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# Improving Massive Open Online Course Quality in Higher Education by Addressing Student Needs Using Quality Function Deployment

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**Abstract:** Massive Open Online Courses (MOOCs) are playing an increasingly important role in higher education. However, some MOOCs still suffer from low quality, which hinders the sustainable development of higher education. Course characteristics reflect students' needs for online learning and have a significant impact on the quality of MOOCs. In the course improvement process, existing research has neither improved the MOOC quality from the perspective of student needs nor has it considered resource constraints. Therefore, to deal with this situation, we propose a student-needs-driven MOOC quality improvement framework. In this framework, we first map students' differentiated needs for MOOCs into quality characteristics based on quality function deployment (QFD). Then, we formulate a mixed-integer linear programming model to produce MOOC quality improvement policies. The effectiveness of the proposed framework is verified by real-world data from China's higher education MOOCs. We also investigate the impacts of budget, cost, and student needs on student satisfaction. Our results revealed that to significantly improve student satisfaction, the course budget needs to be increased by a small amount or the course cost needs to be greatly reduced. Our research provides an effective decision-making reference for MOOC educators to improve course quality.

**Keywords:** MOOCs; higher education; student needs; quality function deployment; mixed-integer linear programming

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## 1. Introduction

As the highest level of national education, higher education is the main way to cultivate high-quality and innovative talents. With the development of educational information technologies, Massive Open Online Courses (MOOCs) are becoming increasingly prominent in the higher education teaching system. In China, the number of MOOCs has reached over 34,000. However, there are still many online courses that suffer from low quality [1]. Therefore, effectively improving the quality of MOOCs is vital for the sustainable development of China's higher education.

Improving the quality of MOOCs has attracted many researchers' attention. Next, we review the existing studies from the following perspectives: course quality assessment, course design, and course quality characteristics. We searched the above perspective-related keywords on the Web of Knowledge platform and Google Scholar. Then, the papers we reviewed were screened out of the search results.

### 1.1. Related Works

In the area of MOOC quality assessment, Qiu and Ou [2] employed the fuzzy analytic hierarchy process (AHP) as a methodological approach to assess the quality of courses.

Yousef et al. [3] identified six categories of criteria for online courses design, i.e., instructional design, assessment, user interface, video content, learning and social tools, and learning analytics. Qi and Liu [4] utilized a combination of Latent Dirichlet Allocation (LDA), an auto-encoder, and the Bi-LSTM text classification model to evaluate curriculums. Miranda et al. [5] leveraged the techniques of data mining and fuzzy set methods to evaluate MOOCs. They constructed an evaluation framework that encompassed five primary indicators: course content, instructional design, interface design, media technology, and curriculum management. Nie et al. [6] introduced a systematic method for assessing the quality of courses. This methodology integrated data-mining techniques, expert commentary, standardized rubrics, and emotion detection capabilities within the framework of the AHP. Zaremohzzabieh et al. [7] constructed a model that amalgamated the Unified Theory of Acceptance and Use of Technology, Task-Technology Fit, and Theory of Planned Behavior. This integrated model was utilized to investigate the determinants influencing the acceptance and utilization of online courses within higher education institutions, with the aim of enhancing the quality of these online courses. Olivares et al. [8] used a mixed-method study design to assess the quality dimensions of online courses. Ossiannilsson et al. [9] discussed how institutions enhanced and assured quality through MOOC practices.

However, the above-mentioned studies mainly used questionnaire surveys as the research method, and the cost of collecting information was relatively high [10–12]. Machine learning has been attracting some researchers' attention in the area of course quality assessment. For example, Cross et al. [13] used natural language processing and online course analytics to identify areas for revision to enhance the quality of online courses.

In the studies that explored the improvement of MOOC course design, Stracke and Tan [14] developed an online course quality reference framework to improve the design of online courses. Wang et al. [15] investigated potential correlations between the quality of instructional design and student reviews. They conducted a systematic examination of instructional designs in conjunction with a sentiment analysis of student reviews for 18 courses, all of which were part of the Class Central Top 20 MOOCs and used a framework based on ten principles to evaluate the quality of the instructional design. Fianu et al. [16] examined the factors that influenced the adoption of online courses in selected Ghanaian universities. Their findings indicated that the quality of instruction significantly and positively influenced both the students' satisfaction and utilization of MOOCs. Goopio and Cheung [17] studied the online course dropout phenomenon and retention strategies and showed that enhancements in the designs of MOOCs could potentially deter students from discontinuing their courses. Bustamante-León et al. [18] created an instructional design for online courses to improve the quality of MOOCs. The instructional design was predicated on the information system success model proposed by DeLone and McLean [19], as well as the quality principles put forth by Merrill [20], Margaryan [12], Locke [21], and Latham and Seijts [22]. The outcome presented an instructional design that incorporated high-quality content, clearly defined objectives, and effective learning strategies. Finally, the quality of the course was improved by the instructional design. Kim et al. [23] delved into the interrelationships between the factors of online course design, learner commitment, self-directed learning, and intentions for future learning. This investigation was based on survey responses gathered from 664 learners who participated in large-scale courses. They offered strategies for designing effective learner–content interactions in the context of large-scale, self-paced MOOCs. However, the above-mentioned research rarely considered the personalized needs of students in MOOC studies, neglecting the role of students' needs in course quality improvement [24,25].

Finally, the characteristics of courses have an important impact on the quality of MOOCs [26] and many studies have concentrated on quantifying the importance of various quality characteristics of MOOCs. Hsieh [27] employed a series of analytical cross-measurements. These measurements were conducted using the Quality Function Deployment method in the house of quality model in conjunction with the Multiple-Criteria Decision-Making methodology. The purpose of these cross-measurements was to cross-evaluate the weighted results derived from questionnaires. Lizarelli and Osiro [28] put forth an integrative framework that incorporated the SERVQUAL model, an Analytical Kano, and QFD using fuzzy methods. This framework was designed to ascertain the significance of student needs. Chytrý et al. [29] discussed the impact of the educational elements on distance teaching. Chytry et al. [30] explored the significant factors influencing satisfaction with distance education among college students. Comprehensive data were collected from 1283 respondents. Meanwhile, descriptive, inferential, and multidimensional statistics were used for data evaluation in the research.

However, in the above-mentioned studies related to course quality characteristics, resource constraints were usually not considered, which may have resulted in the failed implementation of the course improvement solutions [31].

### *1.2. Research Gap and Our Objective*

Based on the above analysis, it can be seen that existing research has neither improved the quality characteristics of MOOCs from the perspective of student needs nor has it considered resource constraints in the course improvement process. Therefore, we aimed to close this gap by constructing a student-needs-driven MOOC quality improvement framework.

Our contributions are summarized as follows: (a) we mapped students' differentiated demands for MOOCs into quality characteristics based on QFD. (b) To produce course quality improvement policies, we developed a mixed-integer linear programming (MILP) model that considered technical and resource constraints to maximize student satisfaction. (c) The effectiveness of the proposed method was verified with real-world data from China's higher education MOOCs. The impacts of budget, cost, and student needs on student satisfaction were also analyzed.

The remainder of this paper is organized as follows: Section 2 presents the student-needs-driven MOOC quality improvement framework. Sections 3 and 4 discuss in detail the two parts of our framework, i.e., identifying MOOC quality characteristics considering student needs and optimizing course quality characteristics based on MILP. In Section 5, we discuss the experiments that verified our framework with real-world data from a Chinese University's MOOC platform. The last section concludes the paper and discusses future research directions.

## **2. Student-Needs-Driven MOOC Quality Improvement Framework**

Students' needs for MOOC teaching are diversified and hierarchical. By analyzing the existing literature on MOOC quality, we categorized the needs into six dimensions, i.e., the online learning objectives, online learning content resources, online learning process, online learning evaluation, online learning environment, and online learning effectiveness (Table 1). These dimensions reflected students' needs from the perspectives of students (S), teachers (T), and professionals trained in the specialty (P). From the students' perspective, they wanted to know about the learning objectives, content, processes, environments, and effectiveness. From the teachers' perspective, they needed to ensure the availability of appropriate teaching resources and the effectiveness of courses. From the perspective of professionals trained in the specialty, the effectiveness of courses needed to be evaluated to ensure that students acquired the necessary professional competencies. The above three perspectives are also identified in the second column of Table 1.

Identifying the importance of students' various needs has guiding significance for improving the quality of MOOCs [33]. We proposed a MOOC quality improvement framework from the perspective of student needs (Figure 1). Our framework consisted of two parts:

(a) Student-needs-driven MOOC quality characteristic identification. Based on the student needs data that described various demands and their importance in online courses, the QFD method was used to transform student needs into quality characteristics. Table 2 shows six typical online course quality characteristics [32,38]. This transformation was completed by constructing a house of quality in the online course environment. The house of quality also included a correlation matrix, which reflected the correlation between student needs and quality characteristics, and an autocorrelation matrix, which represented the degree of correlation between each quality characteristic.

(b) MOOC quality characteristic optimization based on MILP. Based on the house of quality, the quality characteristic optimization model based on MILP was constructed to maximize student satisfaction with the MOOCs while satisfying technical and budget constraints. The solving results of the model showed which quality characteristics needed to be improved as well as the improvement values for each characteristic.

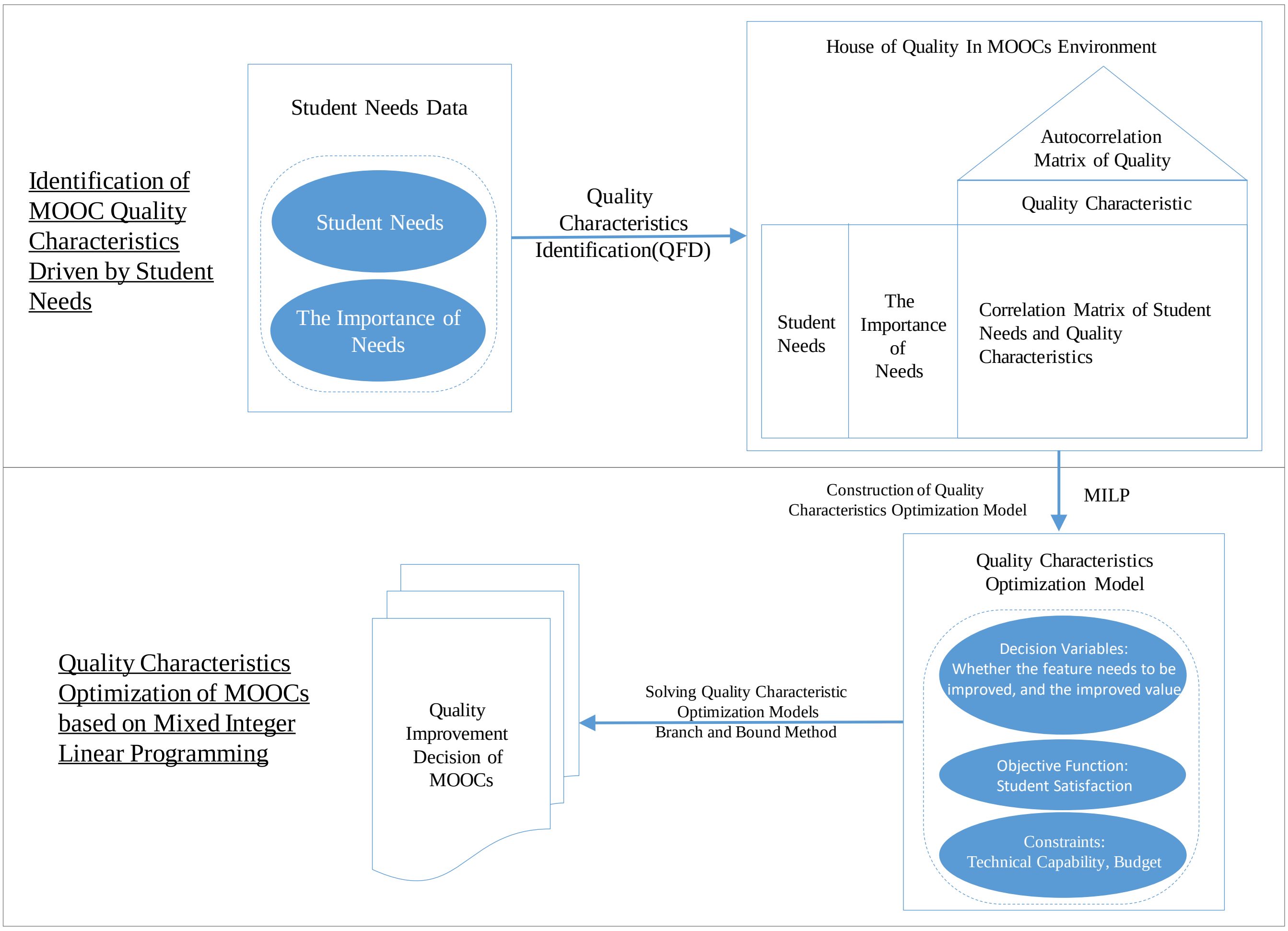


**Figure 1.** Student-needs-driven MOOC quality improvement framework.

**Table 1.** Student needs for MOOCs.

| Dimension | Student Needs | Reference |
|---|---|---|
| Online Learning Goals | Consistent with talent development goals (S, T, P). Tailored to the knowledge and skill level of the learners (S). | Reina et al. [32] |
| Online Learning Content & Resources | Complete course structure and clear modules (S). Cutting-edge and innovative course content (S). Experienced teaching team (S, T). Diverse types of digital resources (S). | Cladera [33] |
| Online Learning Process | Well-organized course schedule (S, T). Facilitating extensive interaction between teachers and students (S). | Daumiller et al. [34] |

**Table 1.** *Cont*.

| Dimension | Student Needs | Reference |
| --- | --- | --- |
| Online Learning Evaluation | Offline and online support and other assessment methods (T).<br>Focus on the comprehensive evaluation of the learning process, and results (T, P). | Peng and Xu [35] |
| Online Learning Environment | The learning platform has a simple interface and runs stably and smoothly (S, T).<br>Supports learning on multiple-end devices (S). | Dominici and Palumbo [36] |
| Online Learning Effectiveness | Able to fully grasp the knowledge of the course (S). | Hew et al. [37] |

**Table 2.** Typical Quality Characteristics in Online Courses.

| Quality Characteristics | Description |
| --- | --- |
| Teaching Goals | Academic major training needs for colleges and universities. |
| Teaching Method | Teaching methods and instructional tools. |
| Level of teaching interaction | Interactivity during the teaching process. |
| Teaching schedule | Course structure and time management, etc. |
| Teaching content resources | Teachers, learning resources, and instructional content. |
| Teaching assessment methods | Exercises, assignments, and other learning assessment methods. |

In the following sections, we further discuss the two main parts of the framework and the experiments that validated its effectiveness.

## 3. Identifying MOOC Quality Characteristics Considering Student Needs

We constructed a house of quality (Figure 2) based on the QFD method to map student needs into quality characteristics [39]. This process included three steps.

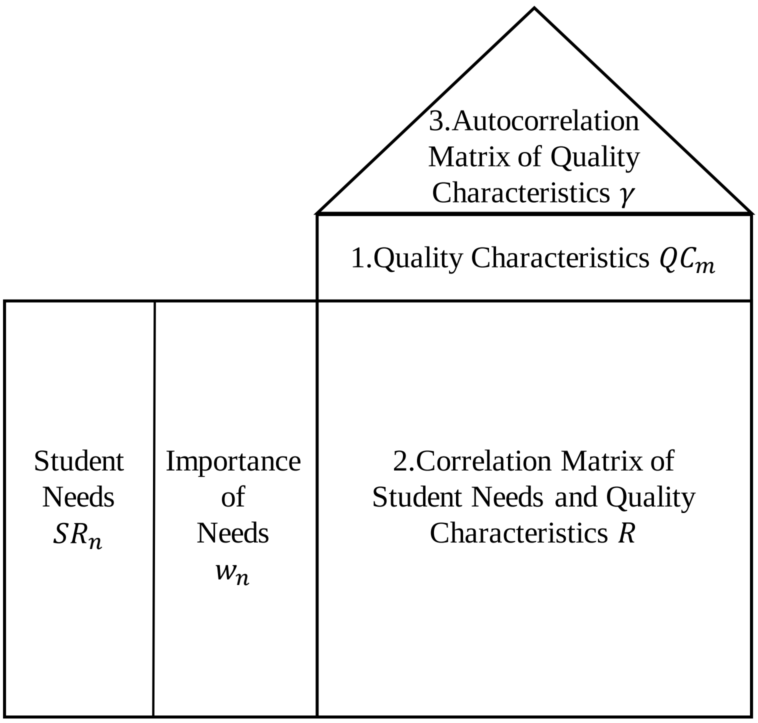


**Figure 2.** House of quality in the context of MOOCs.

First, for the student needs data in the online courses, the course quality characteristics were determined through in-depth communication with the teaching team to clarify which quality characteristics were needed to meet the needs of students. Let $N$ represent the total number of student needs in online course learning, $SR_n$ represent the $n$-th student needs, and $w_n$ represent the importance of the student needs, then $SR_n$, $n = 1, 2, \ldots, N$. Assume that the total number of quality characteristics related to these $N$ student needs is $M$, and $QC_m$ represents the $m$-th quality characteristic in MOOCs, then $m = 1, 2, \ldots, M$.

Second, we constructed the relationship matrix $R$ reflecting the degree of correlation between student needs and quality characteristics. In $R$, we used a discrete scale of 1/3/9 to quantitatively indicate the strong, moderate, and weak correlation between each student need and quality characteristic [40].

Finally, the self-correlation matrix $\gamma$ reflecting the degree of association between each quality characteristic was constructed. When quantifying the degree of relationship (positive/negative; strong/moderate/weak) between each quality characteristic in the matrix $\gamma$, a numerical sequence of $\pm 0.1/0.3/0.9$ was used [40].

To better express the relationship between student needs and quality characteristics, we needed to normalize the relationship matrix in the house of quality based on Equation (1) [40]:

$$R_{nm}^{Norm} = \frac{\left(\sum_{k=1}^{M} \gamma_{km}\right) R_{nm}}{\sum_{m=1}^{M} \left(\sum_{k=1}^{M} \gamma_{km}\right) R_{nm}} \tag{1}$$

where $R_{nm}^{Norm}$ is the element of the normalized relationship matrix $R^{Norm}$. $R_{nm}$ and $\gamma_{km}$ represent the elements of matrices $R$ and $\gamma$ ($k = 1, 2, \ldots, M$), respectively.

## 4. MOOC Quality Characteristics Optimization

In MOOC quality characteristic optimization, we needed to determine the key quality characteristics and their improvement values under the constraints of the course budget and technical capabilities. The goal was to maximize student satisfaction.

A quality characteristic $QC_m$ may or may not have been selected, and the improvement value of the selected quality characteristic depended on the resource constraints. In order to formulate an optimization model, we first introduced a 0–1 decision variable $t_m$ to indicate whether the quality characteristic $QC_m$ was selected: if it was selected, then $t_m = 1$; otherwise, $t_m = 0$. In addition, a real decision variable $x_m \in [0, 1]$ was introduced to represent the improvement value of the quality characteristic $QC_m$. Then the MILP for the MOOC quality characteristic optimization is as follows:

$$\max \sum_{n=1}^{N} w_n \times y_n \tag{2}$$

$$\text{s.t. } y_n = \sum_{m=1}^{M} R_{nm}^{Norm} \times x_m \quad n = 1, \ldots, N \tag{3}$$

$$QCL_m \leq x_m \leq QCH_m \quad m = 1, \ldots, M \tag{4}$$

$$x_m \leq t_m \times P_m \quad m = 1, \ldots, M \tag{5}$$

$$\sum_{m=1}^{M} (D_m \times t_m + c_m \times x_m) \leq B \tag{6}$$

$$t_m \in \{0, 1\} \quad m = 1, \ldots, M \tag{7}$$

$$0 \leq x_m \leq 1 \quad m = 1, \ldots, M \tag{8}$$

The objective Equation (2) measures the satisfaction of students with MOOC teaching. $y_n$ indicates the degree of satisfaction of student needs $SR_n$. Formula (3) is based on the normalized matrix $R^{Norm}$ of student needs and quality characteristics and converts the improvement value $x_m$ of each quality characteristic into the realization degree $y_n$ of each student's needs (the improvement of student needs satisfaction is reflected by the improvement of quality characteristics). Constraint (4) ensures that the improvement value of each quality characteristic is within the known technical capability range. The minimum and maximum levels of improvement value for the $m$-th quality characteristic are $QCL_m$ and $QCH_m$, respectively. Constraint (5) indicates that no improvement was made to unselected quality characteristics (ensuring that when $t_m = 0$, $x_m = 0$), $P_m$ represents any number, and when $t_m = 1$, make sure that $t_m \times P_m \geq QCH_m$. Constraint (6) ensures that the total cost of course quality improvement does not exceed the given budget. Note that cost was related to constraints in our optimization model and was not treated as a quality characteristic. The improvement cost of online course quality characteristics was composed of fixed and variable costs. The fixed cost for improving the $m$-th quality characteristic is $D_m$ and the unit variable cost is $c_m$. Then, the total fixed and variable cost cannot exceed the given course budget $B$. Constraint (7) shows that $t_m$ is a binary variable. Constraint (8) limits the value range of $x_m$ to between 0 and 1.

The solving results of the above model gave the key quality characteristics to be improved and their improvement values. We could design targeted course improvement strategies for MOOCs based on the results. This is further discussed in the next section.

## 5. Experiments

### *5.1. Data and Baseline Scenario*

To validate our framework, we performed experiments on data from the course "Information Technology" obtained from a Chinese University's MOOC platform (https://www.icourse163.org/course/CAVTC--1206150813, accessed on 1 May 2023). Based on the methods of Li et al., 2023 [41], we identified 10 student needs for this course: the strong teaching proficiency of instructors $SR_1$, practical content $SR_2$, reasonable course structure $SR_3$, improved vocational skills $SR_4$, convenient teacher–student interactions $SR_5$, support for learning assessment $SR_6$, flexible learning time $SR_7$, moderate course difficulty $SR_8$, smooth learning platform $SR_9$, and rich learning materials $SR_{10}$. The importance $w_n$ of these needs was also calculated.

Using the above data and the method of Section 3, we constructed a house of quality for the baseline scenario (Figure 3). Table 3 shows the five course quality characteristics in this house of quality, as well as the student needs and other characteristics related to these quality characteristics. In this baseline scenario, there was a moderate correlation between student needs and quality characteristics and between different quality characteristics (i.e., the value of $R_{nm}$ was 3 and the value of $\gamma_{km}$ was 0.3 in Figure 3). Accordingly, based on Equation (1), a normalized correlation matrix of student needs and quality characteristics $R^{Norm}$ was obtained.

In addition, we set the course budget to $B = 22$, which meant that the average cost of building a high-quality MOOC was about CNY 220,000. The average unit variable cost $\bar{c}$ for improving the quality characteristics was $\frac{\sum_{m=1}^{M} c_m}{M}$ and the average fixed cost was $\overline{D} = \frac{\sum_{m=1}^{M} D_m}{M}$. In the baseline scenario, it was assumed that the values of $\bar{c}$ and $\overline{D}$ were both within the interval $(0, B)$, and at the median value, that is $\bar{c} = \overline{D} = 11$. Based on this, the values of $c_m$ and $D_m$ were randomly generated (Table 4). Table 4 also provides the data for the technical capability constraints of the quality characteristics ($QCL_m$ and $QCH_m$).

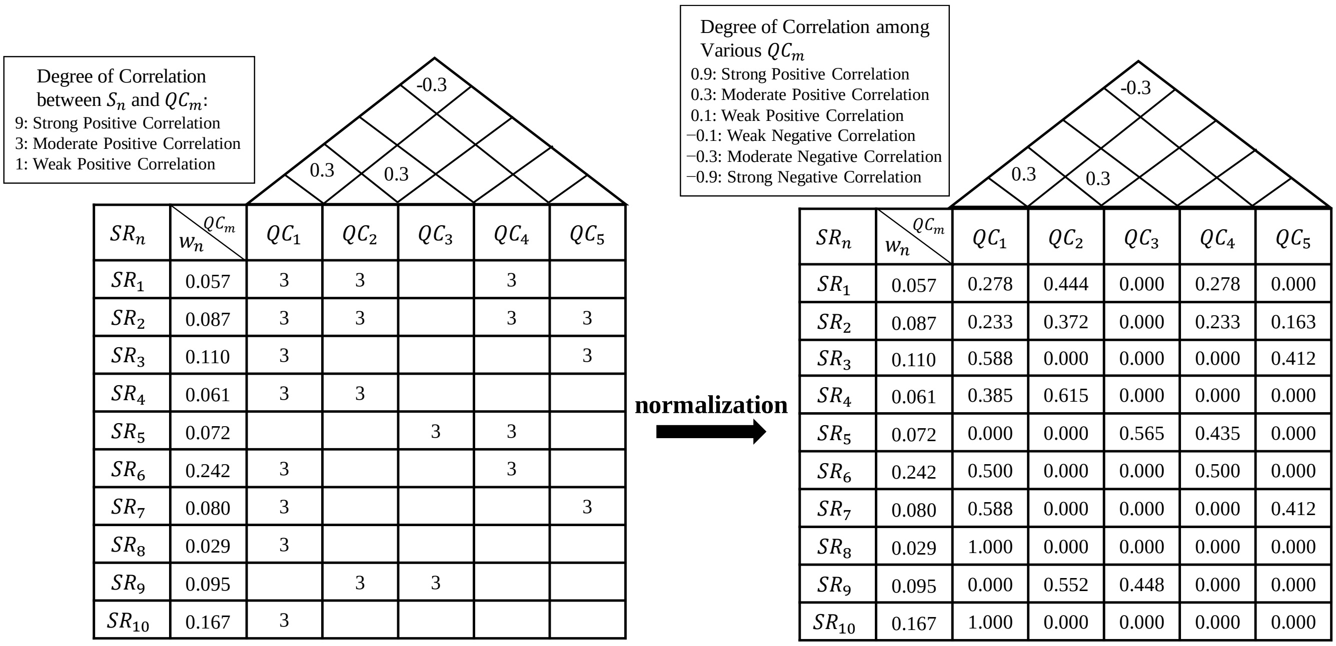


**Figure 3.** House of quality for the baseline scenario.

**Table 3.** Quality characteristics in the baseline scenario.

| Quality Characteristics | Relevant Student Needs | Other Relevant Quality Characteristics |
|---|---|---|
| Online teaching content and resources $QC_1$ | $SR_1$, $SR_2$, $SR_3$, $SR_4$, $SR_6$, $SR_7$, $SR_8$, $SR_{10}$ | $QC_2$ (positive), $QC_5$ (negative) |
| Online teaching methods and techniques $QC_2$ | $SR_1$, $SR_2$, $SR_4$, $SR_9$ | $QC_1$ (positive), $QC_3$ (positive) |
| Online teaching interactivity $QC_3$ | $SR_5$, $SR_9$ | $QC_2$ (positive) |
| Online teaching evaluation methods $QC_4$ | $SR_1$, $SR_2$, $SR_5$, $SR_6$ | |
| Online teaching plan $QC_5$ | $SR_2$, $SR_3$, $SR_7$ | $QC_1$ (negative) |

**Table 4.** Baseline scenario data.

| Quality Characteristics $QC_m$ | Minimum Technical Capability $QCL_m$ | Maximum Technical Capability $QCH_m$(=$P_m$) | Unit Variable Cost $c_m$ | Fixed Cost $D_m$ |
|---|---|---|---|---|
| $QC_1$ | 0 | 0.8 | 11.024 | 11.652 |
| $QC_2$ | 0 | 0.7 | 16.169 | 16.100 |
| $QC_3$ | 0.1 | 0.9 | 5.962 | 5.550 |
| $QC_4$ | 0 | 0.9 | 5.627 | 5.700 |
| $QC_5$ | 0 | 0.8 | 16.218 | 15.998 |

*5.2. Optimization Results for the Baseline Scenario*

We used Lingo 11 to solve the MOOC quality characteristic optimization model for the baseline scenario. For the solving results, the student satisfaction was 24.5%; the key quality characteristics to be improved were $QC_3$ and $QC_4$ ($t_3 = t_4 = 1$), both with improvement values of 0.9 ($x_3 = x_4 = 0.9$). Other characteristics did not need to be improved ($t_1 = t_2 = t_5 = 0$).

Therefore, the MOOC quality improvement policy in the baseline scenario was to improve the quality characteristics of 'online teaching interactivity' and 'online teaching evaluation methods', i.e., to invest as many resources as possible into improving student–peer evaluation, discussion areas, post-class tests, assessment systems, etc. Schools also need to maximize the degree of interaction between teachers and students, as well as between students themselves during the teaching process, and improve various learning evaluation methods such as exercises and homework. Our results were in line with the study of Albelbisi et al. [42], in which they revealed that MOOC quality had a significant influence on satisfaction, indicating that the higher the quality of the MOOCs, the more likely the learners were to be satisfied with using online courses.

### *5.3. Decision Effect Analysis under Different Scenarios*

In this section, we investigate the impacts of budget, cost, and student needs on student satisfaction. This analysis was based on different scenarios generated by varying the baseline scenario. The results provided a valuable reference for decision makers in uncertain environments.

#### 5.3.1. Impact of the Course Budget on Student Satisfaction

To study the impact of the course budget on student satisfaction, we generated four scenarios corresponding to different budget situations. The scenarios were obtained by varying the value of budget ($B$) in the baseline scenario as follows:

- Scenario 1 (SB1): tight budget. The budget was reduced by 20% compared with the baseline scenario.
- Scenario 2 (SB2): low budget. The budget was reduced by 10% compared with the baseline scenario.
- Scenario 3 (SB3): high budget. The budget was increased by 10% compared with the baseline scenario.
- Scenario 4 (SB4): Sufficient budget. The budget was increased by 20% compared with the baseline scenario.

For each scenario, we solved the corresponding quality characteristic optimization model and calculated the growth rate of student satisfaction compared with the baseline scenario. The growth rate of student satisfaction in the four scenarios is shown in Figure 4. It can be found that when the course budget was reduced, student satisfaction decreased. Moreover, the growth rate of student satisfaction doubled or was more than the proportion of the budget increase, while its decline rate was almost proportional to the proportion of budget reduction. This meant that adding a small amount of budget (10%) could significantly improve student satisfaction, while reducing a large amount of budget investment (20%) would not cause a significant decline in student satisfaction. Hew [43] also confirmed that an increase in the course budget led to an improvement in the quality of educational resources. And improving the quality of educational resources could greatly enhance student satisfaction with learning.

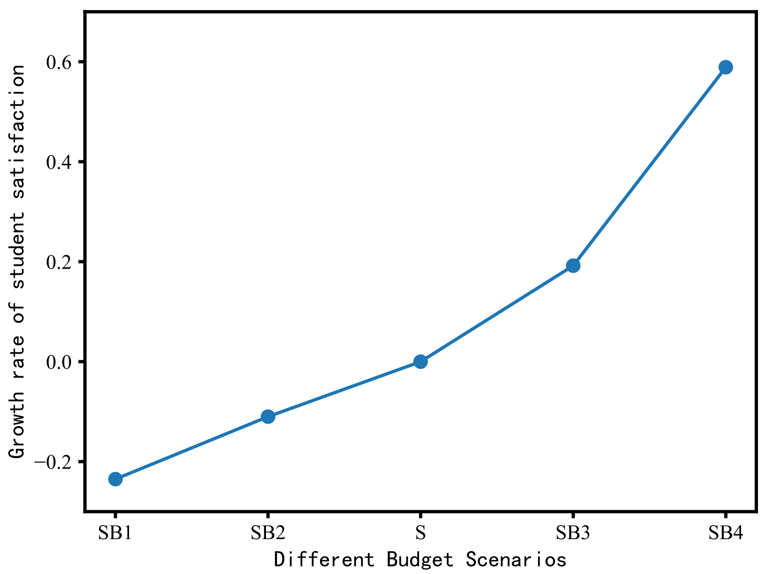


**Figure 4.** Growth rate of student satisfaction under different budget scenarios.

5.3.2. Impact of the MOOC Improvement Cost on Student Satisfaction

This section investigates the impact of the course improvement cost on student satisfaction. The following four scenarios were generated by changing both the variable cost ($c_m$) and fixed cost ($D_m$) in the baseline scenario:

- Scenario 1 (SC1): very low cost. The cost was reduced by 50% compared with the baseline scenario.
- Scenario 2 (SC2): low cost. The cost was reduced by 10% compared with the baseline scenario.
- Scenario 3 (SC3): high cost. The cost was increased by 10% compared with the baseline scenario.
- Scenario 4 (SC4): very high cost. The cost was increased by 50% compared with the baseline scenario.

Figure 5 displays the growth rate of student satisfaction in the four scenarios. We can see that the course cost had a negative impact on student satisfaction. There was a minor variation in student satisfaction when the cost slightly increased or decreased, and the student satisfaction significantly changed when the cost decreased or increased at a high rate. In addition, compared with the average unit variable cost, the average fixed cost had a greater impact on student satisfaction. This was similar to the findings of Hollands and Tirthali [44], in which they suggested that improving the quality of MOOCs required more investment in human, material, and financial resources. For example, appropriately reducing the cost of courses while improving the level of educational resources could enhance the quality of MOOCs and student satisfaction to some extent.

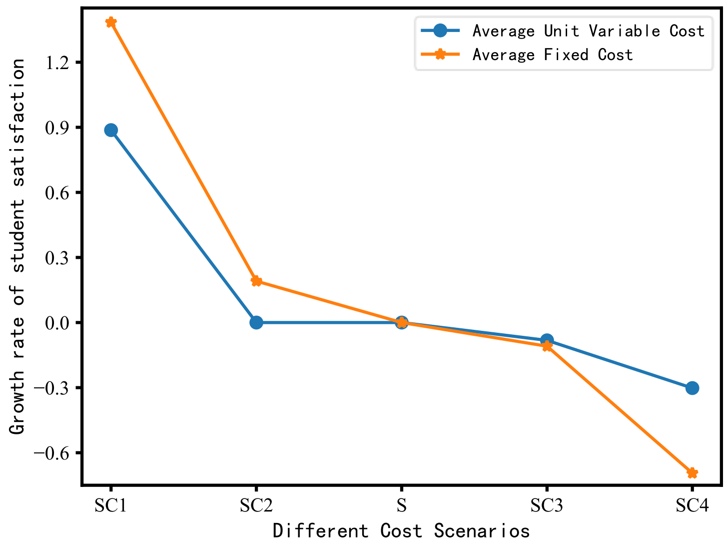


**Figure 5.** Growth rate of student satisfaction under different cost scenarios.

5.3.3. Impact of the Budget and Cost

We were also interested in how the growth rate of student satisfaction changed when course budgets and costs simultaneously changed. Therefore, we generated the following four scenarios by combining scenarios SC2 and SC3 with scenarios SB2 and SB3:

- Scenario 1 (SM1): low budget and low cost. SM1 = SC2 and SB2.
- Scenario 2 (SM2): low budget and high cost. SM2 = SC2 and SB3.
- Scenario 3 (SM3): high budget and low cost. SM3 = SC3 and SB2.
- Scenario 4 (SM4): high budget and high cost. SM4 = SC3 and SB3.

The growth rate of student satisfaction in the four scenarios is shown in Figure 6. It can be seen that when the budgets and costs varied in the same direction, the student satisfaction hardly changed. But, when they decreased or increased in opposite directions, the student satisfaction significantly changed. In accordance with the previous two subsections, since budget and cost were positively and negatively correlated with student satisfaction, respectively, significant changes in student satisfaction occurred when the budget and cost changed in opposite directions. Therefore, appropriately increasing the course budget while reducing the course cost could enhance student satisfaction.

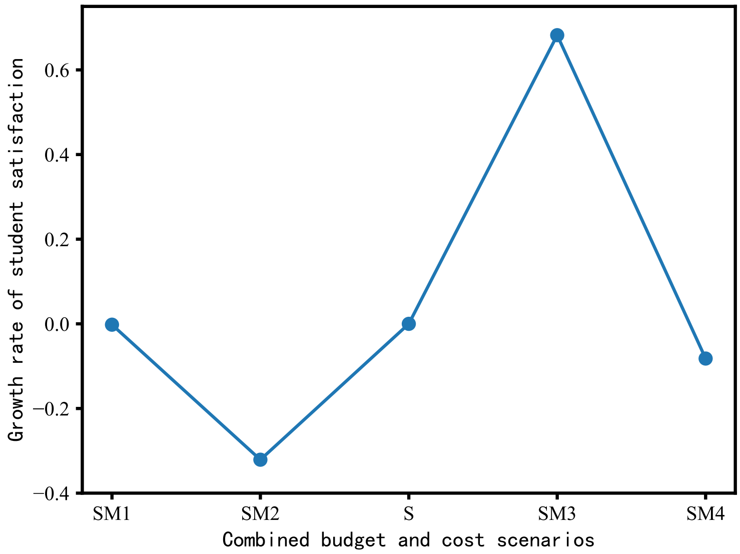


**Figure 6.** Growth rate of student satisfaction under combined budget and cost scenarios.

### 5.3.4. Impact of the Student Needs on Student Satisfaction

This section analyzes the impact of student needs on student satisfaction. We produced two scenarios by changing the importance of student needs ($w_n$) in the baseline scenario: in scenario SW1 (SW2), the average importance of student needs increased (decreased) by 50%. Figure 7 shows the analysis results, and the growth rate of student satisfaction was proportional to the importance of student needs. Our result was also supported by Shang et al. [45], in which they showed that improving student needs could increase student satisfaction with MOOC learning.

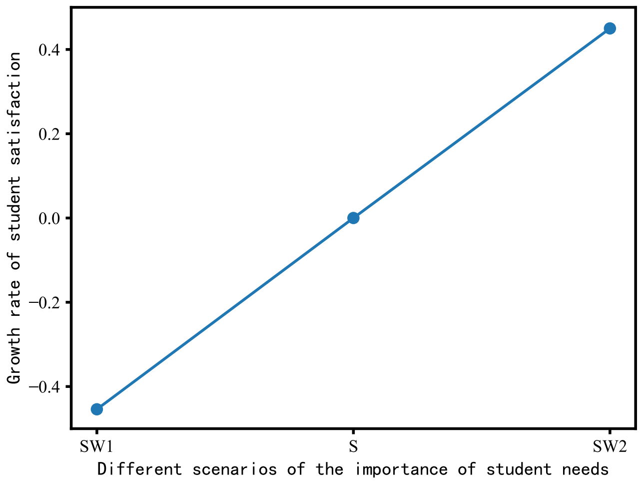


**Figure 7.** Growth rate of student satisfaction under different student needs scenarios.

## 6. Conclusions and Future Research

To support decision making for MOOC quality improvement, we propose a student-needs-driven quality improvement framework for college MOOCs. With this framework, we first mapped students' differentiated needs for MOOCs into quality characteristics based on QFD. Then, we formulated a mixed-integer linear programming model to produce course quality improvement policies, in which we maximized student satisfaction by determining the key quality characteristics and their improvement values. To validate our framework, we performed experiments with real-world data from a Chinese university's MOOC platform. We also investigated the impacts of budget, cost, and student needs on student satisfaction.

Our results showed that student satisfaction was positively correlated with the course budget and negatively correlated with the cost of optimizing quality characteristics. The importance of student needs was proportional to the growth rate of student satisfaction. Additionally, a significant increase in student satisfaction with online learning did not require a substantial increase in the budget, but strict cost control was required. When the course budget slightly decreased or the cost slightly increased, the decrease in student satisfaction was small. However, the decrease in student satisfaction was significant when the course budget decreased and the cost simultaneously increased. Therefore, to significantly improve student satisfaction, the course budget could be increased by a small amount or the cost of quality characteristic optimization could be greatly reduced.

Our student-needs-driven quality improvement framework provides an effective decision-making reference for MOOC educators to improve course quality. Future research should explore the impact of other factors on the improvement of online course quality.

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