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Application of fuzzy logic to improve the Likert scale to measure latent variables

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ABSTRACT

The research studied the process of improving the Likert scale based on fuzzy logic to measure latent variables and to compare the quality of the data as measured by the improved Likert scale with data measured by the Likert scale. Qualitative study and survey study were used as the research methodology. Data analysis included content analysis and statistics comprising the arithmetic mean, standard deviation, standard error, consensus index, and the Kolmogorov–Smirnov test. It was found that the Likert scale could be improved by using Mamdadi fuzzy inference which included four important steps: (1) fuzzification, (2) fuzzy rule evaluation, (3) aggregation, and (4) defuzzification. A comparison of the two different approaches showed that the data measured using the improved Likert scale was more suitable to be analyzed with the arithmetic mean and standard deviation than the data measured using the Likert scale. More importantly, the distribution of data measured by the improved Likert scale was normal with a lower standard error, making it appropriate for data analysis for statistical inference.

Introduction

Internal validity of quantitative research is a measured validity. Thus, the instrument which is used to collect data on the variables measured is important. Subjective variables are latent traits—they are not directly observable or measurable. Instead, they are measurable through feelings, behaviors, expressions, and personal opinions, and data can be acquired using a questionnaire. The Likert scale is one of the popular instruments to measure such latent traits. The scale was introduced by Likert (1932) and consists of a series of questions which are indicators of the latent traits. Each question has a five-scale response: least, less, moderate, more, and most with the scores for the scale being 1, 2, 3, 4, and 5, respectively. Edward (1957) stated that the scores in question are based on an interval scale as they are acquired through psychological scaling. The latent variables are measured by the combined scores of all questions, which are on an interval scale (Tirakanan, 2008, p. 57). However, many scholars have argued that naturally, in the Likert scale, the choice or answer is only the data organized on an ordinal scale (Hodge & Gillespie, 2003; Pett, 1997). With reference to the Likert scale, Cohen, Manion, and Morrison (2000) stated that the interval range of different levels are not equal in value. The Likert scale, thus, should be arranged on an ordinal level. It is inappropriate to analyze the data using addition, subtraction, division, or multiplication. Furthermore, it is inappropriate to analyze such data using the arithmetic mean and standard deviation (Clegg, 1998). Thus, it is inappropriate to measure the latent variables by combining the scores of all the items from a Likert scale. In addition, Sukasem and Prasitratsin (2007, p. 2) explained that researchers in general would combine the scores from each item, and then use the combined scores to measure

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the variables, which is incorrect as each item is unequal in its weight.

Because of the problems described above, many attempts have been made to deal with this issue and to develop a suitable scale. One of the methods is fuzzy logic. It was developed from a fuzzy set by Zadeh (1965). Lalla, Facchinett, and Mastroleo (2004) and Li (2013) applied fuzzy logic to improve the Likert scale, which resulted in a new scale known as the fuzzy Likert scale (FL). Li also compared the efficiency of this scale with the Likert scale and found that measuring the variables using the fuzzy Likert scale was more accurate than measuring with the general Likert scale. For the reasons described, the current research tried to determine the process for applying fuzzy logic to the Likert scale to measure the latent variables in a more valid and efficient manner. It is expected that the research would lead to measuring methods which are more effective and appropriate.

Literature Review

Attitude Measuring Using the Likert Scale

Attitude is an important variable with latent traits. According to Saiyot and Saiyot (2000, pp. 52–60) attitude means the emotions and feelings of a person coming from an experience in learning something called a target. From learning, there appears a feeling of like or dislikes, agreement or disagreement. That tendency runs from a low to a high intensity. Likert (1932) was the first to propose the method to measure an attitude by combining the scores of each question. This method was called summated rating (Tirakanan, 2008, pp. 191–192). However, the Likert scale has a disadvantage; it is unclear whether the data measured are based on an ordinal level or interval level (Jamieson, 2004). Although Likert assumed the data acquired were based on an interval level, it can be observed that the data measured by the Likert scale are based on ordinal order (Hodge & Gillespie, 2003; Pett, 1997). Data on an interval level show an equal range for two consecutive values, whereas the feeling measured by the Likert scale has a different interval range between two levels (Cohen et al., 2000). As a result, the Likert scale cannot estimate varying interval ranges between data (Russell & Bobko, 1992). What can be measured by the Likert scale is only the information which cannot distinguish the interval. Furthermore, alternative forms of the Likert scale are similar. Respondents have to choose only one option, which is unrealistic and unreliable (Hodge & Gillespie, 2003; Orvik, 1972).

Consequently, due to these explained disadvantages of the Likert scale, it is apparent that the data acquired may be unreliable. Several academics have attempted to improve the Likert scale. Chang (1994) proposed that more levels of the scale should be added so that more details could be obtained. However, it may be difficult for respondents to identify their genuine feelings at such a level of detail (Russell & Bobko, 1992). Albaum (1997) proposed two steps. First, there are only two choices: agree or disagree. After that the respondents have to answer according to the intensity level: less or more. By doing this, it is possible to avoid the answer of 'moderate'. Hodge and Gillespie (2003) proposed that the question should be divided into two parts. First, the leading question was raised to encourage respondents to express their feelings, which was followed by a secondary question on the contents of the leading questions, both positive and negative. The respondents can choose from 0 to 10 depending on the intensity. However, this method may not be effective, as the respondents can get lazy in answering all the questions. Li (2013) proposed the construction of the fuzzy Likert scale (FLS). The respondents have only one choice. Its membership value lies between 0 and 1. That is, if an opinion is inclined towards that choice, its value is set at 1. On the contrary, if the opposite happens, the answer is an ordered pair. The first is an answer and the second is the value of membership. The acquired answer is adjusted into the fuzzy Likert scale:

$$FLS = \frac{\sum u_o A_o}{\sum A_o} \tag{1}$$

where, FLS is the fuzzy Likert scale. u_o is to the level of an opinion according to the Likert scale, and A_o is the area of the membership function that is truncated by the membership value. Although the improved scale may provide more details and greater reliability, there are disadvantages as respondents may find it hard to decide and they may get bored. As a consequence they may not give genuine answers.

Fuzzy Logic

Fuzzy logic originated from the dissertation of Zadeh (1965). It is based on the principles that out of all things in the world, there is a small portion that is certain. Things are mainly uncertain. The things which are uncertain are characterized by two traits: random and fuzzy.

The classical set is an undefined term, as it characterizes a group consisting of various members which are identifiable. However, there are a lot of groups which cannot be explicitly identified. The group having such characteristics is called a fuzzy set. It refers to the set of things for which it cannot be identified whether each thing in question is a member of the set or not. Nevertheless, it is possible to indicate the tendency of something to be a member of a set through the membership function whose value ranges between 0 and 1. If the membership value of something gets closer to 1, that has a high level of membership. By contrast, if the membership value gets closer to 0, it has a low level of membership.

Definition. If X is not an empty set, x is any member of X and A is a fuzzy set whose membership function is μ_A, then fuzzy set A can be written in the form of a pair set as follows:

$$A = \{(x, \mu_A(x))/x \in X\}, \ \mu_A(x) : X \rightarrow [0, 1]$$

Membership function is used to determine the membership level for x. There are many types of membership function. Which type is to be used depends on suitability and relevant information based on the expert's consideration. The types include triangular membership function, trapezoidal membership function, Gaussian membership function, and bell-shaped membership function. Each function has different parameters and shape. For example, the triangular membership function has parameters consisting of three values: real number a, b, c, for $a \le b \le c$. The function value can be set as follows (see Figure 1).

$$\mu_A(x) = \begin{cases} (x-a)/(b-a), & a \le x \le b \\ (c-x)/(c-b), & b < x \le c \\ 0, & elsewhere \end{cases} \tag{2}$$

Any given system consists of input and output. System experts know the relations relating to these two factors. The input is the cause and the output is the result. Both are explained in linguistic variables as follows: less, moderate and more. The variable is explainable by a fuzzy set. To control the system, the experts will design the causal relations between input and output: IF input THEN output. This is called a fuzzy rule. The number of fuzzy rules depends on the number of linguistic variables used to explain input and output. A general form of the fuzzy rules can be determined as follows.

Supposing that a system has n inputs and 1 output. Causal relation between the factors can be illustrated with L rules. The input is explained with linguistic variable: A_{ij}; $i = 1,2,3,\ldots,L$ and $j = 1,2,3,\ldots,n$. The output is explained with the linguistic variable: C_i; $i = 1,2,3,\ldots,L$. Let $x = [x_1,x_2,x_3,\ldots,x_n]$ be a value of the input and y be a value of the output. A general form of ith rule of the fuzzy rule of Mamdani is:

$$IF\ (x_1\ \ is\ \ A_{i1})\ \ AND\ \ (x_2\ \ is\ \ A_{i2})\ \ AND\ \ \ldots$$
$$AND\ \ (x_n\ \ is\ \ A_{in})\ \ THEN\ \ (y\ \ is\ \ C_i)$$

Application of Fuzzy Logic

Fuzzy logic can be applied to decide or control a system through the principle of fuzzy inference. Fuzzy inference has two important methods: Mamdani fuzzy inference and Sugeno fuzzy inference. In this paper, only the former is described. Mamdani fuzzy inference was first proposed in 1975 by Professor Ebrahim Mamdani of London University (Mamdani & Assilian, 1975). The fuzzy inference in question consists of four stages:

Stage 1: Fuzzification: in this stage, experts take into account details concerning input, output, and results. The input and output are considered as input and output variables. Then, defined linguistic variables are used to explain each variable. The linguistic variables determine the fuzzy set and its membership function. Then, the fuzzy rules are established to show the relations between input and output.

Stage 2: Fuzzy rule evaluation: the membership function value of each rule is established using Equation (3).

$$\mu_L(x) = \min\left[\mu_{A_{L1}}(x_1), \mu_{A_{L2}}(x_2), \ldots, \mu_{A_{Ln}}(x_n)\right] \tag{3}$$

If the value of the membership function of any rule is equal to zero, it will not be considered. If the value of a membership function is not equal to zero, the value will be used to truncate or scale the shape of the output membership function in this rule.

Stage 3: Aggregation: the fuzzy set of the output in stage 2 is combined by a union operation.

Stage 4: Defuzzification: the fuzzy set which results from the combined rules in stage three is changed into a crisp value. There are several methods, one of which is seeking a center of gravity (COG). The COG of fuzzy set in the range $[a,b]$ can be determined using Equation (4).

$$COG = \frac{\int_a^b \mu_A(x)x\,dx}{\int_a^b \mu_A(x)\,dx} \tag{4}$$

Methods

Participants

The target population was first year students in the Faculty of Science Ubon Ratchathani Rajabhat University in

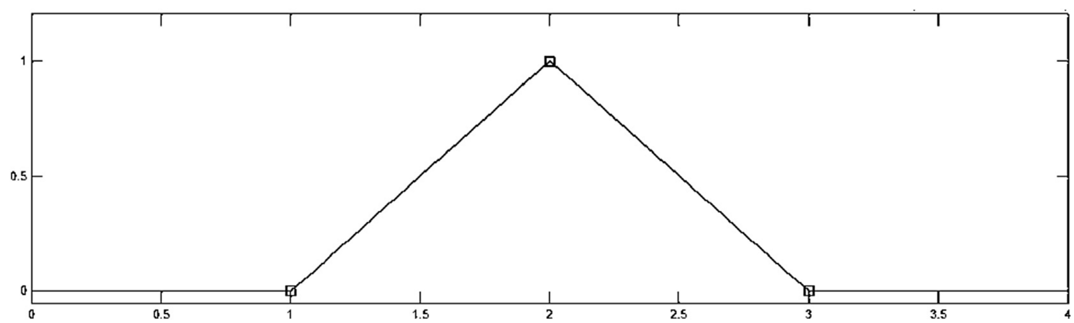

Figure 1 Triangular membership function with parameter a = 1, b = 2 and c = 3

the 2014 academic year. The total number of the students in the study was 302 (Policy and Plan Division, 2014).

Data Collection

The research instrument was a fifteen-item questionnaire to assess attitude toward mathematics based on a five-point Likert scale. The format in question was adapted from the one used by Saiyot and Saiyot (2000, p. 98). Five experts were asked to evaluate its validity. It was found that the value of index of item-objective congruence (IOC) ranged from 0.6 to 1. Then, the questionnaire was tried out with 50 first year general science students in the Faculty of Education Ubon Ratchathani Rajabhat University in the 2014 academic year. Items having a discrimination value of greater than 0.2 were selected. As a result, 12 items were acquired. The questionnaire of 12 items was administered with the target population. Data were collected using the questionnaire from 302 students who were first year students in the 2014 academic year regarding their attitude towards mathematics. Samples were chosen from the 302 respondent questionnaires based on simple random sampling with sample sizes of 30, 40, 50, ..., 200, respectively. Data from each sample size were collected to compare the quality of data in each sample size with regard to inference.

Data Analysis

Fuzzy logic was applied to improve the Likert scale using content analysis. The MATLAB software was then used to acquire a suitable response based on the applied process. The quality of data which were acquired from the improved Likert scale was compared with data acquired from the Likert and fuzzy Likert scales. The statistics used were arithmetic mean ($\overline{X}$), standard deviation (*S.D.*), standard error (*S.E.*) and consensus index (*Cns*) (Tastle & Wierman, 2007). The consensus index can be computed using Equation (5).

$$Cns(X) = 1 + \sum_{i=1}^{n} p_i \log_2\left(1 - \frac{|x_i - \mu_x|}{d_x}\right) \tag{5}$$

where, $Cns(X)$ is consensus; X is an opinion; x_i is an opinion level i; n stands is the number of the opinion level; p_i ids the ratio of the sample whose opinion is at level i; d_x is the difference between the maximum and minimum for an opinion; μ_x is the mean of an opinion for all samples. The index of consensus ranged from 0 to 1. If it is close to 1, it indicates that the opinion of the samples is in accordance with the issue of their interest. On the contrary, if it is close to 0, it indicates that the opinion of the samples is contradictory to the issue in question.

Results

Process to Improve Likert Scale

By applying fuzzy logic, we assume that the latent variable is measureable by using the question about that variable. The respondent should be asked how much he or she agreed or disagreed. An opinion should have five levels based on the Likert scale: strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree. All these levels cannot be categorically separated. In other words, one level overlaps with others where there is an ambiguous opinion. In addition, the ambiguity of opinion depends on the quality of the question in terms of validity and discrimination. Thus, the answer is not real. Hence, to measure the value of latent variables, it is necessary to consider sharing the validity and discrimination with the answer of each item. Thus, we can apply fuzzy logic to improve the answer from the Likert scale by using Mamdani inference in four stages.

Stage 1: fuzzification: in each question, it is necessary to determine three inputs: opinion of respondents (O), validity (V), and discrimination (R). The output is a suitable answer (T). The linguistic variables which are used to explain the opinion are Strongly disagree (SD), Disagree (D), Neither agree nor disagree (NN), Agree (A) and Strongly agree (SA). Validity could be explained in terms of less (L), moderate (M), and more (G). Discrimination could be explained in terms of less (L), moderate (M), and more (G). The suitable answer can be explained in terms of least (SL), less (L), moderate (M), more (G), and most (SG). The membership function of the linguistic variables is shown in Figures 2–5.

In total, 29 fuzzy rules were made by the experts. Some of them are given below.

Rule 1 IF (O is SD) and (V is L) and (R is L) THEN (T is SL)
Rule 2 IF (O is SD) and (V is L) and (R is L) THEN (T is L)
⋮
Rule 28 IF (O is A) and (V is G) and (R is G) THEN (T is G)
Rule 29 IF (O is SA) and (V is G) and (R is G) THEN (T is SG)

Stage 2: Fuzzy rule evaluation: the value of inputs including the opinion level, validity, and discrimination is used to find the membership value of each input from each fuzzy rule. If the rule has a membership function value equal to zero, it is not considered. If the value of membership function is not equal to zero, it is used to truncate the shape of the output membership function.

Stage 3: Aggregation: the fuzzy set of the output, which is truncated, is combined by a union operation.

Stage 4: Defuzzification: getting a suitable answer by converting the fuzzy set which was combined in stage 3 into a crisp value through COG; the value acquired is a suitable answer for the question. It is called an improved Likert scale.

Comparison of the Quality of Data

The answer for each item of the Likert scale that was improved by using the process of the prior section is shown in Table 1. The attitude toward mathematics as measured by the Likert scale and the improved Likert scale is shown in Table 2.

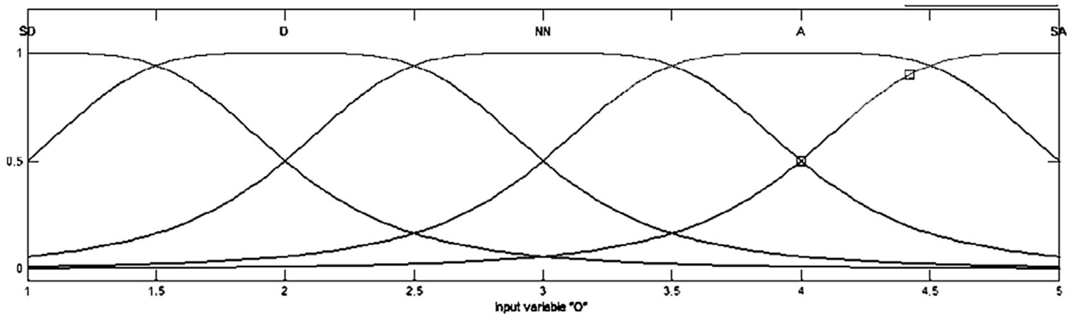

Figure 2 Bell-shaped membership function used to explain the opinion of the respondents

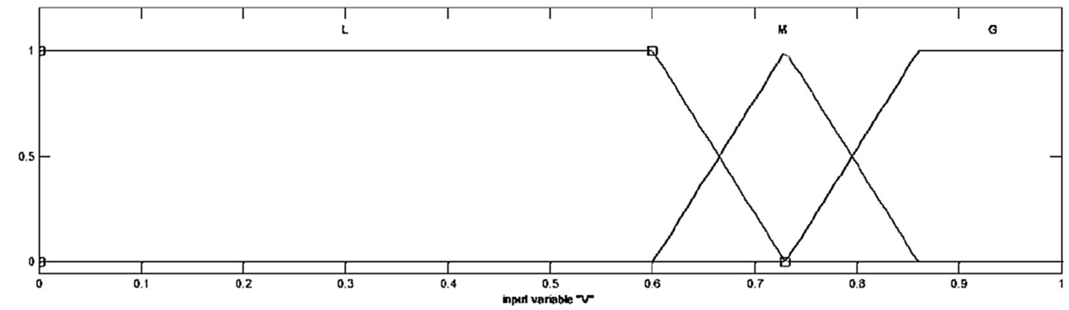

Figure 3 Trapezoidal membership function and triangular form used to explain validity

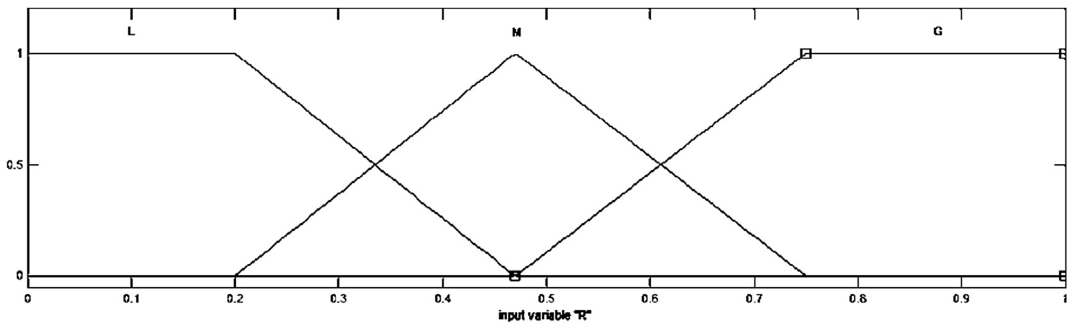

Figure 4 Trapezoidal membership function and triangular form used to explain discrimination

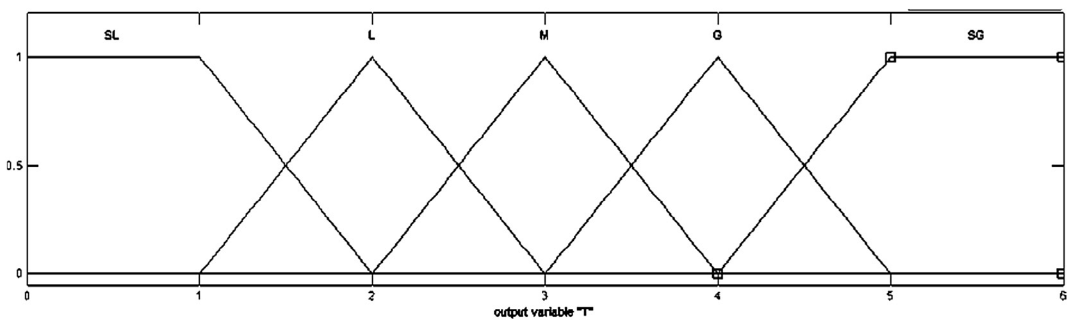

Figure 5 Trapezoidal membership function and triangular form used to explain suitable answers

Table 1
Likert scale improved by applying fuzzy logic

Item	IOC	Discrimination	Likert scale				
			1	2	3	4	5
1	0.8	0.551	1.46	2.24	3.07	4.05	4.55
2	1	0.401	1.33	2.22	3.06	4.05	4.68
3	0.8	0.359	1.46	2.24	3.07	4.05	4.55
4	1	0.576	1.40	2.23	3.07	4.05	4.61
5	1	0.369	1.40	2.23	3.07	4.05	4.61
6	1	0.651	1.39	2.23	3.07	4.05	4.62
7	1	0.356	1.43	2.24	3.07	4.05	4.58
8	0.8	0.29	1.57	2.18	3.10	3.98	4.44
9	0.6	0.62	1.50	2.24	3.08	4.04	4.51
10	1	0.44	1.27	2.22	3.06	4.05	4.74
11	1	0.621	1.46	2.24	3.07	4.05	4.55
12	1	0.464	1.23	2.22	3.06	4.05	4.78

Table 2
Population mean and standard deviation of attitude toward mathematics measured by the Likert scale and the improved Likert scale

Item	Likert scale		Improved Likert scale	
	μ	σ	μ	σ
1) I study mathematics with relative comfort.	2.65	0.84	2.80	0.72
2) Solving mathematical questions is fun.	2.80	0.89	2.91	0.78
3) Solving mathematical questions is boring.	3.27	0.97	3.34	0.82
4) Learning mathematics is boring.	3.32	1.02	3.37	0.87
5) Mathematic is basic to life.	3.54	1.09	3.53	0.89
6) I like calculating without the help of a calculator.	2.66	0.97	2.79	0.83
7) Mathematic knowledge is fundamental to all subjects.	3.33	0.97	3.38	0.81
8) Mathematics is most valuable.	3.35	1.01	3.35	0.79
9) I turn my face away when I see mathematics books.	3.37	1.00	3.41	0.82
10) I like to think about or reflect on mathematics.	2.74	0.84	2.86	0.75
11) Mathematics is a terrible subject.	3.46	1.00	3.48	0.82
12) The majority of people do not like mathematics.	2.68	1.12	2.78	1.03
Attitude towards mathematics	3.09	0.45	3.17	0.38

By using the method explained by Li (2013) to compare the quality of data, the samples of 100 students were set in the research. Their attitude toward mathematics is measured by the first question by using the Likert scale, the fuzzy Likert scale and the improved Likert scale. The improved Likert scale involved improvements based on the Mamdani inference in four stages. The result from the inference was 1.46, 2.24, 3.07, 4.05, and 4.55, respectively. The answers of the samples are distributed in three cases. Statistical values of data were calculated and details are provided in Tables 3–5.

From Tables 3–5, it was found that the arithmetic means of data as measured by the Likert scale and the fuzzy Likert scale were equal to 3 in all cases, which shows that the arithmetic mean determined using the two scales did

Table 3
Statistics according to distribution of data as measured by the Likert scale

Case	Likert scale					$\overline{X}$	S.D.	*Cns*
	1	2	3	4	5			
1	0	0	100	0	0	3	0	1
2	50	0	0	0	50	3	2.01	.00
3	15	15	40	15	15	3	1.23	.58

not truly reflect the data. However, data as measured by the improved Likert scale had a different arithmetic means in all cases with 3.10, 3.01, and 3.07 respectively, showing that the arithmetic mean could truly reflect the data. In case 3, the standard deviation of data as measured by the Likert scale and the fuzzy scale was equal to 1.23, which shows that the standard deviation obtained by using the two scales cannot reflect the data. However, the data as measured by using the improved Likert scale had a standard deviation equal to 0.99, which was more coherent($Cns = 0.55$) and the standard deviation used to analyze data could truly reflect the data.

Table 6 shows that the data measured using the Likert scale had a distribution different from a normal distribution with a statistical significance of .05. The data measured by the improved Likert scale showed a normal distribution at the .05 significance level.

Table 7 shows that the standard error of the sample mean of the data measured by the improve Likert scale was less than the standard error of the sample mean of the data measured by the Likert scale.

Discussion

The improved Likert scale with fuzzy logic was more effective than the Likert scale and the fuzzy Likert scale because its scale is continuous. In addition, the mean and standard deviation reflect the fact that the data were measured using the improved Likert scale. In particular, the standard deviation of the data is in accord with the consensus index. Furthermore, the standard error of the data measured using the improved Likert scale is less than all others in all cases of sample size, so the sample mean is closer to the population mean. Most importantly, the data measured by the scale is normally distributed, indicating the inferential statistics are appropriate for the analysis. Thus, data measured using the improved Likert scale can be applied for data analysis implementing descriptive statistics. The data analysis is more appropriate than for the data measured using the Likert scale. In addition, as the improved Likert scale uses a measuring tool like the Likert scale, it is more convenient to collect data by the improved Likert scale than with the scales proposed by Chang (1994), Albaum (1997), and Hodge and Gillespie (2003). In particular, it more convenient to collect data than using the fuzzy Likert scale proposed by Li (2013) because the fuzzy Likert scale is appropriate only for specific topics, where there is usually some quantitative data obtained from respondents used to assign the membership value for their answer which is slightly complicated. However, constructing and improving the Likert scale with fuzzy logic may cause

Table 4
Statistics according to the distribution of data as measured by the fuzzy Likert scale

Case	Fuzzy Likert scale									$\overline{X}$	S.D.	*Cns*
	1	1.5	2	2.5	3	3.5	4	4.5	5			
1	0	0	0	30	40	30	0	0	0	3	0.39	.88
2	25	25	0	0	0	0	0	25	25	3	1.78	.16
3	10	10	10	10	20	10	10	10	10	3	1.23	.54

Table 5
Statistics according to the distribution of data as measured by the improved Likert scale

Case	Improved Likert scale					$\overline{X}$	S.D.	*Cns*
	1.46	2.24	3.07	4.05	4.55			
1	0	0	100	0	0	3.10	0.00	1
2	50	0	0	0	50	3.01	1.56	.00
3	15	15	40	15	15	3.07	0.99	.55

difficulties when adjusting the scale in the fuzzy inference process. The validity of measurement depends greatly on key factors such as an appropriate membership function and suitable fuzzy rules. These factors mainly depend on the expert's discretion.

Conclusion and Recommendation

Although the Likert scale had been widely used to measure latent variables, data content from the scale is on an ordinal level and it is not appropriate to analyze the data using the arithmetic mean and standard deviation or to apply any inferential statistical methods. The statistical method often applied to analyze data measured using a Likert scale merely depends on the assumption of Likert (1932) that the data is on an interval level. The current research successfully transferred the Likert scale to a suitable scale by using fuzzy logic. This research found that the Likert scale could be improved by applying the fuzzy inference of Mamdadi which consisted of four important steps: (1) fuzzification, (2) fuzzy rule evaluation, (3) aggregation, and (4) defuzzification. Furthermore, a comparison of data quality showed that the data measured using the improved Likert scale with fuzzy logic was more suitable to be analyzed with the arithmetic mean and standard deviation than data measured by the Likert scale. Importantly, the data were normally distributed and the standard error was lower. Therefore, it was appropriate to analyze the data by using statistical inference. For these reasons, researchers should undertake data collection by latent

Table 6
Normal distribution testing using Kolmogorov–Smirnov test

Scale	μ	σ	Absolute	Positive	Negative	*z*	*p*
Likert scale	3.098	0.452	0.08	0.079	−0.08	1.395*	.041
Improved Likert scale	3.168	0.379	0.058	0.037	−0.058	1.012	.257

*$p < .05$.

Table 7
Sample size, mean, standard error and standard deviation for different Likert scale approaches

n	Likert scale ($\mu = 3.098$)			Improved Likert scale ($\mu = 3.168$)		
	$\overline{X}$	S.E.	S.D.	$\overline{X}$	S.E.	S.D.
30	3.1556	0.07928	0.43425	3.2111	0.06712	0.36762
40	3.1167	0.07716	0.48803	3.1754	0.06237	0.39445
50	3.1750	0.06659	0.47088	3.2290	0.05561	0.39320
60	3.0806	0.05176	0.40097	3.1507	0.04347	0.33674
70	3.0250	0.06411	0.53639	3.1057	0.05362	0.44859
80	3.1542	0.05880	0.52589	3.2105	0.04932	0.44110
90	3.1185	0.04291	0.40710	3.1864	0.03663	0.34751
100	3.0867	0.04639	0.46389	3.1534	0.03840	0.38398
110	3.1136	0.04326	0.45374	3.1811	0.03616	0.37923
120	3.0785	0.04567	0.50027	3.1478	0.03791	0.41529
130	3.0929	0.04261	0.48587	3.1633	0.03590	0.40933
140	3.1339	0.03806	0.45034	3.1976	0.03181	0.37640
150	3.0972	0.03873	0.47440	3.1669	0.03224	0.39482
160	3.0656	0.03359	0.42486	3.1418	0.02844	0.35977
170	3.1015	0.03582	0.46698	3.1700	0.02998	0.39088
180	3.0917	0.03472	0.46578	3.1593	0.02904	0.38961
190	3.0825	0.03495	0.48181	3.1522	0.02926	0.40328
200	3.0712	0.03157	0.44642	3.1439	0.02653	0.37519

variable measurement using the Likert scale improved by fuzzy logic. However, future research could investigate the appropriate criteria to translate the arithmetic mean of data measured using the improved Likert scale.

Conflict of Interest

There is no conflict of interest.

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