to demonstrate the actual computational process of an attitude survey by using the approach proposed in this paper.

Keywords: Fuzzy Measure, Fuzzy Integral, Web-Based Attitude Survey, Likert Scale, Continuous Scale.

1. Introduction

In an instructional design, an evaluation acts as a test of validity to verify final effectiveness of the instructional activity or material, i.e., a summative evaluation; or serves as a checkpoint for further revision, i.e., a formative evaluation. In a summative evaluation of the instructional design, the learning performance of target students is usually measured by the difference between the pretest and the posttest score. The instructional design must be in its final form and the learners should be representative of the target students [1].

A formative evaluation is usually performed by instructors/designers, since these people are those who determine the necessary revisions. In a formative evaluation, students' opinions and performance are also important. An instructional designer usually obtains a small number of attitude data from both students and instructors to carry out a qualitative analysis on his/her prepared instructional activity or material. To assess the outcome of an evaluation, an evaluator may conduct a multi-factor tool to verify different categories of incidents or opinions, and each category consists of several homogeneous items or questions. A commonly used format for designing an item or a question is a 5-level or 3-level Likert scale, which is used to ask evaluators to indicate their opinions, for example, from "Strongly Agree" to "Strongly Disagree". However, in most of the formative evaluations, the designer has very few data to be analyzed, because the data are normally collected from three to five evaluators. Therefore, a designer must use his/her own decision to determine what changes should be made in the prepared instructional activity or material [2].

On the other hand, since the evaluation information is obtained from different groups of evaluators, learners and specialists, the degree of agreement among the groups is important for further improvement of the prepared instructional activity or material. Although Jonassen [3] has suggested that fuzzy theory should be applied to the instructional design in the field of Instructional Technology (IT), there is still no existing literature that demonstrates exactly how to apply the fuzzy theory in IT. Since a formative evaluation only requires a small number of evaluators to evaluate intermediate products, it is difficult to obtain any result, which is of statistical significance, and to make any decision, which is based on any conventional statistical method. This paper focuses on formative evaluations to discover how to use fuzzy approaches to obtaining a meaningful conclusion from a small number of evaluators, although the proposed approach can also be applied to summative evaluations.

Instead of using the statistical or intuitive knowledge to summarize the information obtained from the questionnaire in a formative evaluation, a fuzzy approach is proposed by Li and Yen [4] to measure the quality of the instructional activity or material. Li and Yen's measure does not consider the degree of agreement, if attitude surveys are obtained from different group of evaluators. Therefore, the measure of the degree of agreement is developed in this paper to compare the inclination among different groups of evaluators.

2. Introduction to Fuzzy Theory

While Aristotelian two-valued logic describes the membership of an element to a set, the possible values for the possession of the element could be either true or false. To illustrate the above situation, for a given universal set X, a membership function or characteristic function can be defined that declares which elements of X are members of a given set A or not. Mathematically, a membership function is defined,

$$X_A(x) = \begin{cases} 1 & x \in A \\ 0 & x \notin A \end{cases}$$

Which is formally expressed by

$$X_A:\ X \ \rightarrow \{0,1\}$$

This expression illustrates that for each $x \in X$, when $X_A(x) = 1$, x is declared to be a member of A; when $X_A(x) = 0$, x is declared as not being a member of A.

However, Zadeh [5] gives an important evolution of the modern development of fuzzy theory. The theory gives another point of view to describe the membership of a given element. If A is a fuzzy set and x is a relevant element, the ownership for the element x does not need to be either true or false, but it may be true in some degree, the degree to which x belongs to A. As defined in the previous discussion for a membership function of a crisp set, the membership function of a fuzzy set A is denoted by

$$\mu_A : X \rightarrow [0,1]$$

In this case, each membership function maps elements of a given universal set X, which is always a crisp set, into real numbers in [0,1].

The concept of fuzzy sets can be used to describe the nature of vagueness. For example, the verbal words, “little”, “moderately” and “very”, illustrate some degree of vagueness. There are no exact boundaries among the words. Therefore, it is reasonable to apply fuzzy theory on the design of a questionnaire. To demonstrate the use of fuzzy theory, the design of a continuous scale, which is different from the conventional Likert scale, is proposed in the following section.

3. Likert Scale and Continuous Scale Design

In this section, the comparisons between conventional Likert scale and continuous scale is introduced, and the technique for the fuzzification of continuous scale is also developed.

3.1 The Conventional Likert Scale v.s. the Continuous Scale

Kochen’s experiments [6] show that the use of a continuous scale can represent the strength of belief while a evaluator is asked to make a judgment for a given statement, and may increase the degree of precision. Figure 1 demonstrates an example of the forms of a continuous scale and a conventional 5-level Likert scale commonly used in a questionnaire to measure the belief of a given question.

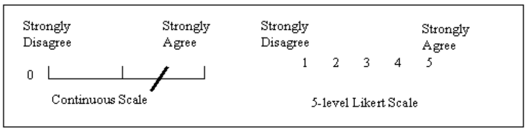

Figure 1: A continuous scale and a 5-level Likert scale

3.2 Fuzzification of the Continuous Scale

Let the left end be 0 and the right end denoted as L, where L is the length of the continuous scale. For any given mark x, a membership function can easily be defined to represent the degree of belief:

$$\mu_A(x) = \frac{x}{L} \qquad (1)$$

Therefore, $\mu_A \in [0,1]$. Eq. (1) determines the fuzziness of a evaluator’s response. Unlike the conventional 5-level Likert scale, which only represents 5 discrete responses, the continuous scale reflects some kind of vagueness in response. For example, if a evaluator thinks that he/she would like to give a personal judgment for a given question between level 3 and level 4, i.e., “a little bit agree with” but not “agree or strongly agree with”, the continuous scale can help a questionnaire designer measure such a kind of ambiguous judgment.

4. Multi-Factorial Measure and Determination of Overall Quality

The questions in an attitude survey may consist of several factors in order to retrieve subjects’ opinions from complex problem domain. The skills for determining overall quality of subjects’ opinions and measuring factors of questions are introduced in this section.

4.1 Distribution of Quality Measures

The design of a questionnaire that is used to measure the quality of the instructional activity or material may be formatted with several criterion or factors such as attention (interest), relevance, confidence, clarity, and satisfaction [2]. To study the outcome of a questionnaire is a multi-group and multi-factorial problem.

Li and Yen [4] propose a fuzzy approach to measuring multi-factorial estimation of quality. The method is good for our use in the situation described above. The overall procedure for multi-factorial estimation of quality is as follows.

Let $F=\{f_1, f_2, \ldots, f_n\}$ be a set of factors used for the measure of the quality of an instructional activity or material. Each of the factors could have several questions. Let $P=\{p_1, p_2, \ldots, p_r\}$ be a group of evaluators. For factor f_i ($i = 1, 2, \ldots, n$), evaluator p_j ($j = 1, 2, \ldots, r$) independently assigns one mark for each of the questions on the continuous scales. The range of these marks is denoted by $[a_{ij}, b_{ij}]$, where a_{ij} and b_{ij} denote the minimum and the maximum of the jth person's evaluation on the ith factor, respectively. Note that a_{ij} and $b_{ij} \in \mu_A(X)$. Thus, for each factor i ($i = 1, 2, \ldots n$), the quality measure a_i^* obtained from all the r evaluators on the ith factor can be defined as

$$a_i^* = \frac{\sum_{j=1}^{r}(b_{ij}-a_{ij})\left(\frac{a_{ij}+b_{ij}}{2}\right)}{\sum_{j=1}^{r}(b_{ij}-a_{ij})} = \frac{\sum_{j=1}^{r}(b_{ij}^2-a_{ij}^2)}{2\sum_{j=1}^{r}(b_{ij}-a_{ij})} \qquad (2)$$

where $a_{ij} = \wedge_{p_j f_i} \mu_A(X)$ and $b_{ij} = \vee_{p_j f_i} \mu_A(X)$, in which the operation $\wedge$ represents the minimum function min( ), and the operation $\vee$ represents the maximum function max( ).

Let $A = \{a_1^*, a_2^*, \ldots, a_n^*\}$. Then A is a distribution of quality measures on the n factors. In addition, A is also a fuzzy vector. Each component a_i^* in A reflects a quality estimation for the ith factor in a questionnaire. If a component a_i^* obtains a higher value than the other components, it is concluded that the ith factor of the instructional activity or material is well designed such that the evaluators give the factor higher rating. Eq. (2) offers a tool to measure the quality of each factor. If the overall quality is considered, a simple maximum operator can be used.

$\sum : X \rightarrow \sum X = \sum_{i=1}^{n} a_i a_i^*$, where $a_i \in [0,1]$, and

$$\sum_{i=1}^{n} a_i = 1 \qquad (3)$$

where a_i represents the weight or the importance of the ith factor. To transform the value obtained from the above quality evaluation equation into verbal variables like "Bad", "Average" and "Good", Fig. 2 depicts the transformation graphically.

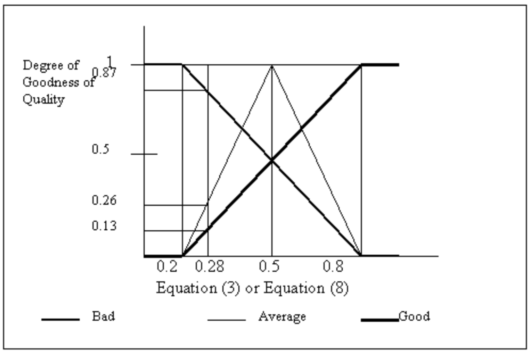

Figure 2. Transform Overall Quality Measure into Verbal Variables

4.2 Measure of Overall Quality Using Sugeno's Method

Although eq. (3) with the maximum operator provides a simple computational model to estimate the overall quality, it only simply discards the small values and does not consider the cross effects of factors. The mathematical tool proposed by Sugeno [7] is applied in this paper to measure the overall quality with a consideration of the effects of other factors in a more complex manner.

Sugeno defines a fuzzy measure g over a finite set X (a universe of discourse with the subsets E, F, …), which satisfies the following conditions [7]:

$g(\emptyset) = 0, g(X) = 1$ (4)

If $E \subset F$, then $g(E) \leq g(F)$ (5)

A fuzzy measure is a Sugeno's measure (or a λ-fuzzy measure), if it satisfies the following additional condition for some $\lambda > -1$ and $\lambda \neq 0$.

If $E \cap F = \emptyset$, then $g_\lambda(E \cup F) = g_\lambda(E) + g_\lambda(F) + \lambda g_\lambda(E)\, g_\lambda(F)$ (6)

The value of λ can be calculated regarding to the condition g(X)=1,

$$\lambda = \prod_{i=1}^{n}(1+\lambda g(f_i)) - 1 \qquad (7)$$

In an application of any attitude survey, the set X can be defined as the set of factors, for example, X={f_1, f_2, f_3, …, f_n}, where f_i denotes the ith evaluation factor in the questionnaire design. Furthermore, the fuzzy density $g(f_i)$ represents the degree of preference (i.e., the weight) of the ith factor. $g(f_i)$ is a fuzzy membership function. Then, the Sugeno's measure $g_\lambda(E\cup F)$ represents the degree of importance of possible factor combination. Note that $(E\cup F)\in$ power(X).

Then, a fuzzy integral can be defined as the following:

$$\int h(f')\circ g = \bigvee_{i=1}^{n}\left[h(f_i')\wedge g(H_i)\right] \quad \text{with}$$

$$H_i = \{f_i', f_{i+1}', ..., f_n'\},\ 1\le i \le n \qquad (8)$$

where $f' \in X$ and h(f') denotes the confidence value delivered by evaluation factors f'. h(f') is arranged in an ascendant order, i.e., $h(f_1') \le h(f_2') \le ... \le h(f_n')$. For example, if n = 3 and h(f') is arranged in an ascendant order, $H_1 = \{f_1', f_2', f_3'\}$, $H_2 = \{f_2', f_3'\}$, and $H_3 = \{f_3'\}$. A computational example for H_i is shown in Section 6.

How does a fuzzy integral be used in the evaluation of an attitude survey? $h(f_i')$ are the components in a fuzzy vector calculated by using eq. (2). In other words, $h(f_i')$ are the ascendantly ordered a_i^*. Thus, a fuzzy integral is a measure of the overall quality of an instructional activity or material regarding to the degree of preference of possible factor combination.

The Sugeno's measure indicates the preference of factors. If a questionnaire designer considers that some factors should be weighted more than the others, then the weights represent the preference of factors and are defined in Sugeno's measure for calculating fuzzy integral.

5. Measure of the Degree of Agreement

Consider the situation of the evaluation of an instructional activity or material. Suppose that B=$\{b_1^*, b_2^*, ..., b_n^*\}$ is obtained from another group of evaluators. Then, B is also a fuzzy vector as well as a distribution of quality measures. For example, A is obtained from a group of specialists and B is obtained from a group of target students. Since Li and Yen's measure cannot determine the degree of agreement between vectors A and B, an enhancement of Li and Yen's measure is proposed in this section.

The degree of agreement between the two fuzzy vectors A and B is calculated by defining the degree of agreement G_{AB} as

$$G_{AB} = \frac{A \bullet B}{|A||B|} \qquad (9)$$

where A•B denotes the inner product of A and B, and $|A|$ and $|B|$ denote the norm of the two fuzzy vectors, respectively. Therefore, $G_{AB} \in [0,1]$ is the fuzzy measure of the degree of agreement between the two different groups of evaluators. Actually, according to the above discussion, G_{AB} is a membership function, and its independent variables are two fuzzy vectors A and B. To assess the degree of agreement, Fig. 3 gives a sample to help a designer determine the degree of agreement. For example, if G_{AB} is 0.28, the value of "Very Consistent" is 0.13, the value of "Undecided" is 0.26, and the value of "Contradictory" is 0.87. The maximal value 0.87 is chosen, and this value's correspondent line "Contradictory" is used to address the degree of agreement estimation of G_{AB} . In other words, while G_{AB} is 0.28, the measure of the degree of agreement of the fuzzy vectors A and B is "contradictory".

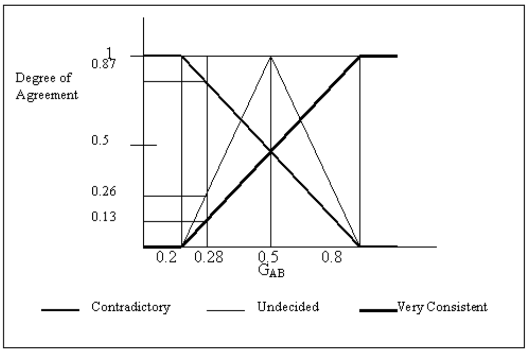

Figure 3. Degree of agreement

6. An Example

The Division of Continuing Education (DCE) in Northern Illinois University offers online courses to students. To revise the products, a survey of students' opinions about primitive prototypes is needed. There are only a small number of students and instructors, who live in different geographic areas, participate in the experimental online course. It is difficult to offer them conventional pencil-and-paper questionnaire. Therefore, an online questionnaire is developed. Table 1 demonstrates a sample online questionnaire.

As shown in Table 1, each question is not evaluated by a discrete Likert scale. A scroll bar is designed to emulate a continuous scale. Online users are able to use their web browser to answer the questions. Each scroll bar can represent integer numbers from 0 to 32767, from left to right. Therefore, in eq. (1), the variable L is assigned to the maximum value 32767, and the variable X is assigned by the position of each slider, the small movable square. There are three factors in this sample online questionnaire, i.e., “Attention”, “Relevance” and “Clarity”. After a user moves a slider to give his/her opinion about the questions, a fuzzy value of the answer for each question is immediately obtained by computing eq.(1).

Table 1. A sample online questionnaire designed in HTML format

I. Attention: To what degree did the following instructional activities hold your interest or attention?	
Question	Attention Level Little Very Attentive
1. Online discussion board aids cooperative interaction	
2. Instructor is used to encourage group cooperation to solve problem remotely.	
3. Student may obtain online help to solve their questions in real time.	
II. Relevance: To what degree do you believe the following skills are relevant to help you get used to enroll in a future online course?	
Question	Relevance Level Little Very Relevant
4. Recognizing how to cooperate with other online classmates.	
5. Participating in an online group discussion	
6. Taking online exams	
III. Clarity: What level of clarity do you believe the following instructional materials and activities have?	
Question	Clarity Level Little Very Clear
7. Session Introduction	
8. Objectives for session	
9. Online video	
10. Online recorded voice	

During the formative evaluation, there are three students and two instructors who participated in the online survey. In this case, they form two groups of evaluators, students and instructors. Table 2 and Table 3 demonstrate the results obtained from the two groups of evaluators, respectively.

Table 2. Survey results obtained from students

Evaluator Group: Students											
p_j	Attention (f_1)				Relevance(f_2)				Clarity(f_3)		
	1	2	3		1	2	3		1	2	3	4
1	30114	24906	28875		21589	25776	31048		31011	30912	16023	16001
2	29418	29039	27503		18065	26425	27711		30965	28700	16399	16142
3	24891	26445	27002		20043	30198	26066		29049	29556	13119	12201

Table 3. Survey results obtained from instructors

Evaluator Group: Instructors												
p_j	Attention (f_1)				Relevance(f_2)				Clarity(f_3)			
	1	2	3		1	2	3		1	2	3	4
1	28848	31011	27999		20041	24123	27595		29109	31003	14051	15448
2	27012	28812	30126		18797	22485	30640		31466	30718	15866	16389

To analyze the data, eq. (1) is used to transform each raw integer number measured to a fuzzy number as shown in Table 4 and 5.

Table 4. Data in Table 2 transformed to fuzzy numbers

Evaluator Group: Instructors												
p_j	Attention (f_1)				Relevance(f_2)				Clarity(f_3)			
	1	2	3		1	2	3		1	2	3	4
1	0.92	0.76	0.88		0.66	0.79	0.95		0.95	0.94	0.49	0.49
2	0.90	0.89	0.84		0.55	0.81	0.85		0.95	0.88	0.50	0.49
2	0.76	0.81	0.82		0.61	0.92	0.80		0.89	0.90	0.40	0.37

Table 5. Data in Table 3 transformed to fuzzy numbers

Evaluator Group: Instructors												
p_j	Attention (f_1)				Relevance(f_2)				Clarity(f_3)			
	1	2	3		1	2	3		1	2	3	4
1	0.88	0.95	0.85		0.61	0.74	0.84		0.89	0.95	0.43	0.47
2	0.82	0.88	0.92		0.57	0.69	0.94		0.96	0.94	0.48	0.50

The fuzzy vector of the instructors' group is calculated by using eq. (2):

$$b_1^* = \frac{(0.95^2 - 0.85^2) + (0.92^2 - 0.82^2)}{2 \times [(0.95 - 0.85) + (0.92 - 0.82)]} = 0.9$$

$$b_2^* = 0.75$$

$$b_3^* = 0.71$$

Thus, B=(0.9, 0.75, 0.71). Similarly, eq. (2) is used to find the fuzzy vector for the students' group. The following results are obtained.

$$a_1^* = 0.82$$

$$a_2^* = 0.76$$

$$a_3^* = 0.69$$

A=(0.82, 0.76, 0.69).

Therefore, the degree of agreement of opinions between the two groups is formed by computing eq. (9):

$$G_{AB} = \frac{A \bullet B}{|A||B|} = \frac{1.7979}{1.7997} = 0.999$$

Suppose that “very consistent”, “undecided” and “contradictory” are defined as in Figure 3. It is seen that the two groups of evaluators have a very strong degree of agreement for the quality of the experimental online course. However, this calculation does not give the account of whether the consistence of opinions is overall “positive” or “negative”.

Suppose that eq.(3) is used with a_i=1/3, i.e., the preference of each factor is regarded to be equal to each other. From student survey vector A, applying eq. (3), the overall quality measure is (1/3)*0.82+(1/3)*0.76+(1/3)*0.69=0.76. From Fig.2, it is concluded that the quality of the instructional activity or material is about “good”. Similarly, from instructor survey vector B, the value of the overall quality is obtained to be 0.79.

To calculate Sugeno's measure, X is defined as X={Attention, Relevance, Clarity}.

Suppose

$$g(\mathrm{f_i}) = \begin{cases} 0.3 & \text{if } \mathrm{f_1} = \text{Attention} \\ 0.4 & \text{if } \mathrm{f_2} = \text{Relevance} \\ 0.9 & \text{if } \mathrm{f_3} = \text{Clarity} \end{cases}$$

Since $g(f_i)$ represents the degree of preference of factors, the effect of the factor "Clarity" is more preferred than the other two in this example.

$\lambda = (1+0.3\lambda)(1+0.4\lambda)(1+0.9\lambda)-1$ is obtained by applying eq. (7). The solutions are $\lambda = \{-6.022, -0.926, 0\}$. Since the conditions $\lambda>-1$ and $\lambda \neq 0$ must be satisfied, $\lambda=-0.926$ is the only solution. The Sugeno's measure can then be constructed as follows:

Table 6. Computation of Sugeno's Measure

H_i	Sugeno Measure $g(H_i)$
{Attention}	0.3
{Relevance}	0.4
{Clarity}	0.9
{Attention, Relevance}	$g(H_i)=g(\{Attention\})+g(\{Relevance\})+\lambda g(\{Attention\})g(\{Relevance\})=$ 0.59
{Attention, Clarity}	$g(H_i)=g(\{Attention\})+g(\{Clarity\})+\lambda g(\{Attention\})g(\{Clarity\})=0.95$
{Relevance, Clarity}	$g(H_i)=g(\{Relevance\})+g(\{Clarity\})+\lambda g(\{Relevance\})g(\{Clarity\})=0.97$
{Attention, Relevance, Clarity}	$g(H_i)=g(X)=1$

Furthermore, h(Attention)=0.82, h(Relevance)=0.76, and h(Clarity)=0.69 are equivalent to the components a_i^* in the fuzzy vector A, which is previously obtained from the student attitude survey. To compute the fuzzy integral, the $h(f_i')$ are rearranged in an ascendant order $h(f_1') \leq h(f_2') \leq ... \leq h(f_n')$, $f_i' \in X$, $1 \leq i \leq n$, i.e., h(Clarity) $\leq$ h(Relevance) $\leq$ h(Attention). Therefore f_1' = Clarity, f_2' = Relevance, and f_3' = Attention. Note that

$H_1 = \{f_1', f_2', f_3'\}$ = {Clarity, Relevance, Attention} = X

$H_2 = \{f_2', f_3'\}$ = {Relevance, Attention}

$H_3 = \{f_3'\}$ = {Attention}

Finally, from eq. (8), the fuzzy integral is obtained by computing the following:

$$\int h(f') \circ g = \bigvee_{i=1}^{n} [h(f_i') \wedge g(H_i)]$$

$$= \vee[h(f_1') \wedge g(\{f_1', f_2', f_3'\}), h(f_2') \wedge g(\{f_2', f_3'\}), h(f_3') \wedge g(\{f_3'\})]$$

=max[min(0.69, 1), min(0.76, 0.59), min(0.82, 0.3)]

=max[0.69,0.59,0.3]

=0.69.

It is concluded that, from the students' point of view, the instructional activity or material is about "good" by using Fig. 2.

7. Conclusions

Instead of using discrete Likert scales to measure the response to a survey, Kochen [6] suggests that the continuous scale reflects a response better than the Likert scale. It is difficult to measure the length of a response on a continuous scale, if the questionnaire is in a conventional paper-and-pencil style. It is necessary to use a ruler to obtain the length of every mark on a continuous scale in order to fuzzify an evaluator's response. In this paper, a computerized online questionnaire is proposed and fuzzification can be completed automatically, i.e., a membership function can be defined as the ratio of the segments in the continuous scale.

Since a questionnaire is usually assigned to people who have different background to investigate the effects or opinions for a prepared instructional design, a method to measure the degree of agreement among different groups is proposed in this paper. If there are m groups of evaluators, $C_2^m = \frac{m \times (m-1)}{2}$ times of calculations are performed to compare the degree of agreement among groups.

The combination of Li and Yen's and Sugeno's methods with the degree of agreement measure proposed in this paper helps to investigate the quality measure of an instructional activity or material. The aforementioned combined methods conquer the difficulty of applying conventional statistical or intuitive observation methods to investigate the quality of an instructional activity or material with a small number of evaluators. During the development process of an instructional design, what is concerned about is the quality of the instructional activity or material and the degree of agreement among the groups of evaluators. Consequently, applying the proposed fuzzy measure is appropriate to reflect the vagueness of the evaluation judged by human beings.

Since the evaluation of human attitudes is complicated with many factors, an instructional designer should be very careful to interpret the evaluation data. In the simplified example in Section 6, there are only three factors to be surveyed. A real-life attitude survey may have more than 5 factors, and each factor may consist of more than 3 questions, i.e., more than 15 questions in an attitude survey. Moreover, a complete formative evaluation usually needs to test the students' performance after a prototype of the instructional material has been tried out. Hence, a complete fuzzy quality measure should consider at least three results: the students' attitude survey, the instructors' (professional) attitude survey and the student test score. The student test score is not a homogeneous data from the other two. Most instructional designers use their "professional experience" to analyze these three different types of data. Thus, future research is suggested to include the pretest, the posttest, the student's attitude and the instructors' attitude surveys all together to establish a complete fuzzy evaluation system.

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