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Assessing Knowledge Quality Using Fuzzy MCDM Model

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Abstract: The purpose of knowledge management is to excavate the tacit knowledge accumulated by each enterprise member through the knowledge proposal system. Each knowledge proposal must be assessed, and after passing the quality assessment, the knowledge proposal will be stored in the knowledge repository and shared with other employees who need the knowledge at work. In the long run, the capabilities of all employees will gradually enhance and the competitiveness of enterprises will naturally increase. The correct assessment of knowledge quality is the key to the success of knowledge management. Some scholars propose to use the AHP (analytical hierarchical process) to determine the quality of knowledge. The problem with this approach is that the AHP can only obtain the relative quality of all knowledge, not the actual quality of knowledge. Therefore, this study proposes a fuzzy assessment model to measure knowledge quality, which includes a knowledge quality fuzziness index (KQFI) and a checking gate. First, experts conduct linguistic evaluation on the weight of criteria and knowledge quality. All linguistic evaluations are then integrated into a knowledge quality fuzziness index (KQFI), which is compared with a fuzzy threshold (FT); then, the level of goodness of KQFI to FT is obtained. If it is greater than 0.5, it means that the quality of the knowledge proposal is qualified; otherwise, it means that the quality of the knowledge proposal is unqualified. This study uses a case including five experts and nine knowledge proposals to demonstrate the applicability of the method. The results show that the method finally judges six knowledge instances as qualified and three as unqualified. The results show that the proposed method can indeed assist enterprises to effectively screen knowledge proposals.

Keywords: knowledge management; fuzzy theory; multi-criteria decision making

MSC: 03B52; 03E72; 90B50

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1. Introduction

Enterprises are facing stiff global competition, and the best way to effectively lead competitors is to develop new products, new services, and new business models [1]. One of the ways to achieve this goal is to promote knowledge management. First, establish a culture of knowledge sharing; then, collect, review, store, and reuse existing knowledge within the enterprise. Employees can socialize, externalize, combine, and internalizing existing knowledge to create new knowledge [2,3]. Enterprise knowledge includes tacit knowledge and explicit knowledge; each can be subdivided into personal knowledge and organizational knowledge [4,5]. Explicit organizational knowledge includes operating standards, procedures, and manuals. Tacit organizational knowledge refers to the knowledge that a group of people can effectively complete a project. Explicit personal knowledge includes notes and computer files. Tacit personal knowledge includes work experience, work skills, techniques, etc. Tacit organizational knowledge and tacit personal knowledge generally remain in the brains of individuals. Therefore, when personnel retire or leave the enterprise, this knowledge is permanently lost. Most importantly, tacit knowledge is the most critical knowledge that enterprises can win the competition. Therefore, enterprises must be equipped with knowledge management systems to preserve these tacit knowledge [6,7]. The method most often used to preserve tacit knowledge is to set up a knowledge community (community of practice) with a reward system to establish a collaborative work culture so that knowledge can be transferred from one person's brain to another [8,9]. In this way, problems that only one person could solve in the past can now be solved by many people and everyone's ability will gradually improve. When the company needs to cope with competition, the company's personnel can quickly and effectively develop new products and new services to overcome challenges.

The community of practice must correspond to the strategy of the enterprise. For example, the enterprise hopes to establish independent product design and development capabilities; so, several related communities of practice can be established and each with a clear objective to achieve. Each community of practice has a management team and a process for receiving and reviewing knowledge proposals. Finally, people are encouraged to participate in communities of practice and rewards are offered for knowledge proposals. The knowledge proposals put forward by community members will be reviewed by senior personnel in related fields, and the knowledge that passes the review will be shared, published, and stored in the knowledge base. Obviously, if the judgment on the quality of knowledge is wrong, poorer knowledge will also pass the review; so, the overall ability of the enterprise will not be improved. On the contrary, if quality knowledge fails to pass the review all the time, after a period, the ability of the enterprise will become worse and worse.

The criteria of measuring knowledge quality in different fields may be different but most of them must be evaluated from multiple aspects at the same time. In the past, scholars mentioned that measuring knowledge quality should include correctness, completeness, consistency, relevance, etc. [10]. Some studies mentioned that measuring knowledge quality should include certainty, accuracy, and operability [11], while Arora et al. (2013) believed that measuring knowledge quality should include completeness, timeliness, accuracy, transparency, and relevancy [12]. The assessment of knowledge quality is a multi-attribute decision-making problem. In practice, when experts assess the quality of knowledge, they do not only make qualitative and subjective judgments; more importantly, it is difficult to make a completely correct quality judgment while considering multiple aspects at the same time. Further, academically, there have been very few papers on knowledge quality assessment in the past. The methods used mainly included the AHP and statistical analysis of questionnaires [10,13,14]. The problem with the AHP is that it is necessary to compare the relative importance of all knowledge proposals at the same time. When there are many knowledge proposals, it is difficult to know what is wrong with the large matrix obtained by pairwise comparison. If the consistency checks fail, the adjustment process will be very complicated, not to mention that the quality of knowledge should be an absolute judgment of good or bad rather than a comparison of relative good or bad. Moreover, most papers on statistical analysis of questionnaires discuss the impact of knowledge quality on corporate innovation and operational performance rather than measuring the quality of knowledge.

Obviously, a method that can correctly assess knowledge quality is nonexistent. In addition, it is difficult for humans to give specific numbers to measure the quality of knowledge. It is relatively easy to use fuzzy linguistic assessment of very good, good, fair, poor, and very poor to evaluate the quality of knowledge. Therefore, the objective of this study is to develop a multi-criteria knowledge quality assessment model, including a knowledge quality fuzziness index and a checking gate, to effectively determine the quality of knowledge proposals. This study can improve the shortcomings of existing methods, assist enterprises to screen out high-quality knowledge, and improve the performance of enterprise knowledge management.

2. Literature Review

This section reviews literature related to this study, including knowledge quality, and fuzzy set and group decision making.

2.1. Knowledge Quality

Quality is defined by the Oxford Dictionary as the degree of excellence of a thing; relative nature or kind or character of a thing; or class or grade of something determined by this [1]. Additionally, qualities need to be described using some attributes. For example, the quality of products is expressed in terms of functionality and reliability while the quality of services is measured in terms of responsiveness and empathy [15]. Enterprises determine the specifications of products and services, while quality is judged by customers. Enterprises usually use many methods to try to tap customers' needs for products and services, and hope that products and services can meet customers' requirements 100%. However, it has been proved in practice that this is almost an impossible task. For example, even for a company as large as Microsoft, the development of Windows Vista still cannot meet customer needs and is called the biggest failure of Microsoft ever [16]. Product development not only involves product-related knowledge but also involves marketing-related knowledge. Both must conform to the overall strategy of the enterprise, and the quality of knowledge must be accurately evaluated to ensure that the retained and stored knowledge can enhance the competitiveness of the enterprise [13,14].

Chakrabarti et al. (2018) proposed an approach to relate knowledge quality with elements that consist of attributes; thus, an enterprise can discover which element provides the most effective direction to improve knowledge quality [10]. Lim et al. (2013) examined the relationship between sentiment and quality of knowledge shared among knowledge workers and job performance [17]. It was indicated that data quality and information quality are often used to assess knowledge quality, and a reliable knowledge quality measure is nonexistent [11]. Zhou et al (2022) explored the impact of knowledge transfer among supply chain members on firm innovation and operational performance, and how knowledge quality affects the relationship between them [18]. Abdollahbeigi and Salehi (2021) found that the quality of knowledge significantly affects the innovation of enterprises, and the ability of innovation will have a significant impact on non-financial performance [19]. Ganguly et al. (2019) concluded that the transfer of tacit knowledge and the quality of knowledge are positively related to the innovation ability of enterprises [20]. Zhou et al. (2022) discovered that the knowledge quality of relational capital and cognitive capital positively affects product innovation performance but structural social capital does not affect the quality of knowledge [18,21]. From these past literatures, it can be found that up to now, no effective assessment method of knowledge quality has been proposed that can assist enterprises to correctly measure the quality of knowledge.

2.2. Fuzzy Set and Group Decision Making

Deterministic and quantifiable information with values between 0 and 1 are usually handled using classical set theory; however, when the information contains uncertainties that cannot be quantified, classical sets cannot be used. The evaluation of knowledge proposals is uncertain, and quantitative methods cannot be used to judge whether they meet the quality requirements. Therefore, classical set theory is not applicable. This situation where the value can vary continuously between zero and one is where fuzzy theory comes in handy. Fuzzy theory uses membership functions to express the degree of membership between components and sets. A fuzzy set A can be expressed as Equation (1).

$$A = \{(x, \mu_A(x))|x \in X\} \tag{1}$$

where X is a universe of discourse and $\mu_A(x)$ indicates the degree of membership between component x and fuzzy set A.

Because the triangular fuzzy function has been proven to be very suitable for dealing with the imprecision and uncertainty of the multi-criteria decision-making process [12], this study uses the triangular fuzzy function to evaluate the attribute weight and knowledge quality. Let triangular fuzzy number A $= (a, b, c)$; then, the membership function of A can be expressed as Equation (2) [22–24].

$$\mu_A = \begin{cases} \frac{(x-a)}{(b-a)} & a \leq x \leq b \\ \frac{(c-x)}{(c-b)} & b \leq x \leq c \\ 0 & otherwise \end{cases} \tag{2}$$

The α-cut is applied to convert a fuzzy number into a crisp set, and the α-cut of a triangular fuzzy number A can be described as Equation (3), where A_α is a crisp set [25,26].

$$A_\alpha = \{x | \mu_A(x) \geq \alpha\} \quad \alpha \in \{0, 1\} \tag{3}$$

The confidence of interval α-level of A_α can be described as Equation (4), and A_α implies the confidence level of a decision maker in the evaluation outcome.

$$A = [(b-a)\alpha + a, c - (c-b)\alpha] \tag{4}$$

Chen (2000) indicated that precise quantified information and solving real problems are not necessarily relevant [22]. Li et al. (2022) pointed out that linguistic variables can be used in fuzzy theory to manipulate the operations [27]. When assessors judge the importance of the criteria using fuzzy method, the linguistic variables can be converted into a fuzzy number and results can be obtained using fuzzy algebra [28]. For instance, the linguistic variables of very good, good, fair, poor, and very poor in Table 1 can be used to assess the quality of the knowledge proposal, and the assessment of a knowledge proposal can be obtained using the triangular fuzzy number (TFN).

Table 1. Weight, quality, and TFN of knowledge proposal.

Weight	Quality	TFN
VL (Very low)	VP (Very poor)	(0, 0, 0.1)
L (Low)	P (Poor)	(0, 0.1, 0.3)
ML (Medium low)	MP (Medium poor)	(0.1, 0.3, 0.5)
M (Medium)	M (Medium)	(0.3, 0.5, 0.7)
MH (Medium high)	MG (Medium good)	(0.5, 0.7, 0.9)
H (High)	G (Good)	(0.7, 0.9, 1.0)
VH (Very high)	VG (Very good)	(0.9, 1.0, 1.0)

Because the measurement of knowledge quality involves imprecise information that cannot be quantified, and the quality of knowledge must be evaluated by a group of experts and several attributes at the same time, it is suitable to use the fuzzy multi-criteria group decision making method [29]. Past studies mostly used the average value as the final group decision [26,30–33]; however, average of opinion cannot accurately reflect the overall judgment. Therefore, Hsu and Chen proposed a similarity aggregation method (SAM) [34,35], and Lee developed an optimal aggregation method (OAM), to help obtain the consistence of fuzzy opinion [1,36]. Because OAM is an effective method for integrating expert opinions, this study adopts OAM to consolidate the opinions of experts. The steps of OAM can be described as below:

(1) Let the fuzzy number of the expert's opinion of A and B be $\widetilde{A} = (a_1, a_2, a_3)$ and $\widetilde{B} = (b_1, b_2, b_3)$; then, the distance between $\widetilde{A}$ and $\widetilde{B}$ can be computed using Equation (5), and the similarity between $\widetilde{A}$ and $\widetilde{B}$ can be obtained using Equation (6).

$$d_2(\widetilde{A}, \widetilde{B}) = \sqrt{\sum_{i=1}^{3} (|a_i - b_i|)^2} \tag{5}$$

$$S_2(\widetilde{A}, \widetilde{B}) = 1 - \frac{(d_2(\widetilde{A}, \widetilde{B}))^2}{4u^2} \tag{6}$$

where $u = \max(U) - \min(U)$, U is the universe of discourse, and $0 \le S_2(\widetilde{A}, \widetilde{B}) \le 1$.

(2) Set the initial aggregated weight as the weight of the first expert. $0 < w_i^{(0)} < 1$ and $\sum_{i=1}^{n} w_i^{(0)} = 1, i = 1, 2, \ldots, n$, n is the number of criteria, and iteration $l = 0,\ 1,\ 2,\ \cdots$.

$$\sum_{i=1}^{n} w_i^l = 1 \tag{7}$$

(3) Compute aggregated opinion using Equation (8); $\widetilde{R}_i$ is the i^{th} expert's individual opinion.

$$\widetilde{R}^{(l+1)} = \frac{\sum_{i=1}^{n} \left(w_i^{(l)}\right)^m \widetilde{R}_i}{\sum_{i=1}^{n} \left(w_i^{(l)}\right)^m}, \text{where } m \text{ is an exponential weight.} \tag{8}$$

(4) Let aggregated weight $W^{(l)} = (w_1^{(l)}, w_2^{(l)}, \ldots, w_n^{(l)})$, and compute $W^{(l+1)}$ using Equation (9).

$$w_i^{(l+1)} = \frac{\left(\frac{1}{(c - S_2(\widetilde{R}_i, \widetilde{R}^{(l+1)}))}\right)^{\frac{1}{m-1}}}{\sum_{j=1}^{n} \left(\frac{1}{(c - S_2(\widetilde{R}_j, \widetilde{R}^{(l+1)}))}\right)^{\frac{1}{m-1}}}, \text{where } c \text{ is an integer constant.} \tag{9}$$

(5) If $\left\| W^{(l+1)} - W^{(l)} \right\| \le \varepsilon$, stop; otherwise, $l = l + 1$, go to Step (3).

In terms of literature on multi-criteria decision-making (MCDM), Stojčić et al. (2019) reviewed the application of MCDM methods in sustainable engineering. From a review of 108 related literatures from 2008 to 2018, they found that MCDM methods are very suitable for sustainable engineering [37]. Zavadskas et al. (2014) also reviewed the relevant literature on MCDM and believed that there is a need for research to compare the strengths and weaknesses of different decision-making methods [38]. Jamwal et al. (2021) explored how MCDM methods were applied in sustainable manufacturing and found that most of the methods used are based on fuzzy theory [39]. Kumar et al. (2017) developed an insight into various MCDM methods, and the application progress in renewable energy and prospects [40].

From past fuzzy theory literature and knowledge management literature, no papers have been found that use fuzzy MCDM to measure the quality of knowledge; thus, this study should be the latest attempt.

3. Model Formulation

This section describes the proposed method, including knowledge quality fuzziness index, fuzzy gate selection, and implementation procedures.

3.1. Knowledge Quality Fuzziness Index

Based on the fuzzy weight average (FWA) method [30–32,41–45], this study proposes a knowledge quality fuzziness index (*KQFI*) to help make the Go/No go decision of the knowledge proposal. *KQFI* can be described as Equation (10), where r_i and w_i are the fuzzy assessment and fuzzy weight of the knowledge proposal, respectively, and i denotes the criteria for evaluating the knowledge proposal.

$$KQFI = \frac{\sum_{i=1}^{n} (r_i \otimes w_i)}{\sum_{i=1}^{n} w_i} \tag{10}$$

Because the computation of FWA can reach $O(n \ \log \ n)$ [35,46], Kao and Liu proposed a fractional programming approach (FPA) to solve the above problem [47]. Conducting α-cut to r_i and w_i of *KQFI* produces $(r_i)_\alpha = [(r_i)_\alpha^L, (r_i)_\alpha^U]$ and $(w_i)_\alpha = [(w_i)_\alpha^L, (w_i)_\alpha^U]$, and let $t = \frac{1}{\sum_{i=1}^{n} w_i}$ and $v_i = tw_i$; then, the membership function of *KOFI* can be obtained using Equations (11) and (12) by employing different values of α-cut.

$$\begin{aligned} KQFI_\alpha^L = Min \quad & \sum_{i=1}^{n} v_i (r_i)_\alpha^L \\ s.t. \quad & t(w_i)_\alpha^L \le v_i \le t(w_i)_\alpha^U \\ & \sum_{i=1}^{n} v_i = 1 \\ & t \ge 0 \end{aligned} \tag{11}$$

$$\begin{aligned} KQFI_\alpha^U = Max \quad & \sum_{i=1}^{n} v_i (r_i)_\alpha^U \\ s.t. \quad & t(w_i)_\alpha^L \le v_i \le t(w_i)_\alpha^U \\ & \sum_{i=1}^{n} v_i = 1 \\ & t \ge 0 \end{aligned} \tag{12}$$

For example, a triangular membership function (0.42, 0.57, 0.69) of KQFI is obtained by solving Equations (11) and (12) at α-cut = 0 and α-cut = 1. When α-cut = 0, one can obtain $KQFI_\alpha^L$ = 0.42 and $KQFI_\alpha^U$ = 0.69; when α-cut = 1, one can obtain $KQFI_\alpha^L$ = 0.57 and $KQFI_\alpha^U$ = 0.57.

3.2. Fuzzy Gate Selection

Based on previous researches [48–52], this study proposes a checking gate to screen the knowledge proposals (see Figure 1). Enterprises can choose a fuzzy threshold (*FT*) according to strategic objectives, and *FT* is used to decide if a knowledge proposal meets the minimum quality level. Figure 1 shows that the farther the *FT* is to the right, the higher the standard for reviewing knowledge quality. The dotted line in the figure represents FT.

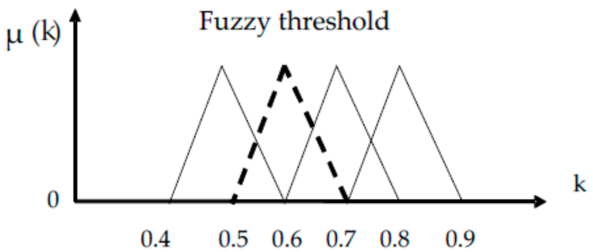

Figure 1. Checking gate.

The procedure for making the Go/No go decision of a knowledge proposal is listed as below:

(a) Compute fuzzy preference z based on Equation (13).
(b) Conduct α-cut to z and obtain $z_\alpha^l < 0$ and $z_\alpha^u > 0$ as in Figure 2 and Equation (14).
(c) Compute the level of goodness e_{KFT} of $KQFI$ to FT using Equations (15) and (16); if $e_{KFT} > 0.5$, then the knowledge proposal is qualified and accepted.

$$z = KQFI - FT \tag{13}$$

$$z_a = \left[z_\alpha^l, z_\alpha^u\right] \tag{14}$$

$$e_{KFT} = \frac{S_1}{S_1 + S_2} \tag{15}$$

$$\text{where } S_1 = \int_{x>0} \mu_{\tilde{z}}(x)dx,\ S_2 = \int_{x<0} \mu_{\tilde{z}}(x)dx \tag{16}$$

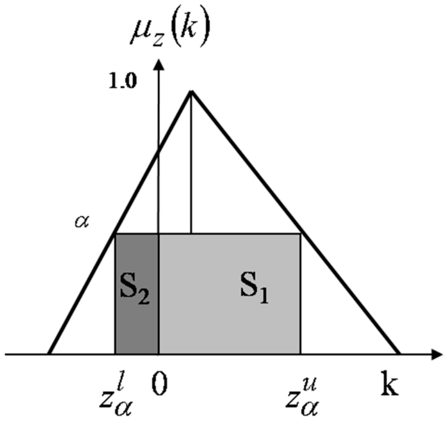

Figure 2. e_{KFT}.

3.3. Implementation Procedures

The flowchart of the proposed model is depicted in Figure 3, and the implementation procedures are described as below:

a. The expert penal receives the knowledge proposal and decides the assessment criteria, the linguistic variables, and the fuzzy number.
b. Experts assess the criteria weight and quality performance of knowledge proposals, and obtain the consensus of the expert decision.
c. Obtain the membership function of the *KQFI* for each knowledge proposal.
d. Specify the *FT* value according to enterprise strategic objectives.
e. Compute fuzzy preference z and level of goodness e_{KFT}, and make a Go/No go decision for each knowledge proposal.

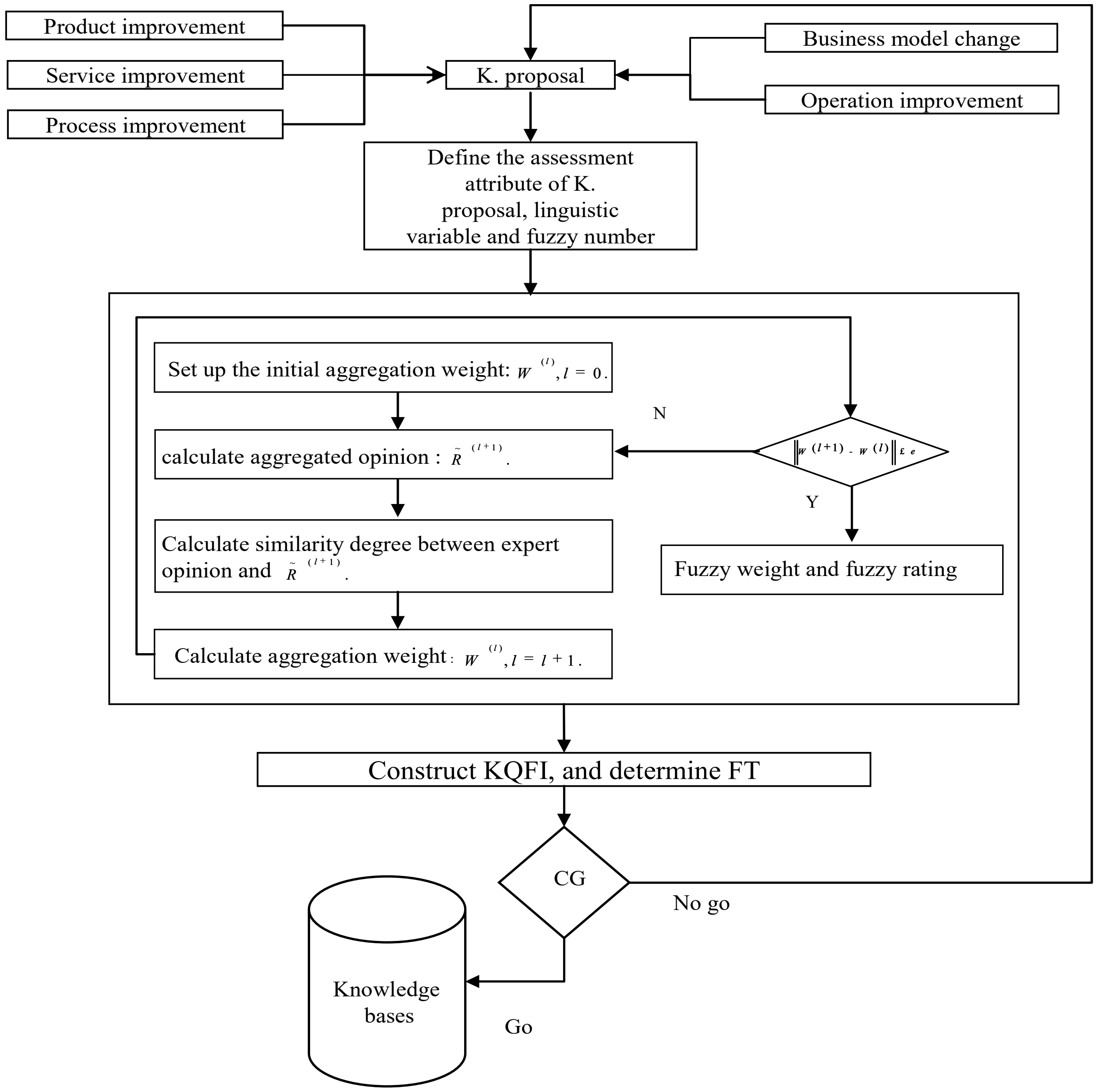

Figure 3. Flowchart of the proposed model.

3.4. Size of Expert Panel

Past studies did not agree on the number of group decision-making experts. Lynn (1986) believed that 5 experts was enough to produce good judgments, and even as few as 3 experts was possible [4]. Hashmi et al. (2023) mentioned that the optimal number is 5 to 7 people [53]. Emmerling and Rooders (2022) believed that the number of experts should be controlled at 3 to 5 [54]. Axtell (2018) researched that the optimal number of participants in a meeting is 8 people [55,56]. From the above research, it can be found that the number of people making group decisions is between 3 and 8 people. Therefore, this study uses five experts to measure the quality of knowledge proposals.

4. Case Implementation

This section uses an example to demonstrate the applicability of the proposed model. The knowledge assessment expert panel of a company wants to select qualified knowledge from nine knowledge proposals, and the detailed steps are as follows:

a. The expert panel composed of five experts receives nine knowledge proposals; decides the assessment criteria of knowledge quality as (1) originality (A_1), (2) applicability (A_2), (3) practicality (A_3), (4) value (A_4), and (5) uniqueness (A_5); and uses linguistic variables of very good, good, fair, poor, and very poor, and the triangular fuzzy number listed in Table 1, to assess the criteria weight and knowledge quality.

b. Experts assess the criteria weight and quality performance of knowledge proposals (Table 2) and obtain the consensus of the expert opinion. D_1 to D_5 indicate experts and K_1 to K_9 represent knowledge proposals in Table 2. The consensus of the expert decision is described below.

A_1, K_8 (Table 2), and Table 1 are used to obtain the consensus of the expert opinion.

(i) Let c = 1.5, m = 2, and $u = \max(U) - \min(U) = 0.7$, where the initial aggregated weight is set as the weight of the first expert, i.e., $W^{(0)} = (1, 0, 0, 0, 0)$. Then, the aggregated opinion $\widetilde{R}^{(1)}$ can be obtained using Equation (8), and $\widetilde{R}_i$ is the opinion of an individual expert.

$$\widetilde{R}^{(1)} = \frac{\sum_{i=1}^{5} (w_i)^2 \widetilde{R}_i}{\sum_{i=1}^{5} (w_i)^2} = W(1)^{(0)} \otimes \widetilde{R}_1 + W(2)^{(0)} \otimes \widetilde{R}_2 + W(3)^{(0)} \otimes \widetilde{R}_3 + W(4)^{(0)} \otimes \widetilde{R}_4 + W(5)^{(0)} \otimes \widetilde{R}_5$$
$$= 1 \otimes \mathrm{M} + 0 \otimes \mathrm{M} + 0 \otimes \mathrm{MG} + 0 \otimes \mathrm{M} + 0 \otimes \mathrm{MG}$$
$$= 1 \otimes (0.3, 0.5, 0.7) + 0 \otimes (0.3, 0.5, 0.7) + 0 \otimes (0.5, 0.7, 0.9) + 0 \otimes (0.3, 0.5, 0.7) + 0 \otimes (0.5, 0.7, 0.9)$$
$$= (0.3, 0.5, 0.7)$$

(ii) The similarity between the individual $\widetilde{R}_i$ and the aggregated $\widetilde{R}^{(1)}$ are computed using Equation (6), where u = 0.7.

$$S_2(\widetilde{R}_1, \widetilde{R}^{(1)}) = 1 - \frac{(d_2(\widetilde{R}_1, \widetilde{R}^{(1)}))^2}{4u^2} \quad S_2(\widetilde{R}_2, \widetilde{R}^{(1)}) = 1 - \frac{(d_2(\widetilde{R}_2, \widetilde{R}^{(1)}))^2}{4u^2}$$
$$S_2(\widetilde{R}_3, \widetilde{R}^{(1)}) = 1 - \frac{(d_2(\widetilde{R}_3, \widetilde{R}^{(1)}))^2}{4u^2} \quad S_2(\widetilde{R}_4, \widetilde{R}^{(1)}) = 1 - \frac{(d_2(\widetilde{R}_4, \widetilde{R}^{(1)}))^2}{4u^2}$$
$$S_2(\widetilde{R}_5, \widetilde{R}^{(1)}) = 1 - \frac{(d_2(\widetilde{R}_5, \widetilde{R}^{(1)}))^2}{4u^2}$$

(iii) The new aggregated weight can be computed using Equation (9) and obtained as $W^{(1)} = (0.2864, 0.2864, 0.1811, 0.2462, 0.2864)$. $W^{(l)} = (w_1^{(l)}, w_2^{(l)}, \ldots, w_n^{(l)})$ and $w_1^{(1)}$ can be computed as below:

$$w_1^{(1)} = \frac{\left(\frac{1}{(1.5 - S_2(\widetilde{R}_1, \widetilde{R}^{(1)}))}\right)^{\frac{1}{2-1}}}{\sum_{j=1}^{n}\left(\frac{1}{(1.5 - S_2(\widetilde{R}_j, \widetilde{R}^{(1)}))}\right)^{\frac{1}{2-1}}}, \mathrm{c} = 1.5, \mathrm{m} = 2$$

(iv) The new aggregated opinion can be computed using Equation (8) as below:

$$\widetilde{R}^{(2)} = \frac{\sum_{i=1}^{n} \left(w_i^{(1)}\right)^m \widetilde{R}_i}{\sum_{i=1}^{n} \left(w_i^{(1)}\right)^m} = \frac{\sum_{i=1}^{n} \left(w_i^{(1)}\right)^2 \widetilde{R}_i}{\sum_{i=1}^{n} \left(w_i^{(1)}\right)^2}, \mathrm{m} = 2,$$

$\widetilde{R}^{(2)}$ can be obtained as $(0.4583, 0.6583, 0.6583, 0.8444)$.

(v) Repeat the above steps, the consensus of the fuzzy weight of A_1 can be obtained, and it will converge to (0.4334, 0.6334, 0.6334, 0.8144) (Table 3) at $l = 8$, meaning that the consensus of the experts toward the criteria has been reached. Table 4 lists the results.

c. Obtain the membership function of $KQFI_1$ to $KQFI_9$ using Equations (11) and (12) at different values of α-cut. The results are listed in Table 5.

d. Specify FT value as (0.5, 0.6, 0.7) according to the enterprise strategic objectives.

e. Compute fuzzy preference z and level of goodness e_{KFT} using Equations (13) and (15); $KQFI_8$ is demonstrated at α-cut $= 0.5$ in Figure 4, and the values of z, $z_{0.5}$, and

Go/No go decisions are listed in Table 5. The level of goodness e_{KFT} of knowledge K_6, K_7, and K_8 are less than 0.5; therefore, they are rejected.

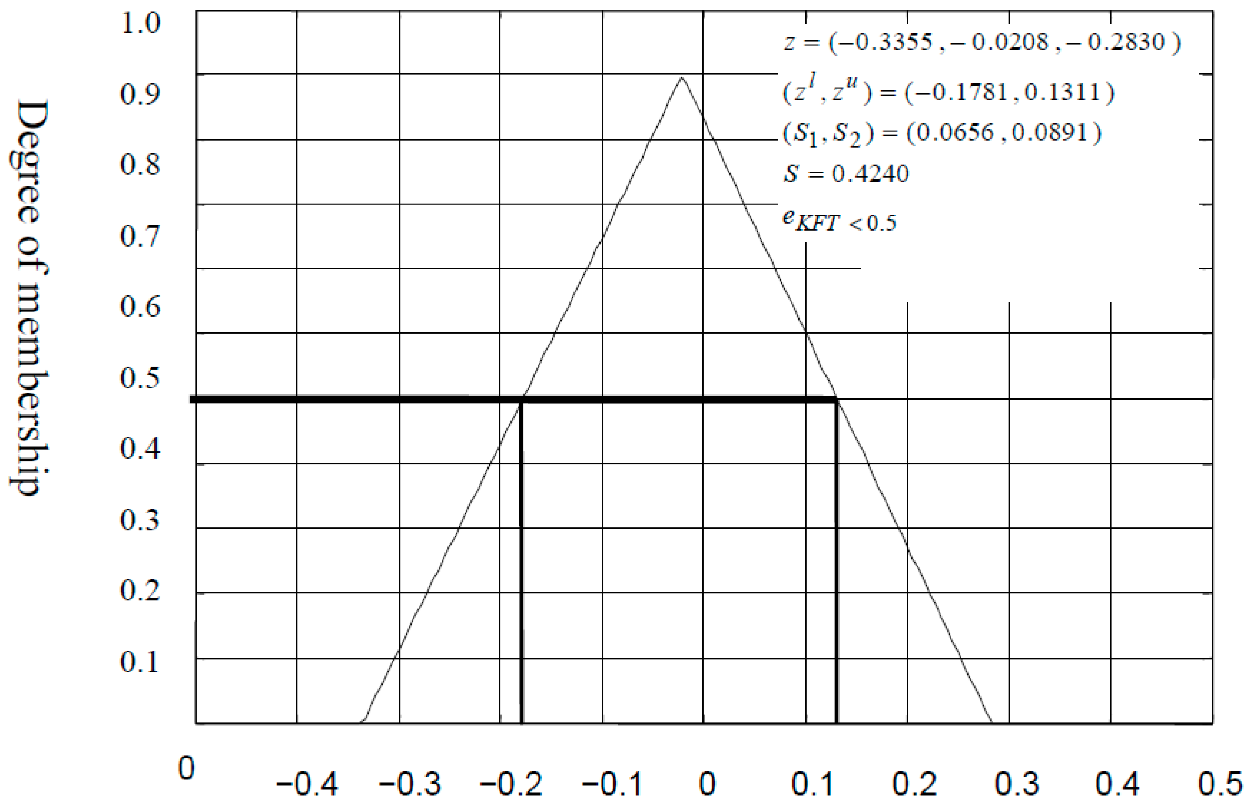

Figure 4. The e_{KFT} of knowledge proposal K_8 (α-cut = 0.5).

4.1. Summary

This section summarizes the method proposed in this study as follows: (1) Experts assign weights to the criteria and evaluate the quality of knowledge proposal based on the fuzzy linguistic scale. (2) Aggregate the weights and evaluations, including (a) setting the initial integrated weight, (b) computing the aggregated evaluation, (c) computing the similarity between the individual evaluation and the integrated evaluation, (d) computing the new integrated weight according to the similarity, (e) computing the new integrated evaluation based on the integrated weight, and repeating these steps until the integrated weight and the integrated evaluation converge to one unchanged state. (3) Use the integrated weight and integrated evaluation to find the fuzzy membership function of *KQFI*. (4) Compute z = *KQFI*—*FT* (fuzzy threshold). (5) Obtain S_1 and S_2 according to the z membership function; then, calculate e_{KFT}. If e_{KFT} > 0.5, it indicates that the knowledge proposal is qualified; otherwise, it is not qualified.

The whole process described above can be computerized and combined with the existing knowledge management system of the enterprise; every time the system receives a new knowledge proposal, it will notify the experts to evaluate the knowledge proposal. Experts only need to conduct linguistic fuzzy evaluation on the weight and knowledge quality. The rest can be completed by the computer, because the fuzzy threshold can be set in advance; the system will finally make a qualified or unqualified judgment on the knowledge proposal, and the qualified knowledge proposal will be automatically stored in the knowledge repository so that the burden on personnel can be greatly reduced and the efficiency of the knowledge management system can be significantly improved.

Table 2. Criteria weight and fuzzy assessment of knowledge proposal.

Criteria \ Expert	W					K_1					K_2					K_3					K_4				
	D_1	D_2	D_3	D_4	D_5	D_1	D_2	D_3	D_4	D_5	D_1	D_2	D_3	D_4	D_5	D_1	D_2	D_3	D_4	D_5	D_1	D_2	D_3	D_4	D_5
A_1	M	M	H	MH	M	G	VG	G	MG	MG	G	M	MG	M	MG	M	MP	M	MG	M	G	VG	MG	MG	MG
A_2	MH	M	H	VH	MH	G	G	M	M	G	G	G	MG	G	G	M	M	VG	VG	G	MG	MG	M	M	G
A_3	H	VH	MH	H	H	G	G	MG	MG	G	G	M	M	M	G	G	MG	G	MG	G	MG	G	M	MG	G
A_4	MH	M	H	H	M	G	G	G	MG	G	G	G	G	MG	MG	M	MG	MG	MG	M	G	G	G	MG	G
A_5	MH	M	H	H	M	MP	MG	M	MG	M	M	MG	MG	MG	M	M	M	G	MG	MG	MG	MG	MG	G	MG

Criteria \ Expert	K_5					K_6					K_7					K_8					K_9				
	D_1	D_2	D_3	D_4	D_5	D_1	D_2	D_3	D_4	D_5	D_1	D_2	D_3	D_4	D_5	D_1	D_2	D_3	D_4	D_5	D_1	D_2	D_3	D_4	D_5
A_1	M	M	MG	G	MG	G	G	M	G	MG	MP	M	M	M	MG	M	M	MG	M	MG	G	M	MG	M	MG
A_2	M	M	MG	M	G	M	M	M	G	G	MP	M	G	M	G	MG	G	MG	M	G	MG	G	G	MG	M
A_3	G	G	MG	M	MG	M	MP	M	M	G	G	MG	MG	MG	M	MG	M	M	MG	M	M	G	M	M	M
A_4	MP	MG	MG	M	M	MP	M	MG	M	G	M	MG	MG	MG	G	MP	M	M	M	G	MP	M	M	MG	M
A_5	MG	MG	MG	G	MG	M	MG	MG	MG	M	M	M	M	MG	G	MG	MP	G	M	M	M	MG	MG	MG	M

Table 3. Consensus of criteria A_1.

l	$W^{(l)}$					$R^{(l+1)}$			
0	1	0	0	0	0	0.3000	0.5000	0.5000	0.7000
1	0.2865	0.2865	0.1812	0.2463	0.2865	0.3981	0.5981	0.5981	0.7854
2	0.2651	0.2651	0.2073	0.2630	0.2650	0.4228	0.6228	0.6228	0.8058
3	0.2592	0.2592	0.2152	0.2668	0.2591	0.4302	0.6302	0.6302	0.8118
4	0.2574	0.2574	0.2176	0.2679	0.2573	0.4324	0.6324	0.6324	0.8134
5	0.2569	0.2569	0.2184	0.2682	0.2568	0.4331	0.6331	0.6331	0.8141
6	0.2567	0.2567	0.2186	0.2683	0.2566	0.4333	0.6333	0.6333	0.8143
7	0.2567	0.2567	0.2187	0.2684	0.2567	0.4334	0.6334	0.6334	0.8144
8	0.2567	0.2567	0.2187	0.2684	0.2567	0.4334	0.6334	0.6334	0.8144

Table 4. Consensus of fuzzy weight and fuzzy assessment.

Knowledge \ **Criteria**	$\mathbf{A_1}$	$\mathbf{A_2}$	$\mathbf{A_3}$	$\mathbf{A_4}$	$\mathbf{A_5}$
Weight	(0.4332, 0.6332, 0.8142)	(0.6131, 0.7931, 0.9155)	(0.6002, 0.8002, 0.9503)	(0.6552, 0.8552, 0.9776)	(0.5686, 0.7686, 0.9158)
K1	(0.7065, 0.8837, 0.9516)	(0.5002, 0.7002, 0.8502)	(0.6001, 0.8001, 0.9501)	(0.6601, 0.8601, 0.9801)	(0.3572, 0.5476, 0.7287)
K2	(0.4332, 0.6334, 0.8142)	(0.6601, 0.8601, 0.9801)	(0.3576, 0.5574 0.7432)	(0.6601, 0.8601, 0.9801)	(0.3652, 0.5652, 0.7652)
K3	(0.3001, 0.5001, 0.7001)	(0.5883, 0.7402, 0.8443)	(0.6001, 0.8001, 0.9501)	(0.4586, 0.6584, 0.8586)	(0.4586, 0.6584, 0.8586)
K4	(0.6328, 0.8141, 0.9475)	(0.4001, 0.6001, 0.8001)	(0.5016, 0.7018, 0.8797)	(0.6601, 0.8601, 0.9801)	(0.4332, 0.6334, 0.8144)
K5	(0.3186, 0.5186, 0.7141)	(0.3436, 0.5436, 0.7436)	(0.5688, 0.7686, 0.9158)	(0.3652, 0.5652, 0.7652)	(0.5018, 0.7016, 0.8795)
K6	(0.6424, 0.8424, 0.9568)	(0.3574, 0.5576, 0.7432)	(0.2537, 0.4539, 0.6537)	(0.3001, 0.5001, 0.7001)	(0.4586, 0.6584, 0.8586)
K7	(0.2547, 0.4547, 0.6547)	(0.3204, 0.5203, 0.7032)	(0.5447, 0.7448, 0.9226)	(0.4561, 0.6564, 0.8562)	(0.346, 0.5436, 0.7436)
K8	(0.3416, 0.5414, 0.7416)	(0.5016, 0.7016, 0.8797)	(0.4001, 0.6001, 0.8001)	(0.2537, 0.4537, 0.6537)	(0.4023, 0.6025, 0.7811)
K9	(0.4332, 0.6332, 0.8142)	(0.6001, 0.8001, 0.9501)	(0.3574, 0.5574, 0.7432)	(0.3001, 0.5001, 0.7001)	(0.4586, 0.6584, 0.8586)

Table 5. Decision outcome of knowledge proposal.

α = 0.5	*KQFI*	z	(z^l, z^u)	(S_1, S_2)	e_{KFT}	Result	Decision
K1	(0.5352, 0.7561, 0.9101)	(−0.1648, 0.1561, 0.4102)	(−0.0042, 0.2833)	(0.1415, 0.0023)	0.9851	>0.5	Go
K2	(0.4721, 0.7007, 0.8838)	(−0.1648, 0.1563, 0.4102)	(−0.0635, 0.2422)	(0.1213, 0.0317)	0.7923	>0.5	Go
K3	(0.4675, 0.6786, 0.8614)	(−0.2323, 0.0786, 0.3616)	(−0.0768, 0.2202)	(0.1101, 0.0385)	0.7412	>0.5	Go
K4	(0.5028, 0.7207, 0.8986)	(−0.1972, 0.1207, 0.3984)	(−0.0382, 0.2598)	(0.1297, 0.0192)	0.8718	>0.5	Go
K5	(0.4019, 0.6226, 0.8247)	(−0.2982, 0.0226, 0.3247)	(−0.1378, 0.1737)	(0.0868, 0.0688)	0.5578	>0.5	Go
K6	(0.3642, 0.5901, 0.7982)	(−0.3358, −0.0097, 0.2982)	(−0.1728, 0.1443)	(0.0722, 0.0865)	0.4548	<0.5	No go
K7	(0.3694, 0.5912,0.8047)	(−0.3306, −0.0088, 0.3047)	(−0.1698, 0.1481)	(0.0741, 0.0847)	0.4657	<0.5	No go
K8	(0.3646, 0.5791, 0.7831)	(−0.3354, −0.0207, 0.2831)	(−0.1782, 0.1312)	(0.0657, 0.0892)	0.4241	<0.5	No go
K9	(0.4092, 0.6272, 0.8276)	(−0.2909, 0.0273, 0.3276)	(−0.1318, 0.1775)	(0.0886, 0.0658)	0.5736	>0.5	Go

4.2. Comparisons with Past Method

In the past, one scholar used the AHP to measure the quality of knowledge [10]. Therefore, this section compares the proposed fuzzy method with the AHP method. Table 6 shows the results of the comparison. It can be seen from the table that both methods need to form an expert panel and both need to decide the criteria of knowledge quality. To measure the weight of criteria, this research invites experts to directly conduct intuitive fuzzy linguistic assessments while AHP requires a pairwise comparison of criteria. Pairwise comparisons can easily lead to inconsistent importance. When there are many criteria, the adjustments can be challenging. Furthermore, for the evaluation of knowledge proposals, the proposed method asks experts to evaluate the quality of knowledge proposals one by one according to the criteria, while AHP needs to conduct pairwise evaluation of all knowledge proposals for each criterion. Relative comparisons, therefore, will produce inconsistencies. Most importantly, the proposed method directly evaluates the quality of each knowledge and, thus, obtains absolute knowledge quality while AHP makes an indirect relative comparison and obtains relative knowledge quality. The problem with the quality of relative knowledge is that knowledge may not be very useful; in fact, because other knowledge is worse, it is considered relatively good knowledge, which may not help the enterprise at all in the long run. Finally, this study has a very clear Go/No checking threshold. Knowledge above the threshold is qualified knowledge. On the contrary, AHP has no qualified judgment threshold. Therefore, how to screen out relatively high-quality knowledge from the comparison results in the end is a difficult task because the relative ranking of knowledge does not represent the quality of knowledge. Based on the above comparison, one can find that the proposed method can indeed measure the knowledge quality of enterprises more accurately than AHP.

Table 6. Comparisons between the proposed method and AHP.

Method	Expert Penal	Criteria	Weight	Knowledge Evaluation	Knowledge Quality	Go/No Threshold
Proposed	v	v	Linguistic assessment	direct	absolute	v
AHP	v	v	pairwise comparison	indirect	relative	x

5. Conclusions

Knowledge management has been proven to be an effective management method for enterprises to enhance core capabilities, and one of the important tasks is to screen quality knowledge into the knowledge repository. Current industrial and academic methods cannot ensure that quality knowledge is screened out. This study proposes a multi-attribute fuzzy group decision-making model, which can effectively integrate the opinions of experts into a knowledge quality fuzziness index and then compare it with the fuzzy threshold set by the enterprise; finally, it can discover whether the quality of knowledge meets the enterprise quality threshold. There have been very few studies on measuring knowledge quality in the literature. The contribution of this study is twofold. First, this study can fill the academic research gap. Secondly, the systematic method of this study can assist enterprises to screen out genuine quality knowledge, directly promote the success of knowledge management, and improve the innovation ability and business performance of enterprises. The implication of this study to management practice is that the quality of knowledge proposals is the key to whether an enterprise can promote its competitiveness, and the correct knowledge evaluation method must be adopted in order to allow the enterprise's knowledge repository to accumulate knowledge that can truly enhance core competencies.

Finally, this study uses the triangular fuzzy function to measure the criteria weight and knowledge quality; however, it cannot be determined whether it is the best choice. Subsequent research can use other fuzzy membership functions to verify and compare the results.

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