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A hybrid DEMATEL and social network analysis model to identify factors affecting learners' satisfaction with MOOCs

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A R T I C L E I N F O

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A B S T R A C T

Massive Online Open Courses (MOOCs) offer free access to training in various topics in all fields. However, the low percentage of course completion by learners is a significant challenge for these platforms. Previous studies on this challenge have investigated user behavior and concerned topics in discussion forums, but these data are mostly momentary and cannot be used for long-term improvement. Thus, this study aimed to address this gap by analyzing learners' comments to identify the factors affecting user satisfaction and prioritize them to improve MOOC platforms. The purpose was to analyze the feedback and actual experiences of users shared through their comments on MOOC online platforms to explore factors affecting user satisfaction to optimize MOOC platforms. To achieve this, sentiment analysis and topic modeling techniques were applied to the user feedback on courses with popular topics, such as Skills for Data Science Teams and Data-Driven Decision Making, available on Coursera.com. The study used DEMATEL analysis, which uses a relation matrix of factors to rank them based on their interrelationships, and network analysis to prioritize the factors that should be improved to achieve the highest user satisfaction. The effect of the proposed approach was investigated through a case study on a course from Coursera. The findings demonstrate that the suggested method has the potential to assist MOOC platforms in several ways. Firstly, it enables the identification of course strengths and weaknesses. Secondly, it allows for the identification of factors that influence learner satisfaction by analyzing user feedback. Lastly, it aids in prioritizing the factors that should be enhanced to attain optimal user satisfaction, thus leading to overall improvement in the status of the MOOC platform.

1. Introduction

Massive Open Online Courses (MOOCs) have resulted in important educational developments aimed at unlimited participation and free access to high-quality educational resources. Despite all strengths of these platforms, there are also some challenges. One of these challenges is users' dissatisfaction with the quality of platform services, resulting in a low completion rate of courses (between 7% and 20%) [1–4]. The question arising here is, "What does a user expect from online courses?"

Numerous studies have been conducted to answer this question. In most of them, scholars have concentrated on the user interface (UI) of MOOC systems, learners' interaction with MOOC sites, and their experiences [5,6]. Some studies showed that a group of

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learners dropped out of courses due to the bad user experience of these platforms in all stages of learning. The deficiencies in providing appropriate services can lead to users' dissatisfaction and cause them to drop out (Firdaus and Surarso [7]).

Some researchers tried to validate successful MOOCs to understand their success factors in fulfilling learners' needs. They concluded that the three distinct factors of (1) system quality, (2) attitude, and (3) course quality has a significant influence on learner satisfaction in MOOC platforms [8,9].

The previous studies have not considered learners' perspectives to investigate their satisfaction and improve MOOC systems. While some studies have explored users' behavior and their concerns through examination of discussion forums [10,11], the data extracted from these forums mostly pertain to transient issues and are insufficient for long-term improvements. Consequently, it is more beneficial to utilize the comments section, where learners share their genuine course experiences and opinions. Recognizing this gap, our research focuses on analyzing learners' comments as a starting point. The primary objective of this study is to analyze user feedback and actual experiences, as shared through comments on MOOC online platforms. This analysis aims to identify the key factors that influence user satisfaction and prioritize them, leading to the development of a plan to enhance MOOC platforms and ultimately increase user satisfaction. The following are the main questions of our research:

1. What are the factors affecting MOOC users' satisfaction based on their opinions?

The purpose of this question is to identify the main influential factors by analyzing users' feedback on courses and investigating the effect of these factors on user satisfaction. This will enable us to understand different aspects of learners' satisfaction by analyzing their actual experiences and feelings shared on the online platform.

2. What is the relationship between these factors?

Users, in their comments, mention the influential factors together. Mentioning multiple factors in the comments can be modeled as a graph/network. From this network, the possible clusters, the centrality of each factor in the network and the degree of impact and effectiveness of the factors in the whole network are determined and based on this, the factors are prioritized to achieve an improvement plan.

3. How are these factors prioritized to improve the quality of MOOC platforms?

The goal of this question is to find the most important factors based on the analysis of users' feedback. To achieve higher user satisfaction, platform owners should focus on these factors to plan for improving the online MOOC platforms.

To answer the questions above, we performed an analysis of learners' comments on the courses with popular topics that are available via Coursea.com, with text analysis techniques to identify perceptions. In addition, with the help of network analysis techniques, we determined the priority of each factor to improve the quality of MOOCs.

Due to the high cost and time required to address all factors for enhancing service quality on MOOC platforms, it becomes crucial to prioritize them. Additionally, it is essential to take into account the interdependencies among these factors during the prioritization process. In order to demonstrate the efficacy of this approach, conducting a case study was indispensable. Through this case study, we effectively highlighted our contribution towards improving MOOC systems.

In the following sections, we first review the literature on this subject. Then, the methodology of the study is explained. In the end, the results of a case study conducted on a course on Coursera.com are presented and discussed.

2. Literature review

2.1. MOOC design quality

The quality of design in MOOC platforms is one of the important factors affecting learners, teachers, and other users. Based on the results of previous studies, MOOC design indicators can be categorized into six categories as follows: instructional design, assessment, user interface, video content, social tools, and learning analytics, among which the last category is the most important one [12–14]. In addition, Jansen, and Rosewell [15] showed that Quality needs to be assured at institutional and course levels simultaneously, the focus must include process and outcome product.

On the other hand, the quality of services can be considered a part of design quality. To investigate the quality of services, Firdaus and Surarso [7] evaluated the gap between users' perceptions and expectations. Their results indicated that reliability exhibited the largest disparity, whereas assurance showed the smallest difference. However, there remained a significant gap between the overall expectations and the users' perception.

User experience is one of the crucial factors affecting design quality. Since there is a high rate of dropout among MOOC students, a study should be conducted to solve this problem [5,6]. The high dropout rate can be a consequence of inadequate design features that affect users' experiences. To enhance these features, their effectiveness should be analyzed and optimized. Additionally, in certain instances, the development of new features may be necessary. For instance, implementing an automated dialogue-based system within the MOOC platform could enable 24/7 response to learners' inquiries in a cost-effective manner [16].

Quality of teaching is another critical element of design quality. It is crucial to design an online course that can teach learners effectively. Liu [17] reported investment time, course content, chapter objectives, course objectives, education level, learning motivation, learning time, learning participation, and academic examination as the factors affecting the teaching. They also showed that investment time, course content, chapter objectives, and course objectives had the most significant impacts among all factors.

Since the design quality of MOOC platforms plays a vital role in their effectiveness, it is essential to study the weaknesses and strengths of design. Accordingly, we investigated users' opinions on design quality to optimize the effectiveness of platforms.

2.2. Dropout

In addition to the numerous advantages offered by MOOC platforms, there are several challenges that affect their effectiveness. As previously mentioned, one of these challenges is the high dropout rate experienced within these systems. Extensive research has been conducted on this issue, exploring various reasons and factors contributing to course non-completion. For instance, enrollment out of interest in exploring the course content may lead to not completing the course. Similarly, encountering highly challenging course material may lead to early dropout. Moreover, users may also discontinue their participation due to a negative user experience [6].

Likewise, Onah et al. [18] have identified several reasons for learners' dropout: no real intention to complete, lack of time, course difficulty and lack of support, lack of digital skills or learning skills, bad experiences, expectations, starting late and peer review. According to some studies [19–23], bad experience includes inappropriate behavior of peers in forums, lack of focus and coordination

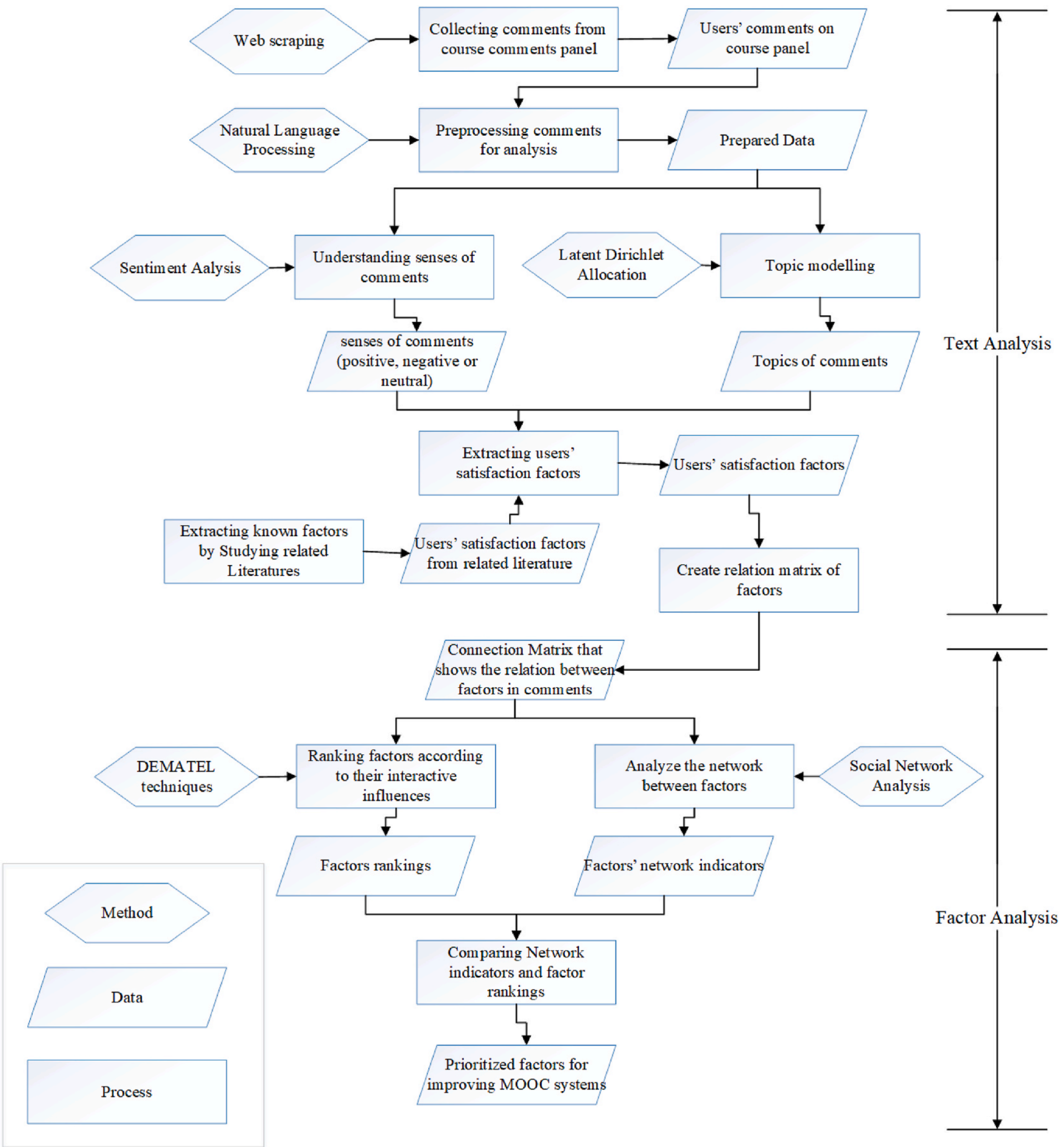

Fig. 1. The research methodology.

in forums, depletion of study groups due to attrition, poor quality and incorrect learning materials, and technical problems in the MOOC platform.

In some research, the context of dropout was investigated from the angle of continuance intention to use MOOC platforms. For instance, Gamage et al. [1] have explored the factors affecting users' continuance intention to use MOOC platforms. The results of Gamage's study showed that the perceived usefulness and user satisfaction are the key factors affecting users' continuance intention to use MOOC platforms. In similar studies, from comparing the perceived user experience with the users' expectation, the results indicated expectation fulfillment affects users' satisfaction, thus affecting the continuance intention [2,3].

Due to the influence of user experience on the dropout rate of learners and their satisfaction level, we investigated users' opinions on this matter to find proper ways of optimizing MOOC platforms with the aim of improving users' satisfaction.

2.3. Learners' satisfaction

The satisfaction of learners is the key to success in MOOC platforms. Plenty of factors, such as system quality, attitude, and course quality, influence users' satisfaction [8]. Moreover, users' intentions can be highly influenced by their satisfaction levels [24]. Some studies have also shown that user satisfaction is influenced by course quality, entertainment value, and course usefulness [24,25].

The comments sections of courses offer valuable insights into user satisfaction. Previous studies examining comments have revealed a significant correlation between satisfaction, flow, and interest, which in turn influence user behavior. Consequently, users can be categorized into two distinct groups: completers and non-completers. These groups have differences in their interactions on MOOC platforms. Completers tend to share their comments actively, expressing satisfaction upon obtaining certification. In contrast, non-completers tend to react to others' opinions and express their dissatisfaction with technical issues [26–28].

As another resource to understand the users' satisfaction, discussion forums can be analyzed to investigate the feelings of the learners, ways of increasing knowledge, challenges, and needed tools in these forums [10]. However, there is a problem with them. Since only the learners who enroll in the courses can participate in discussion forums, other potential learners cannot know the participants' opinions about the courses.

Since analyzing data to investigate users' satisfaction is time-consuming, some scholars have provided multiple options to make it easier and faster. For example, Zhang Liu [29] used machine learning methods for data analysis. The findings can be valuable for learners in determining the suitability of a course for their needs. Additionally, teachers can utilize these results as feedback on their instructional efforts. Moreover, employing the LDA method, theme analysis, and a multi-level approach in conjunction with student evaluation of teaching (SET) on a large scale can provide further assistance [30]. Latent Dirichlet Allocation (LDA), as a topic modeling method, extracts the topics of comments based on the meaning and understandable concepts of words in a text.

A review of previous works on discussion forums and comment panels revealed a gap in the analysis of user opinions to improve the quality of courses and platforms. In the comments section, learners can talk about their whole experiences of a course [31], giving other users and instructors useful insights. Accordingly, in this paper, we used Natural Language Processing models, that work by finding relationships between the constituent parts of language, to analyze the users' comments on courses along with relying on insights from previous studies that gave us on processing comments and text data [29–31]. While previous studies [8,17] focused on finding the existing factors of effective MOOCs and user satisfaction, we aim to identify users' major concerns and problems to improve their satisfaction level and optimize MOOCs.

3. Methodology

As mentioned earlier, the comments section of a course, exclusively accessible to learners, serves as a valuable resource for gaining insights into their satisfaction factors. To initiate our investigation, we collected learners' comments and employed text analysis techniques to prepare the data. Subsequently, we conducted two stages of analysis, as illustrated in Fig. 1. In the first stage, sentiment analysis and topic modeling were employed to identify the most influential factors affecting learners' satisfaction. In the second stage, two methods were applied for factor analysis to examine the interplay of factors within the system. Firstly, fuzzy methods such as DEMATEL were utilized to measure the mutual effects of factors on one another. Secondly, network analysis methods were employed to assess the network indicators of these factors. Finally, the results obtained from the DEMATEL method and network analysis were compared to prioritize the factors. Fig. 1 provides an overview of the entire process undertaken to achieve the objectives of this research.

3.1. Text analysis

3.1.1. Data collection

To achieve the research goal, it was necessary to gather all the comments provided by learners in the course comments sections. Given the multitude of MOOC platforms offering numerous courses, we decided to narrow our focus and selected Coursera as our case study. In Coursera, courses are rated on a scale of one to five stars, based on user feedback, and courses with higher ratings generally tend to receive a greater number of positive comments. Initially, we tested the proposed model on 10 highly rated courses, and subsequently expanded our analysis to include an additional 90 courses. These 90 courses were selected from nine popular topics that attracted a substantial number of learners. From each topic, we chose four courses with lower ratings and six courses with higher ratings for our analysis. Employing Python, we utilized web-scraping techniques to collect the comments from the Coursera website.

The data collected in this phase included the texts of the comments and the ratings assigned by the users for the courses. Since we wanted to find the most important factors of user satisfaction, we had to consider both negative and positive comments. Sentiment analysis reveals whether a comment is negative or positive.

3.1.2. Data preprocessing

The data had to be prepared for analysis. To this end, it was necessary to eliminate any noises, punctuation marks, stop-words, web URLs, and numbers. We used the NLTK (Natural Language Toolkit) library of Python to remove these components of comments, as shown in Fig. 2. Afterward, our data was ready for analysis.

For the next part of the research, we first needed to comprehend the sentiment (positive, negative, or neutral) and topics expressed in the collected data. To achieve this, we employed machine-learning methods to analyze the sentiments and topics present in the comments. Additionally, we gathered the established factors of user satisfaction from the findings of previous research. By combining these known factors, the sentiment of the comments, and the identified topics, we extracted the factors influencing user satisfaction, categorizing them into strengths and weaknesses. Once the factors were identified, we employed two parallel methods to examine the networks and relationships between them. The DEMATEL method was utilized to assess the impact of each factor on the others, while simultaneously; we analyzed the communication network between the factors using Gephi software. Ultimately, the results obtained from these two methods were compared to determine the prioritization of factors relative to one another. The following explains two stages of the analysis performed in this research:

3.1.3. Sentiment analysis

Sentiment analysis algorithms are used to understand the sense of the speeches or texts. To this end, researchers train machines with large datasets of words with their embedded emotions and establish these algorithms to be used by other researchers. These algorithms indicate whether a comment has a positive, negative, or neutral theme as senses of speeches and texts. We used sentiment analysis algorithms to specify each of the extracted factors as weaknesses or strengths.

A combination of the TF-IDF algorithm [32,33] and SVM classification [34,35] was applied to find the sentiment of each comment. The TF-IDF method was used to convert text to vectors that could be classified in the SVM method. The TF-IDF (Eq. (1)), IDF (Inverse Document Frequency) (Eq. (2)), and TF (text frequency) (Eq. (3)) were calculated as follows:

$$(word, doc) = TF(word, doc) * IDF(word) \tag{1}$$

$$TF(word, doc) = \frac{Frequency\ of\ words \in doc}{Number\ of\ words \in doc} \tag{2}$$

$$IDF(word) = \log\left(1 + \frac{Number\ of\ docs}{Number\ of\ docs\ with\ word}\right) \tag{3}$$

After converting texts into vectors, we used the SVM method to classify the comments as positive, negative, or neutral. In this classification, we specified each factor of a comment as a weakness or a strength.

3.1.4. Topic modeling

Topic modeling is a technique to understand the main purpose of dialogue or part of a conversation. We needed to use the available algorithms of topic modeling, which other researchers have already trained and tested them, and every other research fellow can use them in their investigations.

In our analysis, we employed the LDA model in Python to extract the topic of each comment. LDA, which stands for Latent Dirichlet Allocation, operates on the principle that every document comprises a combination of topics, and each topic is composed of a mixture of words. Therefore, comments contain latent topics that can be discerned from particular words. Fig. 3 shows the main concept of the LDA algorithm.

In this figure, each letter denotes a variable, as follows:

M: Number of documents
N: Number of words in each document (N_i words for document i)
α: Prior parameter of the Dirichlet distribution for topic distribution in each document
β: Prior parameter of the Dirichlet distribution for word distribution in each topic
θ_i: Topic distribution in document i
φ_k: Word distribution in topic k
Z_{ij}: Topic of the jth word in document i
W_{ij}: each specific word

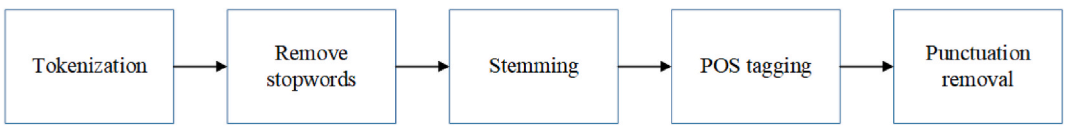

Fig. 2. The preprocessing flowchart.

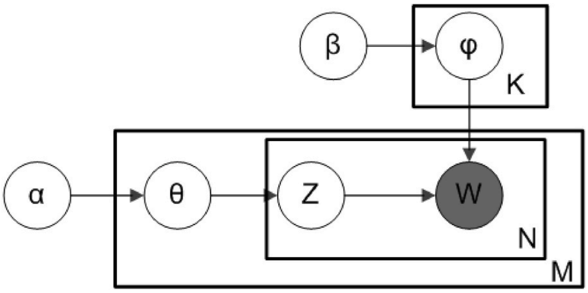

Fig. 3. LDA algorithm for topic-word distribution.

In this algorithm, the only observable variable is W, and the others are latent. The LDA algorithm follows this generative process:

1. As an input, we assume that the number of topics (K) is known and fixed.
2. The algorithm scrolls through the document and randomly assigns each word in each document to one of the topics. From this step, i and k can be achieved
3. To improve the obtained distributions of the last step, the algorithm repeats the following steps for each text:
   a. Repeat the following steps for each word j in the text
   b. Calculate two factors for each topic:
      1. A fraction of the words in document i that are attributed to topic k, i.e., p (topic k | document i)
      2. A ratio of all the texts attributed to topic k provided they have the word j, i.e., p (word j | topic k)
   c. Assign a new topic to j. For this purpose, select the new topic of the word j from the available topics with the possibility of p (topic k | document i) *p (word j | topic k). According to our generative model, this is precisely the probability that the topic k created the word j. In fact, at this point, it is assumed that all topics attributed to all words, except word j, are correct. Therefore, using the model of the probability distribution of the previous step, the topic of word j is calculated and then updated.

After repeating the above steps in large numbers, a relatively constant situation is reached in which the topics attributed to each word no longer change, and the resulting model is the thematic model of the text collection.

3.2. Factor analysis

3.2.1. Creating relation matrix

We gathered satisfaction factors from previous studies, combined them with the extracted topics, and determined sentiments of the comments in order to pinpoint the factors influencing user satisfaction. Through analyzing the emotions expressed in comments, whether positive, negative, or neutral, and comparing the modeled topics with the factors identified in other previous studies, we were able to determine whether a specific factor, derived from a comment, represents a weakness or strength for the overall system.

After defining the factors, a matrix of relationships between them, i.e., $Z = [z_{ij}]_{n \times m}$, was created. If two factors were present in a comment, we put 1 in their relationship array; otherwise, it was set considered 0.

3.2.2. DEMATEL

The DEMATEL method uses a relation matrix of factors to rank them based on their interrelationships [36]. From the results of this method, factors would be categorized as influence dispatcher factors or influence receiver factors [37]. To categorize the factors, we needed to go through the following steps:

Step 1. Normalizing the connection matrix $Z = [z_{ij}]_{n \times m}$ to calculate the normalized matrix $X = [x_{ij}]_{n\times m}$ (Eq. (4), Eq. (5) and Eq. (6)) and:

$$0 \le x_{ij} \le 1 \tag{4}$$

$$X = s.Z \tag{5}$$

$$s = \frac{1}{Max_{1\le i\le n} \sum_{j=1}^{n} Z_{ij}} i,j = 1,2,\dots n \tag{6}$$

Step 2. Calculating the total-relation matrix (T) (Eq. (7)), which indicates the relations between factors are direct or indirect. In the equation below, I is the identity matrix.

$$T = X(I - X)^{-1} \tag{7}$$

Step 3. Calculating the summation of each row and column of the matrix T. R is the sum of the row vectors of T, showing the influence of each factor on others. J is the sum of the column vectors, showing the influence of other factors on each of them.
Step 4. Calculating (R + J) and (R- J) for each factor. A diagram is plotted whose x-axis and y-axis are (R + J) and (R-J), respectively, as shown in Fig. 4.

The high value of (R + J) shows that a factor is both dispatching and receiving, while a high value of (R-J) means the activity is more likely to dispatch the influence. In other words, we have the following logic:

- If R > J → R-J>0 → The factor is influence dispatcher.
- If R < J → R-J<0 → The factor is influence receiver.
- Factors with high positive values of (R-J) are called dispatchers.

3.2.3. Network analysis

With the help of Gephi software [38], we analyzed the networks between factors. We used the normalized connection matrix $X = [x_{ij}]_{n\times m}$. We drew a network whose nodes and edges were the factors of matrix X and the relations between them, respectively. The Gephi provided the network metrics, such as betweeness centrality, closeness centrality, authority, and modularity class of each factor.

Betweeness centrality is a value assigned to each node of a graph showing its influence. This metric is a more important statistical property of a network. It is applied in numerous real-world problems, such as finding influential people in a social network, finding crucial hubs in a computer network, and finding border-crossing points, which have the largest traffic or trade flow. The betweeness centrality of a node is an indicator of its centrality or importance in the network. It is the ratio of the number of shortest paths between all pairs of network nodes passing through node i to the total number of shortest paths in the network. The betweeness centrality of node x can be calculated as (Eq. (8)):

$$g(x) = \sum_{s\neq x\neq t} \frac{\sigma_{st}(x)}{\sigma_{st}} \tag{8}$$

where σ_{st} is the total number of shortest paths from node s to node t, and $\sigma_{st}(x)$ is the number of paths that pass through node x.

The closeness centrality of each node shows how much it is close to others. It indicates how long it takes for information from a given node to reach other nodes in the network. The smaller the value, the more central role the node plays in the network. It is equal to the reciprocal of the sum of the length of the shortest paths between a node and all other nodes in the graph (Eq. (9)):

$$C(x) \frac{1}{\sum_y d(y,x)} \tag{9}$$

where d(y,x) is the distance between vertices x and y.

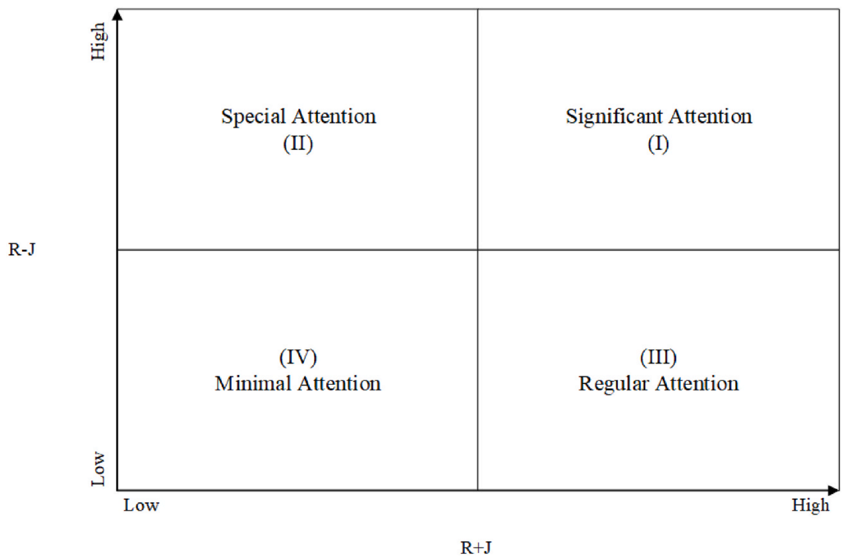

Fig. 4. DEMATEL matrix.

3.3. Prioritizing the factors based on their influence on other factors and network indicators

To understand the priority of each node, we needed to compare their network metrics with each other. Since the betweeness centrality can be cited more than other network indices in determining the effect of a node in the graph, to compare the results of network analysis and DEMATEL analysis, we only compared the value of R with the value of the betweeness centrality. In the DEMATEL approach, each node with a higher R-value (influence of each node on others) has a higher priority in comparison to its peers.

In order to prioritize the factors based on their influence on other factors and network indicators, we adopted a management matrix, as shown in Fig. 5. The vertical axis represents the value of R in the DEMATEL technique, and the horizontal axis represents the betweenness centrality index of the obtained network.

The factors in the significant attention segment (I) are crucial for MOOC systems, as they influence other factors. Therefore, every benefactor of the MOOC system should pay close attention to them and prioritize them for improvement since improving these factors has a direct impact on other factors. The factors in the special attention segment (II) need to be planned for long-term improvement. The factors in the regular attention segment (III) need to be noticed regularly and checked timely to ensure that they are in good condition. While the factors in the minimal attention segment (IV) are not considered a priority for improvement and should only be noted once other factors are improved enough.

3.4. Case study

In order to demonstrate the practical implications of our research, we conducted a case study on one of the courses offered on the Coursera platform. The primary objective of this case study was to investigate the operational impacts of our research. To achieve this, we selected a course from a popular topic that had an average rating compared to other courses. Choosing a course from a popular topic ensured that we had an adequate number of comments to analyze. Furthermore, by selecting a course with an average quality rating, we could gather a range of positive and negative comments, allowing us to gain insights into user satisfaction.

In this case study, we utilized sentiment analysis to comprehend the sentiments expressed by learners in the comments of the selected course. Additionally, we employed topic-modeling techniques, which were previously used for factor extraction, to identify the topics discussed in each comment. Through this analysis, we were able to identify the factors influencing learner satisfaction for this particular course.

By comparing the findings from this case study with the results obtained from the DEMATEL and Social Network Analysis, we validated the applicability of our methodology in understanding user satisfaction and identifying strategies to enhance courses to meet user expectations.

4. Results

The purpose of this study was to identify the factors affecting learners' satisfaction by analyzing their opinions and ultimately prioritizing these factors to improve MOOC systems. To this end, besides reviewing similar previous studies and extracting the factors identified in them, we extracted and reviewed the opinions of users of Coursera.com as MOOC platforms shown in Table 2. These comments included the opinions of Coursera's users who had registered in different courses on popular topics, which are expressed in

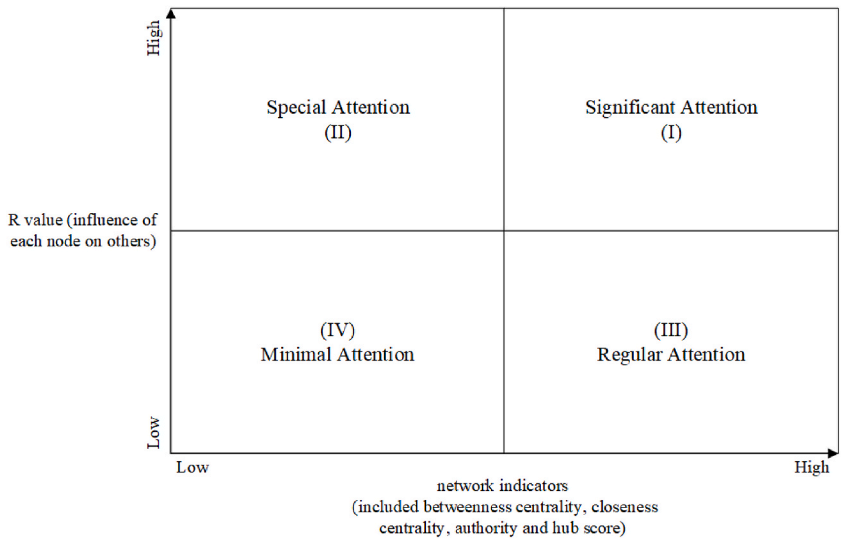

Fig. 5. Management matrix for prioritizing the factors.

the comments section of courses. The demographic characteristics of users are unknown as they are not publicly accessible.

Coursera.com incorporates a rating system that relies on users' evaluations of their course experiences. Courses are assigned ratings ranging from one to five stars, reflecting the cumulative assessments provided by users. A higher star rating indicates a course that has satisfied users across various aspects, whereas lower-rated courses tend to receive more comments that are negative and higher-rated courses tend to receive more positive comments. Notably, courses with ratings below 3 are not displayed on the platform.

For our research, we found value in both positive and negative comments to identify the most significant course features from the users' perspective. To achieve this, we selected 20 courses from popular topics for each rating category (from 1 star to 5 stars). We analyzed the comments posted by users in the respective comment sections of these courses. Approximately 40% of the comments were extracted from courses rated below 3, while the remaining 60% were obtained from courses rated above 3. In total, this section yielded nearly 12,000 comments for analysis.

The popular topics considered for course selection are (1) Skills for Data Science Teams, (2) Data-Driven Decision Making, (3) Software Engineering Skills, (4) Management Skills, (5) Marketing Skills, (6) Skills for Sales Teams, (7) Product Manager Skills, (8) Skills for Finance and (9)Web Developer Career Guide. We decided to use them because these topics attracted more learners, which would be helpful for us in validation of the results. In each topic 10 courses were selected for the analysis (4 of them were chosen from the courses with rates lower than 3 and the other 6 courses from the courses with rates above 3).

To test the proposed model, 10 courses that are shown in Table 1 and have a popularity rate above 3 were selected. These courses have enough number of enrolments and comments. After the test results fulfilled our expectations, we considered another 90 courses.

After using the NLTK library in Python to prepare the text data for analysis (Table 3), we analyzed the preprocessed data using the LDA algorithm and sentiment analysis methods (Table 4). In parallel, the factors affecting satisfaction were collected from the results of previous studies. After extracting the topics and sentiments from users' comments, by matching them with the factors obtained from the literature, the following factors (Table 5) were identified as factors affecting user satisfaction in MOOC platforms. Based on the sentiment analysis, factors having a W code were created to analyze the impact of negative indicators, and factor codes beginning with the letter S were created to examine the impact of positive indicators.

Once the factors were identified, we proceeded to construct a relationship matrix (see Appendix 1). For this purpose, we examined the factors in pairs and assigned a value of 1 to the corresponding cell in the matrix if two factors coexisted in one or more user comments. This process was carried out using Python data frame codes. Subsequently, we normalized the matrix using the formulas outlined in the previous section to prepare it for factor analysis techniques (see Appendix 2). The matrix was then analyzed using two models simultaneously: DEMATEL and network analyses.

In this part of the research, after presenting the factors and the network obtained from their relations, the results of the analyses are presented.

The final factors obtained are classified into five groups as follows:

1. Factors related to the content of the courses. These factors are associated with the textual content of the courses, including video scripts, exercise text, quizzes, and their impact on learners.
2. Factors related to course instructors. These factors concern the course instructors and their assistants. User comments primarily address the performance of the instructors and analyze their influence on user satisfaction.

Table 1
Examples of courses.

Subject	Name of the Course	Course Description	Course Rate	# of Enrollment	# of Reviews
Finance	Python and Machine Learning for Asset Management	This course will enable you mastering machine-learning approaches in the area of investment management.	3.1	15,070	126
Mobile and Web Development	How to Create a Website in a Weekend!	Teach design, build, and publish a basic website that incorporates text, sound, images, hyperlinks, plug-ins, and social media interactivity.	3.3	189,980	194
Data Analysis	Clinical Natural Language Processing	This course teaches the fundamentals of clinical natural language processing.	3.5	4592	10
Statistics	Causal Inference	This course offers a rigorous mathematical survey of causal inference at the Master's level.	3.3	15,057	28
Machine Learning	Reinforcement Learning for Trading Strategies	The final course from the Machine Learning for Trading specialization	3.6	13,712	59
Data Analysis	Analyzing Big Data with SQL	An in-depth look at the SQL SELECT statement and its main clauses.	4.9	24,703	140
Machine Learning	Natural Language Processing with Probabilistic Models	An introduction to NLP Probabilistic models such as Hidden Markov model.	4.7	54,481	258
Business Essentials	Excel Fundamentals for Data Analysis	The fundamentals of Excel for data analysis in business.	4.8	117,305	795
Sustainability	GIS Data Acquisition and Map Design	The aim of this course is to teach GIS data gathering for projects, and create well-designed maps.	4.9	23,603	173
Statistics	Improving your statistical inferences	This course aims to help you to draw better statistical inferences from empirical research.	4.9	67,738	247

Table 2
Example of raw comments.

Stars	Comment
2	<p>Many NLP concepts were left out of this course including ontologies, preferred terms, synonyms, linguistic wildcards, negation etc. When is the next class in the specialization offered?<p>
1	<p>Don't believe what coursera says<p>Coursera advertised the course as "at your own place" what a lie. After completing the course I had to pay another $100 just to wait for the final assignment to be marked to get my certificate. <p>The courses for the specialization keep getting pushed back, so you have to shell out a subscription for another month while you wait for them to come out. <p>I've spent far more time paying just to wait than actually doing any of the course materials.<p>
1	<p>Errors in tasks. Missing data for final quiz. The whole NLP thing in R is REGEXPS (sic!). Time wasting.<p>
1	<p>Extremely poor course. No usefull information, proposed NLP is regexps on R <p>
3	<p>Everything regarding content was amazing and easy to learn, the only issue was the evaluation of the last test to get the certification, I waited for over a month and had to pay two times more in the meantime. Quite frustrating to say the least. <p>
4	<p>Very interesting and useful. A few glitches in the multiple choice questions during the tests.<p>
2	<p>The material given are interesting but more explanation as an educating and teaching material should be included especially regarding the big query usage.<p>I love to learn but this course urged me to unenroll due to lack of educational material regarding the course <p>I tried my best and even had to web search more info and youtube search to learn more because the course content was not enough <p>And with all the time spent and effort to complete this course i found it impossible to be complete. Which was a big disappointment to me <p>
5	<p>Excellent course. Well paced, well thoughtout and put together.<p>
4	<p>The course details an approach of NLP which is efficient. It may open to other technics used in this field as ML. The next course ?<p>

Table 3
Example of prepared data.

Row	Comment
0	pmany nlp concepts were left out of this course including ontologies preferred terms synonyms linguistic wildcards negation etc When is the next class in the specialization offeredp
1	pdont believe what coursera saysppcoursera advertised the course as at your own place what a lie after completing the course i had to pay another just to wait for the final assignment to be marked to get my certificateppthe courses for the specialization keep getting pushed back so you have to shell out a subscription for another month while you wait for them to come outppive spent far more time paying just to wait than actually doing any of the course materialsp
2	perrors in tasks missing data for final quiz the whole nlp thing in r is regexps sic time wastingp
3	pextremly poor course no usefull information proposed nlp is regexps on r p
4	peverything regarding content was amazing and easy to learn the only issue was the evaluation of the last test to get the certification i waited for over a month and had to pay two times more in the meantime quite frustrating to say the least p
5	pvery interesting and useful a few glitches in the multiple choice questions during the testsp
6	pthe material given are interesting but more explanation as an educating and teaching material should be included especially regarding the big query usageppi love to learn but this course urged me to unenroll due to lack of educational material regarding the course ppi tried my best and even had to web search more info and youtube search to learn more because the course content was not enough ppand with all the time spent and effort to complete this course i found it impossible to be complete which was a big disappointment to me p
7	pexcellent course well paced well thoughtout and put togetherp
8	pthe course details an approach of nlp which is efficient it may open to other technics used in this field as ml the next course p

3. Factors related to the structure of courses. These factors revolve around the overall organization and structure of the courses. This includes course materials, videos, financial and certification aspects, as well as valuable features and workshops provided within each course.
4. Factors related to the effects of courses. These factors are linked to the effects of the courses on users after the commencement of the learning process. They can be assessed by examining the courses' usefulness for individuals with diverse goals.
5. Factors related to course support. These factors pertain to the support provided to learners throughout the course, addressing any issues or concerns they may encounter.

After identifying the factors, we examined their effects on the communication network. Using the two techniques of DEMATEL and network analysis, the effect of each factor on others and network indicators were determined (Appendix 3 and 4).

4.1. DEMATEL and social network analysis results

Based on the DEMATEL analysis, helpful peers (S17), good for self-learning courses (S23), difficult exercises (W12), challenging courses (W16), bad instructors (W17), bad assistants (W18), and useless labs (W20) were obtained as dispatcher factors, i.e., they have a greater influence on other factors. The two factors of too many auto grader issues in assignments (W27) and need for guidance in projects (W36) were independent factors, not affecting or being affected by others.

From the results of the DEMATEL method, we classified the factors based on the values of R-J and R + J. Fig. 6 shows the classification chart of factors. According to the results of the DEMATEL analysis, the factors located above the x-axis are more effective than others are. This suggests that by improving these factors, other parts of the system will also improve. Fig. 6 shows the classification of attention to each group.

Table 4
Example of outcomes of LDA model.

Row	Comment	need to teach more NLP models	need unnecessary payments	errors in tasks	missing data for final quiz	not useful lab	need to web search	good course
0	pmany nlp concepts were left out of this course including ontologies preferred terms synonyms linguistic wildcards negation etc When is the next class in the specialization offeredp	1						
1	pdont believe what coursera sayspp coursera advertised the course as at your own place what a lie after completing the course i had to pay another just to wait for the final assignment to be marked to get my certificatepp the courses for the specialization keep getting pushed back so you have to shell out a subscription for another month while you wait for them to come outppive spent far more time paying just to wait than actually doing any of the course materialsp		1					
2	perrors in tasks missing data for final quiz the whole nlp thing in r is regexps sic time wastingp			1	1	1		
3	pextremly poor course no usefull information proposed nlp is regexps on r p						1	
4	peverything regarding content was amazing and easy to learn the only issue was the evaluation of the last test to get the certification i waited for over a month and had to pay two times more in the meantime quite frustrating to say the least p		1					1
5	pvery interesting and useful a few glitches in the multiple choice questions during the testsp				1			1
6	pthe material given are interesting but more explanation as an educating and teaching material should be included especially regarding the big query usageppi love to learn but this course urged me to unenroll due to lack of educational material regarding the course ppi tried my best and even had to web search more info and youtube search to learn more because the course content was not enough ppand with all the time spent and effort to complete this course i found it impossible to be complete which was a big disappointment to me p	1					1	1
7	pexcellent course well paced well thoughtout and put togetherp							1
8	pthe course details an approach of nlp which is efficient it may open to other technics used in this field as ml the next course p	1						

Based on the results of DEMATEL method, we have factor priorities as Table 6. Since the main purpose of this study is based on the effect of the factors in their networks, the R value, which shows the influence of each factor on others, is chosen as our scale for prioritization. According to Table 6, from the first group factor “clear and complete content (S1)”, from the second group factor “well-explained materials (S13)”, from the third group factor “good and short videos (S20)” and from the forth group factor “good for self-learning (S23)” have the highest priority among other factors in the same group.

According to Table 7, the highest values of centralities, authority, and hub score belong to factor S1, and the highest value of betweeness centrality has been obtained for factor W7. This table also shows that factors W10, W27, and W36 have the lowest values of obtained indicators among all factors.

Fig. 7 demonstrates the graph of the relationships between the factors. This graph is obtained from the analysis of the relationship matrix between the factors using the Gephi software. As shown in Fig. 7, the factors located in the middle of the network are more important and effective in the network. The betweeness centrality of these factors is higher than others are, due to its association with more factors. In contrast, the factors in the corners are less important and effective due to the lack of centrality and other network characteristics. Factors W27 and W36 are independent of other factors and are separate from others in the graph.

In the next step, we used the management matrix to examine the priority of each factor. Since the betweeness centrality is more reliable than other network indicators in determining the effect of a node in the graph, to compare the results of network analysis and DEMATEL analysis, we only compared the value of the influence of each factor on others (R) with the value of the betweeness centrality. In the management matrix shown in Fig. 8, the vertical axis represents the value of R in the DEMATEL technique, and the horizontal axis represents the betweeness centrality index of the obtained network. To divide this matrix into four parts according to Fig. 8, we used the average of each of the R values and betweeness centrality.

By summarizing the results shown in Fig. 8, Table 7, and the DEMATEL matrix in Fig. 6, the final prioritization of factors was

Table 5
Final factors affecting user satisfaction.

Type	Code	Factor	Type	Code	Factor
Factors related to the content of the courses	S1	clear & complete content	Factors related to the structure of courses	S14	good course material
	S2	Applicable content		S15	useful lab
	S3	good resources		S16	provide helpful features
	S4	easy exercises		S17	helpful peers
	S5	valuable content		S18	good design
	S6	Visible results		S19	well organized (structure, assessments and Quizzes)
	S7	easy to understand		S20	good & short videos
	S8	great Quizzes and Assignment		S21	Free Course
	S9	good quality		W19	need unnecessary payments
	S10	engaging course		W20	useless lab
	S11	easy to follow		W21	worst course of specialization
	W1	broken assessment		W22	Bad course materials (videos. Slides)
	W2	errors in lectures		W23	just fast & short videos only provide reading materials
	W3	problems in quizzes		W24	misleading description & name for course
	W4	need more exercises		W25	need more time for learning and practice
	W5	need more details		W26	need lab
	W6	Errors in tasks		W27	Too many auto grader issues in assignments
	W7	Missing data for final quiz		W28	problems with certification
	W8	confusing content	Factors related to the effects of courses	S22	Good for job
	W9	repeated contents from previous courses		S23	good for self-learning
	W10	Poor exercises		S24	good for students
	W11	simple theory		S25	good for PhD students & researchers (scientist) specially social scientists
	W12	difficult exercises		S26	good for all experience levels
	W13	Advertising Content		W29	least practical
	W14	need references		W30	not helpful
	W15	workbooks need update		W31	need prior knowledge
	W16	Challenging		W32	need more finance application
Factors related to course instructors	S12	good instructor		W33	not informative
	S13	well explained		W34	not good for developers
	W17	bad instructor	Factors related to course support	W35	no Answers in discussion forums
	W18	bad instructors (PhD students)		W36	need guidance for projects

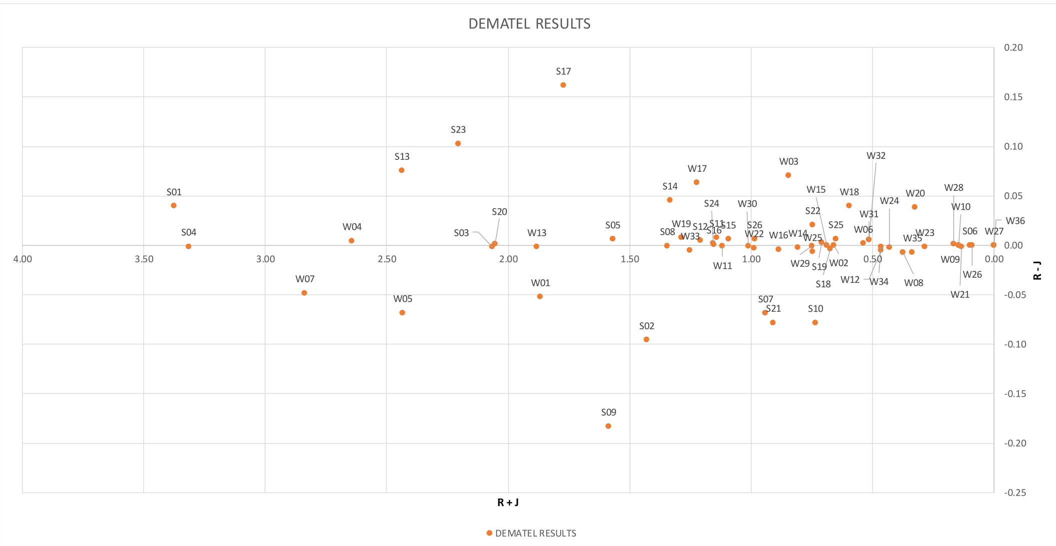

Fig. 6. DEMATEL results and classification based on attention.

Table 6
Factor priority and their groups based on R value of DEMATEL results.

Type	Code	R	Priority	Type	Code	R	Priority
Factors related to the content of the courses	S1	1.56	1	Factors related to the structure of courses	S14	0.54	20
	S2	0.52	21		S15	0.41	27
	S3	0.96	8		S16	0.45	25
	S4	1.45	2		S17	0.78	11
	S5	0.62	15		S18	0.25	42
	S6	0.04	59		S19	0.26	41
	S7	0.37	31		S20	0.79	10
	S8	0.61	17		S21	0.30	37
	S9	0.66	13		W19	0.61	16
	S10	0.27	40		W20	0.14	53
	S11	0.49	22		W21	0.05	58
	W1	0.74	12		W22	0.41	26
	W2	0.24	44		W23	0.11	54
	W3	0.34	34		W24	0.16	50
	W4	1.11	4		W25	0.39	28
	W5	1.00	6		W26	0.03	60
	W6	0.20	47		W27	0.00	61
	W7	1.19	3		W28	0.07	55
	W8	0.14	52	Factors related to the effects of courses	S22	0.28	38
	W9	0.06	56		S23	0.96	7
	W10	0.06	57		S24	0.47	23
	W11	0.56	19		S25	0.24	45
	W12	0.24	46		S26	0.37	32
	W13	0.88	9		W29	0.27	39
	W14	0.37	33		W30	0.37	29
	W15	0.33	35		W31	0.19	48
	W16	0.37	30		W32	0.19	49
Factors related to course instructors	S12	0.45	24		W33	0.57	18
	S13	1.10	5		W34	0.25	43
	W17	0.63	14	Factors related to course support	W35	0.16	51
	W18	0.31	36		W36	0.00	62

determined. As shown in Fig. 8, factors of the first category require significant and constant attention for system optimization due to their high impact numbers (R) and remarkable betweeness centrality. Factors of the second category need special attention, contrary to other factors.

Herein, special attention is devoted to long-term planning for the related factors so that they are continuously planned to improve. Such planning needs to be implemented due to the high impact of these factors on others. Moreover, low attention means that the related factors are not very important compared to others. It is better to consider related factors when the most important factors are in their optimal state or when optimizing these factors is required.

As can be seen in the results, the following factors are among the strengths of these platforms, which have a great impact on user satisfaction: clear and complete content (S1), good resources (S3), easy exercises (S4), valuable content (S5), good quality (S9), good instructor (S12), well-explained materials (S13), good and short videos (S20), good for self-learning (S23), and good for all experience levels (S26). On the other hand, need for more exercises (W4), need for more details (W5), missing data for final quizzes (W7), advertising content (W13), and bad instructors (W17), as major weaknesses in MOOC systems, have a negative impact on user satisfaction and need to be minimized. Based on the prioritization results, these factors fall into the category that requires significant attention, and since all factors are related to course providers, the result obtained in this section can be used to provide users with valuable courses. It is suggested that the managers of these training platforms consider these factors in reviewing the performance indicators of providers.

The next category of the prioritized factors includes the strengths of the platforms in offering applicable content (S2), great quizzes and assignments (S8), easy-to-follow courses (S11), good course materials (S14), useful labs (S15), helpful features (S16), helpful peers (S17), and good for students courses (S4). On the other hand, the weaknesses of the platforms in broken assessments (W1), need for unnecessary payments (W19), and not informative courses (W33). In this category, which needs special attention, it is necessary to form well-written and long-term planning to maintain the strengths at their best while eliminating the negative points.

In the regular attention group, we had a simple theory (W11), bad course materials (W22), and need for more finance applications (W32), as the weaknesses of MOOC systems that had to be noticed regularly and checked timely to ensure that they are in good condition.

According to the results, other factors were considered in the minimal attention group, i.e., they are not considered a priority for improvement and should only be noted once other factors are improved enough.

4.2. Case study

By conducting a case study on one of the courses of Coursera named as "Reinforcement Learning for Trading Strategies" by Jack

Table 7
Order of factors based on network indicators and R values.

Rate	closeness centrality	betweeness centrality	Authority	Hub-Score	R	Rate	closeness centrality	betweeness centrality	Authority	Hub-Score	R
1	S01	W07	S01	S01	S01	32	W34	S15	W29	W16	S07
2	S04	S01	S04	S11	S04	33	W29	S10	W14	W22	S21
3	W07	S04	W07	S04	W07	34	W02	W30	S22	W29	W14
4	W04	W04	S13	S13	W04	35	W15	W15	S24	W14	S22
5	S13	W11	W04	W07	S13	36	S22	W08	W03	S21	W29
6	W05	W05	W05	W04	W05	37	S24	S26	S19	S19	W25
7	S03	S03	S03	S03	S23	38	W06	W02	W16	W15	S19
8	W13	W17	W13	W05	S03	39	S10	W18	W15	S10	W15
9	W01	S05	W01	W13	S20	40	S11	W34	W34	W34	S18
10	W17	S12	S09	S17	S17	41	S26	S22	S25	S18	W02
11	S09	S13	S20	W01	W13	42	W12	S24	S18	S25	S25
12	S17	W13	S08	S20	W01	43	S18	W29	W02	W02	S10
13	S20	S09	S05	S08	S05	44	S19	W20	W31	W18	W18
14	S08	S20	W19	W33	S09	45	S23	W23	W32	W31	W06
15	W19	W22	W33	S09	S14	46	W18	W06	S23	W32	W31
16	W33	S17	S02	S05	S08	47	W31	S18	W06	S23	W32
17	S02	W01	S17	W19	S02	48	W32	W35	W18	W06	W34
18	S12	W12	S14	W17	W19	49	S25	S11	W12	W12	W12
19	S05	W25	W17	S14	W17	50	W35	S19	W35	W35	W24
20	S15	W19	S15	S02	W33	51	W24	S23	W08	W08	W08
21	S14	S02	S12	S15	S12	52	W08	W31	W24	W24	W20
22	W03	S07	S16	S12	S24	53	W20	W32	W20	W20	W35
23	W11	S16	S26	S16	S16	54	W23	S25	W23	W23	W23
24	W22	S14	S11	S26	S11	55	W21	W21	W21	W21	W28
25	S16	S08	W11	W30	W11	56	W28	W28	W28	W28	W09
26	W14	W14	W30	W11	S15	57	W26	W26	S06	S06	W10
27	W16	W33	S21	W03	W30	58	S06	S06	W26	W26	W21
28	W30	W03	S07	W25	S26	59	W09	W09	W09	W09	S06
29	S07	W16	S10	S07	W22	60	W10	W10	W10	W10	W26
30	S21	W24	W25	S22	W03	61	W27	W27	W27	W27	W27
31	W25	S21	W22	S24	W16	62	W36	W36	W36	W36	W36

Farmer, we investigated the effect of prioritization proposed in this research on it. As the final course from the Machine Learning for Trading Specialization of Coursera, the course introduces reinforcement learning (RL) and the benefits of using it in trading strategies. To be successful in this course, learners should have advanced competency in Python programming and familiarity with pertinent libraries for machine learning, such as Scikit-Learn, Stats Models, and Pandas. 9852 users have enrolled in this course, by the time we started our investigation. This course had 47 comments, 172 rating from the learners, and the rate 3/7 from 5.

We understood its pros and cons from the comments section of this course. Most of the learners had dealt with the non-usefulness of the course content, not fully covering the topic, and the advertising content provided by Google Cloud promotion. They also needed more exercises to learn more about what was taught in the courses.

Based on the positive comments from users regarding this course, it can be inferred that even among individuals with a favorable opinion of the course, there were criticisms regarding the course content and educational materials.

Based on the results of this case study and comparing them to outcome of DEMATEL and Social Network Analysis model, this course can be improved through the following strategies: (1) By providing appropriate educational content, along with sufficient exercises and quizzes in harmony with the content, this first step can be taken to satisfy users. This is what we obtained in this research as factors of the significant attention category. (2) Most of the comments from users indicated the existence of advertising content for Google Cloud. As educational content is not a good place to present advertising content, it is suggested to replace this part of the content with a complete explanation of the main topic of the course. (3) In order to satisfy the learners and create a sense of usefulness of the course for them, it is suggested to provide more practical exercises to increase the user experiences in the relevant field in addition to theoretical knowledge. This can be a long-term plan for optimizing the course. These two strategies are associated with the factors of the special attention category obtained in this research.

To ensure learner satisfaction in each new course, it is essential to consider the following factors: (1) Establishing clear objectives for the course and communicating them to prospective learners. (2) Providing comprehensive content and course materials, including exercises and quizzes, aligned with the established objectives. (3) Offering support services to assist learners in attaining their goals.

5. Discussion and conclusion

The purpose of this study is to investigate the factors that affect user satisfaction to optimize MOOC platforms. To bridge the analytical gap in previous research, we developed a research model using the DEMATEL model and Network Analysis techniques, and conducted an empirical analysis based on user perceptions. This analysis focuses on identifying the key features and elements that influence user satisfaction, shedding light on factors that have significant effects on MOOC platforms. The results of this analysis

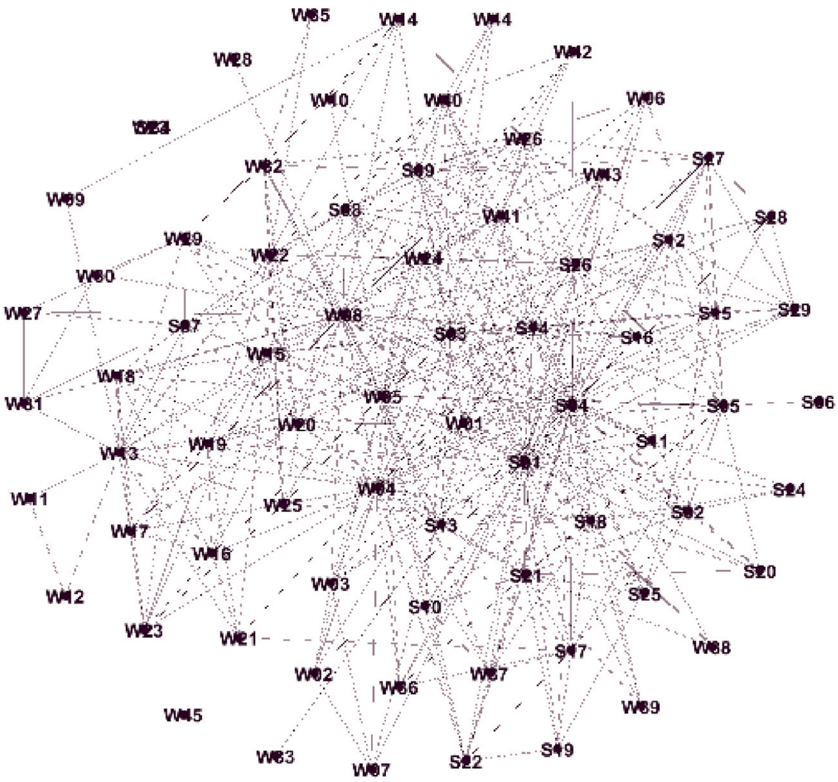

Fig. 7. The graph of the relationships between the factors.

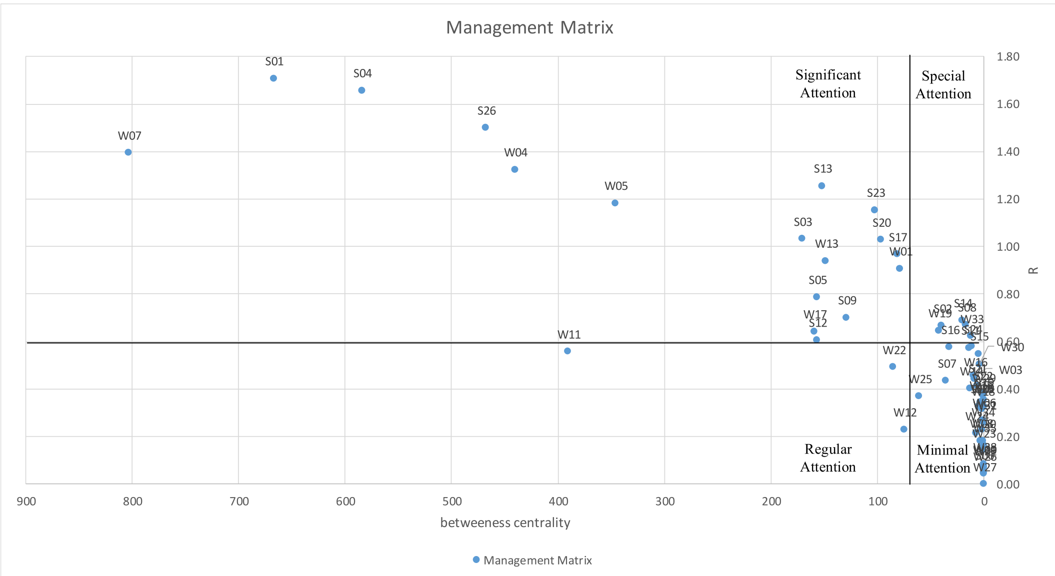

Fig. 8. The management matrix for the final prioritization of the factors.

address the three research questions outlined in the Introduction. In this section, we discuss the major findings and implications of the results.

Firstly, we identified the factors that contribute to user satisfaction. To address the first question, by analyzing users' feedback and comments on the Coursera online platform, we extracted 62 influential factors using text-mining techniques. This highlights the unique contribution of analyzing user opinions, distinguishing our study from previous research. We categorized these factors into five groups related to the content, structure, instructors, effects, and support of the courses.

Furthermore, the analysis addressed the second research question by establishing the network of relationships among the factors. Using the DEMATEL model, we calculated the influence of each factor on others (R) and the influence of other factors on each individual factor (J). Table 6 displays the results of the DEMATEL method, providing insights into the priority of each factor based on its impact on other factors through the R-value. Additionally, employing Network Analysis, we obtained various types of centralities for each factor.

Finally, to address the third research question, we prioritized the factors based on indicators derived from both the DEMATEL and network analysis techniques. Based on this prioritization, the factors of clear and complete content (S1), good resources (S3), easy exercises (S4), valuable content (S5), good quality (S9), good instructor (S12), well-explained materials (S13), good and short videos (S20), good for self-learning (S23), and good for all experience levels (S26), are the most effective ones on users' satisfaction, and the factors of need for more exercises (W4), need for more details (W5), missing data for final quizzes (W7), advertising content (W13), and bad instructors (W17), are the most effective ones on dissatisfaction of users.

This research holds practical value for MOOC providers. Based on our findings, we offer the following recommendations to enhance platform functionality and enhance user satisfaction: (1) Gain a deep understanding of users' needs and the challenges they face during their learning journey. This knowledge will help tailor the platform to address their requirements. (2) Offer a well-balanced blend of educational content and an ample supply of exercises and quizzes. Providing users with practical and engaging learning materials will contribute to their overall satisfaction. (3) Establish a clear and cohesive course structure that guides instructors on how to design and deliver their courses effectively. A well-defined structure ensures consistency and coherence, making it easier for users to navigate and comprehend the course content.

The influential factors also could be considered in terms of Equality, Diversity, and Inclusion (EDI) in education. Working on improving the factors with higher priorities, such as, clear and complete content (S1), well-explained materials (S13), good for all experience levels (S26), can cover the diversity and inclusion aspects of education. For further explanation, providing the courses for a wide range of learners with different levels of professional experience would satisfy learners from all around the world and in various ways. In addition, by improving the mentioned factors, higher levels of user satisfaction will be obtained, and an equal opportunity will be given to all learners around the world to have a chance of accessing high-quality educational content.

However, in this study we only focused on one way of analysis based on DEMATEL and Network Analysis. For future studies, we recommend pursuing other models of analysis on users' experience, especially the models based on Artificial Intelligence, to provide accurate results for improving MOOC platforms.

It will also provide the context required to determine the effect of other aspects of learning on MOOC users; for instance, analyzing students' perspectives of learning and their intentions could be achieved by the method conducted in this paper.

MOOC systems facilitate the learning process for lots of knowledge seekers around the world. However, despite being considered a successful innovation, they have some serious challenges, such as the low completion rate of the courses by the learners. Thus, it is imperative to determine the underlying causes of learner dissatisfaction. To initiate our investigation, we conducted a comprehensive study analyzing users' feedback on courses. Recognizing that learners genuinely express their opinions in the comments section, we opted to identify satisfaction factors based on their firsthand experiences and perspectives, rather than relying on their interactions on websites or questionnaire surveys. The purpose of this study was to extract the factors that affect learners' satisfaction from their feedback, examine the relationships between them, and prioritize them based on their impact on the whole system to determine more important indicators for reviewing and improving the performance of MOOC systems. Our approach had three methodological contributions: (1) we obtained factors affecting user satisfaction through sentiment analysis and topic modeling of the learners' comments instead of using questionnaires. (2) We obtained the communication network between the factors by analyzing the comments. (3) We prioritized the factors by analyzing the obtained communication network with two methods (DEMATEL and network analysis).

As a practical study, we implemented the deployment management approach on the Coursera platform, displaying how the overall state of the courses can be evaluated and enhanced. By considering learners' feedback, we can help MOOC platforms to (a) find the strengths and weaknesses of the courses, (b) identify which factors affect the satisfaction of learners through user feedback, and (c) prioritize the factors that need greater improvement for achieving the highest user satisfaction and, consequently, the overall improvement in MOOC platform status. These are, in fact, operational innovations of this approach and make it valuable for MOOC platforms to manage the influencing factors effectively.

Like most studies, the design of the current study is subject to limitations. The primary limitation regarding generalization of these results is the challenges facing text mining. Text mining is a powerful tool for analyzing user comments to find their satisfaction factors, but it also presents several challenges including (1) the quality of the text data itself as it is often unstructured and noisy and (2) the wide range of language (Spanish, English) with different language patterns. We handled these two challenges by cleaning a large part of the gathered data manually, which was too time consuming and using only English comments in our research. In future research, it is crucial to enhance the accuracy and reliability of text mining techniques when analysing user satisfaction through their comments. This can be achieved by developing more advanced algorithms capable of capturing the subtleties of language more effectively. Improvements should be made to understand idiomatic expressions, identify sarcasm, and accurately detect sentiment, enabling a more nuanced and comprehensive analysis of user feedback.

The second limitation of this research is the demographic characteristics of the users such as age, gender, education level, geographical location and occupation were not available because the characteristics of the users are not publicly accessible on the platforms. Since having these data can improve the accuracy of the results of this type of research in educational contexts, considering them is suggested for future studies.

Credit author statement

Sadra Ahmadi: Conceptualization, Methodology, Writing and Original draft preparation, Supervision
Zahra Nourmohamadzadeh: Software, Data curation, Visualization, Writing Original draft preparation, Investigation
Babak Amiri: Methodology, Validation, Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Appendix

	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11	S12	S13	S14
S01	-	1	1	1	1	0	0	1	1	1	1	1	1	1
S02	1	-	1	1	1	0	0	0	0	0	0	0	0	1
S03	1	1	-	1	0	0	0	1	1	1	1	1	1	1
S04	1	1	1	-	1	0	0	1	1	1	1	1	1	1
S05	1	1	0	1	-	1	0	0	0	0	0	1	0	1
S06	0	0	0	0	1	-	0	0	0	0	0	0	0	0
S07	0	0	0	0	0	0	-	1	0	0	0	0	0	0
S08	1	0	1	1	0	0	1	-	1	0	0	0	0	1
S09	1	0	0	1	0	0	0	1	-	0	0	0	0	0
S10	0	0	1	1	0	0	0	0	0	-	1	0	0	0
S11	0	0	1	1	0	0	0	0	0	1	-	1	0	0
S12	1	0	1	1	1	0	0	0	0	0	1	-	0	1
S13	1	0	1	1	0	0	0	0	0	0	0	0	-	1
S14	1	1	1	1	1	0	0	1	1	0	0	1	1	-

Appendix 1. Example of factors' relation matrix.

	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11	S12	S13	S14
S01	0/0305194	0/0340055	0/0399395	0/0505436	0/0341331	0/0007585	0/0052769	0/0335942	0/0361471	0/0285511	0/0271378	0/0318073	0/029495	0/042796
S02	0/0323681	0/0083574	0/0275031	0/0323254	0/0282604	0/000628	0/0013087	0/0041994	0/0056039	0/0030761	0/0028225	0/0040583	0/005298	0/0293669
S03	0/039258	0/0277865	0/0169097	0/0389929	0/0069473	0/0001544	0/0042197	0/0306854	0/0323882	0/0260569	0/0263601	0/0284145	0/0272092	0/035829
S04	0/0492814	0/0338054	0/0389864	0/0297079	0/0339567	0/0007546	0/0045124	0/0318182	0/0352364	0/0284463	0/0270393	0/0316457	0/029277	0/0418865
S05	0/0340665	0/0295533	0/0075021	0/0340319	0/0102824	0/0224507	0/001403	0/0045566	0/0065082	0/0032204	0/0025279	0/0277341	0/0045809	0/0314818
S06	0/000757	0/0006567	0/0001667	0/0007563	0/0224507	0/0004989	3/118E-05	0/0001013	0/0001446	7/156E-05	5/618E-05	0/0006163	0/0001018	0/0006996
S07	0/0051675	0/0014046	0/0041181	0/0044504	0/0013851	3/078E-05	0/0058247	0/025579	0/0034637	0/0005111	0/0010013	0/0017808	0/0017893	0/0046493
S08	0/0335236	0/0049379	0/0301787	0/0318619	0/0045364	0/0001008	0/0256338	0/0099643	0/0307906	0/0025781	0/0030042	0/0047706	0/0040453	0/031003
S09	0/0332153	0/0043477	0/0080766	0/0325043	0/0049092	0/0001091	0/0032045	0/0287062	0/0112848	0/0026077	0/0024822	0/0037165	0/0039861	0/0088457
S10	0/0044733	0/002377	0/0251383	0/0272804	0/0023952	5/323E-05	0/0003966	0/0017929	0/0025488	0/0040492	0/0236998	0/0021931	0/0021385	0/0029352
S11	0/0036285	0/0021714	0/0254524	0/0259159	0/0017358	3/857E-05	0/0009002	0/0022383	0/0024158	0/023683	0/0028274	0/0239231	0/002007	0/0032656
S12	0/0312873	0/0053264	0/0284852	0/0317288	0/0277488	0/0006166	0/0018087	0/0047913	0/0052012	0/0029417	0/0246411	0/0076188	0/0032815	0/0304737
S13	0/0294513	0/0054947	0/0277244	0/0293473	0/0045805	0/0001018	0/0018307	0/0040873	0/0059244	0/0028526	0/0026939	0/0033013	0/0065571	0/0284622
S14	0/0436952	0/0310426	0/03717	0/0429461	0/0321171	0/0007137	0/0048805	0/0318005	0/0340836	0/0045562	0/0043659	0/0306159	0/0286319	0/0196308

Appendix 2. Example of factors' T matrix.

code	R	J	R+J	R-J	Type	code	R	J	R+J	R-J	Type
S01	1.56	1.5	3.06	0.06	receiver	W06	0.2	0.2	0.4	0	receiver
S02	0.52	0.59	1.11	-0.07	receiver	W07	1.19	1.23	2.42	-0.04	receiver
S03	0.96	0.96	1.92	0	receiver	W08	0.14	0.14	0.28	0	receiver
S04	1.45	1.45	2.91	0	receiver	W09	0.06	0.06	0.12	0	receiver
S05	0.62	0.62	1.23	0	receiver	W10	0.06	0.06	0.12	0	receiver
S06	0.04	0.04	0.07	0	receiver	W11	0.56	0.58	1.13	-0.02	receiver
S07	0.37	0.42	0.79	-0.05	receiver	W12	0.24	0.22	0.46	0.02	dispatcher
S08	0.61	0.61	1.23	0	receiver	W13	0.88	0.87	1.75	0	receiver
S09	0.66	0.8	1.47	-0.14	receiver	W14	0.37	0.37	0.73	0	receiver
S10	0.27	0.33	0.6	-0.06	receiver	W15	0.33	0.33	0.66	0	receiver
S11	0.49	0.49	0.98	0	receiver	W16	0.37	0.34	0.71	0.03	dispatcher
S12	0.45	0.45	0.9	0	receiver	W17	0.63	0.58	1.21	0.05	dispatcher
S13	1.1	1.05	2.15	0.06	receiver	W18	0.31	0.25	0.56	0.06	dispatcher
S14	0.54	0.51	1.05	0.03	receiver	W19	0.61	0.61	1.22	0	receiver
S15	0.41	0.4	0.81	0	receiver	W20	0.14	0.11	0.24	0.03	dispatcher
S16	0.45	0.45	0.9	0	receiver	W21	0.05	0.05	0.1	0	receiver
S17	0.78	0.65	1.43	0.12	dispatcher	W22	0.41	0.41	0.82	0	receiver
S18	0.25	0.25	0.49	0	receiver	W23	0.11	0.11	0.21	0	receiver
S19	0.26	0.26	0.52	0	receiver	W24	0.16	0.17	0.33	0	receiver
S20	0.79	0.79	1.59	0	receiver	W25	0.39	0.39	0.77	0	receiver
S21	0.3	0.36	0.67	-0.06	receiver	W26	0.03	0.03	0.06	0	receiver
S22	0.28	0.27	0.55	0.02	receiver	W27	0	0	0	0	Independent
S23	0.96	0.89	1.85	0.08	dispatcher	W28	0.07	0.07	0.13	0	receiver
S24	0.47	0.47	0.93	0	receiver	W29	0.27	0.27	0.55	0	receiver
S25	0.24	0.24	0.48	0	receiver	W30	0.37	0.37	0.74	0	receiver
S26	0.37	0.36	0.73	0	receiver	W31	0.19	0.19	0.38	0	receiver
W01	0.74	0.81	1.55	-0.07	receiver	W32	0.19	0.19	0.38	0	receiver
W02	0.24	0.24	0.49	0	receiver	W33	0.57	0.58	1.15	0	receiver
W03	0.34	0.29	0.63	0.05	dispatcher	W34	0.25	0.25	0.49	0	receiver
W04	1.11	1.11	2.22	0	receiver	W35	0.16	0.16	0.32	0	receiver
W05	1	1.05	2.04	-0.05	receiver	W36	0	0	0	0	Independent

Appendix 3. DEMATEL results for each factor.

ID	closeness centrality	betweeness centrality	Authority	Hub-Score	ID	closeness centrality	betweeness centrality	Authority	Hub-Score
S01	0.71	667.20	0.30	0.31	W06	0.46	0.61	0.05	0.05
S02	0.52	39.33	0.14	0.12	W07	0.65	803.40	0.24	0.23
S03	0.59	170.70	0.21	0.21	W08	0.42	3.12	0.02	0.03
S04	0.69	584.40	0.29	0.29	W09	0.34	0.00	0.00	0.01
S05	0.51	156.70	0.14	0.14	W10	0.34	0.00	0.00	0.01
S06	0.34	0.00	0.01	0.01	W11	0.50	390.50	0.09	0.09
S07	0.49	35.42	0.08	0.07	W12	0.45	74.85	0.04	0.04
S08	0.54	16.57	0.15	0.15	W13	0.58	148.50	0.19	0.19
S09	0.56	129.10	0.18	0.14	W14	0.49	12.47	0.07	0.07
S10	0.46	4.40	0.08	0.06	W15	0.47	3.36	0.06	0.06
S11	0.45	0.09	0.09	0.37	W16	0.49	8.57	0.06	0.07
S12	0.52	156.60	0.11	0.10	W17	0.56	159.40	0.11	0.13
S13	0.61	151.80	0.23	0.25	W18	0.43	1.57	0.04	0.05
S14	0.50	20.31	0.12	0.12	W19	0.53	42.06	0.14	0.14
S15	0.51	4.80	0.11	0.11	W20	0.41	0.65	0.02	0.02
S16	0.49	32.12	0.09	0.09	W21	0.40	0.00	0.01	0.01
S17	0.55	81.47	0.14	0.17	W22	0.50	84.93	0.07	0.07
S18	0.44	0.59	0.06	0.06	W23	0.41	0.65	0.02	0.02
S19	0.44	0.00	0.07	0.06	W24	0.42	7.41	0.02	0.02
S20	0.55	96.80	0.16	0.16	W25	0.49	60.63	0.07	0.07
S21	0.49	6.43	0.08	0.07	W26	0.34	0.00	0.01	0.01
S22	0.46	1.01	0.07	0.07	W27	0.00	0.00	0.00	0.00
S23	0.44	0.00	0.05	0.05	W28	0.37	0.00	0.01	0.01
S24	0.46	1.01	0.07	0.07	W29	0.48	0.70	0.07	0.07
S25	0.43	0.00	0.06	0.06	W30	0.49	4.09	0.09	0.09
S26	0.45	2.54	0.09	0.09	W31	0.43	0.00	0.05	0.05
W01	0.56	78.68	0.18	0.17	W32	0.43	0.00	0.05	0.05
W02	0.47	1.74	0.06	0.06	W33	0.53	11.87	0.14	0.14
W03	0.50	9.67	0.07	0.08	W34	0.48	1.49	0.06	0.06
W04	0.62	440.60	0.22	0.22	W35	0.43	0.10	0.04	0.04
W05	0.60	346.30	0.21	0.20	W36	0.00	0.00	0.00	0.00

Appendix 4. Network indicators for each factor.

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