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Articles

Mechanism of Continuous Learning Behavior among Massive Open Online Course Learners

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Abstract

In recent years, Massive Open Online Course (MOOC) has been popular with researchers due to its characteristics of supporting autonomous learning and reaching a larger audience than traditional online learning. Nevertheless, there are some obvious shortcomings of recent MOOC, including the low completion rate, unsatisfactory learning effect and high dropout rate subject to various difficulties. The influencing factors of self-regulated learning of MOOC learners, including service quality, attitude and course quality, are derived from the research of Nour and Farrah from the University of Malaysia. An interpretative structural model of the relationship among the influencing factors is further constructed based on the subjective experience of two coders. This procedure not only facilitated the classification of the influencing factors into layers but also clarified the factors and their influence paths on the self-regulated learning of MOOC learners. Finally, based on the above research, constructive suggestions are put forward to promote the continuous learning behavior of MOOC learners.

Keywords: continuance intention, interpretative structural modelling, MOOC, self-regulated learning.

1. Introduction

With the rapid development of the Internet in the information age, "Internet + Education" is increasingly becoming popular with educators owing to the advantages of fast information dissemination, high efficiency and openness of the Internet (Meet, Kala, 2021). Massive Open Online Course (MOOC), as a newly emerged online course development model of "Internet + Education", has been developed, and people have witnessed the rapid development of MOOCs with the emergence of Udacity and Coursera and the official launch of edX. Currently, millions of people of diverse nationalities and levels of education are actively enrolled in MOOCs. The emergence of MOOC promotes personalized education and educational equity and provides high-quality courses for learners to learn independently and efficiently (Chansanam et al., 2021). Although the rapid growth of MOOC courses and learners brings dividends to education, it also faces the problem of low completion rate and low success rate in MOOCs (Abdel-Maksoud, 2019; Alraimi et al., 2015; Hew, Cheung, 2014).

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Self-regulated learning in MOOC refers to the process in which learners actively use and control meta-cognition, motivation and behaviors to ensure learning success, improve the learning effect and achieve learning goals (Vandevelde et al., 2017). It emphasizes that learners can actively motivate themselves to have and use appropriate learning strategies. As a form of online learning, MOOC learners need to take more responsibility for their knowledge and have more ability to self-regulate learning with less supervision and management. Investigation studies demonstrate that learners with a high degree of self-regulated learning are more likely to succeed in MOOC (Kizilcec, Halawa, 2015; Nawrot, Doucet, 2014; You, Kang, 2014). Therefore, improving MOOC learners' self-regulated learning ability and promoting its continuity are vital to alleviate the problem of high dropout rates in MOOCs, which is the impetus of investigating this study.

Research results indicate that some factors influencing MOOC learners' self-regulated learning skills are associated with teaching service quality, online course quality and MOOC learners' attitudes (Albelbisi, Yusop, 2019). Along this line, this study further explores the interrelations among these factors using interpretative structure modeling. Also, the logical hierarchical relationship model among these factors and MOOC learners' self-regulating learning ability is established, further proposing effective strategies to promote MOOC learners to maintain continuous and efficient self-regulating learning.

The remainder of this paper is organized as follows: The sources of factors affecting MOOC learners' self-regulating learning ability are first described, and an interpretive structural model of the factors affecting MOOC learners' self-regulated learning ability is further constructed. Finally, the constructed interpretative structure model is detailed and analyzed, and some suggestions and strategies to promote the continuous self-regulation learning of MOOC learners are given.

2. Materials and methods

Preliminary Screening of Factors for continuous learning behavior of MOOC learners

This paper explores the mechanism of continuous learning of MOOC learners to alleviate the dropout problem. To achieve this, identifying the influencing factors is a key process. After reviewing the literature, it was found that the results of Albelbisi and Yusop (2019) were in line with the needs of this study, so this study selected the results of this article as the source of factors. The statistical results of Albelbisi and Yusop (2019) reveal that factors such as service quality, attitude and course quality influence the self-regulated learning of MOOC learners. The measurement variables corresponding to each construct are shown in the two columns to the left of Table 1, where the quality of service means that the instructor in MOOCs provides the quality of service to the learner, the attitude means learners' beliefs about the experience of using MOOCs, the course quality refers to the degree to which learners believe that MOOCs can offer quality content.

Table 1. Factors Influencing Learners' Self-Regulated Learning Skills in MOOCs

Construct	Measurement variables	Factors	Code names
Service quality	In my MOOC learning experiences, the instructors are good to learners.	Instructor's Dedication to Students	S1
	In my MOOC learning experiences, the instructors are friendly to learners.	Instructor's kindness to Students	S2
	In my MOOC learning experiences, the instructors are knowledgeable enough about the content.	Instructor's mastery of course content	S3
	In my MOOC learning experiences, the instructors are available via e-mail, phone or fax.	Availability of instructors	S4
Attitude	I feel confident in using MOOC.	Confidence in MOOC using	T1

	I enjoy using MOOC for my studies	Interest in MOOC	T2
	I believe that MOOC gives me the opportunity to acquire new knowledge.	Knowledge Acquisition in MOOC	T3
	I believe that MOOC enhances my learning experience.	Learning experience in MOOC	T4
	I believe that convenience is an important feature of MOOC.	Convenience in MOOC using	T5
	I believe that MOOC increases the quality of learning because it integrates all forms of media.	learning quality in MOOC	T6
	I believe that adopting MOOC allows for increased student satisfaction.	learning satisfaction in MOOC	T7
	I believe that studying courses that use MOOC is interesting.	Interest of MOOC courses	T8
	In my MOOC learning experiences, the courses content is up-to-date.	Novelty of course content	T9
Course quality	In my MOOC learning experiences, learning outcomes for the course are summarized in clearly written, straightforward statements.	Clear learning goals	C1
	In my MOOC learning experiences, courses are designed to encourage learners to work together by utilizing problem-solving activities to develop topic understanding.	Emphasis on capacity building	C2
	In my MOOC learning experiences, the course content is communicated well.	Quality of course content	C3

3. Materials and methods

3.1. Factor extraction and coding

The influencing factors in the existing study (Albelbisi, Yusop, 2019) includes five dimensions: system quality, information quality, service quality, attitude, and course quality. However, the statistical results show that only the last three dimensions impact self-regulated learning. Thus, this study used these three dimensions as the source of factors. As shown in Table 1, each dimension includes several measurement variables. Then, according to the specific contents of each measurement variable, its corresponding factors are extracted and coded, as shown in the two columns on the right of Table 1. Its purpose is to facilitate constructing and analyzing subsequent interpreted structural models.

3.2. Interpretative Structural Modeling (ISM)

Interpretive structural modelling (ISM) in MOOCs is an interactive learning process aiming to help people understand complex problems systematically (Attri, Sharma, 2013; Liu et al., 2018). ISM begins with a set of identified factors that are relevant to the problem being solved. These factors can be obtained through literature review, in-depth interviews, questionnaires, etc. By analyzing the binary relationship among these factors, the disordered factor set is transformed into an ordered, visible, hierarchical structure, which aims to facilitate an understanding of the relationships among these factors and their impact on solving the problem. In this study, the "question" means promoting MOOC learners to maintain continuous self-regulated learning. "Factors" refer to the 16 factors mentioned in Table 1.

3.3. Coders

Participants in this study are committed to studying self-regulated learning, especially online learning. One of them is the author of this article, who has a PhD in educational technology and works on learning experience research for online courses. The other is a senior teacher with rich practical teaching experience. One focuses on theoretical research, and the other on experimental research. The two different perspectives of the two coders can be merged to provide more comprehensive and systematic information.

3.4. Overall Research Methodology

This paper mainly adopts the ISM process. The flowchart of the overall methodology is shown in Figure 1. First, the factors used in this study were derived from the existing studies described above. Second, the ISM model was applied to appropriately calculate each factor's relative importance and the interrelations among them. Then, by analyzing the results of ISM, some suggestions were made to promote the continuous learning behavior of MOOC learners.

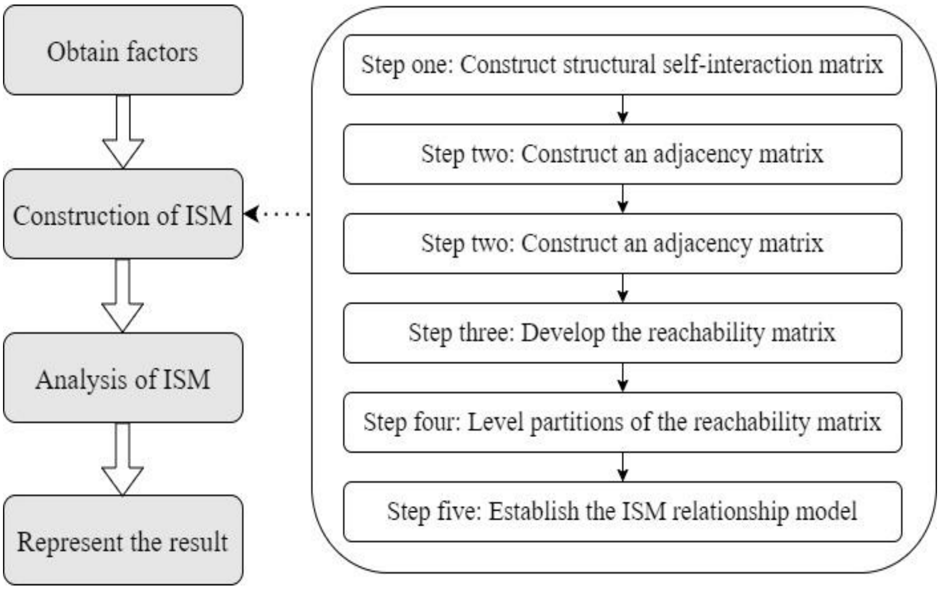

Fig. 1. Flowchart of the methodology

4. Results

4.1. Construction of ISM

The process for ISM development is described below with five steps (Han et al., 2017). Step one: Construct a structural self-interaction matrix (SSIM). According to previous knowledge and experience, two coders judge the contextual relationship between the influencing factors and represent it with four symbols labeled “V”, “A”, “X”, and “O”, where “V” means that factor i affects factor j; “A” means that factor j affects factor i; “X” means that factor i and factor j affect each other; and “O” means that factor i and factor j do not affect each other. Therefore, a complete SSIM is obtained based on four symbols, “V”, “A”, “X”, and “O”, as shown in Table 2.

Table 2. SSIM of factors influencing MOOC learners' self-regulated learning

	S1	S2	S3	S4	T1	T2	T3	T4	T5	T6	T7	T8	T9	C1	C2	C3
S1	O	O	O	O	O	V	O	V	O	V	V	O	V	O	O	O
S2	O	O	O	O	V	V	V	V	O	V	V	O	O	O	O	O
S3	O	O	O	O	O	V	V	V	O	V	V	V	O	O	O	V
S4	O	O	O	O	O	V	V	V	V	V	V	O	O	O	O	O
T1	O	A	O	O	O	X	V	V	V	V	V	O	O	O	O	A
T2	A	A	A	A	X	O	V	V	V	V	V	V	O	O	O	A
T3	O	A	A	A	A	A	O	X	A	V	V	A	A	A	A	A
T4	A	A	A	A	A	A	X	O	A	X	X	A	A	A	A	A

T5	O	O	O	A	A	A	V	V	O	V	V	O	A	O	O	O
T6	A	A	A	A	A	A	A	X	A	O	X	A	A	A	A	A
T7	A	A	A	A	A	A	A	X	A	X	O	A	A	A	A	A
T8	O	O	A	O	O	A	V	V	O	V	V	O	O	A	A	A
T9	A	O	O	O	O	O	V	V	V	V	V	O	O	O	O	O
C1	O	O	O	O	O	O	V	V	O	V	V	V	O	O	O	O
C2	O	O	O	O	O	O	V	V	O	V	V	V	O	O	O	O
C3	O	O	A	O	V	V	V	V	O	V	V	V	O	O	O	O

Step two: Construct an adjacency matrix. The relational value is denoted as 1 if factor i affects factor j, and vice versa. The adjacency matrix is constructed by transforming SSIM. That is, "V" and "X" become 1, and "A" and "O" become 0. The adjacency matrix is obtained, as shown in Table 3.

Table 3. Adjacency matrix of factors influencing MOOC learners' self-regulated learning

	S1	S2	S3	S4	T1	T2	T3	T4	T5	T6	T7	T8	T9	C1	C2	C3
S1	0	0	0	0	0	1	0	1	0	1	1	0	1	0	0	0
S2	0	0	0	0	1	1	1	1	0	1	1	0	0	0	0	0
S3	0	0	0	0	0	1	1	1	0	1	1	1	0	0	0	1
S4	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0
T1	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0
T2	0	0	0	0	1	0	1	1	1	1	1	1	0	0	0	0
T3	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0
T4	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0
T5	0	0	0	0	0	0	1	1	0	1	1	0	0	0	0	0
T6	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0
T7	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0
T8	0	0	0	0	0	0	1	1	0	1	1	0	0	0	0	0
T9	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0
C1	0	0	0	0	0	0	1	1	0	1	1	1	0	0	0	0
C2	0	0	0	0	0	0	1	1	0	1	1	1	0	0	0	0
C3	0	0	0	0	1	1	1	1	0	1	1	1	0	0	0	0

Step three: Develop the reachability matrix. The reachability matrix refers to the degree that can be reached after a certain length of the path between nodes of a directed connection graph in matrix form. In this research, we develop it using MATLAB, as shown in Table 4.

Table 4. Reachability matrix of factors influencing MOOC learners' self-regulated learning

	S1	S2	S3	S4	T1	T2	T3	T4	T5	T6	T7	T8	T9	C1	C2	C3
S1	1	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0
S2	0	1	0	0	1	1	1	1	1	1	1	1	0	0	0	0
S3	0	0	1	0	1	1	1	1	1	1	1	1	0	0	0	0
S4	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0
T1	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0
T2	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0
T3	0	0	0	0	0	0	1	1	0	1	1	0	0	0	0	0
T4	0	0	0	0	0	0	1	1	0	1	1	0	0	0	0	0
T5	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0

T6	0	0	0	0	0	0	1	1	0	1	1	0	0	0	0	0
T7	0	0	0	0	0	0	1	1	0	1	1	0	0	0	0	0
T8	0	0	0	0	0	0	1	1	0	1	1	1	0	0	0	0
T9	0	0	0	0	0	0	1	1	1	1	1	0	1	0	0	0
C1	0	0	0	0	0	0	1	1	0	1	1	1	0	1	0	0
C2	0	0	0	0	0	0	1	1	0	1	1	1	0	0	1	0
C3	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	1

Step four: Level partitions of the reachability matrix. This process further clarifies the hierarchical relationship among factors in the system. The method is that if the reachability set of a factor is the same as the intersection set, then this factor belongs to the first level of ISM, where the reachability set includes this factor itself and other factors that it can affect. The antecedent set includes this factor itself and other factors that can affect it. The intersection set is the union of the reachability and antecedent sets. Therefore, the first level factors of ISM are determined, and the first level factors are further removed from the reachability matrix and continue this operation. Finally, the factor set at each level of ISM is obtained, as shown in Table 5.

It is obvious to see from Table 4 that factors T1 and T2 have exactly the same row and column values. The integration of factors T1 and T2 has defined a new factor labelled by TD. Similarly, factors T3, T4, T6 and T7 are integrated into a new factor labelled by TS.

Table 5. Level partitions of reachability matrix

Factor	Reachability Set	Antecedent Set	Intersection Set	Level
S1	S1、TD、TS、T5、T8、T9	S1	S1	
S2	S2、TD、TS、T5、T8	S2	S2	
S3	S3、TD、TS、T5、T8	S3	S3	
S4	S4、TD、TS、T5、T8	S4	S4	
T1	TD、TS、T5、T8	S1、S2、S3、S4、TD、C3	TD	
T2	TD、TS、T5、T8	S1、S2、S3、S4、TD、C3	TD	
TS	TS	S1、S2、S3、S4、TD、TS、T5、T8、T9、C1、C2、C3	TS	1
T5	TS、T5	S1、S2、S3、S4、TD、T5、T9、C3	T5	
T8	TS、T8	S1、S2、S3、S4、TD、T8、C1、C2、C3	T8	
T9	TS、T5、T9	S1、T9	T9	
C1	TS、T8、C1	C1	C1	
C2	TS、T8、C2	C2	C2	
C3	TD、TS、T5、T8、C3	C3	C3	
S1	S1、T1、T2、T5、T8、T9	S1	S1	
S2	S2、T1、T2、T5、T8	S2	S2	

S3	S3、T1、T2、T5、T8	S3	S3	
S4	S4、T1、T2、T5、T8	S4	S4	
T1	T1、T2、T5、T8	S1、S2、S3、S4、T1、T2、C3	T1、T2	
T2	T1、T2、T5、T8	S1、S2、S3、S4、T1、T2、C3	T1、T2	
T5	T5	S1、S2、S3、S4、TD、T5、T9、C3	T5	2
T8	T8	S1、S2、S3、S4、TD、T8、C1、C2、C3	T8	2
T9	T5、T9	S1、T9	T9	
C1	T8、C1	C1	C1	
C2	T8、C2	C2	C2	
C3	T1、T2、T5、T8、C3	C3	C3	
S1	S1、T1、T2、T9	S1	S1	
S2	S2、T1、T2	S2	S2	
S3	S3、T1、T2	S3	S3	
S4	S4、T1、T2	S4	S4	
T1	TD	S1、S2、S3、S4、TD、C3	TD	3
T2	TD	S1、S2、S3、S4、TD、C3	TD	3
T9	T9	S1、T9	T9	3
C1	C1	C1	C1	3
C2	C2	C2	C2	3
C3	T1、T2、C3	C3	C3	
S1	S1	S1	S1	4
S2	S2	S2	S2	4
S3	S3	S3	S3	4
S4	S4	S4	S4	4
C3	C3	C3	C3	4

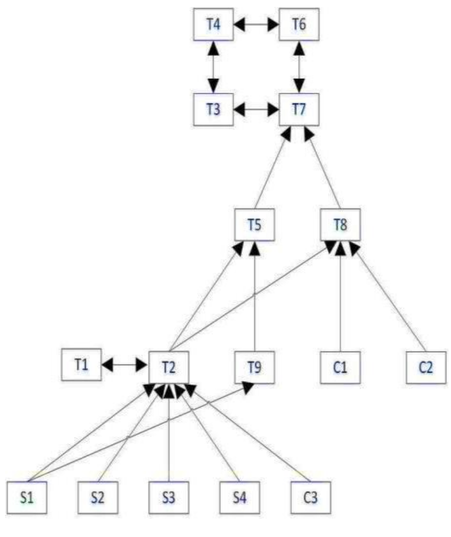

Fig. 2. Relationships among factors

Step five: Establish the ISM relationship model. According to the hierarchical results of the reachability matrix, the correlation diagram among the factors is depicted in Figure 2. The direction of the arrow indicates that the former factor affects the latter factor. Then, the specific contents of the factors are replaced by the code, and we can get the ISM model, as shown in Figure 3.

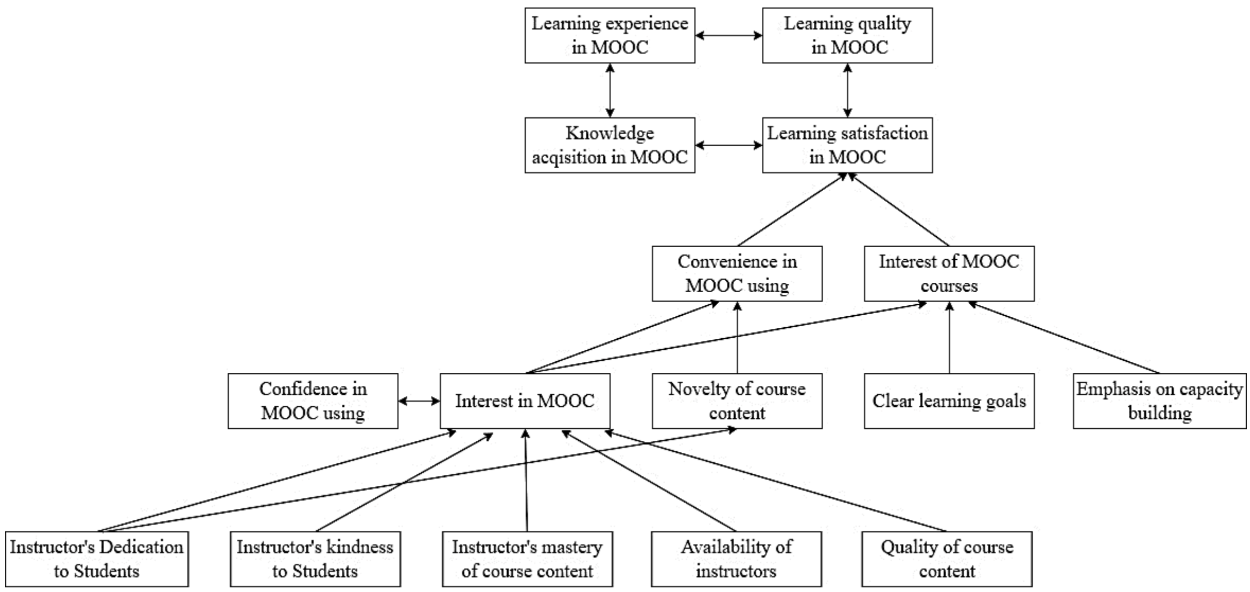

Fig. 3. ISM of factors influencing MOOC learners' self-regulated learning

4.2. Analysis of ISM

Several observations can be made from Figure 2. First, this mode is asymmetric. All factors can be divided into four levels. c T3, T4, T6 and T7 are at the top level of this structure. Factors S1, S2, S3, S4 and C3 are at the deepest level of this structure. The rest of the factors are in the middle. Third, factors T3, T4, T6 and T7 have bidirectional relationships. So are factors T1 and T2. Additionally, relatively more factors point to factor T2.

5. Discussion

Understanding how factors affect MOOC learners' continuous learning is essential to promote the MOOC learning experience and alleviate the dropout problem of MOOC learners. The ISM mode (Figure 3) disclosed some valuable insights into the relative importance of these factors as well as the interdependencies among them.

Five factors related to instructors' service are in the deepest level of the mode, which means that these factors have a significant potential influence on other dimension factors. They are the instructor's dedication to students (S1), the instructor's kindness to students (S2), the instructor's mastery of course content (S3), the availability of instructors (S4), and the quality of course content (C3). This finding is consistent with previous research (Albelbisi, Yusop, 2019; Zhao, 2016). They found that the instructor's service quality can increase learners' engagement and improve learning effectiveness in MOOC learning. In particular, the effect size of instructors' service quality is the smallest. In other words, the factors related to instructors' service quality are the lowest and the most basic among all the factors affecting the continuous learning of MOOC learners, playing the role of foundation support. In addition, research has shown that although the relationship between online learners and instructors does not directly lead to perceived learning gain and satisfaction, it can indirectly affect self-regulated learning, thereby affecting learning satisfaction (Zhou et al., 2021). Thus, this is similar to the findings of this study.

Four factors at the top level have a direct impact on the continuous learning of MOOC learners: knowledge acquisition in MOOC (T3), learning experience in MOOC (T4), learning quality in MOOC (T6) and learning satisfaction in MOOC (T7). These factors can directly affect the continuous learning of MOOC learners and cannot influence other factors. In addition, the remarkable thing is that these four factors affect and interact with each other. This shows that if only you can learn something in MOOCs, you can have a good learning experience and satisfaction. Learning gains and the learning process experience are interlinked and mutually reinforcing. This finding is similar to existing studies (Al-Amri, 2022; Rossi et al., 2021), which reported that online learning engagement or experience could improve learners' performance on multiple skills.

The factors influence the factors in the middle levels at the deepest level and directly influence the factors in the top level, thus serving as a link between the levels above and below. Moreover, it is obvious that interest in MOOC (T2) has the maximum number of relationships, as it is influenced by factors S1, S2, S3, S4 and C3 and directly influences factors T5 and T8. Furthermore, it has a bidirectional relationship with T1. All of these relationships show that this factor plays a vital role in effectively alleviating the dropout problem of MOOC learners. It is proved that learning interest has a positive relationship with continuance intention to learn via MOOCs (Tsai et al., 2018). Therefore, it is recommended to increase learners' interest in MOOCs in various ways, such as improving instructors' social skills, increasing the readability of course content, and so on.

6. Conclusion

The facilitation of the continuous learning of MOOC learners is a complex issue with many uncertain factors. Analyzing its inner logic is conducive to maintaining a high degree of learning participation in MOOC learning. Unlike previous studies' structural equation modelling techniques (Albelbisi, Yusop, 2019; Tsai et al., 2018; Yang et al., 2017), this study used the ISM model to explore this issue and obtained the same results as theirs. In summary, the findings of this study lead to three recommendations. First, instructors' service quality plays a fundamental role in retaining learners to continue MOOC learning, including instructors' humanistic care for learners, teaching ability, etc. Especially in online learning, learners need more interaction and communication. Therefore, it is recommended that instructors should actively carry out interactive activities to improve learners' learning engagement in MOOCs. Second, learners' interest in MOOC positively correlates with continuance intention to learn via MOOCs. On the one hand, the instructors' high-quality teaching services can increase learners' interest in MOOC; on the other hand, cultivating learners' IT skills is also a kind of advice that can be referred to. Third, learners' attitude is directly related to continuous learning in MOOC. Thus, paying attention to learners' MOOC use experience and investigating their needs and suggestions are decisive measures to improve MOOC courses to retain learners to continue learning via MOOCs.

7. Limitations

The findings of this study help promote the continuous learning of MOOC learners and validate existing research. However, there may be errors in the data encoding in the ISM process, which requires further verification. In addition, MOOC learning includes many activities, and its influencing factors are also varied. Therefore, more factors need to be collected to support future research.

8. Declaration of Competing Interest

The manuscript's author declares that there is no interest in conflict, and all reference materials were dully acknowledged.

References

Abdel-Maksoud, 2019 – *Abdel-Maksoud, N.F.* (2019). Factors Affecting MOOCs' Adoption in the Arab World: Exploring Learners' Perceptions on MOOCs' Drivers and Barriers. *Higher Education Studies*. 12(11): 164-177.

Al-Amri, 2022 – *Al-Amri, A.N.A.* (2022). Saudi EFL University Students' perceived Linguistic Gains and Learning Experiences in Flipped Classrooms. *Arab World English Journal (AWEJ) Special Issue on CALL*. (8): 192-204.

Albelbisi, Yusop, 2019 – *Albelbisi, N.A., Yusop, F.D.* (2019). Factors influencing learners' self–regulated learning skills in a massive open online course (MOOC) environment. *Turkish Online Journal of Distance Education*. 20(3): 1-16.

Alraimi et al., 2015 – *Alraimi, K.M., Zo, H., Ciganek, A.P.* (2015). Understanding the MOOCs continuance: The role of openness and reputation. *Computers & Education*. 80: 28-38.

Attri et al., 2013 – *Attri, R., Dev, N., Sharma, V.* (2013). Interpretive structural modelling (ISM) approach: an overview. *Research Journal of Management Sciences*. 2(2): 3-8.

Chansanam et al., 2021 – *Chansanam, W., Poonpon, K., Manakul, T., Detthamrong, U.* (2021). Success and challenges in MOOCs: A literature systematic review technique. *TEM Journal*. 10(4): 1728-1732.

Han et al., 2017 – Han, Y., Zhu, Q., Geng, Z., Xu, Y. (2017). Energy and carbon emissions analysis and prediction of complex petrochemical systems based on an improved extreme learning machine integrated interpretative structural model. *Applied Thermal Engineering*. 115: 280-291.

Hew, Cheung, 2014 – *Hew, K.F., Cheung, W.S.* (2014). Students' and instructors' use of massive open online courses (MOOCs): Motivations and challenges. *Educational Research Review*. 12: 45-58.

Kizilcec, Halawa, 2015 – *Kizilcec, R.F., Halawa, S.* (2015). Attrition and achievement gaps in online learning. *Proceedings of the second (2015) ACM conference on learning*. Pp. 57-66.

Liu et al., 2018 – *Liu, P., Li, Q., Bian, J., Song, L., Xiahou, X.* (2018). Using interpretative structural modeling to identify critical success factors for safety management in subway construction: A china study. *International Journal of Environmental Research and Public Health*. 15(7): e1359.

Meet, Kala, 2021 – *Meet, R.K., Kala, D.* (2021). Trends and future prospects in MOOC researches: A systematic literature review 2013-2020. *Contemporary Educational Technology*. 13(3): e312.

Nawrot, Doucet, 2014 – *Nawrot, I., Doucet, A.* (2014). Building engagement for MOOC students: Introducing support for time management on online learning platforms. *Proceedings of the 23rd International Conference on World Wide Web*. Pp. 1077-1082.

Rossi et al., 2021 – *Rossi, I.V., de Lima, J.D., Sabatke, B., Nunes, M.A.F., Ramirez, G.E., Ramirez, M.I.* (2021). Active learning tools improve the learning outcomes, scientific attitude, and critical thinking in higher education: Experiences in an online course during the COVID-19 pandemic. *Biochemistry and Molecular Biology Education*. 49(6): 888-903.

Tsai et al., 2018 – *Tsai, Y.H. , Lin, C.H. , Hong, J.C., Tai, K.H.* (2018). The effects of metacognition on online learning interest and continuance to learn with MOOCs. *Computers & Education*. 121: 18-29.

Vandevelde et al., 2017 – *Vandevelde, S., Van Keer, H., Merchie, E.* (2017). The challenge of promoting self-regulated learning among primary school children with a low socioeconomic and immigrant background. *The Journal of Educational Research*. 110(2): 113-139.

Yang et al., 2017 – *Yang, M., Shao, Z., Liu, Q., Liu, C.* (2017). Understanding the quality factors that influence the continuance intention of students toward participation in MOOCs. *Educational Technology Research & Development*. 65: 1195-1214.

You, Kang, 2014 – *You, J.W., Kang, M.* (2014). The role of academic emotions in the relationship between perceived academic control and self-regulated learning in online learning. *Computers & Education*. 77: 125-133.

Zhao, 2016 – *Zhao, H.* (2016). Factors influencing self-regulation in e-learning 2.0: Confirmatory factor model. *Canadian Journal of Learning and Technology*. 42(2): n2.

Zhou et al., 2021 – *Zhou, X., Chai, C.S., Jong, S.Y., Xiong, X.B.* (2021). Does relatedness matter for online self-regulated learning to promote perceived learning gains and satisfaction? *The Asia-Pacific Education Researcher*. 30(3): 205-215.