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Research Article

User-Characteristic-Oriented Bilateral Matching between Online Learning Service Demanders and Providers

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Under the background of information technology and the Internet era, the matching problem in different application scenarios is becoming increasingly prominent. With respect to the matching problem in knowledge services, enabling users to choose suitable knowledge out of massive information has become an urgent demand to be satisfied. Initiating from interdisciplinary perspective, this paper proposes a matching method for online learning services according to user characteristics, which focuses on the matching of decision making for knowledge service with user relevance and characteristic under social network environment. Firstly, the complex network among users is constructed, and the user group is subcategorized into subgroups, thereby aggregating the subgroup information effectively. Secondly, the weight of the indices that evaluate the matching subject is determined by conducting the best-worst method. Thirdly, considering the difference between the expectation and actual levels of the matching subject, the cumulative prospect theory is adopted to calculate the satisfaction degree of both sides. Aiming at maximizing the satisfaction degree of the subjects, a multi-objective optimization model is established to obtain the optimal matching pairs. Finally, the validity and rationality of the proposed method are verified, offering interdisciplinary perspective and theoretical foundation for knowledge service matching and the education reform of humanities.

1. Introduction

As the Internet and information industry continue to prosper, the exponentially rapid growth in online educational sources and services undoubtedly results in mixed qualities, to which the first and foremost thing for people to finish before self-teaching is to carefully discriminate between the expected online services and the confusing lousy commercials [1, 2]. The former can further be personalized for end-users according to their different requirements, whereas the latter may bring them nothing but a waste of money and energy, not to mention the underlying unpleasant and disappointing experiences induced. As for users who crave online educational services, they are forced to bear the bulk of the deleterious junk information reluctantly, which severely disturbs their initial pursuit of educational knowledge and learning skills [3–6]. Therefore, according to users' practical needs, it is of critical necessity to conduct in-depth analysis on their intrinsic characteristics such as learning interests and preferences in advance before the optimal tailor-made online educational services can be matched and recommended for them [7].

In this study, we therefore perform in-depth investigation on end-users' preferences from the perspective of social network analysis (SNA) and decision-making analysis. Considering the expectations of users and providers of online educational services, we propose a bilateral matching method for these two sides. Firstly, we establish and analyze the framework of our proposed matching method. Secondly, considering the relevance among users, we subcategorize users into different subgroups according to the results of SNA, upon which we adopt cumulative prospect theory to calculate the satisfaction degree between users and online educational services. Thirdly, we establish a matching model of knowledge services, generating the optimal matching pairs for users and services.

The key contributions of this study can be formulated as follows:

(1) From the perspective of SNA, we first mine the relevance between users, and then, we conduct GN algorithm to detect the community of user groups and subcategorize them into multiple user subgroups to realize the optimal matching between user groups and online educational services, thereby improving the matching efficiency between two sides.

(2) We introduce decision analysis method into the scenario of supply-demand matching for online educational services. Considering the differences in their expectations and actual levels, which exist between users and online services, we introduce cumulative prospect theory to characterize the satisfaction degrees that exist between users and online educational services, establishing a tailor-made bilateral matching model between these two sides. Our proposal not only helps users determine the strategy of how to make the best choice among diverse online educational services but also matches the most appropriate users for online service providers.

(3) Initiating from interdisciplinary perspective, we establish a set of online educational service matching methods according to users' preferences and apply them to facilitating the optimal selection of online English learning services in colleges and universities, which not only solves the problem of supply-demand matching in educational knowledge services but also offers innovative approaches and theoretical foundation for China's education reforms of humanistic disciplines.

The remainder of this paper is organized as follows. Section 2 outlines the related work of knowledge matching and decision-making problems. Section 3 highlights the corresponding problem description of our study. Section 4 formulates the methodologies adopted in this study, involving social network analysis, decision matrix aggregation, and multi-objective model construction. Section 5 elaborates a real case study that is engaged to validate the rationality of our proposed matching model. Section 6 discusses our future research focus and summarizes conclusions of this paper.

2. Related Work

During the past several decades, the matching problems that occur in the field of knowledge service have attracted much attention to foreign and domestic, which can be basically categorized into two aspects: the matching among online teaching/learning services and that among diverse knowledge services. One of the most important educational and knowledge services is to determine the appropriate knowledge matching pair (MP) between end-users and online services, which can be regarded as a representative and typical bilateral matching problem. The bilateral matching was firstly proposed by Gale and Shapley as a classic decision-making method [8] in response to conducting marriage matching and solving problems concerning higher education recruitment, and was further applied in various applications and fields [9–16].

Concerning online learning services, Lee discussed the quality of online learning services in South Korea and the United States in 2010. Through conducting empirical study adopting factor analysis, structural equation, and other models, the results suggested that online learning services are useful to students in different regions and countries worldwide, and the awareness of the quality of online learning services is an important factor affecting students' online acceptance and satisfaction degree [17]. In 2019, He et al. argued that online learning services are closely correlated with students' performances. After discussing and analyzing the influence of online learning services on students' satisfaction degree and learning results, He et al. reported that the use and frequency of online learning services depend heavily on students' participation paradigm and involvement [18]. Later, Zhao et al. provided a new set of teaching evaluation methods for online learning services and used the Internet big data to obtain learning process data from online learning service platforms, thereby deeply mining learners' characteristics and preferences. The study not only established learners' evaluation system and methods but also further provided students with intelligent and personalized services [19]. In 2021, Jung et al. explored online distance learning under the influence of COVID-19 and adopted AMOS21.0 model to conduct empirical study. The results revealed that online learning services and the quality of corresponding information and systems have positive impact on students as well as on their satisfaction degrees [20].

Regarding knowledge matching problems, Chen et al. proposed a knowledge supply and demand matching model in 2016, which aimed to maximize the satisfaction degree between demanders and suppliers [21]. Compared with our proposed method that characterizes with diverse user attributes and parameters, this approach also conducted the matching between knowledge demander and supplier; however, it adopted fuzzy linguistic information from the principle of axiomatic design.

In 2017, Li et al. proposed a decision-making method for matching experts and demand groups under the background of fuzzy language environment [22]. This approach targeted on optimizing the matching between expert groups and demand groups to elevate the efficiency of tacit knowledge sharing. Moreover, the approach further expanded the research work of tacit knowledge sharing methodologies and was widely applied in other fields where matching decision-making problems predominate. In contrast to our proposed method, this approach focused on tacit knowledge and emphasized the significance of experts, during which process the fuzzy linguistic environment was considered.

Considering network effect, Chang et al. developed a matching method for digital platforms [23] in 2019, which adopted fuzzy multi-attribute decision-making model to calculate the value of the network with respect to the platform, which solved the matching problem between

knowledge providers and demanders on digital platforms. This approach conducted knowledge matching with respect to three major dimensions, which focused on the operating rules of digital platforms rather than the platform service model. By contrast, our proposed method does not depend on platforms and/or their operating rules, by which the robustness and the flexibility of our proposal are therefore highlighted.

Later, in view of the matching for online learning in service platforms, in 2020, Pan et al. proposed an algorithm for online situational learning and resource allocation based on perishable resources [24]. Instead of making decisions between supply and demand, this approach was motivated by one healthcare application and can be easily extended to other service applications. Specifically, Pan et al. incorporated contextual learning with online healthcare service platforms, in which customers' arrival satisfies nonstationary Poisson process and the corresponding rewards can be predicted for subsequence resource allocation. Compared with our proposed method, the rationale of this approach can be understood as "random" and "iterative" rather than "stationary," while our proposal is more "dynamic" and "comprehensive" without requiring any iteration epochs.

In 2021, Zhang et al. considered the self-confidence fuzzy preference relevance of decision makers, proposing a bilateral matching method [25] based on FPRs-SC. This method was further applied to studies of supply-demand matching of knowledge services. In his research, Zhang et al. firstly proposed an extended logarithmic least squares method (LLSM) to derive a priority weight vector, upon which the bilateral matching decision-making approach was proven to be effective for the matching between knowledge suppliers and demanders. It is worth noting that this approach adopted an unbiased weight attribute to conduct the optimal matching decision making, during which the improved algorithms were validated by practical examples, providing enlightening and constructive theoretical foundation for our study. Based on this approach, we further apply more specific matching decision making with respect to other sort of demanders and suppliers from an interdisciplinary perspective.

In addition, Gao et al. proposed an entropy beta method in 2021, which was based on the dynamic matching process of user knowledge to achieve the optimal matching between users and knowledge services [26]. Differentiating from our proposal that selects various user preferences as multi-attributes, Gao et al. introduced the expert knowledge recommendation system (EKRS), which were further improved by the entropy beta algorithm in terms of accuracy, efficiency, dynamic regulation, etc. The principle of this approach can be translated as to filter out and obtain the optimal matching probability through the established algorithm and matching model, thereby proving the effectiveness and validity of both the algorithm and the model dynamically. The above two cases have great thought-provoking significance on our works.

3. Problem Description

In order to solve the problem of knowledge service matching in the context of the Internet, this study introduces the bilateral matching theory into the effective matching between users and online learning services, in which the users are regarded as demanders, while the online services are providers. Considering the preferences of users, we select appropriate online services for users and vice versa, thus realizing the optimal matching between supply and demand.

Online learning service matching is a matching problem involving multiple subjects under the Internet background. When users choose suitable online learning services on their own discretion, they usually seek for advices from people around them and make choices according to their personalized needs. Online learning services offer knowledge services to users who need them, throughout the whole process the service providers can also choose users. Therefore, concerning the problem of knowledge service matching between users (demanders) and online learning services (providers), users' preferences must not be neglected, and the requirements of online learning services should be further considered. Therefore, in this section, we investigate how to generate an optimal matching for users and online learning services according to their expectations and needs for each other.

The following lists out corresponding descriptions and definitions of the sets and variables involved in the decision-making problem of online educational service matching.

$D = \{d_i | i = 1, 2, \ldots, m\}$: a nonempty set with m users.

$S = \{s_j | j = 1, 2, \ldots, n\}$: a nonempty set with n language learning services.

$C = \{c_p | p = 1, 2, \ldots, l\}$: a nonempty set with l properties evaluating online learning services.

$W = \{w_1, w_2, \ldots, w_l\}$: a set of attributes weight of online learning services properties.

$A = \{a_q | q = 1, 2, \ldots, k\}$: a nonempty set with k properties of evaluating users.

$V = \{v_1, v_2, \ldots, v_k\}$: a set of attributes weight of user properties.

$B = [b_{ii'}]_{m\times m}$: the associative adjacency matrices among m users, where $b_{ii'} = 1$ denotes the association existing between the i-th and i'-th user, and $b_{ii'} = 0$ denotes no association between them.

$E = [e_{ip}]_{m\times l}$: it denotes the decision matrix of users' expectation level of online learning service, where $e_{ip} \in U$.

$R = [r_{jq}]_{n\times k}$: it denotes the decision matrix of online language learning service regarding users' expectation level, where $r_{jq} \in U$.

$E' = [e'_{jp}]_{n\times l}$: it denotes the decision matrix of the actual level of online language learning services, where $e'_{jp} \in U$.

$R' = [r_{iq}']_{m\times k}$: it denotes the decision matrix of user's actual level, where $r_{iq}' \in U$.

In this study, the research objective can be elaborated as the problem of matching decision making that exists between online learning services and users, in which users' learning interest and the relevance among them are considered. Specifically, we first subdivide the users into subgroups based on the relevance among users, after which the expectations of users within the subgroups are aggregated. Then, through combining the decision matrices of the expectation levels of users and of online learning services with those of the actual levels, we determine the optimal matching pairs for users and online learning services.

4. Methodology

In this study, we propose a matching method of decision making for online learning services, which considers users' learning preferences and the relevance among them. Firstly, according to the relevance among users who choose online learning services, we adopt social network analysis [27] (SNA) to subcategorize them into different subgroups. Secondly, based on multiple attributes of the users, the decision matrices of their expectation level and those of the actual level of the user subgroups are aggregated. Furthermore, considering the difference between the expectation and the actual levels of the user subgroups and the online learning services, we calculate the satisfaction degree matrices of user subgroups and those of online learning services adopting cumulative prospect theory. Finally, we establish a multi-objective optimization model to obtain the optimal matching pairs between users and online services, to which the specific details of our proposal are formulated as follows.

4.1. Community Detection-Based Algorithm for Division and Aggregation of User Subgroup. Considering the actual online learning services, we must accurately acquire diverse users' learning demands, preferences, and interests. Moreover, we need precisely obtain on whom the major and key groups of different online learning services target before achieving the optimal pairwise matching. Unfortunately, in real world, the enormous number of users and different user demands are posing disadvantageous obstacles and great challenges to the matching. Since users are intercorrelated with each other rather than isolated individuals in real world, they usually share the same preferences for choosing the same one or several services. Therefore, by referring to the principle of complex network theory, in this study, we adopt the notion of undirected weighted graph in network to demonstrate the incidence matrix among users, after which we subcategorize the user group into different subgroups and aggregate the preference information of subgroups, thereby realizing the optimal bilateral matching between users and services. The specific steps of user subgroup division and aggregation through using community detection algorithm are presented as follows.

Step 1. Divide user subgroups.

Firstly, in this study, we adopt topological graph $G = (D, H)$ in complex network to represent the association network among users, where G denotes undirected network connection graph, and $D = \{d_1, d_2, \ldots, d_m\}$ denotes a collection of nodes within the network. The users within the network are regarded as the nodes of the network, and $H = \{h_1, h_2, \ldots, h_o\}$ denotes the edges of the network, where o is the number of edges being expressed as $o = m(m-1)/2$. The weight of the edges can be expressed by the following adjacency matrix B.

$$B = \begin{bmatrix} b_{11} & b_{12} & \ldots & b_{1m} \\ b_{21} & b_{22} & \ldots & b_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \ldots & b_{mm} \end{bmatrix}, \tag{1}$$

where $b_{ii'}$ is the edge weight between i-th node and i'-th node (in this study, $b_{ii'}$ refers to the correlation degree between i-th user and i'-th user). In order to perform effective subgroup division with respect to users group, based on the weighted adjacency matrix among user groups, this study adopts the GN algorithm [28] used in community detection algorithm to divide user groups into subgroups, and the divided subgroups can be expressed by

$$\mathfrak{R} = \{\mathfrak{R}_1, \mathfrak{R}_2, \ldots, \mathfrak{R}_Y\}. \tag{2}$$

Step 2. Calculate user weights.

After subcategorizing the user group into user subgroups, we determine the weight of each individual user included in the subgroups, thereby aggregating the expectation levels of online learning services of users in the same user subgroup. Within the same subgroup, the user weight can be determined by

$$\overline{\xi}(d_i) = \sum_{i'}^{\#\mathfrak{R}_y} b_{ii'}, \tag{3}$$

where $d_i, d_{i'} \in \mathfrak{R}_y$, $\mathfrak{R}_y$ denotes the y-th user subgroup and $y = 1, 2, \cdots, o$, $\#\mathfrak{R}_y$ denotes the number of users included in the y-th user subgroup. The weight of each individual user within the subgroup can be obtained by normalizing $\overline{\xi}(d_i)$, which is expressed as

$$\xi(d_i) = \frac{\overline{\xi}(d_i)}{\sum_{d_i \in \mathfrak{R}_y} \overline{\xi}(d_i)}, \tag{4}$$

where $\xi(d_i)$ denotes the weight of user d_i in the y-th subgroup.

Step 3. Aggregate the decision matrices of user subgroups.

In order to aggregate users' expectation levels concerning online learning services within the same user subgroup, this study uses network density operator to aggregate

the user's decision matrix, to which the specific process is expressed by

$$NDWA\left(d_i \in \mathfrak{R}_y\right) = \sum_{d_i \in \mathfrak{R}_y} \xi(d_i) \Lambda D_y. \tag{5}$$

In the above equation (5), $NDWA$ represents the operator of network density-weighted averaging (NDWA) [29], Λ represents the information aggregation operator, And D_y is the clustering of the y-th user subgroup.

4.2. Calculation of Attribute Weights Based on Best-Worst Method. According to the aforementioned user subgroup division and decision matrix aggregation, this study adopts best-worst method (BWM) [30, 31] and cumulative prospect theory to calculate the satisfaction degree between user subgroups and online learning services, thereby measuring the matching degree between the expectation level and actual level of users and online learning services. Firstly, the BWM is performed to calculate the weights of corresponding indicators, to which the specific procedures are presented as follows.

Step 4. Determine the set of evaluation indicators.

Taking as an example the attribute set of online learning services, the evaluation indicator set to be accessed can be expressed as

$$C = \{c_1, c_2, \ldots, c_l\}. \tag{6}$$

Step 5. Determine the most and least important indicators in the evaluation indicator set.

The most important indicator and the least important indicator within the evaluation indicator set are represented by c_B and c_W, respectively.

Step 6. Construct relative preference vector.

We use the scale ranging from 1 to 9 to construct the vector of the most important indicator U_B relative to other indicators (also known as the best-to-others vector), as well as the vector of other indicators U_W relative to the least important indicator (also known as the others-to-worst vector), which are expressed as

$$U_B = \left(u_{B1}, u_{B2}, \ldots, u_{Bl}\right). \tag{7}$$

$$U_W = \left(u_{1W}, u_{2W}, \ldots, u_{lW}\right). \tag{8}$$

In the above equation (7), each element in U_B denotes the relative preference information of the most important indicator relative to other indicators, where $u_{BB} = 1$. In the above equation (8), each element in U_W denotes the relative preference information of other indicators relative to the least important ones, where $u_{WW} = 1$.

Step 7. Solve the optimal weight.

The optimal weight of the indicator can be solved by using the following linear programming model.

$$\begin{aligned} &\min \max_p \left\{ \left| \frac{w_B}{w_p} - u_{Bp} \right|, \left| \frac{w_p}{w_W} - u_{pW} \right| \right\}, \\ &s.t. \sum_{p=1}^{l} w_p = 1, \\ &w_p \geq 0, p = 1, 2, \ldots, l. \end{aligned} \tag{9}$$

For ease of calculation, the above model is transformed into the following linear model for solution

$$\begin{aligned} &\min \varsigma, \\ &s.t. \left| w_B - u_{Bp} w_p \right| \leq \varsigma, \\ &\left| w_p - u_{pW} w_W \right| \leq \varsigma, \\ &\sum_{p=1}^{l} w_p = 1, \\ &w_p \geq 0, p = 1, 2, \ldots, l. \end{aligned} \tag{10}$$

By using lingo software to solve the above model, we obtain the weight W and the optimal target value ς^* of each attribute l of online learning services.

Step 8. Verify the consistency.

In order to further verify the consistency and effectiveness of the evaluation results, the consistency ratio can be calculated using the following equation:

$$CR = \frac{\varsigma^*}{CI}, \tag{11}$$

where CR is the consistency ratio, and CI is the consistency index whose specific values are listed out in the following Table 1. When $CR < 0.1$, it can be considered that the evaluation results satisfy the consistency requirements.

Performing the same method, the weight V of attributes of users can be obtained.

4.3. Prospect Theory-Based Calculation of Satisfaction Degree. During the actual process of matching decision making, the individual preferences of both sides to be matched may impose certain impact on decision-making results. For instance, the difference between the user's expectation level of online learning services and the actual level of the services themselves may affect the users' choice. Therefore, from the perspective of cumulative prospect theory proposed by Kahneman and Tversky [32], this study fully considers the expectation level and actual level of users and online learning services, thereby matching the satisfaction degree of both sides. The detailed steps of calculating satisfaction degree based on cumulative prospect theory are presented as follows.

Table 1: Consistency indices.

a_{BW}	1	2	3	4	5	6	7	8	9
CI	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

Step 9. Determine the set of evaluation indicators.

Taking as an example the assessment of the online learning services with a set of l attributes, the set of evaluation indices to be assessed is represented by

$$C = \{c_1, c_2, \ldots, c_l\}. \tag{12}$$

Step 10. Determine the reference point.

Setting as the reference point the expectation level of online learning service of the user subgroups, the reference point regarding user subgroup $\mathfrak{R}_y$ can be expressed as

$$E_y = \left[e_{y1} \;\; e_{y2} \;\; \ldots \;\; e_{yl} \right]. \tag{13}$$

Step 11. Determine the benefit.

Concerning different types of indicators, the gains between the actual level of online learning services and the expectation level of users are calculated by

$$G_{yj}^p = \begin{cases} e_{jp}' - e_{yp}c_p \text{ is the cost attribute,} \\ e_{yp} - e_{jp}'c_p \text{ is the benefit attribute,} \end{cases} \tag{14}$$

where G_{yj}^p denotes the gain value of the p-th index of the j-th online learning services of the user subgroup $\mathfrak{R}_y$, $G_{yj}^p > 0$ denotes the value of gains, and $G_{yj}^p < 0$ denotes the value of losses.

Step 12. Determine the value function.

The value function is commonly expressed as

$$v\left(G_{yj}^p\right) = \begin{cases} \left(G_{yj}^p\right)^\alpha G_{yj}^p \geq 0 \\ -\lambda\left(-G_{yj}^p\right)^\beta G_{yj}^p < 0 \end{cases}, \tag{15}$$

where $v(G_{yj}^p)$ denotes the value of the p-th index of the j-th online learning services of the user subgroup $\mathfrak{R}_y$; α and β denote the coefficients of incomes and losses, respectively; and λ denotes the risk aversion coefficient. According to the study results of Kahneman and Tversky [32], in this study, we set $\alpha = \beta = 0.88$, and $\lambda = 2.25$.

Step 13. Determine the prospect value.

According to the value function, we calculate the prospect value of user subgroups about online learning services, which can be express by

$$f_{yj} = \sum_{p=1}^{l} \pi_p^+ v\left(G_{yj}^p\right) + \sum_{p=1}^{l} \pi_p^- v\left(G_{yj}^p\right), \tag{16}$$

where f_{yj} denotes the prospect value of the user subgroup $\mathfrak{R}_y$ regarding the j-th online learning service provider, and π_p^+ and π_p^- denote the probability weight function that is used to evaluate the p-th attribute gains and losses of online learning, respectively. The probability weight function can be calculated by

$$\begin{aligned} \pi_p^+ &= \frac{\left(w_p\right)^\gamma}{\left(\left(w_p\right)^\gamma + \left(1 - w_p\right)^\gamma\right)^{1/\gamma}}, \\ \pi_p^- &= \frac{\left(w_p\right)^\sigma}{\left(\left(w_p\right)^\sigma + \left(1 - w_p\right)^\sigma\right)^{1/\sigma}}, \end{aligned} \tag{17}$$

where γ and σ denote the probability weight coefficients of gains and losses, respectively. According to the study results of Kahneman and Tversky [32], the values of γ and σ are 0.61 and 0.69, respectively.

Step 14. Determine the satisfaction degree.

According to the prospect value f_{yj} of the user subgroup $\mathfrak{R}_y$ regarding the j-th online learning service provider, we obtain the prospect value matrix F of the user subgroup about the online learning services, which can be expressed as

$$F = \left[f_{yj}\right]_{o\times n} = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1l} \\ f_{21} & f_{22} & \cdots & f_{2l} \\ \vdots & \vdots & \ddots & \vdots \\ f_{o1} & f_{o2} & \cdots & f_{ol} \end{bmatrix}_{o\times n}. \tag{18}$$

By normalizing F, we obtain the satisfaction degree f_{yj}' of the user subgroup $\mathfrak{R}_y$ with the online learning service provider s_j, which is calculated by

$$f_{yj}' = \frac{f_{yj} - \min\left\{f_{yj} | y = 1, 2, \ldots, o\right\}}{\max\left\{f_{yj} | y = 1, 2, \ldots, o\right\} - \min\left\{f_{yj} | y = 1, 2, \ldots, o\right\}}. \tag{19}$$

Through conducting the same method, we obtain the satisfaction degree t_{yj}' of the online learning service provider s_j on the user subgroup $\mathfrak{R}_y$.

4.4. Online Learning Matching Method considering User's Characteristics. Based on the above analysis, we obtain the satisfaction degree f_{yj} of the user subgroup $\mathfrak{R}_y$ regarding the online learning service provider s_j, as well as the satisfaction degree t_{yj}' of the service provider s_j regarding the user subgroup $\mathfrak{R}_y$, through which a multi-objective optimization model can be established to maximize the satisfaction degree of users and online learning service providers, thereby achieving the best result of matching the satisfaction degree of both sides.

Specifically, this study introduces the variable x_{yj} that ranges from 0 to 1 to describe the matching between users and online learning services, to which $x_{yj} = 1$ suggests that a matching exists between the user subgroup $\mathfrak{R}_y$ and the online learning service provider s_j, whereas $x_{yj} = 0$ indicates that a mismatching exists between these two sides. In order to solve this bilateral matching problem between users and online learning services, we establish a multi-objective optimization model as follows:

$$\max Z_1 = \sum_{y=1}^{Y}\sum_{j=1}^{n} x_{yj} f_{yj}',$$
$$\max Z_2 = \sum_{y=1}^{Y}\sum_{j=1}^{n} x_{yj} t_{yj}',$$
$$s.t. \sum_{j=1}^{n} x_{yj} \le 1, y = 1, 2, \ldots, Y,$$
$$\sum_{y=1}^{Y} x_{yj} \le 1, j = 1, 2, \ldots, n,$$
$$x_{yj} = 0 \, or \, 1, y = 1, 2, \ldots, Y; j = 1, 2, \ldots, n. \tag{20}$$

The above multi-objective optimization model determines the most appropriate matching pairs between the two sides by maximizing the satisfaction degree of users and online learning service providers. There are various methods to solve the multi-objective optimization model, among which the commonly used approach is to transform two objectives into a single-objective underlying the rationale of linear weighting method. Following the principle of linear weighting, we therefore transform the above multi-objective optimization model into a single-objective optimization model, which can be expressed by

$$\max Z = \tau_1 \times \sum_{y=1}^{Y}\sum_{j=1}^{n} x_{yj} f_{yj}' + \tau_2 \times \sum_{y=1}^{Y}\sum_{j=1}^{n} x_{yj} t_{yj}',$$
$$s.t. \sum_{j=1}^{n} x_{yj} \le 1, y = 1, 2, \ldots, Y,$$
$$\sum_{y=1}^{Y} x_{yj} \le 1, j = 1, 2, \ldots, n,$$
$$x_{yj} = 0 \, or \, 1, y = 1, 2, \ldots, Y; j = 1, 2, \ldots, n,$$
$$\tau_1 + \tau_2 = 1,$$
$$0 \le \tau_1, \tau_2 \le 1, \tag{21}$$

where τ_1 and τ_2 are weighting coefficients. This single-objective optimization model can be solved by using MATLAB software, thereby obtaining the optimal matching pairs between users and online learning services.

5. Case Study

In this section, we introduce a real case to verify the effectiveness and rationality of our proposed online learning service matching model, in which the users' learning interests and relevance are considered.

In spite of science and engineering or humanities, China's higher education highly emphasizes English-related courses, which accounts for a high proportion throughout the teaching syllabus of almost all courses of nonlanguage majors. As the Internet and information technology boom, China's higher education is accelerating the implementation of sound and comprehensive informatization in colleges and universities. Characterizing with accessibility, convenience, and efficiency under this social background, online teaching/learning and online educational resources have becoming a popular pedagogy for both teachers and learners.

In recent years, a large number of universities in China have been launching a series of online English teaching and learning services, including online courses and online interactive platforms, which help teachers and students to jointly make their own choices. Nevertheless, many students often feel confused when choosing among diverse online English learning services, which may inhibit them from making the most appropriate preferences. It has become an increasingly prominent problem for those students who deserve the right choices that match their own inherent characteristics involving learning preferences, interests, and advantages. On the one hand, students may choose certain services they like according to their own interests. On the other hand, students may also choose some services following the advices from their classmates and/or friends.

For online service providers such as colleges and universities, offering diversified optional services for students is to enable students to improve their English proficiency according to their own characteristics. Therefore, they may consider many factors that originate from students, such as students' examination results and fields of expertise, thus recommending appropriate courses for students. Therefore, in order to realize the optimal matching between students and online English learning services, how to comprehensively consider students' learning interests and association as well as the expectations of online English learning service providers is a crucial and urgent problem to be solved for the education and teaching reform of China's colleges and universities.

In this study, we take X University of China as an example to investigate the influences of four online English teaching/learning services offered by the University for its students. These online services for students to choose are special training of English writing (s_1), special training of English reading (s_2), special training of English listening comprehension (s_3), special training of oral English (s_4), special training of translation and interpretation (s_5), and special training of English grammar (s_6). When launching the above special training courses, the University mainly considers the following six aspects: student's willingness to study abroad (c_1), student's learning interest (c_2), student's grade (c_3), student's major (c_4), student's score (c_5), and student's personal preference (c_6). The students choose online English learning services mainly based on the following points: course credits (a_1), course hours (a_2), course difficulty (a_3), course practicality (a_4), course emphasis (a_5), and course type (a_6) that can only be selected for certain majors.

We randomly selected thirty undergraduate students in the X University. They were asked to choose their own online English teaching services according to their own learning interests and the association among them. Specifically, the incidence matrix among students is presented in Table 2, the expectation level of students about online services is shown

Table 2: The incidence matrix and adjacency matrix among students.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
1	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0
3	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0
4	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
5	0	0	1	1	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0
6	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0
7	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	1	0	1	0	1	1	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0
9	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	1	0	0	1	0	0	0
10	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	1	0	0	1	0	0	0	0	0	0	1	0	0	0
12	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0	1	0	0
13	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	0	1	1	0	0	0	0	0
14	0	1	0	0	0	0	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1
15	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0
16	0	0	1	0	1	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
17	0	0	1	0	1	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0
18	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0
19	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0
20	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0
21	0	0	0	1	1	0	0	0	1	0	0	0	1	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
22	1	0	1	0	0	1	1	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
25	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0
26	0	1	0	0	0	1	0	0	0	0	0	0	0	1	1	0	1	1	0	1	0	0	0	0	1	0	0	0	0	0
27	0	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
30	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0

The significance for bold value represents different students.

in Table 3, the expectation level of the X University about students is listed out in Table 4, the actual level of students themselves is demonstrated in Table 3, and the actual level of online English teaching services is illustrated in Table 4.

Firstly, based on the incidence adjacency matrix among thirty students, these students are subdivided into six subgroups by performing GN algorithm, as shown in Table 5.

Then, the weight of each student within the four subgroups is calculated, to which the results are listed out in Table6.

Through using the weight of students in the subgroups, the decision matrix of students' actual level and that of their expectation level about online learning services are aggregated, thereby obtaining the actual level of students' subgroups and their expectation level about online English learning services, as shown in Table 7.

Further, the weight of each attribute is determined by performing BWM, and five experts are invited to assess the indicators of evaluating students and online services, to which the decision matrix of these experts is shown in Tables 8 and 9.

Taking as an example the evaluation of the attributes of online English learning services, we establish the following linear objective programming model based on BWM.

$$\begin{aligned}
&\min \varsigma,\\
&s.t. \left|w_4 - 5w_1\right| \le \varsigma, \left|w_4 - 6w_1\right| \le \varsigma, \left|w_4 - 4w_2\right| \le \varsigma, \left|w_4 - 3w_2\right| \le \varsigma,\\
&\left|w_4 - 3w_3\right| \le \varsigma, \left|w_4 - 2w_3\right| \le \varsigma, \left|w_4 - 3w_5\right| \le \varsigma, \left|w_4 - 2w_5\right| \le \varsigma,\\
&\left|w_4 - 6w_6\right| \le \varsigma, \left|w_4 - 5w_6\right| \le \varsigma, \left|w_1 - 2w_6\right| \le \varsigma, \left|w_1 - 3w_6\right| \le \varsigma,\\
&\left|w_2 - 3w_6\right| \le \varsigma, \left|w_2 - 4w_6\right| \le \varsigma, \left|w_3 - 5w_6\right| \le \varsigma, \left|w_3 - 4w_6\right| \le \varsigma,\\
&\left|w_3 - 5w_6\right| \le \varsigma, \left|w_4 - 6w_6\right| \le \varsigma, \left|w_4 - 3w_6\right| \le \varsigma, \left|w_4 - 2w_6\right| \le \varsigma,\\
&\sum_{p=1}^{l} w_p = 1,\\
&w_p \ge 0, p = 1, 2, \ldots, l.
\end{aligned} \tag{22}$$

By using MATLAB software to solve the above model, we obtain the weight of evaluating the attributes of online English learning services, which can be expressed as

$$W = \left[\, 0.0845 \;\; 0.1268 \;\; 0.1690 \;\; 0.3944 \;\; 0.1690 \;\; 0.0563 \,\right], \tag{23}$$

where the consistency ration CR is expressed by

$$CR = \frac{\varsigma^*}{CI} = \frac{0.1127}{3.00} = 0.0376 < 0.1. \tag{24}$$

Table 3: Students' actual level and their expectation level about online English teaching services.

	c_1	c_2	c_3	c_4	c_5	c_6	a_1	a_2	a_3	a_4	a_5	a_6
d_1	2	4	3	2	3	3	3	4	3	2	3	3
d_2	1	3	4	3	2	4	4	3	4	3	3	2
d_3	1	3	4	3	2	3	4	2	4	3	3	4
d_4	1	3	3	4	2	3	3	2	3	2	3	4
d_5	1	2	4	3	3	3	4	3	4	3	4	3
d_6	2	4	3	3	3	2	3	4	3	2	2	3
d_7	1	3	3	4	3	4	4	3	4	4	3	3
d_8	2	3	4	4	3	3	4	2	4	4	3	2
d_9	3	2	2	4	3	4	2	3	2	4	2	3
d_{10}	2	4	3	2	2	2	3	4	2	2	3	2
d_{11}	4	3	3	3	2	2	2	1	3	2	3	4
d_{12}	4	4	3	3	3	2	2	1	3	2	3	3
d_{13}	3	3	2	3	2	3	2	3	2	3	2	4
d_{14}	1	3	3	3	3	4	3	2	3	3	3	2
d_{15}	3	4	3	3	3	3	3	3	2	3	2	3
d_{16}	4	3	4	3	3	2	3	2	4	3	2	3
d_{17}	1	3	4	4	2	3	4	2	4	3	2	4
d_{18}	1	3	3	4	2	3	4	3	4	3	2	3
d_{19}	2	4	3	2	3	3	3	3	3	2	3	3
d_{20}	2	3	4	4	2	3	3	3	4	3	3	3
d_{21}	3	3	4	3	4	4	3	2	2	3	3	4
d_{22}	2	3	2	3	3	2	4	3	3	2	3	2
d_{23}	4	3	3	4	3	2	4	3	4	3	2	3
d_{24}	3	3	2	3	4	3	2	3	3	4	3	3
d_{25}	1	3	4	3	3	4	3	3	4	3	3	3
d_{26}	2	3	3	4	2	3	4	3	4	3	3	2
d_{27}	2	3	3	2	3	3	3	2	3	3	4	4
d_{28}	1	4	1	2	2	1	3	4	3	2	4	3
d_{29}	2	4	1	3	3	2	3	3	2	3	3	3
d_{30}	1	3	1	2	2	2	4	3	3	2	3	4

Table 4: Online English learning services' actual level and their expectation level about students.

	a_1	a_2	a_3	a_4	a_5	a_6	c_1	c_2	c_3	c_4	c_5	c_6
s_1	2	2	2	2	3	2	2	3	2	2	2	3
s_2	2	2	1	2	2	3	2	3	2	1	2	4
s_3	3	3	3	2	4	2	1	3	4	2	3	3
s_4	4	3	4	3	3	3	3	3	3	3	2	2
s_5	3	4	3	2	2	4	4	3	2	2	3	3
s_6	2	3	3	4	3	4	2	2	3	4	4	2

Table 5: Subgroup division result of 30 students.

Subgroup	Students
$\mathfrak{R}_1$	d_1, d_6, d_{10}, d_{19}, d_{22}
$\mathfrak{R}_2$	d_3, d_4, d_5, d_{17}, d_{18}
$\mathfrak{R}_3$	d_2, d_7, d_8, d_{14}, d_{20}, d_{25}, d_{26}
$\mathfrak{R}_4$	d_9, d_{13}, d_{15}, d_{21}, d_{24}, d_{27}
$\mathfrak{R}_5$	d_{11}, d_{12}, d_{16}, d_{23}
$\mathfrak{R}_6$	d_{28}, d_{29}, d_{30}

Through verifying the consistency, the rationality of the above weight is therefore validated.

By performing the same method, we obtain the weight of evaluating students' attributes, which is written as

$$V = \left[\, 0.1662 \;\; 0.3878 \;\; 0.0554 \;\; 0.0997 \;\; 0.1662 \;\; 0.1247 \,\right]. \tag{25}$$

Using the obtained attribute weights, we can calculate the satisfaction degree matrix between the student subgroups and the online English learning services, as listed out in the following Tables 10 and 11.

Subsequently, according to the satisfaction degree matrices of the two sides, we establish a bilateral matching model between the student subgroups and the online English learning services, in which the weighting coefficient $\tau_1 = \tau_2 = 0.5$ is taken. By using MATLAB software, we therefore obtain the matching results between the student subgroups and the online English learning services, to which the schematic diagram is presented in Figure 1.

Table 6: Students' weight in subgroups.

$\mathfrak{R}_1$	Student	d_1	d_6	d_{10}	d_{19}	d_{22}		
	Weight	0.1600	0.2000	0.1200	0.1600	0.3600		
$\mathfrak{R}_2$	Student	d_3	d_4	d_5	d_{17}	d_{18}		
	Weight	0.2069	0.1034	0.2414	0.2414	0.2069		
$\mathfrak{R}_3$	Student	d_2	d_7	d_8	d_{14}	d_{20}	d_{25}	d_{26}
	Weight	0.0811	0.0811	0.1892	0.1892	0.1351	0.1081	0.2162
$\mathfrak{R}_4$	Student	d_9	d_{13}	d_{15}	d_{21}	d_{24}	d_{27}	
	Weight	0.1875	0.2188	0.1563	0.2188	0.0938	0.1250	
$\mathfrak{R}_5$	Student	d_{11}	d_{12}	d_{16}	d_{23}			
	Weight	0.2857	0.2857	0.2857	0.1429			
$\mathfrak{R}_6$	Student	d_{28}	d_{29}	d_{30}				
	Weight	0.5000	0.1250	0.3750				

Table 7: Student subgroups' actual level and their expectation level about online English learning services.

	c_1	c_2	c_3	c_4	c_5	c_6	a_1	a_2	a_3	a_4	a_5	a_6
$\mathfrak{R}_1$	2.0000	3.6400	2.6400	2.5600	2.8800	2.3200	3.3600	3.4800	2.8800	2.0000	2.8000	2.5200
$\mathfrak{R}_2$	1.0000	2.7586	3.6897	3.5517	2.2414	3.0000	3.8966	2.4483	3.8966	2.8966	2.7931	3.5517
$\mathfrak{R}_3$	1.5405	3.0000	3.5135	3.6216	2.5676	3.4595	3.5676	2.6216	3.8108	3.2703	3.0000	2.3243
$\mathfrak{R}_4$	2.8756	2.9694	2.7193	3.0631	3.0944	3.4069	2.5005	2.6568	2.2192	3.2819	2.5630	3.5632
$\mathfrak{R}_5$	4.0000	3.2857	3.2857	3.1429	2.7143	2.0000	2.5715	1.5715	3.4286	2.4286	2.5714	3.2857
$\mathfrak{R}_6$	1.1250	3.6250	1.0000	2.1250	2.1250	1.5000	3.3750	3.5000	2.8750	2.1250	3.5000	3.3750

Table 8: The best and worst attributes and corresponding vectors evaluating online English learning services.

	Best—all vectors of attributes							Worst— all vectors of attributes						
	Best	a_1	a_2	a_3	a_4	a_5	a_6	Worst	a_1	a_2	a_3	a_4	a_5	a_6
Expert 1	a_4	5	4	2	1	3	6	a_6	2	3	4	5	3	1
Expert 2	a_4	6	4	3	1	3	5	a_6	3	4	5	5	2	1
Expert 3	a_4	5	3	2	1	3	5	a_6	2	3	4	6	3	1
Expert 4	a_4	6	3	2	1	2	6	a_6	2	3	5	5	3	1
Expert 5	a_4	5	4	2	1	3	6	a_6	3	4	5	6	2	1

Table 9: The best and worst attributes and corresponding vectors evaluating student subgroups.

	Best—all vectors of attributes							Worst—all vectors of attributes						
	Best	c_1	c_2	c_3	c_4	c_5	c_6	Worst	c_1	c_2	c_3	c_4	c_5	c_6
Expert 1	c_2	2	1	5	4	2	3	c_3	4	5	1	2	3	2
Expert 2	c_2	2	1	6	5	3	4	c_3	5	6	1	2	4	3
Expert 3	c_2	2	1	5	4	3	3	c_3	5	5	1	3	3	3
Expert 4	c_2	3	1	6	5	3	4	c_3	4	6	1	2	4	3
Expert 5	c_2	2	1	5	4	3	3	c_3	5	6	1	2	3	3

Table 10: Satisfaction degree of student subgroups on online English learning services.

	s_1	s_2	s_3	s_4	s_5	s_6
$\mathfrak{R}_1$	0.8212	0.8083	0.9737	0.6443	1	0.6714
$\mathfrak{R}_2$	0.1557	0.1579	0.1398	0.2908	0.1257	0.0485
$\mathfrak{R}_3$	0	0	0	0	0	0
$\mathfrak{R}_4$	0.6728	0.6332	0.6764	0.5184	0.6246	0.9470
$\mathfrak{R}_5$	1	1	1	1	0.9093	1
$\mathfrak{R}_6$	0.7208	0.7071	0.8593	0.5883	0.8972	0.6171

Table 11: Satisfaction degree of online English learning services about student subgroups.

	$\mathfrak{R}_1$	$\mathfrak{R}_2$	$\mathfrak{R}_3$	$\mathfrak{R}_4$	$\mathfrak{R}_5$	$\mathfrak{R}_6$
s_1	0.8549	0.8048	0.8483	0.8312	0.7660	0.8453
s_2	1	0.9558	1	1	1	1
s_3	0.7148	1	0.9220	0.6265	0.5395	0.9190
s_4	0	0.1096	0.1214	0.1174	0	0
s_5	0.0516	0	0	0	0.0748	0.1371
s_6	0.4666	0.8001	0.6954	0.5293	0.3542	0.4097

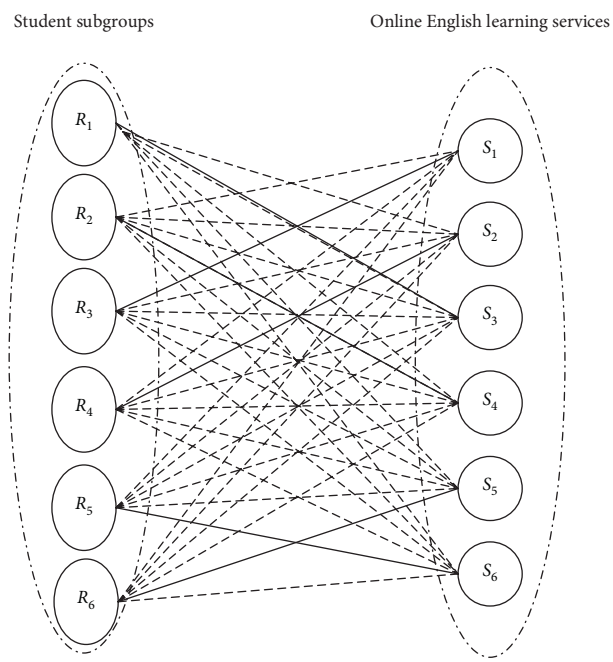

Figure 1: Matching results between student subgroups and online English learning services.

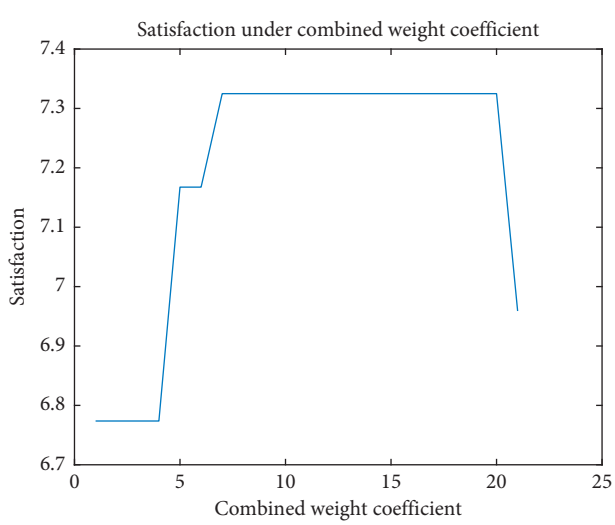

Figure 2: Sensitivity analysis.

It can be observed from Figure 1 that the best/optimal matching pairs between the subgroups and the services are $\mathfrak{R}_1 \leftrightarrow s_3$, $\mathfrak{R}_2 \leftrightarrow s_4$, $\mathfrak{R}_3 \leftrightarrow s_1$, $\mathfrak{R}_4 \leftrightarrow s_2$, $\mathfrak{R}_5 \leftrightarrow s_6$, and $\mathfrak{R}_6 \leftrightarrow s_5$.

Finally, we conduct sensitivity analysis with respect to the weighting coefficients τ_1 and τ_2 in our established model. In response to τ_1 and τ_2, their values adopted in this study are within their value ranges, to which we assign values to τ_1 and τ_2 with a step size of 0.05, satisfying $\tau_1 + \tau_2 = 1$. We performed a total of 21 tests on τ_1 and τ_2, and the result is presented as follows.

It can be observed from Figure 2 that when $\tau_1 \in [0.3, 0.95]$ and the corresponding $\tau_2 \in [0.05, 0.7]$, the matching result between the student subgroups and the online English learning services remains unchanged, to which the maximum satisfaction degree is 7.3249. As τ_1 gradually increases and τ_2 decreases in range $[0, 0.3]$, the above matching result changes, to which the corresponding maximum satisfaction degree also decreases. To summarize, with appropriate generality, in this study, we set $\tau_1 = \tau_2 = 0.5$ in the above case study.

6. Conclusions

Under the current harsh and severe situation of COVID-19 epidemic, the rapid development of the Internet and informatization are ushering in a new wave of opportunities for online learning services. How to choose suitable matching pairs for users and online learning services has become a critical research trend in the study of knowledge service. From the perspective of bilateral matching, we propose an online learning service matching method, which jointly considers user preferences by combining social network analysis (SNA), cumulative prospect theory and best-worst method. In this study, we matched the undergraduate students of X University in China with online English learning services provided by the University and verified the practicability and effectiveness of our proposed method. Our proposal is capable of extending existing studies, making innovative contributions in practice.

Firstly, we extend knowledge service matching method to the matching problem between users and online learning services, thereby proposing a clear logical framework while forming an ingenious perspective. Our proposed decision-making method can be extended to practical matching problems in other domains such as the matching between students and colleges or that between students and job vacancies.

Secondly, when considering the preferences and user demands, we explore the relationship between users from social network analysis perspective, thereby dividing the selected users into subgroups. Compared with conventional bilateral matching methods, the subdividing method we adopted effectively improves the efficiency and accuracy of matching.

Thirdly, performing as one of the most effective approaches to cope with the gap between the actual and the expectation levels, we obtain the satisfaction degree between users and online learning services by adopting cumulative prospect theory, which comprehensively and precisely describes the satisfaction degree of the two sides to be matched.

Despite the above research findings, certain shortcoming may exist in our proposed method, which may potentially

impose detrimental encumbrance or disadvantageous impact on matching decision-making problems. Our future research interests will be focusing on further enriching the relevant evaluation information, enabling more robust generalization ability of the proposed method for solving other matching problems in complicated scenarios [33, 34].

Data Availability

The structured, semistructured, and unstructured data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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