Evaluation of Learning Efficiency of Massive Open Online Courses Learners

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Abstract—This study selected 175 massive open online courses (MOOC) learners of the School of Marxism in a university in Henan Province as respondents. A hierarchical clustering analysis was carried out using SPSS22.0, and the learning styles of learners were classified by k-means clustering. The learning efficiency of learners was estimated by data envelopment analysis (DEA), and the differences of learning styles in learning inputs and learning outputs were analyzed through a variance test. Results demonstrated that according to hierarchical clustering analysis, the learning behavioral indicators of MOOC learners could be divided into four classes. According to the results of k-means clustering, learning styles could be divided into four types, namely, high-input-high-output, high-input-low-output, low-input-high-output, and low-input-low-output. Clustering results could explain significant differences in learning inputs well, thus showing significance (P<0.05). A total of 125 respondents were non-DEA effective, accounting for 71.43%. Moreover, 114 respondents had fixed or increasing returns to scale, accounting for 65.14%. The conclusions of this research are of important significance to analyze the progress effectiveness of students, increase the scientificity and rationality of teaching evaluation theory, train teaching managers to control the teaching effects, and make scientific evaluations of the learning efficiency of university students.

Keywords—MOOC, learning efficiency, evaluation, K-means clustering, hierarchical clustering, DEA

1 Introduction

With the continuous deepening reform in online education in China, higher education around the world is changing significantly. Influenced by the COVID-19 pandemic, schools at different levels and of different types in China implemented the online learning mode, and better MOOC learning resources were proposed. Online learning can solve spatiotemporal isolation problems effectively and help learners to learn positively, thus realizing the high-efficiency utilization of learning resources. Therefore, teaching activities have shifted to “learner-centered” personalized independent study, and teaching resources have been shared at the maximum range. Integrating information technology into education comprehensively can help more universities to use online learning platforms and encourage learners to make more independent learning activities. The MOOC learning mode can benefit more learners and bring them richer ways to acquire knowledge. MOOC is the result of the high integration and rapid development of IT technology and education technology to some extent. This mode of learning is the representative of the full sharing of teaching resources, and it is one of the important online learning modes.

However, with the large-scale development of MOOC learning, some learners encounter negative problems, such as attending an excessive number of classes, asking others to attend classes, early offline, low learning performance level, and poor learning outcome. Therefore, the learning efficiency of MOOC learners must be distinguished effectively. Moreover, some MOOC courses have low quality due to the large-scale online courses and inadequate time. Some courses even resort to the traditional recording video mode, and traditional classroom teaching videos are simply uploaded into the network, thus resulting in a low learning quality for some learners. In particular, China's traditional education is exam-oriented teaching; learners have weak control over their learning progress, weak initiatives in self-constraint, low learning motivation, and even weaker learning sustainability. All of these factors can easily cause poor learning outcomes for MOOC learners. Hence, in the large-scale applications of MOOC, a scientific evaluation of the learning efficiency of MOOC learners is necessary, as it can reflect the effectiveness of the whole teaching mode. The traditional classroom teaching mode can only evaluate the learning efficiency of students according to the existing exam scores and predict future exam scores according to the existing learning performances. This scientific evaluation can provide references for academic warnings. However, the evaluation factors of exam scores are difficult to control, and they are usually random to some extent. In the teaching process, teachers, other students, courses, and communication media are all related to the learning efficiency of students. The online MOOC system can collect more learning indexes and analyze the interaction mechanism of factors in the online teaching system scientifically by using a more scientific education information technology. This technology can make the evaluation of learning efficiency more scientific and reasonable.

2 Literature review

The estimation of learning efficiency has been a research hotspot in the education circle. In particular, education powers, such as the US, the UK, and Japan attach great attention to the evaluation of education. With the development of MOOC learning, they have begun to make scientific evaluations on the learning efficiency of MOOC learners. Many studies on the learning efficiency of learners in online and classroom environments have been reported. For instance, Cook, D. A., et al. [1] demonstrated that Internet-based teaching and non-computer teaching cost similar time. Teaching strategies that strengthen feedback and interaction usually prolong the learning time, but they can improve learning outcomes under certain circumstances. Demetriadis, S., et al. [2] believed that students can learn introductory courses effectively and be satisfied with the experience flexibility in e-classes. Teachers are recommended to integrate various learning events into nodes of a productive learning network to train teaching cohesion. Rasch, T., et al. [3] pointed out that text-based learning is more successful than text-and-picture learning and can improve the efficiency of schools. Moreover, the visual format can influence the interaction of participants with pictures but may not influence learning outcomes. combine sequential probability ratio test and confidence indicator to achieve real-time assessing student's learning efficiency. Lai, C. H., et al. [4] combined sequential probability ratio test and confidence indicator to achieve real-time assessing student's learning efficiency. Smith, R. L., et al. [5] analyzed the differences of online (n=22) and face-to-face (n=32) postgraduate respondents in terms of learning level and perceived efficiency. Results revealed significant differences between two groups in perceived learning efficiency, with preference to the online teaching mode. Meanwhile, Li, C., et al. [6] demonstrated that the MOOC platform can provide a unique learning path to students by determining learning styles comprehensively and scientifically, thus improving students' ability and learning efficiency significantly. Abuhmaid, A. M. [7] selected 154 students who were learning about computers and divided them into two groups. He found that all students (including online and traditional classroom teaching) maintained a positive attitude to project-based learning activities. He also concluded that classroom teaching had higher learning efficiency than online teaching. In another study, Zaveri, B., et al. [8] proved that learners can complete tasks quickly and recognize the usability of online learning platforms by improving interactive communication, thus enabling students to improve their learning efficiency greatly. Debeer, D., et al. [9] reported that education games can improve learners' ability to adapt to learning environments and improve the learning efficiency of children.

DEA can fully recognize the learning efficiency of learners and make an overall order of learners so that teachers can discriminate the learning efficiency of MOOC learners effectively. Wanke, P., et al. [10] discussed the performance problems of public schools in Australia by using a two-stage DEA network model and found that in the learning efficiency stage, these individual groups help to produce important outputs related to the exam of students and rank of schools. Lee, B. L., et al. [11] quantized the learning efficiency of primary students in Queensland State. Research results inspired policy makers to not only provide preferential resources to schools with lower efficiency to improve students learning through teacher development but also offer financial and non-financial education aids to students with poor social education background and their families. Fuentes, R., et al. [12] evaluated the technical efficiency of the learning-teaching process in higher education through a three-stage program and found that course satisfaction, textbook diversity, and teachers' satisfaction are important influencing factors of the academic performance of MOOC learners. Zhu, Q. [13] demonstrated that research results on the influence of mobile fragmented learning efficiency have low evaluation efficiency. He built an evaluation index system for the influence of mobile terminals on fragmented learning efficiency. This system is highly feasible according to the experimental results. Ersoy, Y. [14] evaluated the performance of the distance education department of Turkey Public Universities in the academic year of 2018–2019 by using DEA and TOPSIS method, in which six input variables and four output variables were used. According to the efficiency analysis based on the CCR-DEA model, seven universities were effective, and some improvement measures were finally proposed. Bowrey, G., et al. [15] investigated the learning efficiency of university students in Australia by using the DEA model from the perspective of success rate. Results showed moderate differences between five universities with the highest efficiency (represented by 1) and universities with efficiency ranging 0.839–0.973. Smirlis, Y., et al. [16] estimated hybrid learning efficiency through DEA and found that the analysis could distinguish the most effective and most feasible teaching designs. Montoneri, B. [17] designed the teaching improvement matrix based on teaching efficiency and performances by combining a management matrix and DEA. The proposed model can divide all evaluated types into four quadrants according to performances and efficiency and offer improvement measures for different evaluated types in different quadrants. Tiancheng, W. [18] put forward a DEA model for academic performance prediction based on multi-dimensional educational data mining and verified its validity through a simulation experiment.

According to existing associated studies, many methods can evaluate the learning efficiency of students. However, the major evaluation goal is still to reflect the ability levels and skills of students quantitatively to be able to feedback to teaching management department. This goal has positive significance in practical teaching. Moreover, the learning process is a typical input-output process, in which the quantitative analysis of the output ratio must be applied. The learning process of students can be viewed as a multi-input-multi-output economic activity. Therefore, the learning efficiency of students and relative learning effectiveness of different learners can be evaluated objectively by the DEA model. On the basis of the existing associated studies, this study explored different behavioral modes of learners by hierarchical clustering and k-means clustering and evaluated the learning efficiency of MOOC learners using the DEA model. Moreover, the study analyzed possible room for improving learning efficiency by comparing learning inputs and thereby providing learners with personalized learning guidance.

3 Methodology

3.1 Research methods

First, a clustering binary tree was built using a hierarchical clustering algorithm, and a broken line graph was plotted with SPSS22.0 using "number of clusters" as the x-coordinate and "coefficient of clustering" as the y-coordinate. Second, different behavioral modes of learners were explored by k-means clustering algorithm. Moreover, a statistical analysis on the behavioral features of different groups and inter-group effect size was carried out. Third, the overall learning efficiency of learners and differences were estimated by DEA. The DEA model is an efficiency evaluation method based on the concept of relative efficiency. It is applicable to the boundary production function of multiple inputs and multiple outputs. The DEA model has been extensively used to study total factor productivity. Now, the DEA has been increasingly used in the education field. In this study, MOOC learners were viewed as the decision-making units (DMUs), and key attention was given to the effective scientific evaluation of the learning efficiency of MOOC learners based on DEA. Taking MOOC learning for example, all learners of one MOOC course were used as one group, and each learner was a DMU. The learning efficiency of learners was related to personal attributes, learning technology, and effort adjustment. Technical efficiency mainly came from learners' mastery and use of learning technologies, including learning strategies, learning methods, and time management skills. Scale efficiency mainly came from the efforts of learners, including participation and persistence to online learning. In this study, the output-oriented BCC model was applied to map the output indexes of the DEA model into the online learning context.

3.2 Evaluation indexes

To evaluate the learning efficiency of university students in MOOC courses comprehensively, this study selected five input indexes according to existing studies, including the number of posts on a forum topic, number of replies on the forum, time spent browsing microlectures, time spent browsing videos, and number of test participations. Three output indexes were chosen, including the midterm exam score of online MOOC, final exam score of online MOOC, and peer evaluation score. Calculation methods of specific indexes are shown in Table 1.

Table 1. Input-output index system for evaluation learning efficiency of MOOC

Index Type	Name of Indexes	No.	Calculation Methods
Input indexes	Number of posts on forum topic	X1	The cumulative times that learners post on the forum topics.
	Number of replies on forum,	X2	The cumulative times that learners reply on the forum topics.
	Times of browsing microlecture	X3	The cumulative time that learners browse microlecture resources (unit: min)
	Times of browsing videos	X4	The cumulative time that learners browse video resources (unit: min)
	Number of test participations	X5	The cumulative times that learners participate in unit tests (unit: min)
Output indexes	Midterm exam score	Y1	Midterm exam score of MOOC (100 scores)
	Final exam score	Y2	Final exam score of MOOC (100 scores)
	Peer evaluation score	Y3	Cumulative times of thumb-ups for the learner's statements on the forum

In this study, 175 students majored in Ideological and Political Education of the School of Marxism in a university in Henan Province were selected as respondents, which included 42 males (24%) and 133 females (76%). Among them, 32 were freshmen (18.29%), 58 were sophomores (33.14%), 62 were juniors (35.43%), and 23 were seniors (13.14%).

4 Results analysis and discussion

4.1 Learners' characteristics

First, a matrix was plotted according to data of five input indexes and three output indexes (Figure 1).

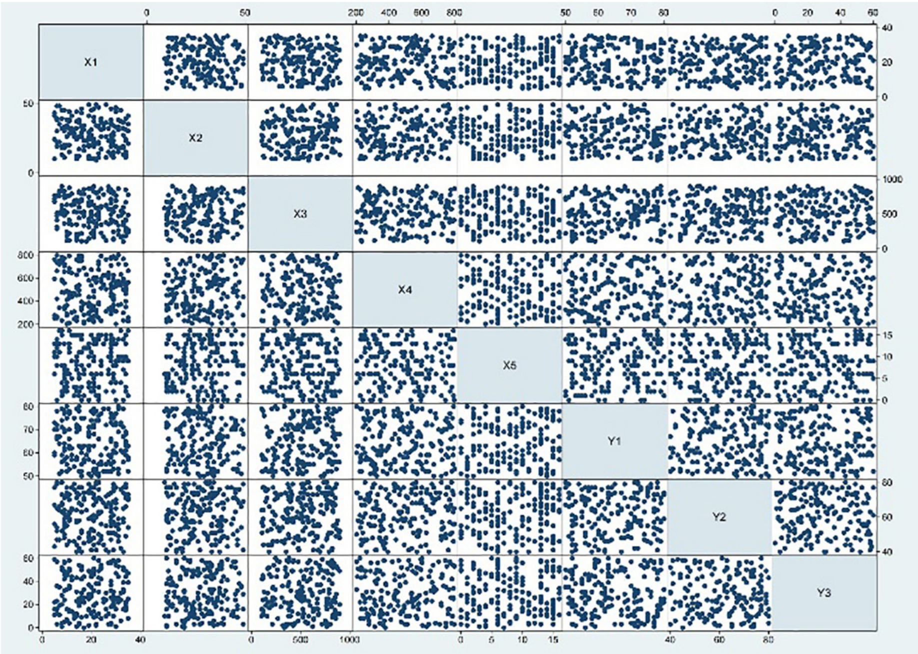

Fig. 1. Input-output matrix of online MOOC of 175 respondents

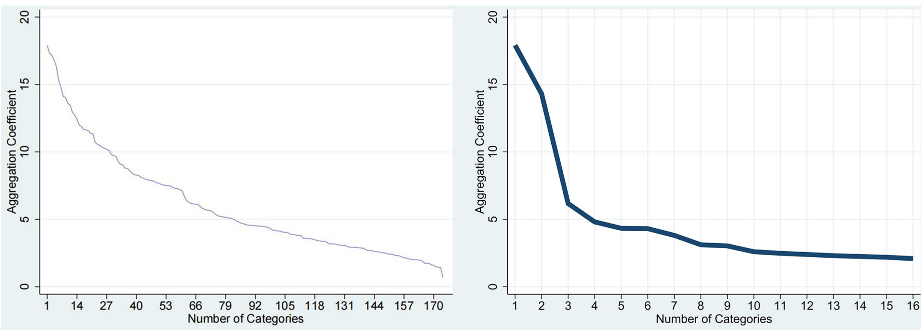

Fig. 2. Hierarchical clustering results of learning behavioral indexes of MOOC learners

Subsequently, hierarchical clustering analysis was carried out by using SPSS22.0. The hierarchical clustering diagraph of behavioral indexes of MOOC learners was plotted. Figure 2 shows that when the number of types was 4 or 5, the descending trend of the broken line slowed down. In this study, the number of types was set to 4. To classify learners with similar learning modes into the same group, k-means clustering analysis was performed using STATA17.0 for the learning behavioral indexes of MOOC learners. All learners were divided into four types, namely, high-input-high-output (HIHO), high-input-low-output (HILO), low-input-high-output (LIHO), and low-input-low-output (LILO). One-way analysis of variance (ANOVA) was carried out to the learning input and output of 175 learners. Results are shown in Table 2.

Table 2. ANOVA results

	LIHO (n=50)	HIHO (n=49)	LILO (n=40)	HILO (n=36)	F	P
Learning input	170.42 ±38.82	270.96 ±32.24	164.39 ±30.39	242.19 ±28.21	115.549	0.000**
Learning output	51.54 ±7.78	53.44 ±7.52	50.63 ±7.73	51.41 ±6.12	1.189	0.316

In view of the learning behavioral input, clustering variables could interpret significant differences in learning input well, thus showing significance ($p<0.05$). Learners with high inputs demonstrated higher mean values of various input indexes than learners with low inputs. In other words, X1, X2, X3, X4, and X5 of high-input learners were far higher than those of low-input learners. However, clustering variables could not elaborate significant differences in the learning output, thus indicating no significant difference of learning output among the four types. K-means clustering clustered input variables and output variables at the same time. However, learning output was influenced by many factors. Hence, such clustering did not show intergroup differences in the learning output.

4.2 Descriptive statistical analysis

The descriptive statistics of the input and output indexes of 175 MOOC learners are listed in Table 3.

Table 3. Descriptive statistics of learning input and output

Name	Min	Max	Mean	SD	Median
X1	5.018	34.559	20.088	8.796	20.285
X2	9.303	48.796	27.743	10.835	27.365
X3	102.165	897.3	514.525	226.377	523.492
X4	202.17	799.896	489.128	177.112	485.018
X5	0.112	15.981	8.302	4.709	8.182
Y1	50.313	79.996	64.753	9.037	63.572
Y2	40.164	79.83	61.691	11.559	62.946
Y3	0.113	59.967	29.063	17.436	26.282

Table 3 shows that the descriptive analysis describes the overall situation of data by mean or median. Moreover, no abnormal value in current data and data could be used for further analysis.

4.3 Learning efficiency

Learning inputs and outputs of 175 MOOC learners were analyzed by DEAP 2.1 software. Estimation results are listed in Table 4.

Table 4. Learning efficiency of 175 learners (partial)

ID	Technical Efficiency (TE)	Scale Efficiency SE (k)	Overall Efficiency OE (θ)	Slack Variable S-	Slack Variable S	Effectiveness
1	1	1	1	0	0	DEA strongly effective
2	0.771	0.943	0.727	74.191	0	Non-DEA effective
3	1	1	1	0	0	DEA strongly effective
4	0.822	0.998	0.82	0.323	7.354	Non-DEA effective
5	0.727	0.936	0.681	326.528	28.046	Non-DEA effective
⋮	⋮	⋮	⋮	⋮	⋮	⋮
172	0.997	0.752	0.75	6.818	3.23	Non-DEA effective
173	0.503	0.812	0.408	146.452	1.549	Non-DEA effective
174	0.574	0.991	0.569	0.741	16.121	Non-DEA effective
175	1	0.873	0.873	74.528	44.239	Non-DEA effective

Table 4 shows that:

(1) In view of the overall efficiency (OE), 50 respondents were DEA strongly effective (28.57%), and 125 respondents were non-DEA effective (71.43%). This distribution fully indicated the low proportion of online MOOC learners with high learning efficiency. It can be explained as follows. MOOC proposes a higher requirement on the independent learning of learners. However, learning efficiency is easily affected by learning attention, learning attitude, learning motivation, and learning interest. Some students can acquire answers from websites for tests or questions provided by the MOOC platform or teachers. Some learners even plagiarize online answers directly after they become familiar with the online teaching mode. Thus, the teaching effect is difficult to achieve. Some learners fail to get a practical and accurate understanding on their learning progresses and methods and fail to achieve high learning efficiency in MOOC courses. Thus, the learning outcome declines accordingly.

(2) In view of the scale efficiency (SE), 114 respondents had fixed or increasing returns to scale (65.14%). This ratio indicated that a lot of learners have low OE. Nevertheless, most learners can further improve their efforts. They can pay close attention to their progress in learning behaviors and learning plans and enrich their learning emotional and cognitive inputs by increasing learning inputs to MOOC courses. For example, learners can prepare tools and debug the online environment before MOOC classes, think about questions of teachers seriously, and participate in classroom interaction.

Moreover, learners can make scientific learning plans and goals according to their own learning abilities. They can also adjust their learning habits, get previews to understand keys of contents, think about questions seriously, propose questions positively, and maintain good learning habits in MOOC. Thus, their learning efficiency can improve.

Table 5. Input redundancy rate and output insufficiency rate analysis

ID	Input Redundancy Rate					Output Insufficiency Rate		
Indexes	X1	X2	X3	X4	X5	Y1	Y2	Y3
1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.2160	0.0000	0.0000	0.1320	0.1440	0.0000	0.0000	0.0000
3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
4	0.0150	0.0000	0.0000	0.0000	0.0000	0.0000	0.1260	0.0000
5	0.2400	0.0510	0.3970	0.0000	0.0610	0.0080	0.0000	7.9160
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
172	0.0000	0.1440	0.0000	0.0000	0.0000	0.0590	0.0000	0.0000
173	0.0000	0.0000	0.1860	0.0000	0.0000	0.0000	0.0000	0.0730
174	0.0000	0.0000	0.0000	0.0000	0.0660	0.0550	0.0000	0.4200
175	0.1630	0.0000	0.1290	0.0000	0.2310	0.1590	0.0000	1.1500
Means	0.0234	0.0172	0.0480	0.0254	0.0584	0.0431	0.0552	2.3070

Table 5 shows that the input redundancy rate and the output insufficiency rate were further analyzed. The output insufficiency rate of 175 respondents was significantly lower than the input redundancy rate. This outcome revealed that although most MOOC learners could use more learning inputs, they failed to attain better performance in the midterm exam and final exam due to influences by learning methods, learning habits, and other factors.

5 Measures to improve learning efficiency of MOOC learners

(1) Stimulate learning motivations of MOOC learners

MOOC teachers can adopt more diversified incentives to stimulate and encourage learners to track their learning process and make scientific evaluations of their learning outcomes. Now, MOOC platforms have formed a reward mechanism based on direct rewards and indirect rewards. Most MOOC platforms can use direct rewards, such as badges, integrals, and transformed scores, to strengthen the behaviors and results of learners. This system provides effective information for learners to perceive personal progresses, reflect on learning performances, and adjust their learning rhythms. Apart from the proper use of direct rewards, teachers shall pay high attention to indirect rewards according to students' learning progress during teaching design, such as setting extensional resources, limits for repeated submission and extended term for submission, priority of feedback, etc. In addition, MOOC platforms should be improved to strengthen the feedback mechanism and build reward information recommendation and visual module with complete functions.

(2) Increase comprehensive quality of MOOC teachers

MOOC teachers should increase their comprehensive quality requirements and business ability, provide more effective personalized services for independent learning of students, and improve their learning outcomes. Furthermore, online teachers should be familiar with the combination of professional knowledge and information technology to present teaching content better and provide richer teaching activities. MOOC teachers can set discussion activities on the forum of the platform in diversified forms to stimulate the learning interest of learners, increase the frequency of interactive communication, and encourage deep reflection. Teachers should also have high-level professional abilities and be good at exhibiting teaching contents in diversified forms. Teachers should be comfortable in front of the camera and explain teaching contents vividly to increase the learning presence of students and eliminate boredom.

(3) Promote high-level cognitive behaviors of MOOC learners

In the MOOC learning process, learners should increase learning enthusiasm fully; strengthen their thinking, expression, and cognition about complicated problems; participate in more teacher-student interaction and peer interactions; and train their high-order thinking ability comprehensively. In MOOC teaching, teams should attach high attention to the role of teachers in holding discussions and answering questions in a timely manner; meet the learning needs of different learners; introduce more open questions for reflection and topic discussion; and stimulate independent discussion consciousness, reflective learning, and high-order thinking ability of diligent students based on questions. Learners can check the course schedule and evaluation results promptly, which can help them to adjust their learning pace. Visual tools, such as learning progress view, should be introduced so that learners can know their learning schedules and learning outcomes clearly. Moreover, students can gain “external stimuli” from the learning performances of their classmates.

6 Conclusions

MOOC is viewed as an effective means to solve education issues. People can pursue higher education conveniently and take high-quality courses from universities independently online at any time and any place. By exploring the real learning context, learning characteristics, and learning behavioral modes of MOOC learners, the scientific evaluation of learning efficiency can optimize MOOC course construction and propose good learning advice and strategies for learners. In this study, hierarchical clustering analysis based on SPSS22.0 was carried out first, and different behavioral modes of learners were explored by k-means clustering algorithm. The OE, TE, and SE of learners were estimated by DEA. Results demonstrated that learners could be divided into four types according to k-means clustering (HIHO, HILO, LIHO, and LILO). The clustering results could explain significant differences in learning input, thus showing significance ($P<0.05$). A total of 125 respondents were non-DEA effective (71.43%). Moreover, 114 respondents (65.14%) had fixed or increasing returns to scale, thus indicating that more learners had to improve their learning efficiency by increasing their efforts. Given the results of the current work, future studies should make a more objective quantitative analysis on learning input and output based on the concept of learning efficiency, perfect input-output indexes of the DEA model for learning efficiency, and further verify the DEA evaluation results in teaching practices.

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