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PAPER

Influencing Factors of the Quality of MOOCs Based on the KANO Model

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ABSTRACT

Massive open online courses (MOOCs) represent a new online course and teaching mode, offering targeted instruction and timely services to learners. They have become a key direction for reforming online education. Although MOOCs have experienced significant growth in recent years, the quality of courses published on platforms varies greatly, and scientific quality evaluation mechanisms are lacking. Existing studies on online course quality have primarily relied on questionnaire survey data. In the online environment, an abundance of comment data on platforms reflects learners' perceptions of course quality, and an analysis mode based on learning comments can address the limitations of questionnaire surveys effectively. In this study, comment texts from learners on Chinese university MOOC platforms were chosen as research data. The influencing factors of online open-course quality were analyzed using the KANO model combined with the ordinal Logit regression method. Results demonstrate that system features, video production, teaching level of teachers, usefulness of teaching content, and comprehensiveness of teaching content are essential quality factors. Course-supporting information is considered an expectant quality factor. Teachers' teaching style and course interaction are categorized as engaging quality factors. This study provides valuable insights for improving MOOC quality in Chinese universities.

KEYWORDS

MOOC, influencing factors of course quality, KANO model, online comment analysis, quality improvement

1 INTRODUCTION

Digital technology reform is not only reshaping social production, lifestyles, and governance models comprehensively but is also creating conditions and environments for lifelong learning, thereby making education digitization an important driving force and innovative pathway for high-quality education development. With the comprehensive development of educational informatization, online

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learning has become a primary method for the public to complete their education. Online learning is characterized by its extensive learning objectives and minimal spatial and temporal limitations, playing a vital role in building a lifelong learning society for everyone. Particularly, online courses have become an important learning mode due to the COVID-19 pandemic. In comparison with traditional face-to-face classroom learning, online learning breaks the spatial and temporal limitations, offering richer learning content and more personalized learning experiences. Learners can create personalized learning contents and progress plans based on their abilities. Massive open online courses (MOOCs) from Chinese universities and their applications play fundamental and leading roles in the reform of wisdom education. The organic integration of MOOCs and classroom teaching in Chinese universities aids in the transformation of traditional teaching concepts, innovation in teaching modes, connectivity of teaching environments, and the implementation of teaching management and evaluation reforms, thereby facilitating the digital transformation of higher education effectively. In the future, MOOCs from Chinese universities will achieve greater success in advancing the digital reform of higher education.

On the basis of the openness of the Internet, MOOCs provide tens of thousands of learners worldwide with access to low-cost, high-quality educational resources, effectively promoting educational fairness and balanced development [1]. However, while maintaining rapid growth, MOOC development also faces some challenges [2], such as uneven course quality and poor alignment between content and learners' practical needs [3]. These issues contribute to low completion rates and high dropout rates [4]. Therefore, understanding learners' expectations for MOOC quality is an urgent problem that needs to be addressed for sustainable MOOC development. The usefulness of massive online comment data and the rapid advancement of data-mining technology effectively reveal learners' emotional attitudes and experiences in online course comments [5]. Existing studies have shown that learners' comments on courses are mainly related to course content and emotional experiences [6]. Emotional experiences mainly pertain to learning content, learners, learning forms, learning activities, course resources, and teachers [7]. However, these studies have not comprehensively revealed the relationship between learners' emotional experiences and course-quality factors, nor have they explored differences among various subjects. To further understand learners' expectations for MOOC quality, considering the distinct features and thinking modes of different subjects [8], the present study investigated the influencing factors of MOOC quality in humanities and social sciences and natural sciences using natural language processing (NLP) technology from the learners' perspective, and examined learners' attitudes toward course quality. On the basis of the classification and correlation analysis of the KANO model [9], different levels of influencing factors of MOOC quality were identified from the learners' perspective to improve course quality and promote the popularization and sharing of high-quality educational resources.

2 LITERATURE REVIEW

MOOC quality is not only related to its sustainable development but also influences the learning outcomes and lifelong sustainable development of learners [10]. Existing studies on MOOC quality have mainly focused on the establishment of course-quality evaluation index systems, using methods such as the Delphi method, grounded theory, and analytic hierarchy process to assess course quality [11]. These studies have typically employed a top-down standardized method using established evaluation indexes at the MOOC platform construction level or from the perspective of education experts. However, few studies have considered the actual experiences of learners. With the development of text mining and learning analytics technologies, valuable information from unstructured text is now possible to extract [12], providing a novel approach to understanding learners' experiences of MOOC quality through online comments. Various methods have been used by researchers to evaluate MOOCs, such as employing NLP technology to examine MOOC learners' comments and identify key factors that determine the success of knowledge- and skill-based courses, as well as their correlations [13]. Emotion analysis methods have been used to study business MOOC comments, concluding that teacher quality, course contents, course structure, course evaluation, and learning materials are important factors that influence MOOC learners' experiences [14]. The influencing degree of four aspects of online learning support services (education teaching, curriculum resources, learning facilities, and management services) on continued intention to use MOOC were analyzed [15]. An emotion analysis of comment texts from 137 high-quality online courses for higher vocational education revealed that significant factors affecting learning experiences include course contents, teaching ability, platform functionality, course evaluation, and learning resources [16]. Combined with the questionnaire and the learner's learning experience, a Japanese-language informatization teaching effectiveness model based on MOOC was constructed. The effectiveness of learning Japanese in MOOC learning mode was demonstrated. The results showed that the MOOC-based Japanese informatization teaching effectiveness model could accurately reflect the learner's learning effectiveness of online Japanese learning [17].

Although existing studies have explored the factors influencing course quality from the learners' perspective using MOOC comment data, the quantity and depth of these studies are relatively limited. They have seldom discussed the characteristics and differences between various subjects, and they have not investigated the relationship between emotional experiences and the influencing factors of MOOC quality. Therefore, methods for identifying the influencing factors of MOOC quality in large-scale comment data from online learners must be developed, and the correlations between these factors and the differences among courses of different subjects should be analyzed, ultimately providing suggestions for MOOC optimization.

The KANO model is a two-dimensional model used to analyze factors influencing user satisfaction. It can prioritize factors and identify differences and commonalities among them [18]. The KANO model has been applied in various fields, including product surveys and quality management [19], and has also been used in education research. Some scholars have used the KANO model to analyze questionnaire survey data and discuss MOOC learners' demands for learning support services [20]. In a study, the KANO model was combined with grounded theory to analyze nearly 2,000 learner comments from an online learning platform, examining MOOC quality [21]. Moreover, the KANO model was used to investigate teachers' and learners' evaluations of the functions of teleconference tools to improve tool quality and support learners in achieving their learning objectives [22].

In summary, most studies using the KANO model have focused on designing questionnaires and analyzing questionnaire data. Several Chinese scholars gradually analyzed comment data of learners using the KANO model; however, they did not verify the relationship between the influencing factors of course quality and learner experiences. The KANO model should still be applied to large datasets of different subjects. Therefore, this study aims to identify the influencing factors of MOOC quality at different levels from the learners' perspective, using the KANO model to analyze satisfaction and concern dimensions. A comparative analysis was conducted between humanities and social science courses and natural science courses to understand learners' preferences based on discipline characteristics in large-scale course comments, addressing the gaps in existing studies on the influencing factors of MOOC quality.

3 METHODOLOGY

3.1 Utility of learners modeling based on the KANO model

The KANO model is a useful tool for classifying and prioritizing user needs, invented by Noriaki Kano, a professor at the Tokyo Institute of Technology. Based on analyzing the impact of user needs on user satisfaction, it reflects the non-linear relationship between product performance and user satisfaction [23]. Course-quality factors were classified using the KANO model. The first step involved converting learners' comment text data into structured data for quantitative analysis. Each comment served as a stimulus for the learners' emotional value. The emotions expressed in the online comment text were used as an indicator of learners' satisfaction with the course, thereby constructing a preference estimation model for learners. This preference estimation model can estimate the influence of course-quality factors on learners' satisfaction. It can generally be divided into vector models, ideal-point models, and score function models. In the vector model, utility of learners may exhibit linear growth with the performance of influencing factors. In the ideal-point model, utility of learners may increase with the improvement of factors but decrease once the ideal point is surpassed. The score function model combines the advantages of the vector and ideal-point models, offering high fitness and improved alignment with the KANO classification. Hence, this study utilized the score function model to estimate learners' preferences for quality factors. The score function model can be expressed as follows:

$$U = \alpha + \sum_{j=1}^{n}\left(\beta_j^{pos} X_j^{pos} + \beta_j^{neg} X_j^{neg}\right) \tag{1}$$

where U (utility) refers to the utility of learners. When the online comment is good, the utility of learners equals 1. When the online comment is moderate, the utility of learners equals 0. When the online comment is bad, the utility of learners equals –1.

$X_j^{pos} = 1$ indicates that learners have positive emotions toward a quality factor j of MOOC. $X_j^{neg} = 1$ indicates that learners have negative emotions toward a quality factor j of MOOC. If learners have moderate comments to a quality factor j of MOOC or have not mentioned the quality factor j, X_j^{pos} and X_j^{neg} are 0. $\beta_j^{pos} = 1$ refers to the influencing weight on U when quality factor j has positive comments. $\beta_j^{neg} = 1$ refers to the influencing weight on U when quality factor j has negative comments. The influencing weight of missing values is defaulted at 0.

Given that the values of utility of learners are 1, 0, and –1, it is a type of fixed data. Moreover, X_j^{pos} and X_j^{neg} belong to orderly classification variables because their values are 0 and 1. Hence, the influencing coefficients (β_j^{pos} and β_j^{neg}) of X_j^{pos} and X_j^{neg} in Eq. (1) can be estimated by the ordinal Logit regression method.

According to utility of learners modeling, the difference of utility (*DU*) of variables was established to express the total influencing degree of quality factor *j* from negative to positive comments on utility of learners. The higher value of *DU* indicates the greater influences of the quality factor *j* on the emotions from the learners' comments regarding the course. *DU* can be expressed as

$$\mathrm{DU}_j = \left|\beta_j^{pos} - \beta_j^{neg}\right| \tag{2}$$

The sum of utility (*SU*) of variables was established to reflect the sum of utility of learners in positive comments and in negative comments of the quality factor *j*. When $SU_j > 0$, the positive comments of the quality factor can improve the utility of learners more significantly compared with negative comments. When $SU_j < 0$, the negative comments of the quality factor can decrease the utility of learners more significantly compared with positive comments. *SU* can be expressed as

$$\mathrm{SU}_j = \beta_j^{pos} + \beta_j^{neg} \tag{3}$$

When $\left|SU_j\right| \le \delta \times DU_j$, the quality factor *j* is an expectant quality factor if $SU_j < 0$. When $\left|SU_j\right| > \delta \times DU_j$, the quality factor *j* is an essential quality factor if $SU_j \le 0$, and an engaging quality factor if $SU_j > 0$.

3.2 Index system

With references to the online top-class approval indexes from the Ministry of Education of the People's Republic of China and building upon the research findings of several scholars, certain course-quality conceptual categories were adjusted, combined, and deleted. Finally, eight course-quality conceptual categories were identified; namely, system features, video production, teachers' teaching style, teaching level of teachers, course interaction, usefulness of teaching content, comprehensiveness of teaching content, and course supporting information. These course-quality conceptual categories were used as the influencing factors of MOOC quality for KANO analysis. The quality factors of MOOC are presented in Table 1.

Table 1. Quality factors of MOOC

Level-1 Indexes	Signs	Level-2 Indexes	Signs
Video production	X1	Whether the video can display course content information explicitly.	X11
		Whether the video has explicit sound, such that users can hear the teacher clearly, without generating excessive cognitive loads.	X12
		Whether the video has subtitles and whether the courseware is produced accurately.	X13
		Whether the video length is moderate.	X14

(Continued)

Table 1. Quality factors of MOOC *(Continued)*

Level-1 Indexes	Signs	Level-2 Indexes	Signs
Teachers' teaching style	X2	Whether teachers explain profound theories in simple language and can stimulate emotions of students with humorous styles.	X21
		Whether the accent of teachers is standard, and whether teachers teach the knowledge at moderate speed and in a clear voice.	X22
Teaching level of teachers	X3	Whether teachers have explicit ideas and teach the knowledge thoroughly.	X31
		Whether the knowledge is transferred effectively and accurately. Whether students are guided to think positively.	X32
Course interaction	X4	Whether teachers interact and communicate with students in class and after class.	X41
		Whether teachers answer students' questions timely and effectively.	X42
Usefulness of teaching content	X5	Whether the knowledge and questions involved in the teaching content are accurate.	X51
		Whether the authority is high enough, so that students have no doubts about accuracy and scientificity of the teaching content.	X52
Comprehensiveness of teaching content	X6	Whether the teaching content is comprehensive and thorough and covers extensive knowledge ranges.	X61
		Whether examples help students to understand the knowledge points and stimulate their learning interests.	X62
Course supporting information	X7	Whether the supporting homework and special exams are moderately difficult and have extensive application users.	X71
		Whether the assisting data of the course is accurate and convenient for download, without causing troubles to learning of students.	X72

4 RESULTS ANALYSIS

4.1 Collection and preprocessing of online comment data

Learners' comment information was obtained from the MOOC platform of Chinese universities and used for KANO analysis of course-quality factors, facilitating iterative optimization of MOOC quality. In this study, 1,183 user comments on the Advanced Mathematics course from the official MOOC website of Chinese universities were collected as the data source. The "Octopus Collector 8" network information collection tool was used to gather webpage information. Each comment data included the comment content, commentator, user scores, comment time, class attendance rate, and number of thumbs up. The collected user comments were saved in an Excel file. Subsequently, each user comment underwent preprocessing, which involved the deletion of repeated comments, comments with missing information (e.g., "very good" and "good" comments that do not provide valid information), default system comments, and comments from users with low class attendance rates. Invalid data might influence integrity and reasonableness of the data, thereby influencing the data analysis results. In total, 789 user comments were collected.

Following the estimation method of the quality factors' influence coefficient, the structured comment data underwent Logit regression analysis using Matlab2014b software. Upon review, the estimated values of each influencing factor of MOOC quality were obtained (Table 2).

Table 2. Estimated values of the influencing factors of MOOC quality

Signs	Quality Indexes	β^{pos}	β^{neg}
X1	Video production	–0.092	0.122
X2	Teachers' teaching style	–0.119	0.047
X3	Teaching level of teachers	–0.066	0.106
X4	Course interaction	–0.159	0.05
X5	Usefulness of teaching content	–0.023	0.167
X6	Comprehensiveness of teaching content	–0.075	0.107
X7	Course supporting information	–0.108	0.034

Data were reviewed, and the *DU* and *SU* values of each quality factor were calculated according to Eqs. (2)–(4), as shown in Table 3.

Table 3. DU and SU values of each quality factor

Signs	Quality Indexes	β^{pos}	β^{neg}
X1	Video production	0.214	0.03
X2	Teachers' teaching style	0.166	–0.072
X3	Teaching level of teachers	0.172	0.04
X4	Course interaction	0.209	–0.109
X5	Usefulness of teaching content	0.19	0.144
X6	Comprehensiveness of teaching content	0.182	0.032
X7	Course supporting information	0.142	–0.074

4.2 KANO analysis of course quality factors

Based on the user comment data for the Advanced Mathematics course on the Chinese universities' MOOC platform, all the data was consolidated through KANO analysis. The sum of each property under each index was calculated, resulting in the total frequency of 16 properties. The KANO model analysis results are summarized in Table 4. According to the KANO model's property classification method, the index's final quality category was determined by the factor with the highest frequency. Specifically, X21 and X22 are engaging attributes; X62 and X72 are expectant attributes; X11, X12, X41, and X52 are essential attributes; X13, X31, X32, X42, X51, and X61 are undifferentiated attributes; X14 and X71 are reverse attributes.

Table 4. Summary of KANO model analysis results

Functions/ Services	A	O	M	I	R	Q	Classification Results
X11(Z) and X11(F)	14.14%	15.15%	36.36%	34.34%	0.00%	0.00%	Essential attributes
X12(Z) and X12(F)	9.09%	13.13%	39.39%	38.38%	0.00%	0.00%	Essential attributes
X13(Z) and X13(F)	12.12%	5.05%	28.28%	42.42%	2.02%	10.10%	Undifferentiated attributes
X14(Z) and X14(F)	0.00%	0.00%	0.00%	28.28%	47.47%	24.24%	Reverse attributes
X21(Z) and X21(F)	58.59%	1.01%	2.02%	31.31%	4.04%	3.03%	Charming attributes
X22(Z) and X22(F)	68.69%	20.20%	2.02%	5.05%	3.03%	1.01%	Charming attributes
X31(Z) and X31(F)	12.12%	10.10%	27.27%	45.45%	5.05%	0.00%	Undifferentiated attributes
X32(Z) and X32(F)	4.04%	5.05%	11.11%	50.51%	7.07%	22.22%	Undifferentiated attributes
X41(Z) and X41(F)	5.05%	4.04%	31.31%	28.28%	21.21%	10.10%	Essential attributes
X42(Z) and X42(F)	4.04%	4.04%	14.14%	42.42%	30.30%	5.05%	Undifferentiated attributes
X51(Z) and X51(F)	4.04%	0.00%	0.00%	54.55%	38.38%	3.03%	Undifferentiated attributes
X52(Z) and X52(F)	6.06%	24.24%	52.53%	10.10%	4.04%	3.03%	Essential attributes
X61(Z) and X61(F)	16.16%	3.03%	10.10%	40.40%	25.25%	5.05%	Undifferentiated attributes
X62(Z) and X62(F)	10.10%	39.39%	7.07%	21.21%	21.21%	1.01%	Expectant attributes
X71(Z) and X71(F)	7.07%	0.00%	0.00%	22.22%	68.69%	2.02%	Reverse attributes
X72(Z) and X72(F)	2.02%	44.44%	0.00%	27.27%	2.02%	24.24%	Expectant attributes

4.3 KANO model analysis of better–worse coefficients

On the basis of existing studies, the exponential algorithm, which calculates the influence degrees of customers' better or worse demands, was integrated into the KANO model. To investigate the indexes of quality factors, better (when the factor is sufficient) and worse (when the factor is insufficient) coefficients must be considered. Table 5 shows the calculated results.

Table 5. Numerical statistics of refined indexes of quality factors based on better–worse coefficients (absolute, %)

Refined Indexes	Better	Worse	Refined Indexes	Better	Worse
X11(Z) and X11(F)	29.29%	–51.52%	X41(Z) and X41(F)	13.24%	–51.47%
X12(Z) and X12(F)	22.22%	–52.53%	X42(Z) and X42(F)	12.50%	–28.13%
X13(Z) and X13(F)	19.54%	–37.93%	X51(Z) and X51(F)	6.90%	0.00%
X14(Z) and X14(F)	0.00%	0.00%	X52(Z) and X52(F)	32.61%	–82.61%
X21(Z) and X21(F)	64.13%	–3.26%	X61(Z) and X61(F)	27.54%	–18.84%
X22(Z) and X22(F)	92.63%	–23.16%	X62(Z) and X62(F)	63.64%	–59.74%
X31(Z) and X31(F)	23.40%	–39.36%	X71(Z) and X71(F)	24.14%	0.00%
X32(Z) and X32(F)	12.86%	–22.86%	X72(Z) and X72(F)	63.01%	–60.27%

The KANO model results show the percentages of the six attributes and classification results. Classification results based on the better–worse coefficients refer to the attribute with the highest percentage among the six attributes. Better (satisfaction influence) and worse (dissatisfaction influence) coefficients were used to assess users' sensitivity to changes in function/service levels. *Better* (satisfaction influence) = (A + O)/(A + O + M + I) and ranges between 0 and 1. A higher *Better* value indicates greater sensitivity and higher priority. *Worse* (dissatisfaction influence) = –1 x (O + M)/(A + O + M + I) and ranges between –1 and 0. A smaller *Worse* value indicates greater sensitivity and higher priority.

4.4 Quadrant diagram analysis of better–worse index and management strategies

To further understand user satisfaction and dissatisfaction conditions, a four-quadrant diagram was used to illustrate the distribution of all quality factor indexes (Figure 1). In this diagram, the *Better* value represents the x-axis, and the absolute value of *Worse* represents the y-axis. The mean of the *Better* value and the mean of the absolute value of *Worse* were used to plot the center lines of the x- and y-axes, respectively. Each quadrant represents different meanings, which is helpful for Chinese universities' MOOCs to select appropriate management strategies based on the characteristics of each quadrant.

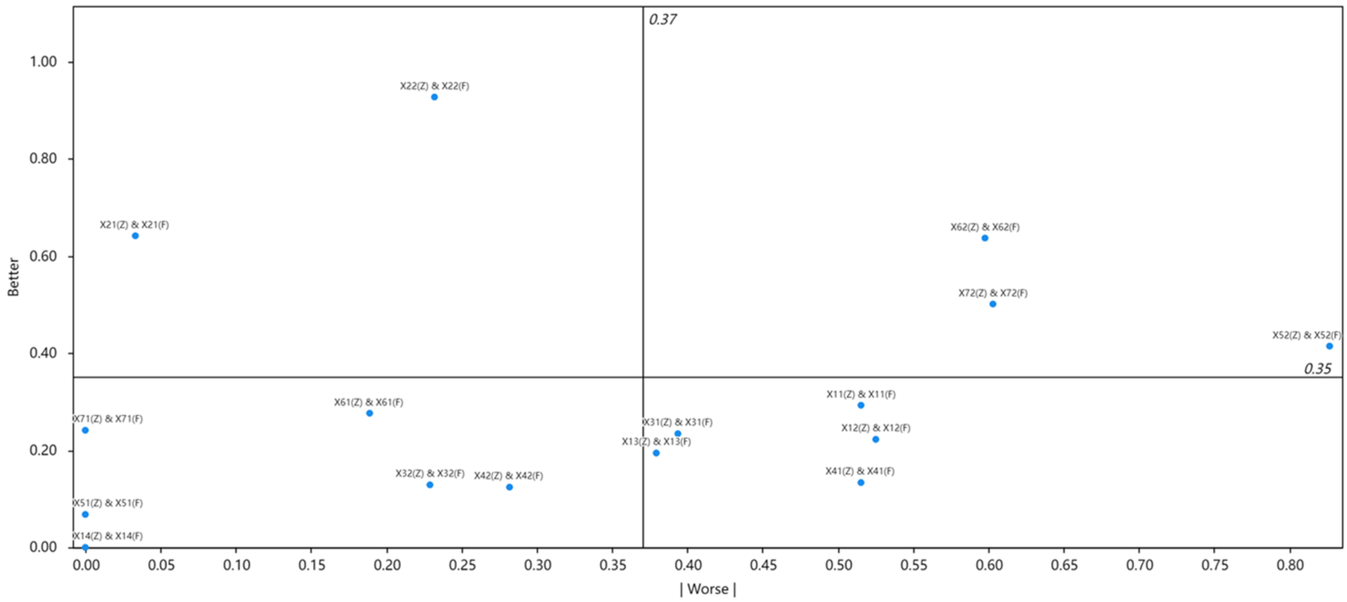

Fig. 1. Diagram of better–worse coefficient

(1) First quadrant: This quadrant contains low *Better* values and low *Worse* values. The factor indexes in this region (i.e., X14, X51, X71, X61, X32, and X42) neither enhance user satisfaction nor prevent user dissatisfaction. To address these indexes, Chinese universities' MOOC developers can: 1) reduce resource input and concerns appropriately, eliminate these indexes if necessary, and minimize unnecessary costs and time consumption; and 2) analyze issues based on practical conditions, improve these indexes, and attempt to transform into improving quality.

(2) Second quadrant: This quadrant contains high *Better* values and high *Worse* values. Factor indexes in this quadrant (i.e., X21 and X22) warrant sufficient attention to enhance user satisfaction and prevent user dissatisfaction. These quality factors are suitable for applying positive service management strategies in E-commerce and should be prioritized for optimization, given limited resources. Thus, Chinese universities' MOOC developers need to invest in innovative construction.

(3) Third quadrant: This quadrant contains high *Better* values but low *Worse* values. Factor indexes in this quadrant (i.e., X62 and X72) can significantly improve user satisfaction but only marginally prevent user dissatisfaction. This characteristic allows Chinese universities' MOOC developers to implement positive management strategies effectively. To enhance user satisfaction, developers should pay particular attention to these indexes.

(4) Fourth quadrant: This quadrant contains low *Better* values but high *Worse* values. Service quality indexes in this quadrant (i.e., X31, X13, X41, X12, X11, and X52) can effectively prevent user dissatisfaction but cannot significantly improve user satisfaction. Chinese universities' MOOC developers should prioritize these indexes to address or prevent user dissatisfaction issues during the service. This method is suitable when developers adopt negative management strategies. Effectively resolving problems in these indexes can significantly improve user dissatisfaction.

4.5 Discussion

In this study, key influencing factors of a national high-quality course were identified from the learners' perspective by combining the KANO model and ordinal Logit regression method based on MOOC comment data. This approach allowed gaining a deep understanding of learners' preferences and provided new ideas for evaluation of MOOC quality. Moreover, an modified quadratic inference functions (MQIF) diagram was plotted based on correlation analysis and KANO analysis results, aiming to help course operation teams recognize the key influencing factors and internal relationships of MOOC quality. This approach has important implications for MOOC optimization and construction. The results reveal the essential attributes of a high-quality MOOC that learners value and uncover the course's differences at various levels of the KANO model.

(1) Essential quality factors: Learning platforms should prioritize system development and webpage maintenance to ensure a stable, smooth operating environment with comprehensive "system features" that provide a positive user experience. Course producers must improve the recording quality of course videos, ensuring appropriate video length, clear visuals, crisp audio, and complete subtitles. Teachers should design teaching content meticulously, considering comprehensiveness, difficulty level, and logical progression to ensure "usefulness of teaching content." Finally, only highly qualified teachers should be selected for course production to guarantee excellent "teaching level of teachers." Addressing these essential quality factors can reduce negative feedback and lay the foundation for improving learner satisfaction.

(2) Expectant quality factors: Course producers should carefully choose homework and exam contents, ensuring moderate difficulty and diverse question types within the scope of knowledge. Moreover, they should promptly upload desired supplementary materials and verify their accuracy, reliability, and availability for download. This approach can provide online learners with a wealth of learning resources.

(3) Engaging quality factors: Teachers should incorporate appropriate question prompts into their lessons to increase learner engagement and focus. In post-class discussions, teaching assistants and teachers should interact with students as much as possible, addressing their questions promptly and effectively to realize "course interaction" reasonably. This approach can boost positive feedback from learners and improve overall teaching quality.

5 CONCLUSIONS

Determining the influencing factors and types of Chinese universities' MOOCs is crucial for guiding the effective iterative optimization of online course quality and holds significant implications for implementing national "top-level class plans" and provincial "top-level class construction plans." On the basis of the actual comments of learners on online course platforms, such as Chinese universities' MOOCs, the influencing factors of MOOC quality are extracted using grounded theory. The influencing factors of online course quality are analyzed by combining the KANO model and ordinal Logit regression method. The results demonstrate that: (1) "video production of courses," "teaching level of teachers," and "usefulness of teaching content" are essential quality factors. "Course supporting information" is an expectant quality factor. "Teachers' teaching style" and "course interaction" are engaging quality factors. (2) The Octopus Collector's big data are transformed into structured comment data for Logit regression analysis, providing estimated values for each influencing factor of online courses. This method allows the major influencing factors of MOOC quality of Chinese universities to be analyzed, thereby obtaining comprehensive and reliable evaluation results. (3) The KANO method increases the scientificity of evaluation results if it is used for the systematic evaluation of the MOOC quality of Chinese universities. The MOOC quality evaluation index system of Chinese universities should be further improved through interviews and questionnaire surveys, and research objects should be expanded in the future.

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