Evaluation of Bilingual Teaching Quality of Navigation Courses Based on Language Decision-Making Method

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Abstract: Bilingual education in maritime courses is an exploratory, experimental, forward-looking and innovative teaching reform experiment, which is implemented in China's colleges and universities in resent years. Overall, the bilingual education of our colleges and universities is still in the stage of exploration and development. Teaching quality assessment is a way to test the effectiveness of teaching, and also is an effective means to determine the students' learning and teacher's teaching effectiveness. With the launching of bilingual teaching, online teaching and other teaching mode, monitoring their teaching effectiveness plays a significant role in guaranteeing educational quality. In order to reflect the uncertainties in the expert evaluation process and the deviation phenomenon of a single expert opinion, the research employs a combination of multi-attribute group decision-making and language-based aggregation techniques to resolve this challenge. The paper recalls group decision making and language aggregation operator, and then the two aggregation operators: LWA_2 and $ULWA$ operators are selected to evaluate the teachers' teaching level on teachers' teaching style and other nine indicators. The established models fully reflect the uncertainty of expert evaluation and the evaluation process of the natural semantics which are easy to understand. This model can also be applied in the appraisal of the overall development of students and scholarships competitions.

Keywords: Maritime Courses; Bilingual Education; Teaching Evaluation; Teaching Reform; Language Decision-Making Method.

1. Introduction

The evaluation of bilingual teaching quality in navigation courses has gained increasing attention due to the globalization of maritime education and the demand for culturally and linguistically competent professionals. Traditional evaluation methods often focus on pedagogical outcomes while overlooking the critical role of language proficiency and decision-making in bilingual contexts. Recent studies have incorporated language decision-making methods to provide a more comprehensive assessment framework, addressing both educational effectiveness and linguistic adaptability.

The evaluation of bilingual teaching quality in navigation courses has been increasingly studied in international academic circles, particularly in countries with strong maritime education systems, such as the UK, Norway, the Netherlands, China, and the Philippines. Researchers have explored language decision-making methods to enhance the objectivity and effectiveness of bilingual teaching assessments, focusing on both pedagogical and linguistic dimensions.

International studies have applied various language decision-making models to evaluate bilingual teaching, including:

Fuzzy Comprehensive Evaluation (FCE): Used in Chinese and European studies to handle the ambiguity of language proficiency assessments.

Analytic Hierarchy Process (AHP): Employed in the UK and Norway to weigh linguistic and pedagogical factors, such as instructor fluency and student engagement. Machine Learning & NLP Techniques: Recent research in the Netherlands and the U.S. has incorporated natural language processing (NLP) to analyze classroom discourse and automate feedback. Multimodal Evaluation Frameworks: Some Scandinavian studies integrate eye-tracking and speech analysis to assess real-time comprehension in bilingual maritime classrooms. Europe (UK, Norway, Netherlands): Research emphasizes standardized language benchmarks (e.g., IMO

SMCP compliance) and cross-cultural communication training in bilingual navigation courses.

Asia (China, Philippines): Studies often focus on English-Chinese bilingual teaching models, assessing how language barriers affect technical knowledge acquisition (Zhang et al., 2021). North America (U.S., Canada): Research highlights immersion-based teaching evaluation, particularly for ESL (English as a Second Language) maritime students.

The linguistic decision-making problem under uncertain environment is a new and important content in decision-making theory. Its theoretical framework and methodologies find broad applications across diverse domains, including engineering design, economics, management, military science, and artificial intelligence [1]. Due to the complexity of things themselves and the incomplete understanding of things by decision makers, decision makers often use interval language values for evaluation, and need to reasonably aggregate the given language evaluation information to make correct decisions, thus bringing economic and social benefits. For these reasons, adopting linguistic decision-making techniques to address real-world scenarios is a highly viable research direction [2].

The bilingual teaching of nautical courses is an exploratory, experimental, forward-looking and innovative teaching reform experiment implemented in many universities in recent years [3]. Following the Ministry of Education's 2001 policy advocating bilingual education, universities across China have progressively incorporated it into their curricula. [4]. The bilingual teaching has become one of the hot spots in the current reform of colleges and universities. Generally speaking, the implementation of bilingual instruction in Chinese universities remains at a developmental and experimental phase. Whether in theory or practice, there are still many problems that need to be studied and solved urgently [5]. For example, teaching materials, teachers, funds, students ' language foundation, evaluation criteria, etc. and in different types and levels of colleges and universities, the above problems have different forms of expression. On the other hand, given that linguistic decision-making is an effective way to solve practical problems at present [6]. Consequently, understanding the current state of bilingual education in higher institutions is crucial for developing effective solutions to these challenges [7]. This paper comprehensively summarizes the evaluation modes and methods of bilingual teaching in colleges and universities, and uses the language value evaluation method to provide feedback, which is conducive to the smooth development of bilingual teaching, and also provides a good theoretical and practical reference content for leaders, researchers, teachers and students at all levels in the field of higher education, which is of great significance [8].

There are only two ultimate goals of teaching evaluation: one is to promote teachers' professional development, and the other is to strengthen performance management [9]. In fact, this reflects the purpose of the two evaluation systems, "developmental evaluation" and "reward and punishment evaluation", both of which have their own advantages and disadvantages, and both aim to improve the quality of teaching [10]. However, there is a contradiction between these two evaluation systems, and a balance should be pursued before the two. Through the combination of ' qualitative evaluation ' and ' quantitative evaluation ', the combination of ' other evaluation ' and ' self-evaluation ', and the establishment of a subject-based, people-oriented feedback mechanism and incentive system, it has achieved the purpose of promoting teachers' professional development and strengthening performance management [11].

Teaching quality evaluation is a method to test the effectiveness of teaching, and it is an effective means to determine the learning effect of students and teachers. With the development of various teaching modes such as vocational education and online teaching, the evaluation of teaching effect has become an key part of ensuring quality of teaching [12]. The evaluation of teaching quality has become an academic issue, which has received extensive attention and in-depth discussion inside and outside the academic circles, and has become a policy difficulty and focus of internal and external universities [13]. The factors involved in the evaluation of teaching quality are diverse, and the evaluation indicators are directly affected by the subjective factors of the evaluators, and most of the factors involved are uncertain descriptions, with distinct vague and random characteristics. If it is directly evaluated based on a single indicator or directly quantified by a small number of experts based on experience, some valuable information is often missed, and it is difficult to objectively reflect the quality of teaching. Therefore, many comprehensive evaluation methods have been formed, such as statistical theory, RBF neural network, machine learning theory [14], fuzzy mathematics, and evidential reasoning [15].

2. Linguistic Multi-Attribute Group Decision Operator Method

Words directly calculate language integration operator: represent $S' = \{s_\alpha \mid \alpha = -t,...,t\}$ as a collection of language scale, where t represent positive integer. If $s_\alpha < s_\beta$ and only if $\alpha < \beta$; There exists a negative operator: $neg(s_\alpha) = s_{-\alpha}$, especially $neg(s_0) = s_0$. s_0 denotes the ' undifferentiated ' evaluation, and the rest of the linguistic scales are symmetrically arranged on both sides of it.

Definition 2.1: Let $s_\alpha, s_\beta \in \bar{S}, \lambda \in [0,1]$, Consequently, the fundamental operating principles can be articulated in the following manner:

1) $s_\alpha \oplus s_\beta = s_{\alpha+\beta}$;

2) $\lambda s_\alpha = s_{\lambda\alpha}$.

Compared with the commonly used linguistic scale sets are:

$$S' = \{s_{-4} = \text{extremely} \quad poor, s_{-3} = very \quad poor, s_{-2} = poor, s_{-1} = \text{slightly} \quad poor, s_0 = fair, s_1 = \text{slightly} \quad good, s_2 = \text{good}, s_3 = \text{very} \quad \text{good}, s_4 = \text{extremely} \quad \text{good}\}$$

From algorithm of definition 2.1, we get $s_{-2} \oplus s_2 = s_0$, which $s_0 = fair$, in fact, we consider two linguistic terms $s_2 = \text{low}$ and $s_4 = \text{high}$ in linguistic scale set :

$$S = \{s_0 = none, s_1 = \text{very} \quad low, s_2 = \text{low}, s_3 = medium, s_4 = \text{high}, s_5 = very \quad high, s_6 = perfect\}$$

And then we have $s_2 \oplus s_4 = s_6$, which $s_6 = perfect$ .Obviously, the scale set representation of language S' should be more in line with the actual situation than S.

Definition 2.2: Let $\bar{S}^n \to \bar{S}$, if

$$LMA_2(s_{\alpha1}, s_{\alpha2}, ..., s_{\alpha n}) = w_1 s_{\alpha1} \oplus w_2 s_{\alpha2} \oplus ... \oplus w_n s_{\alpha n} = s_{\dot{\bar{a}}} \quad (1)$$

Which $\dot{\bar{a}} = \sum_{i=1}^{n} w_j \alpha_j$, $w = (w_1, w_2, ..., w_n)$ is the weighted vector of linguistic term $s_{\alpha i}$, and $w_i \in [0,1], \sum_{i=1}^{n} w_i = 1$, then LWA_2 is called a linguistic weighted average (LWA_2) operator.

LWA_2 is an extension of the operator of the weighted average (WA). Especially, if $w = (1/n, 1/n, ..., 1/n)$, the LWA_2 operator degenerates to the linguistic mean (LA) operator.

Definition 2.3: Let $LOMA_2 : (\bar{S}')^n \to \bar{S}'$, and the associated weighted vector is $w = (w_1, w_2, ..., w_n)$, which $w_i \in [0,1], \sum_{i=1}^{n} w_i = 1$, makes

$$LOWA_2(s_{\alpha1}, s_{\alpha2}, ..., s_{\alpha n}) = w_1 s_{\beta1} \oplus w_2 s_{\beta2} \oplus ... \oplus w_n s_{\beta n} = s_{\bar{\beta}} \quad (2)$$

which $\bar{\beta} = \sum_{j=1}^{n} w_j \beta_j$, and $s_{\beta j}$ is the j-largest value in $s_{\alpha j}$, then we call $LOWA_2$ is an operator of language OWA ($LOWA_2$).

Especially, if $w = (1, 0, ..., 0)$, which $w_1 = 1, w_i = 0, i = 2, ..., n$, then, operator $LOWA_2$ degenerates to operator LM_1 . If $w = (0, ..., 0, 1)$, which $w_i = 0$, $i = 2, ..., n-1$, $w_n = 1$, the operator $LOWA_2$ degenerates to operator LM_2 ; If $w = (1/n, 1/n, ..., 1/n)$, the operator $LOWA_2$ degenerates to operator LA . The basic principle of the $LOWA_2$ operator is to reorder them according to their values and then aggregate them.

The developed operator $LOWA_2$ not only extends operator OWA but also conserves its advantageous features including monotonicity, idempotence, and commutativity, with outputs always lying between the linguistic minimal and maximal operators.

It can be seen from definitions 2.2 and 2.3, the LWA_2 operator is only a parameter weighting, and the $LOWA_2$ operator focuses on sorting weighting. Therefore, the weight is different from the LWA_2 and $LOWA_2$ operator. In order to overcome this shortcoming, Xu proposed a composite integrated language operator.

Definition 2.4: The mixed ensemble (LHA 's) operator of a language is a mapping of LHA : $\bar{S}^n \to \bar{S}$, it has associated vectors $w = (w_1, w_2, ..., w_n)$ and $w_i \in [0,1], \sum_{i=1}^{n} w_i = 1$, which leads

$$LHA(s_{\alpha 1}, s_{\alpha 2}, ..., s_{\alpha n}) = w_1 s_{\beta 1} \oplus w_2 s_{\beta 2} \oplus ... \oplus w_n s_{\beta n} \quad (3)$$

In it: $s_{\beta j}$ is $\bar{S}_{\alpha i}$ ($\bar{S}_{\alpha i} = n\omega_i s_{\alpha i}, i = 1,2,...,n$), $w = (w_1, w_2, ..., w_n)$ is weight vector of $s_{\alpha i}(i = 1,2,...,n)$ and $w_i \in [0,1], \sum_{i=1}^{n} w_i = 1$.

And *n* is the equilibrium coefficient, which plays a balanced role (in this case). If the vector $w = (w_1, w_2, ..., w_n)$ approximates to vector $(1/n, 1/n, ..., 1/n)$, that vector $nw_1 s_{\alpha 1}, nw_2 s_{\alpha 2}, ..., nw_n s_{\alpha n}$ approximates to vector $(s_{\alpha 1}, s_{\alpha 2}, ..., s_{\alpha n})$.

Especially, if $w = (1/n, 1/n, ..., 1/n)$, that operator LHA degenerates to operator LWA_2 ; if $w = (1/n, 1/n, ..., 1/n)$, that operator LHA degenerates to operator $LOWA_2$.

As a natural generalization of operators LWA_2 and $LOWA_2$, operator LHA not only inherits their essential characteristics but also explicitly accounts for the influence of linguistic parameters and their spatial configuration. Xu's proposed approach [15-16] utilizes a novel linguistic aggregation operator system, implementing multi-criteria group decision theory with practical language-based information applications to create a comprehensive evaluation system for academic tenure and promotion reviews.

However, operator $IOWA$ can only be used when the polymerization parameters are exact values. Xu [16] et al. proposed the induced linguistic operator OWA ($ILOWA$), a novel computational framework designed to systematically aggregate and process linguistic parameters through the following operational mechanism:

$$ILOWA(\langle u_1, s_{\alpha 1}\rangle, \langle u_2, s_{\alpha 2}\rangle, ..., \langle u_n, s_{\alpha n}\rangle) = w_1 s_{\gamma 1} \oplus w_2 s_{\gamma 2} \oplus ... \oplus w_n s_{\gamma n} = s_{\bar{\gamma}} \quad (4)$$

Which $\bar{\gamma} = \sum_{i=1}^{n} w_i \gamma_i$, $w = (w_1, w_2, ..., w_n)$ is a weighted vector, and satisfy $w_i \in [0,1]$, $\sum_{i=1}^{n} w_i = 1$, $s_{\gamma j}$ is the weight of OWA to the $s_{\alpha i}$ of jth term u_i in $\langle u_i, s_{\alpha i}\rangle$, and u_i is called as order inducing variable in $\langle u_i, s_{\alpha i}\rangle$, s_i is linguistic term. Especially, if $w = (1/n, 1/n, ..., 1/n)$,then operator $ILOWA$ degenerates to operator LA. If there are $u_i = s_{\alpha i}$ to all i, then operator $LOWA$ degenerates to operator $LOWA_2$.

In practical decision-making scenarios, linguistic variables often cannot be precisely mapped to predefined terms in existing language scale sets. Frequently, evaluators find that their assessments fall between two adjacent terms in the standard linguistic scale. This situation commonly occurs when human judgment involves inherent vagueness or when the evaluated object possesses characteristics that straddle multiple categories. A typical example can be found in product evaluation contexts: when assessing a vehicle's design quality, an expert might determine that the design merits a rating somewhere between "fair" and "good" rather than perfectly matching either single term. This phenomenon reveals a fundamental limitation of conventional linguistic variable systems in handling ambiguous or intermediate evaluations. To address this challenge and better capture the nuances of human judgment, Xu [16] pioneered the concept of uncertain linguistic variables in his seminal work. These innovative variables extend traditional linguistic approaches by allowing assessments to occupy intervals between standard terms. Furthermore, Xu developed a comprehensive set of operational algorithms specifically designed for processing these uncertain linguistic variables. The proposed framework includes specialized methods for aggregation, comparison, and computation with such variables, significantly enhancing the flexibility and applicability of linguistic approaches in decision-making contexts where precise term matching is impractical or unrealistic. This theoretical advancement has proven particularly valuable in domains requiring fine-grained subjective assessments.

Let $\tilde{S}=[s_{\alpha,}s_{\beta}]$, which $s_{\alpha,}s_{\beta}\in\tilde{S}$, s_{α} and s_{β} are the upper and lower limits of .Following established terminology in linguistic computing literature, we identify $\tilde{S}$ as an uncertain linguistic variable. To maintain notational consistency with existing research while enabling new derivations, we let $\tilde{S}$ symbolize the complete class of such variables in our theoretical construct.

For any three uncertain linguistic variables: $\tilde{S}=[s_{\alpha,}s_{\beta}],\ \tilde{S}_1=[s_{\alpha1,}s_{\beta1}]$ and $\tilde{S}_2=[s_{\alpha2,}s_{\beta2}]\in\tilde{S}$, the algorithm is defined as follows:

1) $\tilde{S}_1\oplus\tilde{S}_2=[s_{\alpha1,}s_{\beta1}]\oplus[s_{\alpha2,}s_{\beta2}] =[s_{\alpha1}\oplus s_{\alpha1},s_{\beta1}\oplus s_{\beta2}]$;

2) $\lambda\tilde{S}=[\lambda s_{\alpha},\lambda s_{\beta}],\quad \lambda\in[0,1]$.

In order to compare any two uncertain linguistic values: $\tilde{S}_1=[s_{\alpha1,}s_{\beta1}]$ and $\tilde{S}_2=[s_{\alpha2,}s_{\beta2}]$, Xu [16] introduced a simple formula:

$$p(\tilde{S}_1\geq\tilde{S}_2) =\min\{\max((\beta1-\alpha2)/(l_{\tilde{S}_1}+l_{\tilde{S}_2}),0),1\} \quad (5)$$

Which $l_{\tilde{S}_1}=\beta_1-\alpha_1,\quad l_{\tilde{S}_2}=\beta_2-\alpha_2$. $p(\tilde{S}_1\geq\tilde{S}_2)$ is called as the possibility of $\tilde{S}_1\geq\tilde{S}_2$. $p(\tilde{S}_1\geq\tilde{S}_2)$ has the following properties:

$$0\leq p(\tilde{S}_1\geq\tilde{S}_2)\leq1,\ p(\tilde{S}_1\geq\tilde{S}_2)+p(\tilde{S}_2\geq\tilde{S}_1)=1,\ p(\tilde{S}_1\geq\tilde{S}_1)=0.5 \quad (6)$$

Xu [16] further proposed some operators for the integration of uncertain linguistic information:

Definition 2.5: Let $ULWA:\tilde{S}^n\rightarrow\tilde{S}$, if

$$ULWA(\tilde{S}_1,\tilde{S}_2,...,\tilde{S}_n) =w_1\tilde{S}_1\oplus w_2\tilde{S}_2\oplus...\oplus w_n\tilde{S}_n \quad (7)$$

Which $w=(w_1,w_2,...,w_n)$ is the weighted vector of $\tilde{S}_i$,and $w_i\in[0,1],\ \sum_{i=1}^n w_i=1$, that $ULWA$ will be called as Uncertain linguistic weighted average ($ULWA$) operator.

Definition 2.6: An n-dimensional operator *ULOWA* is a mapping of *ULOW*: $\tilde{S}^n\rightarrow\tilde{S}$ has an associated weighted vector $w=(w_1,w_2,...,w_n)$ and $w_i\in[0,1],\ \sum_{i=1}^n w_i=1$, and the uncertain linguistic variables' $\tilde{S}_1,\tilde{S}_2,...,\tilde{S}_n$ are collected according to the following expression definition:

$$ULOWA(\tilde{S}_1,\tilde{S}_2,...,\tilde{S}_n) =w_1\tilde{S}_{\sigma1}\oplus w_2\tilde{S}_{\sigma2}\oplus...\oplus w_n\tilde{S}_{\sigma n} \quad (8)$$

Which $\tilde{S}_{\sigma j}$ is the j-th largest value of $\tilde{S}_i$. Especially, if $w=(1/n,1/n,...,1/n)$, then operator *ULOWA* degenerates to operator *ULA*.

To arrange these uncertain language parameters $\tilde{S}_i\ (i=1,2,...,n)$, we first need to pass $\Delta:[0,g]\rightarrow S\times[-0.5,0.5),\ \Delta(\beta)=\begin{cases}s_i & i=round(\beta),\\ \alpha=\beta-i & \alpha\in[-0.5,0.5).\end{cases}$ to compare each $\tilde{S}_i$ with all parameter $\tilde{S}_i\ (i=1,2,...,n)$, and let $p_{ij}=p(\tilde{S}_i\geq\tilde{S}_j)$, Then we can construct a complementary matrix: $P=(p_{ij})_{n\times n}$,which

$$p_{ij}\geq0,p_{ij}+p_{ji}=1,\quad p_{ii}=1/2,\quad i,j=1,2,...,n$$

The sum of the elements in each row of the matrix P can be obtained $p_i=\sum_{j=1}^n p_{ij},\quad i=1,2,...,n$. Then we can rank uncertain linguistic variable $\tilde{S}_i\ (i=1,2,...,n)$, and then arranged in descending order according to the $p_i\ (i=1,2,...,n)$.

Definition 2.7: The operator of a mixed aggregation (*ULHA*) of uncertain languages is a mapping to operator *ULHA*: $\overline{S}^n\rightarrow\tilde{S}$ has an associated weighted vector $w=(w_1,w_2,...,w_n)$ and $w_i\in[0,1],\ \sum_{i=1}^n w_i=1$, which leads

$$ULHA(\tilde{S}_1,\tilde{S}_2,...,\tilde{S}_n) =w_1\tilde{S}_{\beta1}\oplus w_2\tilde{S}_{\beta2}\oplus...\oplus w_n\tilde{S}_{\beta i} \quad (9)$$

Which $\tilde{S}_{\beta i}$ is the largest uncertain linguistic weighting parameter in $\overline{S}_i^{'}(\overline{S}_i^{'}=nw_i\tilde{S}_i,\quad i=1,2,...,n)$,

$w=(w_1,w_2,...,w_n)$ is the weighted vector of $\tilde{S}_i(i=1,2,...,n)$ and $w_i\in[0,1]$, $\sum_{i=1}^{n}w_i=1$, n is the balance coefficient, which plays a balancing role.

Especially, if $w=(1/n,1/n,...,1/n)$, then operator *ULHA* degenerates to operator *ULWA*; if $w=(1/n,1/n,...,1/n)$, then operator *ULHA* degenerates to operator *ULOWA*.

Xu [16] further extended the application of operator *ULOWA* and operator *ULHA* to address practical decision-making challenges in supply chain management. Specifically, the author employed these advanced linguistic operators to develop a comprehensive framework for evaluating and selecting optimal enterprise partners. This methodological innovation proved particularly valuable in the context of product maintenance services, where complex linguistic assessments are often required. By implementing these operators, Xu established a systematic approach that could effectively process qualitative judgments and uncertain linguistic information commonly encountered in partner selection processes. The study demonstrated how these mathematical tools could enhance decision-making accuracy when assessing potential collaborators based on multiple criteria, ultimately leading to more reliable partnership formations in business operations. The research highlighted the versatility of operators A and B in solving real-world management problems that involve subjective evaluations and linguistic uncertainty. Similarly to (2.4), defined the following operator to induce uncertainty: *LOWA* (*ULOWA*).

$$IULOWA(\langle u_1,\tilde{S}_1\rangle,\langle u_2,\tilde{S}_2\rangle,...,\langle u_n,\tilde{S}_n\rangle)$$
$$=w_1\tilde{s}_{\sigma 1}\oplus w_2\tilde{s}_{\sigma 2}\oplus...\oplus w_n\tilde{s}_{\sigma n} \quad (10)$$

Which $w=(w_1,w_2,...,w_n)$ is the weighted vector, so that $w_i\in[0,1]$, $\sum_{i=1}^{n}w_i=1$. $\tilde{s}_{\sigma j}$ is $\tilde{S}_i$ which has the largest value u_i to $\langle u_i,\tilde{S}_i\rangle$, and u_i was called as order inducing variable in $\langle u_i,\tilde{S}_i\rangle$ and $\tilde{S}_i$ is the parameter of variables of uncertain language.

Especially, if there have $u_i=\tilde{S}_i$ to each I, then operator *IULOWA* will degenerates to operator *ULOWA*; if there have $u_i=No.i$ to each i, then operator *IULOWA* will degenerate to operator *ULWA*; if $w=(1/n,1/n,...,1/n)$, that operator *IULOWA* will degenerate to operator *ULA*.

3. Evaluation of Bilingual Teaching of Maritime Courses Based on Language Decision-Making Method

3.1 The Evaluation of Bilingual Teaching Quality Based on Operator LWA$_2$

Considering the teaching evaluation of bilingual teaching, a university regards teachers ' teaching level and teachers ' style (G_1), teachers ' professional quality training (G_2), teachers ' bilingual teaching reform achievements and teaching achievements (G_3), the design of teaching content (G_4), arrangement of teaching content (G_5), use of teaching methods and their teaching effects (G_6), the use of information technology (G_7), the construction and selection of foreign language teaching materials (G_8), the construction and application of network resources (G_9), peer evaluation and reputation (G_{10}) and student opinion evaluation (G_{11}).

Its weight vector $w=(0.15,0.05,0.05,0.1,0.05,0.1,0.05,0.15,0.15,0.05,0.1)$.

As a teacher promotion and promotion of a major indicator (attribute). Five decision makers $e_k(k=1,2,3,4,5)$ (Its weight vector $v=(0.2,0.2,0.3,0.1,0.2)^T$). Using additive language to evaluate scales: S_2 ={ s_{-4} =extremely poor, s_{-3} =really bad, s_{-2} =bad, s_{-1} =slightly worse, s_0 =ordinary, s_1 =slightly good, s_2 =good, s_3 =very good, s_4=fabulous}

According to the above eleven indicators, five candidates (scheme) $x_j(j=1,2,3,4,5)$ were selected, the following five decision matrices are given: $R_k(k=1,2,3,4,5)$. In order to sort candidates, the following decision-making steps are given:

Step 1: Use the *LWA$_2$* operational form

$$r_{ij}=LWA_2(r_{ij}^{(1)},r_{ij}^{(2)},...,r_{ij}^{(l)})$$
$$=v_1r_{ij}^{(1)}\oplus v_2r_{ij}^{(2)}\oplus...\oplus v_lr_{ij}^{(l)},i$$
$$=1,2,...,m;j=1,2,...,n$$

All linguistic decision matrices $R_k=(r_{ij}^{(k)})_{11\times5}(k=1,2,3,4,5)$ are integrated to obtain a group linguistic decision matrix $R=(r_{ij})_{11\times5}$.

Step 2: From

$z_j(w)=w_1r_{1j}\oplus w_2r_{2j}\oplus...\oplus w_mr_{mj},\quad j=1,2,...,n$

The comprehensive attribute value $z_j(w)(j=1,2,3,4,5)$: $z_1(w)=s_{0.395}$, $z_2(w)=s_{-0.48}$, $z_3(w)=s_{-0.15}$, $z_4(w)=s_{-0.28}$, $z_5(w)=s_{0.435}$ of the scheme $x_j(j=1,2,3,4,5)$ is obtained.

Step 3: According to the comprehensive attribute value $z_j(w)(j=1,2,3,4,5)$, the five candidate teachers $x_j(j=1,2,3,4,5)$ are sorted, and we get:

$x_5\succ x_1\succ x_3\succ x_4\succ x_2$

Now we arrive the best teacher is x_5.

3.2 The Evaluation of Bilingual Teaching Quality Based on Operator ULWA

When conducting comprehensive assessments of educators' oral language competencies, evaluators frequently encounter situations where precise linguistic categorization proves challenging. A typical scenario occurs when judging a teacher's spoken proficiency - an expert might determine that the individual's ability falls somewhere between the predefined ratings of 'average' and 'good', rather than perfectly matching either discrete category. This common evaluation dilemma highlights the inherent limitations of traditional linguistic assessment scales in capturing nuanced human judgments. To address this widespread issue of linguistic ambiguity in performance evaluation, the current research adopts advanced uncertain linguistic decision-making methodologies. Specifically, this section implements the Uncertain Linguistic Weighted Averaging (ULWA) operator as a sophisticated analytical tool for assessing bilingual teaching quality. The ULWA approach offers distinct advantages by accommodating these intermediate, and uses uncertain linguistic variable $\tilde{S}=[s_\alpha,s_\beta]$ to express expert opinions, where s_α and s_β are the upper and lower limits. If five decision makers $e_k(k=1,2,3,4,5)$ give the following five uncertain linguistic matrices $\tilde{R}_k(k=1,2,3,4,5)$.

In order to sort the candidates, the following steps are given:

Step 1: Use operator *ULWA*

$\tilde{r}_{ij}=ULWA(\tilde{r}_{ij}^{(1)},\tilde{r}_{ij}^{(2)},...,\tilde{r}_{ij}^{(l)})$

$=v_1\tilde{r}_{ij}^{(1)}\oplus v_2\tilde{r}_{ij}^{(2)}\oplus...\oplus v_l\tilde{r}_{ij}^{(l)},i$

$=1,2,...,m;j=1,2,...,n$

All uncertain linguistic decision matrices $\tilde{R}_k=(\tilde{r}_{ij}^{(k)})_{11\times5}(k=1,2,3,4,5)$ are integrated to obtain a group uncertain linguistic decision matrix $\tilde{R}=(\tilde{r}_{ij})_{11\times5}$.

$\tilde{r}_{ij}=ULWA(\tilde{r}_{ij}^{(1)},\tilde{r}_{ij}^{(2)},...,\tilde{r}_{ij}^{(l)})$

$=v_1\tilde{r}_{ij}^{(1)}\oplus v_2\tilde{r}_{ij}^{(2)}\oplus...\oplus v_l\tilde{r}_{ij}^{(l)},i$

$=1,2,...,m;j=1,2,...,n$

We could obtain the uncertain comprehensive attribute value of the scheme $x_j(j=1,2,3,4,5)$,and the value is:

$\tilde{z}_j(w)(j=1,2,3,4,5)$: $\tilde{z}_1(w)=[s_{-0.42},s_{0.58}]$, $\tilde{z}_2(w)=[s_{-0.49},s_{0.61}]$, $\tilde{z}_3(w)=[s_{-0.51},s_{0.5}]$, $\tilde{z}_4(w)=[s_{-0.4},s_{0.61}]$, $\tilde{z}_5(w)=[s_{-2.65},s_{0.78}]$.

Step 2: Use

$$p(\tilde{s}_1\geq\tilde{s}_2)=\min\left\{\max\left(\frac{\beta_1-\alpha_2}{len(\tilde{s}_1)+len(\tilde{s}_2)},0\right),1\right\}$$

To pairwise comparison of $\tilde{z}_j(w)(j=1,2,3,4,5)$, and construct the possibility degree matrix:

$$p=\begin{pmatrix}0.5 & 0.5095 & 0.5423 & 0.4876 & 0.7291\\ 0.4905 & 0.5 & 0.5308 & 0.4787 & 0.7196\\ 0.4577 & 0.4692 & 0.5 & 0.4455 & 0.7095\\ 0.5124 & 0.5213 & 0.5545 & 0.5 & 0.7342\\ 0.2709 & 0.2804 & 0.2905 & 0.2658 & 0.5\end{pmatrix}$$

Step 3: From

$\zeta_i=\frac{1}{n(n-1)}\left(\sum_{j=1}^n p_{ij}+\frac{n}{2}-1\right),\quad i=1,2,...,n$ we can get the ordering vector of the possibility degree matrix P:

$\zeta=(0.2134,0.2110,0.2041,0.2161,0.1554)^T$ Step 4: Use $\zeta_i(i=1,2,3,4,5)$ to sort the uncertain comprehensive attribute values $\tilde{z}_j(w)(j=1,2,3,4,5)$, it is obtained that:

$\tilde{z}_4(w)>\tilde{z}_1(w)>\tilde{z}_2(w)>\tilde{z}_3(w)>\tilde{z}_5(w)$

Sort the five candidate teachers $x_j(j=1,2,3,4,5)$ in turn, and we could get

$x_4 \succ x_1 \succ x_2 \succ x_3 \succ x_5$, Thus the best candidate is x_4.

4. Conclusion

To comprehensively account for potential deviations arising from uncertain factors and variations in individual expert assessments during the evaluation process, this study develops an innovative bilingual teaching evaluation model specifically designed for navigation courses. The proposed framework integrates multi-attribute group decision-making (MAGDM) methodology with advanced linguistic aggregation operators to systematically process and synthesize diverse expert opinions. By employing this combined approach, the model effectively addresses two critical challenges: (1) the inherent uncertainty in qualitative teaching assessments, and (2) the natural divergence among expert evaluators' perspectives. The linguistic operators play a pivotal role in standardizing and aggregating subjective evaluations, while the MAGDM framework ensures a balanced consideration of multiple assessment criteria. This dual methodological approach provides a robust solution for achieving more accurate and reliable evaluations of bilingual teaching quality in specialized navigation education contexts, where precise assessment is particularly crucial for both academic and operational outcomes. According to the five teachers and eleven indexes, the aggregation operator LWA_2 is used to aggregate the evaluation opinions of the five experts. Finally, the group language decision matrix is obtained, and then the ranking of the five teachers is obtained; In order to reflect the uncertainty of the opinions of the evaluation experts, the interval language and *ULWA* is used to evaluate and the opinions are aggregated, and the ranking of the five teachers is obtained by means of the possibility matrix. The two models used in this paper fully reflect the uncertainty of expert evaluation and the evaluation process of natural semantics that is easy to understand. This model can also be applied to the evaluation of students ' comprehensive development and the evaluation of scholarships.

Acknowledgments

This work was supported by the Dalian Maritime University Teaching Reform Program (2024).

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