A SYMBOL-BASED FUZZY DECISION-MAKING APPROACH TO EVALUATE THE USER SATISFACTION ON SERVICES IN ACADEMIC DIGITAL LIBRARIES

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Abstract. Academic libraries play a significant role in providing core services that include research, teaching and learning. User satisfaction is an important indicator for evaluating the performance of library service. This paper develops a method for measuring the user satisfaction in a group decision-making environment. First, the performance of service is evaluated by using questionnaire survey. The scores are recorded by using some simple symbols. Second, the symbol information along with nonresponse items in questionnaires are fused into an intuitionistic fuzzy information. Third, an experimental analysis is provided to illustrate the validity and effectiveness of introduced method in this paper. Finally, the theoretical and practical implications of current model are discussed, the important limitations are recognized, and some main advantages and future research directions of current method are shown in conclusions.

1. Introduction

Customer satisfaction, generally defined as the post-consumption evaluation of a product or a service [57], is essential to successful marketing because satisfied customers are more likely to show loyalty and to spread positive word-of-mouth recommendations [34, 11, 46].

Customer is a very widespread concept, which includes the users of academic libraries. Academic libraries contribute to their universities by acquiring, organizing, and disseminating information; providing space for research activities; and supporting users in finding and using information. Libraries are generally customer-centered and engage in numerous evaluation activities [12].

Digital library development, since its inception in the 1990s, has made significant progress thus far [23]. The development of digital libraries is to satisfy user need. Ensuring user satisfaction and providing the high quality of services are essential for the success of a digital library. Many studies have provided significant contributions to measure the user satisfaction of academic library. However, this review finds that there are some research gaps as follows:

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(1) Some criteria in questionnaires may be contradictory and interacted on each other. How to evaluate user satisfaction with contradictory criteria is one of research gaps.
(2) Some short-answer questions, mainly Fill-in-the-Blank and True/False items, had some nonresponses in the tested questionnaires, on which the responders might be hesitation, or uncertainty, or neglect. The nonresponse items, shown as blank answers, are also useful information. How to utilize and quantify them are another research gap.
(3) Some responders always complain that the questionnaire has too many questions and options because they are pressed for time. Responders prefer the questionnaire that there are fewer options, which are answered by using simple symbols, such as $\surd$, $\times$ and $\bigcirc$, where the symbols $\surd$, $\times$ and $\bigcirc$, denote the satisfaction, dissatisfaction and hesitation or abstention respectively. The third research gap is how to quantify the simple symbols in the tested questionnaires.

As for the problem of conflicting and incommensurable criteria in questionnaires, the multi-criteria decision-making (MCDM) methods [8, 1, 32, 2] are more suitable for dealing with it by using the normalization of attribute values. As for the problem of nonresponse items in the tested questionnaires, the fuzzy logic is a well-adopted theory and method since it exhibits a human-like thinking process. Fuzzy logic, which emerged from the theory of fuzzy set [58], is one of the techniques of soft computing which can deal with the inherent subjectivity, imprecision and vagueness. In fuzzy theory, an intuitionistic fuzzy number (IFN) [48, 33] can provide with three parameters (μ, ν, π): the μ is the percentage (or frequency, or rate) of votes in the voters supporting ($\surd$) the evaluation object; the ν is the percentage of votes in the voters opposing ($\times$) the evaluation object; the π is the percentage of votes in the voters who are uncertain ($\bigcirc$) on the evaluation object. For quantifying the nonresponse items and symbol-based evaluation problems, this model attempts to employ the intuitionistic fuzzy theory to develop the theoretical framework.

It is noted that some evaluations in questionnaire survey might be very positive, while some evaluations might be very negative. The positive and negative information representations are also very useful information. If all individual evaluations are aggregated into a collective decision of decision makers (DMs, or experts), the positive and negative information will be counteracted each other in the summation. To avoid this case, this paper attempts to propose a direct group decision-making (GDM) [42, 47, 51, 50, 55, 52] method. In addition, how to fully utilize the positive and negative information is an important topic in GDM problems. For this, just the TOPSIS (technique for order preference by similarity to ideal solution) technique [53] can help us realize it. The TOPSIS technique can consider not only a positive ideal decision (PID), but also the negative ideal decision(s) (NID(s)). It is a compromise method [7] between PID and NID(s), which is achieved by a relative closeness. The basic framework of this model is based on an extended TOPSIS technique.

To achieve these research goals, this article intends to establish a novel GDM model for evaluating user satisfaction in academic digital library (ADL) services. This new model adopts some simple symbols to represent user perceptions on the questionnaires, then these symbols are aggregated into an intuitionistic fuzzy information to quantify the level of user satisfaction in ADL use. To this end, the rest of the paper is structured as follows. Section 2 reviews the related work. Section 3 presents an evaluation methodology. Section 4 introduces the evaluation procedure in detail. Section 5 makes an experimental analysis. Section 6 gives a discusses for the evaluation methodology and evaluation procedure. And Section 7 gives the conclusions and future research.

2. **Related work**

To measure user satisfaction and expectations concerning library service quality, an early project was undertaken by the Association of Research Libraries in collaboration with Texas A&M University in 1999 [20]. The result of this project is an instrument named LibQual+, which is an extension of the SERVQUAL tool [28]. LibQUAL+ is a suite of services that libraries use to solicit, track, understand, and act upon users' opinions of service quality. These services are offered to the library community by the Association of Research Libraries. The program's centerpiece is a rigorously tested. Web-based survey bundled with training that helps libraries assess and improve library services, change organizational culture, and market the library. Currently, an explanation of the LibQual+ measurement system and its theoretical underpinnings may be found in Web site devoted to it (http://www.libqual.org).

Over the past two decades, a great deal of research has addressed various aspects of user satisfaction concerning service quality, including some quantitative and qualitative studies. In the quantitative studies, the most used approaches are the statistical ones [12]: the multiple regression analysis [29], the discriminate analysis [19], and the conjoint analysis [10]. An interesting exception is Heradio et al. [20], who presented a fuzzy linguistic model to evaluate the quality of library 2.0 functionalities. In addition, Kao et al. [25] introduced the use of descriptive knowledge discovered in the historical circulation data explicitly to support allocating library acquisition budget. Cabrerizo et al. [6] developed a decision support system to the quality management in academic digital libraries. A useful reviews [39] can satisfy the information need for reader.

Decision support system is one of the key tools to transform data to decisions [26]. MCDM is the procedure that finds the best alternative among a set of candidate alternatives [36, 2]. Owing to the increasing complexity of the socio-economic environment, a single DM may be impossible to consider all relevant aspects of a problem. In this case, the MCDM problems require to be further extended to GDM [53, 56, 54, 49, 45, 43].

Recently, the GDM has attracted great attention from researchers [44, 48, 31]. For example, Rao et al. [35] proposed a hybrid GDM method based on grey linguistic 2-tuple. Das and Guha [9] proposed a power harmonic aggregation operator with trapezoidal intuitionistic fuzzy numbers for solving GDM problems. Mousavi et al. [30, 31] introduced two soft computing approaches with applications to the selection problems.

The intuitionistic fuzzy theory [3] has received much attention from researchers and practitioners. For example, Hassaballah and Ghareeb [18] proposed a framework for objective image quality measures based on intuitionistic fuzzy sets. Hashemi et al. [16] developed an extended compromise ratio model with an application to reservoir flood control operation under an interval-valued intuitionistic fuzzy environment. Botía et al. [5] modeled a control algorithm based on intuitionistic fuzzy sets. Hao et al. [15] described an intuitionistic fuzzy decision making models in the framework of decision field theory. Kucukvar et al. [27] proposed a fuzzy MCDM method for the sustainability performance of pavements. Hesamian and Akbari [21] suggested a logistic regression model based on the IFNs. Hashemi et al. [17] designed a compromise ratio method with an application to water resources management with intuitionistic fuzzy information. Baležentis and Baležentis [4] developed a GDM procedure based on trapezoidal IFNs. Gong et al. [14] proposed an optimization spherical distance between two intuitionistic fuzzy sets. Kahraman et al. [24] suggested an intuitionistic fuzzy EDAS method and applied to solid waste disposal site selection. Rong et al. [37] developed a GDM method based on intuitionistic fuzzy theory.

Above-mentioned methods are very useful to deal with the MCDM and GDM problems. The intuitionistic fuzzy theory is very helpful in decision science. However, it is failing to known how to aggregate the symbol information into an intuitionistic fuzzy information in the real life. To fill this knowledge gap, this work intends to establish a novel model, and applies it to assess the user satisfaction in ADL services. The major contributions of this paper are listed as follows:

(1) This work intends to present an aggregation method, in which the symbol information is aggregated into an intuitionistic fuzzy information.
(2) This work intends to provide an evaluation model, in which the user satisfaction on services in ADL is evaluated by using the aggregation method under GDM environment.

3. Evaluation methodology

Before presenting the evaluation methodology, some preliminaries are briefly review as follows.

Atanassov [3] introduced an intuitionistic fuzzy set $A = \{< x_i, \mu_A(x_i), \nu_A(x_i) > |x_i \in X\}$, where the $X = \{x_1, x_2, \ldots, x_m\}$ is a universe of discourse, and the numbers $\mu_A(x_i)$ and $\nu_A(x_i)$ represent, respectively, the membership degree and non-membership degree of the element x_i to the set A with the condition $0 \leq \mu_A(x_i) + \nu_A(x_i) \leq 1,$ for all $x_i \in X$.

For convenience, Xu and Cai [40] called

$$\alpha = (\mu_\alpha, \nu_\alpha) \tag{1}$$

an IFN, with $\mu_\alpha, \nu_\alpha, \pi_\alpha \in [0,1], \mu_\alpha + \nu_\alpha \leq 1, \mu_\alpha + \nu_\alpha + \pi_\alpha = 1$, where μ_α, ν_α and π_α represent, respectively, the supported degree, opposed degree and hesitation degree about an evaluation object.

To aggregate IFNs, Xu and Cai [40] introduced the following operations.

Definition 3.1. Let $\alpha = (\mu_\alpha, \nu_\alpha)$ and $\beta = (\mu_\beta, \nu_\beta)$ be two IFNs, λ be a real number, then

(1) $\alpha + \beta = (\mu_\alpha + \mu_\beta - \mu_\alpha\mu_\beta, \nu_\alpha\nu_\beta)$;
(2) $\lambda\alpha = (1 - (1-\mu_\alpha)^\lambda, \nu_\alpha^\lambda)$, $\lambda > 0$.

Definition 3.2. Let $\alpha = (\mu_\alpha, \nu_\alpha)$ and $\beta = (\mu_\beta, \nu_\beta)$ be two IFNs, then the normalized Hamming distance [41] between α and β is given as follows:

$$s(\alpha, \beta) = \frac{1}{2}(|\mu_\alpha - \mu_\beta| + |\nu_\alpha - \nu_\beta| + |\pi_\alpha - \pi_\beta|), \tag{2}$$

where, by Eq.(1), the $\pi_\alpha = 1 - \mu_\alpha - \nu_\alpha$ and $\pi_\beta = 1 - \mu_\beta - \nu_\beta$.

Definition 3.3. Let $X = (x_{ij})_{m\times n}$ be a matrix, if all elements x_{ij} are IFNs, then X is called an intuitionistic fuzzy matrix.

Similar to Eq.(2), the normalized Hamming distance between two intuitionistic fuzzy matrices $X_1 = ((\mu_{ij}^{(1)}, \nu_{ij}^{(1)}))_{m\times n}$ and $X_2 = ((\mu_{ij}^{(2)}, \nu_{ij}^{(2)}))_{m\times n}$ is defined as follows:

$$S(X_1, X_2) = \frac{1}{2mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(|\mu_{ij}^{(1)} - \mu_{ij}^{(2)}| + |\nu_{ij}^{(1)} - \nu_{ij}^{(2)}| + |\pi_{ij}^{(1)} - \pi_{ij}^{(2)}|), \tag{3}$$

where, by Eq.(1), the $\pi_{ij}^{(1)} = 1 - \mu_{ij}^{(1)} - \nu_{ij}^{(1)}$ and $\pi_{ij}^{(2)} = 1 - \mu_{ij}^{(2)} - \nu_{ij}^{(2)} (i = 1, 2, \ldots, m, j = 1, 2, \ldots, n)$.

For convenience, the terminology and notations are explained as follows.

(1) Alternative, i.e., evaluation object. A set of m feasible alternatives is written as $A = \{A_1, \ldots, A_i, \ldots, A_m\}(m \geq 2), i \in M = \{1, 2, \ldots, m\}$;
(2) Criterion, i.e., evaluation attribute. A set of n criteria is written as $U = \{u_1, \ldots, u_j, \ldots, u_n\}, j \in N = \{1, 2, \ldots, n\}$;
(3) Weight of criterion, i.e., importance of criterion. A weight vector of criteria is written as $w = (w_1, \ldots, w_j, \ldots, w_n)$, with $0 \leq w_j \leq 1$ and $\sum_{j=1}^{n} w_j = 1$;
(4) DM, i.e., expert, or evaluator, who takes part in decision process. A set of t DMs is written as $D = \{d_1, \ldots, d_k, \ldots, d_t\}, k \in T = \{1, 2, \ldots, t\}$.

Suppose that each $d_k(k \in T)$ represents a DMs' class (group), who are composed of s_k DMs. They respond to questionnaires by using $\surd$ or $\times$ or $\bigcirc$. For s_k DMs, let n_{kj}^i and m_{kj}^i represent, respectively, the numbers of $\surd$ and $\times$ of ith alternative A_i with respect to jth criterion u_j in the survey records. Then the evaluative score is obtained as an IFN as follows:

$$x_{kj}^i = (\mu_{kj}^i, \nu_{kj}^i), i \in M, j \in N, k \in T, \tag{4}$$

where the $\mu_{kj}^i = n_{kj}^i / s_k$ and $\nu_{kj}^i = m_{kj}^i / s_k$ satisfy the condition $\mu_{kj}^i + \nu_{kj}^i \leq 1 (i \in M, j \in N, k \in T)$ in Eq.(1).

A GDM problem with t classes (groups) of DMs, m alternatives and n criteria can be contained in the following matrix:

$$X_i = (x^i_{kj})_{t\times n}, i \in M, \tag{5}$$

where the x^i_{kj}, expressed by an IFN in Eq.(4), is the evaluation score.

The goal of GDM is to rank the alternatives $A_i(i \in M)$ according to the scores in $X_i(i \in M)$.

Suppose that the $w = (w_1, w_2, \dots, w_n)$ is the weight vector of criteria, then

$$Y_i = (y^i_{kj})_{t\times n}, i \in M \tag{6}$$

is the weighted decision of X_i, where the $y^i_{kj} = w_j x^i_{kj} = (\tau^i_{kj}, \upsilon^i_{kj}), \tau^i_{kj} = 1 - (1 - \mu^i_{kj})^{w_j}, \upsilon^i_{kj} = (\nu^i_{kj})^{w_j}(i \in M, k \in T, j \in N)$ by Definition 1.

According to the TOPSIS technique, let

$$Y_+ = (y^+_{kj})_{t\times n} \tag{7}$$

be the PID of all $Y_i(i \in M)$, where the $y^+_{kj} = (\tau^+_{kj}, \upsilon^+_{kj})$, $\tau^+_{kj} = \max\limits_{i\in M}\{\mu^i_{kj}\}$ and $\upsilon^+_{kj} = \min\limits_{i\in M}\{\nu^i_{kj}\}(k \in T, j \in N)$. A NID should have the maximum separation from the PID, so let

$$Y_- = (y^-_{kj})_{t\times n} \tag{8}$$

be a NID of all $Y_i(i \in M)$, where the $y^-_{kj} = (\tau^-_{kj}, \upsilon^-_{kj}), \tau^-_{kj} = \min\limits_{i\in M}\{\mu^i_{kj}\}$ and $\upsilon^-_{kj} = \max\limits_{i\in M}\{\nu^i_{kj}\}(k \in T, j \in N)$.

The separation of each Y_i from PID Y_+, S^+_i, is based on the Hamming distance (see Eq.(3)) as follows:

$$S^+_i = \frac{1}{2tn}\sum_{k=1}^{t}\sum_{j=1}^{n}(|\tau^i_{kj} - \tau^+_{kj}| + |\upsilon^i_{kj} - \upsilon^+_{kj}| + |\pi^i_{kj} - \pi^+_{kj}|), i \in M, \tag{9}$$

where τ^+_{kj} and υ^+_{kj} are the same as in Eq.(7), the $\pi^i_{kj} = 1 - \tau^i_{kj} - \upsilon^i_{kj}$ and $\pi^+_{kj} = 1 - \tau^+_{kj} - \upsilon^+_{kj}(i \in M, k \in T, j \in N)$ by Eq.(1).

Similarly, the separations of each Y_i from the NID Y_-, S^-_i, is given as

$$S^-_i = \frac{1}{2tn}\sum_{k=1}^{t}\sum_{j=1}^{n}(|\tau^i_{kj} - \tau^-_{kj}| + |\upsilon^i_{kj} - \upsilon^-_{kj}| + |\pi^i_{kj} - \pi^-_{kj}|), i \in M, \tag{10}$$

where the $\pi^-_{kj} = 1 - \tau^-_{kj} - \upsilon^-_{kj}(i \in M, k \in T, j \in N)$; the $\tau^+_{kj}, \upsilon^+_{kj}$ are the same as in Eq.(7), the τ^-_{kj} and υ^-_{kj} are the same as in Eq.(8); the π^i_{kj} and π^+_{kj} are the same as in Eq.(9).

For each decision Y_i, an extended relative closeness [53] can be defined as:

$$RC_i = \frac{S^-_i}{S^+_i + S^-_i}, i \in M. \tag{11}$$

The alternatives can be ranked in accordance with the order of the relative closeness in Eq.(11). The ranking is based on the criterion that the larger value RC_i means the better alternative A_i.

4. Evaluation procedure

This section focuses on the evaluation procedure of the user satisfaction on services in ADLs. It consists of two parts as follows.

4.1. **Evaluation alternatives, criteria and decision makers.** As literature [38] suggests that the user-centered evaluation of an ADL should be multi-constructed, capable to capture a panoramic view of users' opinions, able to take into account their characteristics and grounded on their perceptions and goals. To this end, this subsection first determines the evaluation objects (alternatives), evaluation criteria (attributes) and evaluators (DMs).

The evaluation object is the user satisfaction on services in the library of a university, where is located in Guangdong, China. The constructions of software and hardware in its library are satisfactory to students and faculty, especially in digital information. To improve the quality of service, this library conducted a survey. The survey is taken over m periods of time. The alternatives $A_i (i \in M)$ in this survey are the user satisfaction during the different time periods in this ADL. The four time periods here are conducted, which are March, April, May and June, 2016, respectively, i.e., the set of alternatives is $A = \{A_1, A_2, A_3, A_4\}$.

The evaluation criteria are based on a theoretical model in literature [13]. The set of evaluation criteria is $U = \{u_1, u_2, u_3\}$={usefulness, usability, performance}. The sub-criteria and their explanations are shown in Table 1. The usefulness defines whether ADL constitutes valuable tools for the completion of users' tasks. The usability includes the ease of use or user-friendliness and consider from interface effectiveness point of view. The performance focuses on the System/Technology view of an ADL.

Three groups composed of faculty, graduate students and undergraduate students, as DMs (or respondents, or evaluators, or voters), are responsible for the grading work, namely, the set of DMs is $D = \{d_1, d_2, d_3\}$ = {faculty, graduate students, undergraduate students}. They are representatives of all active users of faculty, graduate students and undergraduate students in this ADL system in this university.

4.2. **Data collection, aggregation and decision procedure.** A number of techniques, including formal usability testing, diary, questionnaire, interview, think aloud, and log analysis, are employed to collect data from all respondents. The different methods are emphatically used for different categories of users. Specifically, the informal interviews are emphatically used for faculty; the group sessions are emphatically used for graduate students; and questionnaires are emphatically used for undergraduate students.

Respondents evaluate each criterion by using only one of three symbols $\{\surd, \times, \bigcirc\}$. As mentioned in the introduction section, the symbols $\surd, \times, \bigcirc$ represent, respectively, the satisfaction, dissatisfaction and hesitation or abstention. The data collection, statistics, aggregation and ranking of alternatives are detailed in the following steps.

Step 1: Data collection and statistics.

Main-criteria	Sub-criteria	Explanation
Usefulness	Relevance	Relevance is the degree to which the system matches tasks as carried out in the current environment and as specified in the task analysis [22].
	Reliability	Reliability and credibility for the selection of the appropriate resources.
	Level	Achieve specified goals with effectiveness, efficiency and satisfaction.
	Format	Users' format preferences, such as .pdf and .html file formats.
	Coverage	Temporal coverage.
Usability	Ease of use	Convenience.
	Terminology	Terminology refers to the words, sentences, and abbreviations used by a system [22].
	Navigation	Straightforward navigation/links.
	Aesthetics	Aesthetic appearance.
	Learn ability	Easy to learn.
Performance	Precision	The ratio of relevant items in the set of all documents returned by a search [13].
	Response time	The time that a system or functional unit takes to react to a given input [13].
	Recall	The fraction of relevant material that is returned by a search [13].

Table 1. Evaluation criteria and their explanations

Alternative	DM		u_1		u_2		u_3	
	Group	s_k	$n_{kj}^i(\surd)$	$m_{kj}^i(\times)$	$n_{kj}^i(\surd$	$m_{kj}^i(\times)$	$n_{kj}^i(\surd)$	$m_{kj}^i(\times)$
A_1	d_1	200	36	55	26	56	17	50
	d_2	200	80	79	83	75	63	82
	d_3	300	129	132	127	138	129	111
A_2	d_1	200	81	79	84	70	88	84
	d_2	200	78	73	86	76	87	65
	d_3	300	125	119	132	112	137	131
A_3	d_1	200	56	85	86	76	97	80
	d_2	200	87	79	89	75	93	81
	d_3	300	122	102	129	124	122	118
A_4	d_1	200	90	60	86	72	92	85
	d_2	200	81	77	93	69	88	83
	d_3	300	50	120	137	99	125	108

Table 2. Statistics of assessment information

Matrix	DM	u_1	u_2	u_3
X_1	d_1	(0.1800, 0.2750)	(0.1300, 0.2800)	(0.0850, 0.2500)
	d_2	(0.4000, 0.3950)	(0.4150, 0.3750)	(0.3150, 0.4100)
	d_3	(0.4300, 0.4400)	(0.4233, 0.4600)	(0.4300, 0.3700)
X_2	d_1	(0.4050, 0.3950)	(0.4200, 0.3500)	(0.4400, 0.4200)
	d_2	(0.3900, 0.3650)	(0.4300, 0.3800)	(0.4350, 0.3250)
	d_3	(0.4167, 0.3967)	(0.4400, 0.3733)	(0.4567, 0.4367)
X_3	d_1	(0.2800, 0.4250)	(0.4300, 0.3800)	(0.4850, 0.4000)
	d_2	(0.4350, 0.3950)	(0.4450, 0.3750)	(0.4650, 0.4050)
	d_3	(0.4067, 0.3400)	(0.4300, 0.4133)	(0.4067, 0.3933)
X_4	d_1	(0.4500, 0.3000)	(0.4300, 0.3600)	(0.4600, 0.4250)
	d_2	(0.4050, 0.3850)	(0.4650, 0.3450)	(0.4400, 0.4150)
	d_3	(0.1667, 0.4000)	(0.4567, 0.3300)	(0.4167, 0.3600)

TABLE 3. Assessment matrices based on intuitionistic fuzzy information

As above-mentioned method of data collection, the data are collected by using formal usability testing (96), diary (232), questionnaire (128), interview (17), think aloud (11), and log analysis (216). The assessment information is shown in Table 2.

It is worth noting that Table 2 does not involve the symbol ◯. However, this information is not neglected. It is simply regarded as the ◯ being a hesitancy, which are reflected in π^i_{kj}, π^+_{kj} and π^-_{kj} in Eqs.(9) and (10).

Step 2: Establish assessment matrices.

Based on the assessment information in Table 2, the assessment matrices $X_i = (x^i_{kj})_{t\times n}$ in Eq.(5) are established, which are shown in Table 3, where the $M = \{1, 2, 3, 4\}, N = T = \{1, 2, 3\}$.

Step 3: Construct the weighted assessment matrices.

The weight vector of criteria, $w = (w_1, w_2, w_3) = (0.35, 0.35, 0.30)$, is given by experts through consultation. By Eq.(6), the weighted assessment matrices are shown in Table 4, where the $M = \{1, 2, 3, 4\}$ and $N = T = \{1, 2, 3\}$.

Step 4: Determine the ideal decisions.

For the $Y_i (i \in M)$ in Table 4, the ideal decisions are determined by Eqs.(7) and (8), which are shown in Table 5.

Step 5: Calculate the separations of each assessment matrix from the ideal decisions.

The separations of each assessment matrix Y_i from ideal decisions Y_+ and Y_-, S^+_i and S^-_i, are calculated by Eqs.(9) and (10), which the results are shown in Table 6.

Step 6: Calculate the relative closeness.

For each assessment matrix, the relative closeness is calculated by E-q.(11), which is also shown in Table 6.

Step 7: Rank the preference order of alternatives.

Matrix	DM	u_1	u_2	u_3
Y_1	d_1	(0.0671,0.6365)	(0.0476,0.6405)	(0.0263,0.6598)
	d_2	(0.1637,0.7225)	(0.1711,0.7094)	(0.1073,0.7653)
	d_3	(0.1786,0.7503)	(0.1752,0.7620)	(0.1552,0.7421)
Y_2	d_1	(0.1662,0.7225)	(0.1736,0.6925)	(0.1597,0.7709)
	d_2	(0.1589,0.7028)	(0.1786,0.7127)	(0.1574,0.7138)
	d_3	(0.1719,0.7235)	(0.1837,0.7083)	(0.1672,0.7799)
Y_3	d_1	(0.1086,0.7412)	(0.1786,0.7127)	(0.1805,0.7597)
	d_2	(0.1811,0.7225)	(0.1862,0.7094)	(0.1711,0.7625)
	d_3	(0.1670,0.6855)	(0.1786,0.7340)	(0.1450,0.7558)
Y_4	d_1	(0.1888,0.6561)	(0.1786,0.6994)	(0.1688,0.7736)
	d_2	(0.1662,0.7160)	(0.1966,0.6890)	(0.1597,0.7681)
	d_3	(0.0618,0.7256)	(0.1923,0.6784)	(0.1493,0.7360)

TABLE 4. Weighted assessment matrice based on intuitionistic fuzzy information

Decision	DM	u_1	u_2	u_3
Y_+	d_1	(0.1888, 0.6365)	(0.1786, 0.6405)	(0.1805, 0.6598)
	d_2	(0.1811, 0.7028)	(0.1966, 0.6890)	(0.1711, 0.7138)
	d_3	(0.1786, 0.6855)	(0.1923, 0.6784)	(0.1672, 0.7360)
Y_-	d_1	(0.0671, 0.7412)	(0.0476, 0.7127)	(0.0263, 0.7736)
	d_2	(0.1589, 0.7225)	(0.1711, 0.7127)	(0.1073, 0.7681)
	d_3	(0.0618, 0.7503)	(0.1752, 0.7620)	(0.1450, 0.7799)

TABLE 5. Ideal decisions of all assessment matrices

Alternative	S_i^+	Ranking	S_i^-	Ranking	RC_i	Ranking
A_1	0.0752	4	0.0507	4	0.4029	4
A_2	0.0467	2	0.0696	2	0.5981	2
A_3	0.0506	3	0.0650	3	0.5624	3
A_4	0.0440	1	0.0703	1	0.6147	1

TABLE 6. Separations, relative closeness and rankings of alternatives

All alternatives are ranked in descending order in accordance with their relative closeness, which is also shown in Table 6.

Table 6 shows that the order of users' satisfaction at four different sampling periods in this academic library is as follows:

$$A_4 \succ A_2 \succ A_3 \succ A_1.$$

Specifically, the A_4 is the best service, followed by A_2, A_3, and A_1.

Matrix	DM	u_1	u_2	u_3
X_1	d_1	-19	-30	-33
	d_2	1	8	-19
	d_3	-3	-11	18
X_2	d_1	2	14	4
	d_2	5	10	22
	d_3	6	20	6
X_3	d_1	-29	10	17
	d_2	8	14	12
	d_3	20	5	4
X_4	d_1	30	14	7
	d_2	4	24	5
	d_3	-70	38	17

Table 7. Assessment matrices based on crisp values

5. Experimental analysis

To illustrate the validity of algorithm proposed in this paper, this section makes an experimental analysis based on the above-mentioned example.

5.1. **Experimental comparison with crisp values.** At first glance the symbols $\{\surd, \times, \bigcirc\}$ seem to similar to the meanings of the scores $\{1, -1, 0\}$. To show the difference between $\{\surd, \times, \bigcirc\}$ and $\{1, -1, 0\}$ in the quantity of information, an experimental analysis is compared with crisp values for the above-mentioned example.

First the symbols $\{\surd, \times, \bigcirc\}$ is converted to the scores $\{1, -1, 0\}$ respectively, then the numbers of symbols $\{\surd, \times, \bigcirc\}$ in Table 2 can be expressed by the crisp values. The assessment matrices $X_i (i = 1, 2, 3, 4)$ based on crisp values are displayed in Table 7. For example, the x_{11}^1 in X_1 from Table 7 is calculated by $x_{11}^1 = 36 - 55 = -19$.

For the weight vector of criteria, $w = (w_1, w_2, w_3) = (0.35, 0.35, 0.30)$, the weighted assessment matrices $Y_i (i \in M)$ with crisp values are determined by Step 3, which are shown in Table 8.

For the $Y_i (i \in M)$ in Table 8, the ideal decisions are determined by Step 4, which are shown in Table 9.

The separations with crisp values, S_i^+ and S_i^-, are given by Step 5, which are shown in Table 10.

Table 10 shows that the order of users' satisfaction at four different sampling periods in this academic library is $A_2 \succ A_4 \succ A_3 \succ A_1$. This ranking is differ from the ranking based on the intuitionistic fuzzy information in Table 6. This incorrect ranking is caused by the transformation from $\{\surd, \times, \bigcirc\}$ to $\{1, -1, 0\}$. This difference, from one side of information representation, shows the effectiveness and advantages introduced method in this paper.

Matrix	DM	u_1	u_2	u_3
Y_1	d_1	-6.6500	-10.5000	-9.9000
	d_2	0.3500	2.8000	-5.7000
	d_3	-1.0500	-3.8500	5.4000
Y_2	d_1	0.7000	4.9000	1.2000
	d_2	1.7500	3.5000	6.6000
	d_3	2.1000	7.0000	1.8000
Y_3	d_1	-10.1500	3.5000	5.1000
	d_2	2.8000	4.9000	3.6000
	d_3	7.0000	1.7500	1.2000
Y_4	d_1	10.5000	4.9000	2.1000
	d_2	1.4000	8.4000	1.5000
	d_3	-24.5000	13.3000	5.1000

Table 8. Weighted assessment matrices based on crisp values

Decision	DM	u_1	u_2	u_3
Y_+	d_1	10.5000	4.9000	5.1000
	d_2	2.8000	8.4000	6.6000
	d_3	7.0000	13.3000	5.4000
Y_-	d_1	-10.1500	-10.5000	-9.9000
	d_2	0.3500	2.8000	-5.7000
	d_3	-24.5000	-3.8500	1.2000

Table 9. Ideal decisions based on crisp values

Alternative	S_i^+	S_i^-	RC_i	Ranking
A_1	0.9310	0.3115	0.2507	4
A_2	0.3445	0.8980	0.7227	1
A_3	0.4430	0.7995	0.6435	3
A_4	0.4130	0.8295	0.6676	2

Table 10. Separations, relative closeness and ranking of alternatives based on crisp values

5.2. **Experimental comparison with relevant measures.** This section shows an experimental comparison with relevant measures to illustrate the validity and effectiveness introduced method in this paper. To show how and why the algorithm is valid, next research further reviews above-mentioned measures.

It is noted that the $S_{(\cdot)}^+$ in Eq.(9) is also a measure, which can rank the alternatives $A_i (i = 1, 2, 3, 4)$. And the smaller the value S_i^+, the better the alternative A_i is. Similarly, the $S_{(\cdot)}^-$ in Eq.(10) is also a measure to rank the alternatives

$A_i(i = 1, 2, 3, 4)$. And the larger the value S_i^-, the better the alternative A_i is. The rankings of the alternatives based on $S_{(\cdot)}^+$ and $S_{(\cdot)}^-$ in above-mentioned example are also shown in Table 6.

Table 6 shows that the rankings of the alternatives based on $S_{(\cdot)}^+$ and $S_{(\cdot)}^-$ are consistent with $RC_{(\cdot)}$. So the suggested model in this paper is a robust measure.

To illustrate the validity that the model suggested in this paper is a robust measure, next report provides a dynamic analysis for the rankings of four alternatives in above-mentioned example.

For the $n_{32}^1 = 127$ in Table 2, let $n_{32}^1 = \delta$, where the $\delta \in [0, 127]$ is a parameter. Other values are the same as in Table 2. As mentioned above, the S_i^+ in Eq.(9) is also a measure. And the smaller the value S_i^+, the better the alternative A_i is. For convenience in statement and observation, the Eq.(9) is converted to following form:

$$\overline{S}_i^+ = 0.3 - S_i^+, i \in M, \tag{12}$$

where the S_i^+ is the same as in Eq.(9). The larger the value $\overline{S}_i^+$ in Eq.(12), the better the alternative A_i is.

Now let δ increases from 0 to 127, and then observe the changes of rankings of four alternatives based on the $\overline{S}_{(\cdot)}^+$ in Eq.(12). The curves of rankings of A_1, A_2, A_3 and A_4 are shown in Figure 1.

Figure 1 shows that the ranking $A_4 \succ A_2 \succ A_3 \succ A_1$ is stable as δ increases from 0 to 127. Therefore the validity of ranking $A_4 \succ A_2 \succ A_3 \succ A_1$ is supported by $\overline{S}_i^+$ in Eq.(12) under a dynamic environment, and $\overline{S}_{(\cdot)}^+$ in Eq.(12) (and therefore the $S_{(\cdot)}^+$ in Eq.(9)) is a robust measure.

Similarly, let δ increases from 0 to 127, the curves of rankings of A_1, A_2, A_3 and A_4 based on the $S_{(\cdot)}^-$ in Eq.(10) are shown in Figure 2.

Figure 2 shows that the ranking $A_4 \succ A_2 \succ A_3 \succ A_1$ is also stable as δ increases from 0 to 127. Therefore the validity of ranking $A_4 \succ A_2 \succ A_3 \succ A_1$ is supported by $S_{(\cdot)}^-$ in Eq.(10); the robustness of this model is supported by $S_{(\cdot)}^-$ in Eq.(10).

Finally, let δ increases from 0 to 127, and let us observe the changes of rankings of four alternatives based on the $RC_{(\cdot)}$ in Eq.(11). The curves of rankings of four alternatives are shown in Figure 3.

Similar to Figures 1 and 2, the ranking $A_4 \succ A_2 \succ A_3 \succ A_1$ in Figure 3 is also stable as δ increases from 0 to 127. Therefore the ranking $A_4 \succ A_2 \succ A_3 \succ A_1$ is believable; and the model suggested in this paper is a robust measure.

6. Discussion

6.1. **Some differences between $\{\surd, \times, \bigcirc\}$ and $\{1, -1, 0\}$.** The symbols $\{\surd, \times, \bigcirc\}$ and $\{1, -1, 0\}$ are simple and easy-to-use for responders. The information aggregated by $\{\surd, \times, \bigcirc\}$ is an IFN (μ, ν, π); the information aggregated by $\{1, -1, 0\}$ is a real number. As aforementioned, an IFN carries and provides simultaneously the supported degree (μ), opposed degree (ν) and hesitation degree (π) about an evaluation object. If the symbols $\{\surd, \times, \bigcirc\}$ are replaced by the symbols $\{1, -1, 0\}$, then the elements in $X_i(i \in M)$ of Eq.(5) are real numbers. We can specifically see

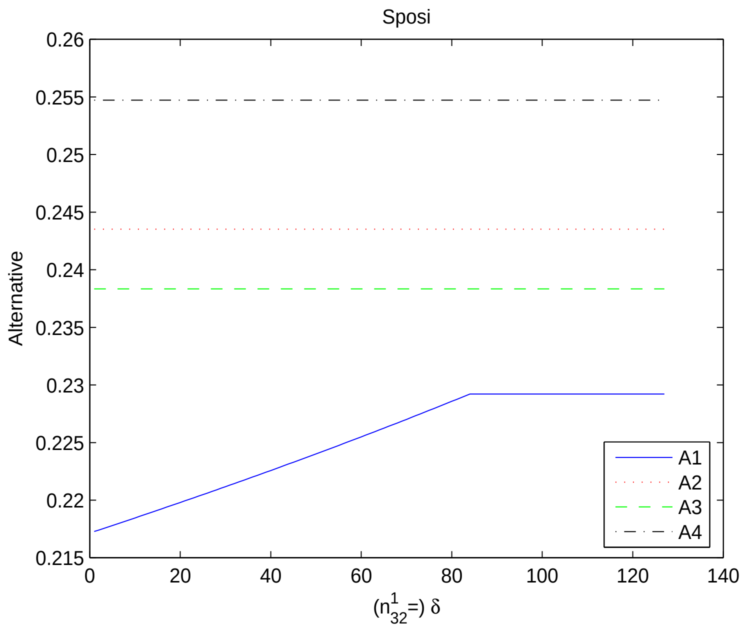

FIGURE 1. Rankings of four alternatives A_1, A_2, A_3, A_4 based on $\overline{S}_i^+$ in Eq.(12)

it in Table 7, whose original information has disappeared. An incorrect ranking is finally generated in Table 10. So the method based on $\{\surd, \times, \bigcirc\}$, in this sense, is a more comprehensive methodology.

6.2. **Notes on the decision makers.** This subsection provides some notes on the DMs in the GDM model. Generally, the DMs are a group of experts in a decision process. A DM is an expert. However, for the decision problems with big data, a DM may be a group of experts, who are responsible for the grading work. For example, the d_2 in X_1 in the above-mentioned example could be some graduate students, who are from the College of Mathematics and Computer Science; while the d_2 in X_2 in the above-mentioned example could be the graduate students, who are from the College of Science. They are a group of graduate students, and they are representatives of all graduate students in this university.

6.3. **Implications.** This study has important implications in both theoretical and practical perspectives. Focusing on the evaluation methods of user satisfaction in current literature, some methods are simple and straightforward but with less theoretical basis; while some methods are very theoretical and abstract but hard to implement. Aimed at these problems, in theory, this paper has solved the problems of effective use and fusion of information of the nonresponse and the symbols

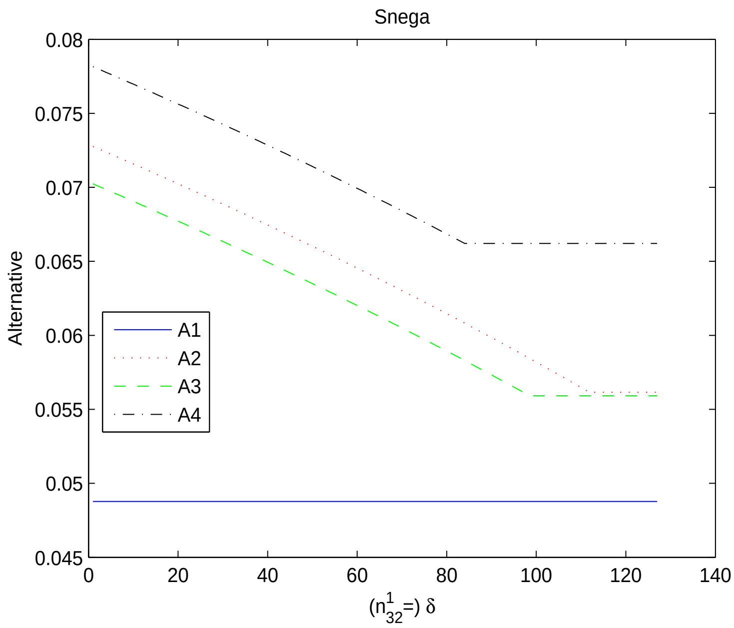

FIGURE 2. Rankings of four alternatives A_1, A_2, A_3, A_4 based on S_i^- in Eq.(10)

$\{\surd, \times, \bigcirc\}$ in questionnaires. And this work has provided an easy-to-use evaluation model with theoretical support.

Without a doubt, academic libraries can contribute their resources to students to improve their quality, to graduate students and teachers to improve their academic level. The current study has provided a practical model to improve the service quality of ADL. And this model can future apply to other domains. So this study has important implications for practice.

6.4. **Limitations.** No doubt this study has its own limitations. First, since the participants come only from a university, the sample and the sample size do not represent a variety of users of digital libraries. Future research should have a large sample size. Second, the weights of DMs are the same for all DMs. However, in some cases, they are different, which need to be extended to different weights in future research. Third, this model evaluates the user satisfaction of ADL in one library. The evaluation alternatives can be applied to multi-ADL with the same criteria in future research. That is to say, this method will make a comparison with two or more libraries concerning users satisfaction. Fourth, the symbol information in questionnaires is aggregated to an intuitionistic fuzzy information. In fact, they may be aggregated to other information, such as the interval-valued intuitionistic fuzzy information.

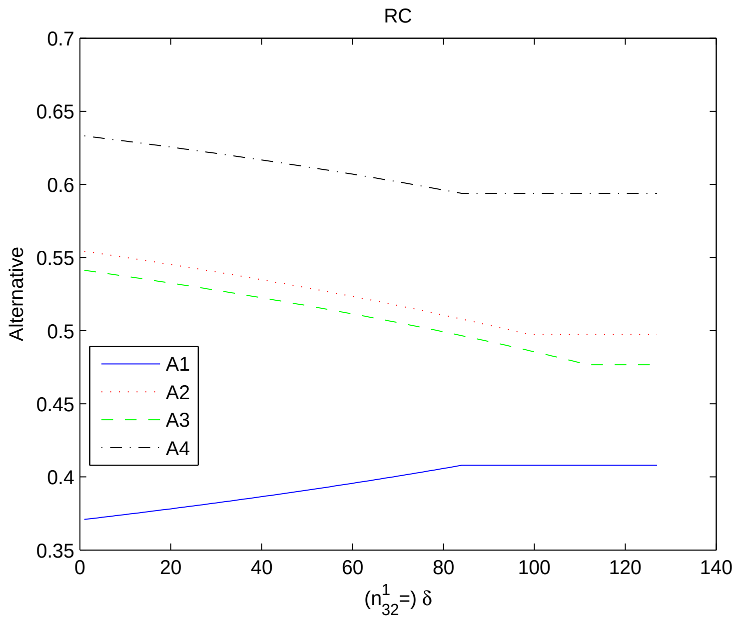

FIGURE 3. Rankings of four alternatives A_1, A_2, A_3, A_4 based on RC_i in Eq.(11)

7. CONCLUSIONS

This paper contributes to the literature an intuitionistic fuzzy model for evaluating users' satisfaction in ADLs. The main advantages of this paper are listed as follows:

(1) The decision model proposed here can handle contradictory evaluation criteria.
(2) The decision method can aggregate symbols $\{\surd, \times, \bigcirc\}$ along with nonresponse items in survey records to form an useful evaluation information.
(3) The proposed model is easy to operate on questionnaires, only use some simple symbols.
(4) The idea of proposed model is straightforward and the algorithm is clear, so can be understand easily.

This approach is based on a well-established decision analysis technique. The theoretical advances have significantly contributed to GDM to solve three common limitations: (1) the inability to deal with contradictory evaluation criteria; (2) some difficulties in converting the qualitative evaluation to quantitative evaluation; and (3) the lack of sample, user-friendly techniques for dealing with a large number of decision information.

The technological advances have significantly contributed to ADL and literature an evaluation methodology with straightforward idea, simple operation and well-founded treatment. This approach is easy to implement in stand-alone personal computers. It is especially applicable for comprehensive ranking of evaluation objects in engineering and management applications. The future research should apply this method to other fields, such as management, market, and education.

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