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Factors affecting student dropout in MOOCs: a cause and effect decision-making model

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Abstract

Massive open online courses (MOOCs) are among the latest e-learning initiative that have gained a wide popularity among many universities. Student dropout in MOOCs is a major concern in the higher education and policy-making communities. Most student dropout is caused by factors outside the institution's control. In this study, a multiple-criteria decision-making method was used to identify the core factors and possible causal relationships responsible for the high dropout rate in MOOCs. Twelve factors, distributed across four dimensions, related to students' dropout from online courses were identified from the literature. Then, a total of 17 experienced instructors in MOOCs from different higher education institutions were invited to assess the level of influence of these factors on each other. The results identified six core factors that directly influenced student dropout in MOOCs, these were: academic skills and abilities, prior experience, course design, feedback, social presence, and social support. Other factors such as interaction, course difficulty and time, commitment, motivation, and family/work circumstances were found to play a secondary role in relation to student dropout in MOOCs. The causal relationships between the primary and secondary factors were mapped and described. Outcomes from this study can offer the necessary insights for educators and decision makers to understand the cause–effect relationships between the factors influencing MOOC student dropout, thus providing relevant interventions in order to reduce the high dropout rate.

Keywords MOOC · Dropout · Online learning environments · Higher education · Lifelong learning

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Introduction

Massive open online courses (MOOCs) have recently received great attention owing to their flexibility and the fact that they are free (Amantha Kumar and Al-Samarraie 2019). They provides the means for students to access to world-class educational resources (Nagrecha et al. 2017). Nowadays, the number and diversity of MOOC courses continues to grow and gain an increased popularity among both students and educators in higher education. In 2018, over 900 universities around the world had launched 11,400 MOOCs. That includes around 2000 new courses that were added to the list (Shah 2018). As is known, MOOCs are open to access and use by all. In addition, over 75% of MOOC participants are adult learners and they are self-directed.

Despite the obvious advantages of MOOC courses over the traditional education, many different challenges are still found (Kim et al. 2017). In addition, although the number of available MOOCs is large, the number of participants is still small (Shah 2018). Several recent reports show that the completion rate in MOOCs is very low as compared to the number of those enrolled in these courses and therefore a high dropout rate (Feng et al. 2019). According to Shah (2018)—now in its seventh year—the modern MOOC movement has surpassed 100 million students. At the same time, there is a decline in the number of students continuing these courses. Chen et al. (2019) stated that most of the dropout occurs in the early stages of learning, which needs further exploration (Breslow et al. 2013; El Said 2017; Jordan 2013). Similarly, Coursera's Social Network Analysis class reported that only 2% of participants have completed the courses. Given that MOOCs are becoming more and more popular all over the world, researchers and educational developer are starting to explore innovative ways to help students participating in these courses to persist longer and learn more (Barak et al. 2016; Chen et al. 2019; Hadi and Gagen 2016).

In addition, the high dropout rate of MOOC courses has led many researchers to find out the reasons and factors behind this high dropout phenomenon. Several models for dropout prediction have been proposed to help MOOC developers and decision makers gain greater insight into refining the future of the MOOC (Nagrecha et al. 2017). Many previous studies have shown that the large number of MOOCs learners who did not complete the course might be due to the large amount of data, lack of motivation (Khalil and Ebner 2014), and limited feedback (Li and Moore 2018). While others, like (Rosé et al. 2014; Yang et al. 2014; Zheng et al. 2015) attributed the high attrition rate in MOOCs to certain social factors (such as interaction, communication with peer, friends and the instructors), personal characteristics (Gütl et al. 2014; Khalil and Ebner 2014; Shapiro et al. 2017), course issues (Shawky and Badawi 2019), and other social and environmental factors (Ma and Lee 2019). Based on these observations, the dropout rate from MOOC courses continues to be a major issue in higher education that should be investigated in more depth. This is because identifying certain dropout factors alone is inadequate to explain the reasons behind the high rate of student dropout in MOOCs. In addition, the majority of the previous studies were mostly limited to a narrow set of fields, behaviors, and activities. As such, it is important to understand the causal relationships between the key factors to gain an insight into this growing dropout rate.

Furthermore, using traditional methods such as surveys, interviews, focus groups, and observations for data collection are time consuming and limited especially when carried out on a large scale (Chen et al. 2019; Xing et al. 2016). This includes providing an in-depth understanding of the main reasons behind the high dropout rate of MOOC student and its prevention measures (Itani et al. 2018). Thus, to understand the most critical factors that cause high rate of dropout in MOOCs and enhance the efficiency of MOOC courses, only factors with strong relationships need to be taken into consideration. To fill this methodological gap in MOOC dropout research, this study proposed examining the key factors affecting student dropout in MOOCs through literature reviews and experts' opinions, particularly to answer two research questions: 'What are the main factors influencing student dropout in MOOCs? 'and 'What are the causal relationships between these factors?' To answer these questions, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method was used in this study to build relationships between dropout factors in order to produce an impact-relation map. DEMATEL is an effective method which collects relevant knowledge, analyzes the interrelationships among factors, and visualizes this structure by cause–effect relationship diagram (Gołąbeska 2018). In addition, examining instructors' perceptions of these interrelationships may lead to a better understanding of student dropout in MOOCs (Bonk et al. 2018). It is anticipated that identifying the core factors and the causal relationships responsible for student dropout in MOOCs would help in giving a clear insight for educational policy makers and system designers to apply the necessary interventions and measures to rectify the situation.

Literature review

This section reviews the literature on the potential factors that may influence student dropout in MOOCs. According to Zheng et al. (2015), aspects related to the time, motivations, interaction, course content, workload and communication were found to be the main factors influencing students' dropout from MOOC courses. Yang et al. (2013) and Rostaminezhad et al. (2013) similarly found that social factors such as interaction and communication (social presence) in addition to university and family support can be used to predict the high rate of dropout among students in online environments. Another study by Yousef et al. (2014) found that factors like feedback, course design, and content quality might contribute to the students' completion of MOOC courses. In addition, other factors related to students' attitudes and motivations were addressed by Shapiro et al. (2017) such as the academic skills and abilities, prior experience, course design, and time spent on the learning task.

Previous studies in the literature have also been more concerned about understanding the reasons behind students' dropout over a wider sample of MOOC users. For example, Jordan (2015) conducted a study on a total of 221 MOOC courses to examine the factors that affect completion rates and analysis of attrition rates in these courses. She found that time factor in term of course length, and course designs (assessment) as well as feedback to be the main indicators of student dropout in MOOCs. Ferguson and Clow (2015) examined students' engagement in four MOOCS platforms in which factors associated content complexity were found to mainly influence their decision to continue engagement in the MOOC courses. Onah et al. (2014) observed users' behavior and participation in MOOCs and found that level of difficulty, timing and lack of experiences and learning skills to be the key factors contributing to students' dropout from the course. Furthermore, Itani et al. (2018) stated that most of the reasons behind the high dropout rates in MOOCs are due to personal circumstances such as lack of time, family situations, lack of online skills, and lack of prior experiences.

Based on these observations, this study anticipated that reasons contributing to student dropout in MOOCs may vary across contexts and settings. Our review of the literature revealed a total of 12 factors that were repeatedly associated with individuals dropping from online courses. To narrow the focus of this study, the 12 factors were classified under four main categories: personal (62.5%), circumstantial/social (50%), course (47.5%), academic (42.5%) (see Table 1). This classification is supported by the literature (e.g., Bonk et al. 2018; Josek et al. 2016; Gütl et al. 2014; Henderikx et al. 2017) in which previous empirical studies on online dropout were mostly found to be associated with certain personal factors, followed by circumstantial/social and course factors.

Personal factors

Certain personal factors such as academic skills, students' abilities and prior experience with online courses have been found in the literature to be related to individual dropout in MOOCs. For example, Henderikx et al. (2017) emphasized that personal differences may play a prominent part in the understanding of the dropout problem in MOOCs compared to the distance education context. Likewise, Khalil and Ebner (2014) found that personal factors in terms of learners' limited experience as well as insufficient online skills are the most significant indicators that cause the high attrition rate in MOOCs. In a study conducted by Yamba-Yugsi and Lujan-Mora (2017), factors such as previous experience of students in the MOOC courses, and the level of satisfaction in the interaction with the platform were found to play a key role in the dropout problem from online courses (Bonk et al. 2018; Ghazal et al. 2018). Furthermore, Greene et al. (2015) found that the prior experience with MOOCs was statistically associated with the decreased likelihood of dropout in which participants who did not have any prior experience with the course were more likely to drop from it. According to Lee and Choi (2011), the most distinctive dropout factors among students in online courses can be linked to personal characteristics including academic and learning skills and prior professional experiences, as well as psychological attributes. This has motivated scholars like Hone and El Said (2016) to examine the influence of individuals' experience of MOOC learning on their level of retention. They found that learners' experience and interaction with the

Table 1 Frequency of factors that influence student dropout in MOOCs

	Studies	Personal			Social			Course				Academic	
		Academic skills and abilities	Prior experience	Family/work circumstances	Social interaction	Social presence	Social support	Course design	Content complexity	Commitment	Time	Feedback	Motivation
1	Feng et al. (2019)				√			√			√		
2	Chen et al. (2019)	√									√		√
3	Itani et al. (2018)				√			√				√	
4	Shapiro et al. (2017)	√	√	√				√			√		
5	Kim et al. (2017)				√								
6	El Said (2017)				√	√		√	√		√		
7	Eriksson et al. (2017)			√		√	√		√		√		√
8	Hone and El Said (2016)				√	√			√			√	√
9	Barak et al. (2016)	√											√
10	Kizilcec and Halawa (2015)		√		√	√		√	√		√		

Table 1 (continued)

	Studies	Personal			Social			Course				Academic	
		Academic skills and abilities	Prior experience	Family/work circumstances	Social interaction	Social presence	Social support	Course design	Content complexity	Commitment	Time	Feedback	Motivation
11	Ferguson and Clow (2015)				√				√				
12	Jordan (2015)							√			√	√	
13	Zheng et al. (2015)				√	√			√	√	√		√
14	Gütl et al. (2014)								√		√		
15	Onah et al. (2014)	√					√		√		√		
16	Rosé et al. (2014)				√		√						
17	Yang et al. (2014)				√	√	√						
18	Jordan (2014)						√	√			√		
19	Khalil and Ebner (2014)	√	√		√	√					√		√
20	Liu et al. (2014)				√			√	√		√	√	
21	Yousef et al. (2014)							√	√			√	

Table 1 (continued)

	Studies	Personal			Social			Course				Academic	
		Academic skills and abilities	Prior experience	Family/work circumstances	Social interaction	Social presence	Social support	Course design	Content complexity	Commitment	Time	Feedback	Motivation
22	Halawa et al. (2014)	√							√		√		
23	Clow (2013)	√					√						
24	Adamopoulos (2013)				√		√	√	√		√	√	
25	Yang et al. (2013)				√	√	√			√			
26	McMahon (2013)			√	√	√			√	√	√		√
27	Rostaminezhad et al. (2013)				√								√
28	Belanger and Thornton (2013)	√	√								√		
29	Nistor and Neubauer (2010)					√					√		
30	Fini (2009)												√
	%	62.5%			50%			47.5%				42.5%	

instructor in the MOOC platform can potentially be used to predict MOOC retention. Few previous studies have emphasized on the impact of relevant family and work circumstances on students' dropout decision. For instance, Park and Choi (2009) stated that students' family background or climate, income, as well as their work conditions (hours of work) can somehow contribute to students' dropout decision from e-learning courses. A survey conducted by Josek et al. (2016) showed that students who receive less support from their family or encountering difficulties at work are likely to dropout from the course more frequently than those with more family support. This is particularly due to the influence of these circumstances on students' persistence in online learning (Baragash and Al-Samarraie 2018a, b; Lee and Choi 2011). Based on these observations, factors related to students' academic skills and abilities, prior experience, and family/work circumstances were grouped under the 'personal' category.

Circumstantial/family factors

Previous studies in online learning and MOOC area have highlighted the strong role of certain circumstantial or social factors such as social interaction and social presence in affecting students' intention to complete their chosen programs (Lee and Choi 2011; Zhang et al. 2016). Since students' active interaction with the content, peers, and instructors synchronously or asynchronously can help deepen understanding of the learning topic, students' low social interaction/communication may trigger their intention to dropout from the learning activity (Lu et al. 2017; Moore 1989; Whitehill et al. 2017; York and Richardson 2012). Yang et al. (2014) stated that factors related to student behavior and social positioning (communication) within discussion forums can be linked to students' decision to withdraw from online courses. In the MOOC context, Barak et al. (2016) reported that students' interaction level with the course can be used to predict their dropout intention from online courses. From a broader perspective, Kizilcec and Schneider (2015) stated that different motivational goals (e.g., meeting new friends and career change) may predict different behavioral patterns among students in the MOOC environment. They found that students who registered with friends were less likely to drop the course and more likely to engage with the course content than their peers. Previous studies (e.g., Appiah-Kubi and Rowland 2016; Chen et al. 2016; Muñoz-Merino et al. 2015) have shown the impact of social presence on the learning experience of students which could possibly contribute to the dropout phenomenon in MOOCs. Other studies like Adamopoulos (2013) and Clow (2013) stated that the amount of support received from family and friends or colleagues can directly influence students' likelihood to complete online courses. Park (2007) found that lack of social support in terms of encouraging and motivating students to complete the course might lead to high dropout rate of students from the online courses. Accordingly, the lack of social interaction, social presence, and social support were grouped under the 'circumstantial and social' category in this study.

Course factors

Course-related factors have also been addressed by many studies as another key determinant that lead students to dropout from MOOCs (Angelino et al. 2007; Hew and Cheung 2014). Adamopoulos (2013) found that course materials and assignments on the web can significantly increase students' completion rates, whereas aspects related to the difficulty of learning content and the duration of a course were found to negatively impact students' completion of online courses (Al-Samarraie 2019). In addition, Feng et al. (2019) and Itani et al. (2018) explored the main dropout reasons of students from the MOOC environment. They found that certain course factors, such as course design, time, and course difficulty, are among the critical factors behind the high student dropout rate in MOOCs (Onah et al. 2014). Lee and Choi (2011) conducted a review on online course dropout in which they argued that course design and institutional supports to be a critical part in driving students' dropout decision. In addition, Greene et al. (2015) found that the level of commitment among students to be strongly associated with the high dropout rate. They stated that students who were unsure of their commitment to the course were more likely to withdraw from the course than those who intended to complete it. Jordan (2015), on the other hand, stated that completion rates of online courses may correspond to the length of the course in which longer courses are likely to be more difficult, thus leading to lower completion rates. Related to this, four factors have been identified and grouped under the 'course' category: course design, difficulty, commitment, and time.

Moreover, the low level of commitment among students might also be attributed to the fact that the course is free of cost in which students may not feel the need to participate (Aldowah et al. 2019). Thus, the high dropout rate in MOOCs might be somehow associated with the students' low level of commitment to the course as a result of zero or low entry cost (Chen 2014). McAuley et al. (2010) stated that the high dropout rate is an almost-inevitable consequence of any open/online activity, mainly because initial commitment is missing. Therefore, a low level of commitment may lead to a low completion rate for MOOCs. This led Yuan and Powell (2013) to argue that since most students who are using MOOCs have a degree, it is not important whether a MOOC carries credit or not. Another study by Daniel (2012) stated that what determines whether a student can obtain a degree or not is determined not by his mastery of the course, but through the admission process at the university. The author asserted that the completion of a MOOC course should not be associated with credits.

Based on these, it can be asserted that the low cost of MOOC courses may partially contribute to the high dropout rate among students. In addition, since the notion of MOOC courses is to make learning easy and accessible to all learners, especially for those who cannot afford studying in universities, it can be said that the low or zero-cost entry may make it possible for learners to change from one course to another. In other words, when learners enroll in a MOOC course, it means they are mainly enrolling to improve their background about the topic or to enhance their job skills. However, when the students find the course to be both not challenging and time-consuming, they are more likely to dropout from it. All these reasons can be attributed, as stated earlier, to various factors such as course design, difficulty of content, commitment, time, and motivation. These factors are explained in the following subsections.

Academic factors

The review of the literature showed that understanding the motivation for online students to learn in MOOC environments is gaining considerable attention among researchers (Barak et al. 2016). Motivation to learn is defined as students' tendency to find relevant academic activities and gain the intended benefits from them so they can be motivated to complete the course on time (Brophy 2013). Hence, academic factors such as feedback and motivation received from the instructors (identified in previous studies) were closely linked with students' completion of online courses. For instance, Gütl et al. (2014) surveyed 134 students who had not completed the MOOC courses and found that only 22% of the students had the intention to complete their study but they were unable to do so due to low motivation, poor feedback, insufficient time, and content complexity. The poor feedback provided by the instructors has been reported to be an important predictor of student dropout in MOOC courses (Halawa et al. 2014; Onah et al. 2014).

So far, MOOC research lacks knowledge about the interrelations between certain academic factors (e.g., motivation and feedback) and the consistently high dropout rate of MOOC learners. Hence, understanding the effect of academic factors is important for both instructors and learners to complete the MOOC. For example, MOOC instructors can design unique learning environments and provide the necessary means for learners to accomplish their goals. According to Barak et al. (2016), given the importance of motivational differences between MOOC participants, the learning process may positively contribute to the students' motivation to learn and complete the MOOC. Conducting a study that investigate the effect of such factors on students' decision to complete or dropout the course would help policy makers to apply the necessary measures to rectify the situation.

Figure 1 presents the proposed categories of MOOCs dropout factors based on the review of prior studies. Yet, findings from previous studies are still not sufficient enough to clearly identify the key dropout factors and causal relationships between them, particularly from the perspective of instructors.

Methods

In this study, a more practical approach was used to determine the key factors and causal relations affecting student dropout in MOOCs. The DEMATEL method contributes to the MOOC literature by modeling cause-and-effect relations. It was first introduced by Geneva Battelle Institute in 1971 based on the concept of the graph theory to build visualized structural approach of complicated causal relationships (a causal–effect) through matrixes or diagrams to show the interdependence relationships between factors in the model (Dalalah et al. 2011). This method has become

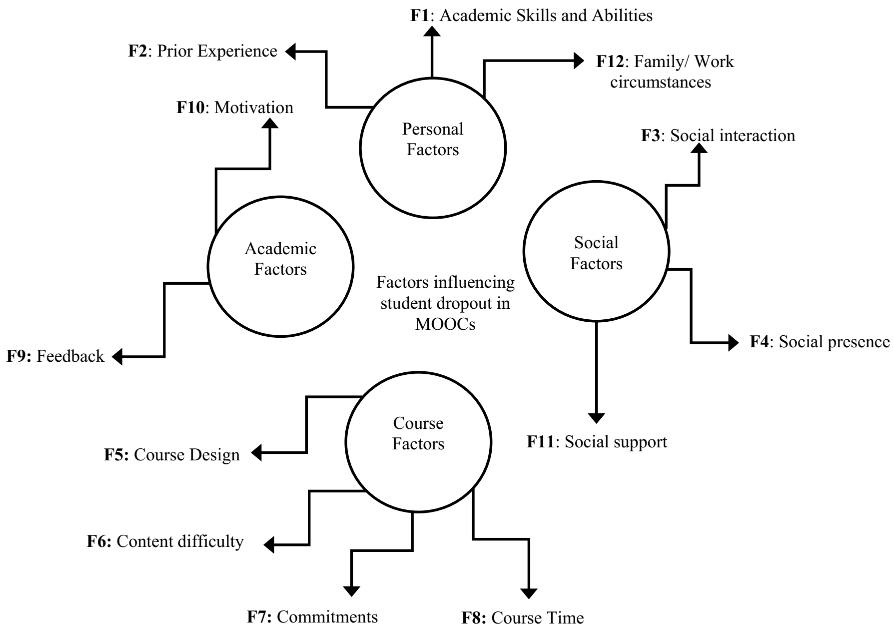

Fig. 1 An illustration of factors influencing student dropout in MOOCs

one of the most commonly used methods for modeling cause and effect relationships between predefined criteria in the evaluation process of any system (Akyuz and Celik 2015). This method has received a great deal of attention in the last decade and has been applied by many researchers to solve complicated system problems in various areas. It is increasingly used to solve many social, educational, and economic or technical problems (Gołąbeska 2018; Al-Samarraie et al. 2018). Since the DEMATEL method is well-known as a type of structural modeling approach, it is especially useful in analyzing the cause and effect relationships among components of a system (Seker and Zavadskas 2017). Precisely, it can be used to confirm interdependence between factors and help in the development of a map to reflect the relationship between the causes and effects of certain criteria (Shieh et al. 2010). The most important aspect of the DEMATEL method in the multi-criteria decision-making field is that it helps visualize the interrelations between criteria (Muhammad and Cavus 2017). The basic steps of DEMATEL are as follows:

Step 1 Calculate the initial average matrix by scores.
Step 2 Calculate the initial influence matrix.
Step 3 Develop the full direct/indirect influence matrix.
Step 4 Set the threshold value.
Step 5 Generate the impact relations map.

In addition, the linguistic variable "influence" was used with a five-level scale containing the following scale items in the group decision-making proposed by Li (1999): no influence, very low influence, low influence, high influence, and very high influence.

Sample and procedure

The identified factors from the literature on student dropout in MOOCs were used to build the interview scheme for the structured interviews. Using a convenience sampling method, a total of 17 instructors (11 males and 6 females), selected from different public universities, were invited to the interview. A total of 100 invitation emails were sent individually to instructors from 20 public universities to obtain a greater diversity of respondents. Only 17 instructors responded. The instructors came from 11 universities. The participants' age ranged from 30 to 45 years old (M = 34.52 years, SD = 4.23 years). They all had experience in using MOOC for teaching at their universities (M = 4.11 years, SD = 0.56 years). Participants were interviewed individually for about 15–20 min each. During the interview, participants were guided on how to assess the level of impact of each factor on others. Then, we asked each participant to respond to a series of closed-ended questions, as shown in Table 2, using a scale of 0 (no influence), 1 (very low influence), 2 (low influence), 3 (high influence), and 4 (very high influence). Precisely, participants were asked to estimate the level of influence of each factor on other factors. The participants' judgment on these influential factors was based on their teaching experience and observation of students' learning in MOOCs. The collected responses were coded individually in order to build the cause–effect relationship diagram from the normalized responses. The following subsections explain the main steps used to generate the cause–effect relationship diagram.

Table 2 The cause-and-effect matrix

Cause-effect matrix	Academic skills/abilities	Prior experience	Social interaction	Social presence	Course design	Course Difficulty	Commitment	Course time	Motivation	Feedback	Social support	Family/work circumstances
Academic skills/abilities												
Prior experience												
Social interaction												
Social presence												
Course design												
Content difficulty												
Commitments												
Course time												
Feedback												
Motivation												
Social support												
Family/work circumstances												

Instructions for filling out the index: 0 = no influence; 1 = very low influence; 2 = low influence; 3 = high influence, 4 = very high influence

DEMATEL model

The result from using the DEMATEL approach is presented in a visual form [a graph that separates components to cause group (on x axis) and effect group (under x axis)]. The impact relationship diagram is produced after obtaining horizontal axis (D+R) (refers to the strength of influence among criteria) and vertical axis (D−R) (refers to the influence relation among criteria). The produced diagram is used to represent a set of complex relationships of factors in an easy and understandable structural model. In the event that the value of (D−R) for a factor is negative, the factor should be considered as an effect factor, which is mostly affected by others. However, in the event that the value of (D−R) for a factor is positive, the factor should be considered as a cause factor (Gharakhani 2012). In order to obtain a suitable impact-relations map, an appropriate threshold value is needed to obtain adequate information for further analysis and decision-making. To apply a DEMATEL method, we intentionally followed the phases shown in Fig. 2.

Based on the figure, the analysis procedures of the DEMATEL method are described as follows (Tsai et al. 2015; Lin 2013):

Step 1: generating the direct-relation matrix

In the first stage of DEMATEL modeling, we constructed the initial matrix for each respondent based on the result captured during the interview session. The influence level between Fs was determined by asking participants to indicate the direct effect for each **F** has on other factors. We started by calculating the average matrix in which the value of column (i) and value of row (j) were estimated based on the level of the influence between these **F**s. We assumed $\mathrm{X}_{\mathrm{ij}}^{\mathrm{k}}$ as the value for representing the influence of **Fi** on **Fj**. As presented in Eq. (1), $\mathbf{F} \times \mathbf{F}$ matrix was constructed, and value 0 was assigned where $\mathbf{i}=\mathbf{j}$ $(\mathbf{F}_{\mathbf{ij}}=\mathbf{0})$ (the diagonal elements of each answer matrix *x ij k* were all set to zero, which means no influence).

$$\boldsymbol{A} = \begin{pmatrix} 0 & F_{12} & \cdots & F_{1n} \\ F_{21} & 0 & \cdots & F_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ F_{n1} & F_{n2} & \cdots & 0 \end{pmatrix}, \quad \boldsymbol{F}_{ij} = \frac{1}{H}\sum_{k=1}^{H} X_{ij}^{k} \tag{1}$$

where $\boldsymbol{H}$ refers to the total number of participants in this study. The finalized direct relation matric is presented in Table 3.

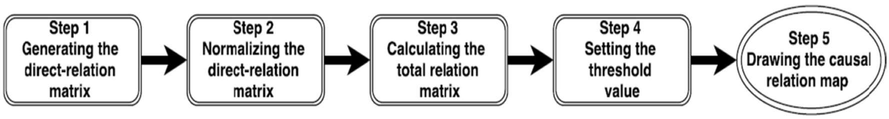

Fig. 2 DEMATEL phases

Table 3 Direct relation matrix

Factors	Code	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
Academic skills	**F1**	0.00	3.00	2.86	3.43	3.43	3.43	3.00	2.43	3.14	3.29	2.57	2.71
Prior experience	**F2**	3.86	0.00	3.43	3.29	3.00	3.14	3.00	2.43	2.14	3.43	2.43	2.86
Social interaction	**F3**	3.14	3.29	0.00	3.71	2.71	3.00	2.14	2.86	3.00	3.14	2.86	2.14
Social presence	**F4**	3.14	3.00	3.43	0.00	2.71	3.14	3.00	2.71	2.86	3.43	2.86	2.43
Course design	**F5**	3.14	2.86	3.57	3.00	0.00	4.00	3.14	3.43	3.00	3.14	2.43	1.14
Content difficulty	**F6**	3.71	2.14	3.29	2.86	3.71	0.00	2.00	3.29	2.14	3.00	2.29	1.29
Commitments	**F7**	3.00	2.57	2.71	2.43	2.43	3.43	0.00	2.71	2.43	3.14	2.43	2.00
Course time	**F8**	2.14	2.71	3.00	2.14	3.14	3.29	3.14	0.00	2.00	3.14	2.71	1.29
Feedback	**F9**	2.14	2.14	3.29	3.43	3.00	3.57	2.57	2.57	0.00	2.57	2.14	2.00
Motivation	**F10**	2.29	2.71	3.86	3.57	2.57	3.00	3.14	2.71	3.14	0.00	2.86	2.43
Social support	**F11**	2.71	2.14	2.43	2.43	2.71	2.86	2.57	2.14	2.29	3.29	0.00	2.14
Family work	**F12**	2.00	1.57	2.57	2.14	1.00	1.00	3.00	1.57	1.43	3.29	1.71	0.00

A high score indicates a belief that a greater improvement in *i* is required to improve *j*. The average matrix A shows the initial direct effects that a factor exerts on and receives from other factors.

Step 2: normalizing the direct-relation matrix for Fs

After obtaining the average matrix, we minimized redundancy in data sets among the average responses. As such, we calculated separately the total value of **Fs** for rows and **Fs** for columns where we used the maximum value ***S*** between both the rows and columns in order to normalize the direct-relation matrix ***A***. As shown in Eqs. (2) and (3), the resulted matrix A was divided by the maximum value ***S***, thus forming matrix ***X.***

$$s = \max\left(\max_{1 \le i \le n} \sum_{j=1}^{n} F_{ij}, \max_{1 \le j \le n} \sum_{i=1}^{n} F_{ij} \right) \tag{2}$$

And the result matrix X was calculated as follow:

$$\boldsymbol{X} = \frac{A}{S} \tag{3}$$

Table 4 shows the normalized initial direct-relation matrix. It represents the total direct effect that criterion *i* gives to the other criteria obtained by summing up each row *i* of matrix **A**. In addition, each column represents total direct effects received by creation *j*.

Table 4 Normalized matrix

Factors	Code	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
Academic skills	**F1**	0.00	0.09	0.08	0.10	0.10	0.10	0.09	0.07	0.09	0.09	0.07	0.08
Prior experience	**F2**	0.11	0.00	0.10	0.09	0.09	0.09	0.09	0.07	0.06	0.10	0.07	0.08
Social interaction	**F3**	0.09	0.09	0.00	0.11	0.08	0.09	0.06	0.08	0.09	0.09	0.08	0.06
Social presence	**F4**	0.09	0.09	0.10	0.00	0.08	0.09	0.09	0.08	0.08	0.10	0.08	0.07
Course design	**F5**	0.09	0.08	0.10	0.09	0.00	0.11	0.09	0.10	0.09	0.09	0.07	0.03
Content difficulty	**F6**	0.11	0.06	0.09	0.08	0.11	0.00	0.06	0.09	0.06	0.09	0.07	0.04
Commitments	**F7**	0.09	0.07	0.08	0.07	0.07	0.10	0.00	0.08	0.07	0.09	0.07	0.06
Course time	**F8**	0.06	0.08	0.09	0.06	0.09	0.09	0.09	0.00	0.06	0.09	0.08	0.04
Feedback	**F9**	0.06	0.06	0.09	0.10	0.09	0.10	0.07	0.07	0.00	0.07	0.06	0.06
Motivation	**F10**	0.07	0.08	0.11	0.10	0.07	0.09	0.09	0.08	0.09	0.00	0.08	0.07
Social support	**F11**	0.08	0.06	0.07	0.07	0.08	0.08	0.07	0.06	0.07	0.09	0.00	0.06
Family work	**F12**	0.06	0.05	0.07	0.06	0.03	0.03	0.09	0.05	0.04	0.09	0.05	0.00

Step 3: calculating the total relation matrix of Fs

After the normalized direct-relation matrix obtained, the total relation matrix $\boldsymbol{T}$ was calculated as in Eq. (4).

$$\boldsymbol{T} = X(I - X)^{-1} \tag{4}$$

where $\boldsymbol{I}$ refers to the value of the identity matrix. Table 5 presents the total affect matrix.

Table 5 Total affect matrix

Factors	Code	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
Academic skills	**F1**	0.57	0.60	**0.70**	**0.68**	0.65	**0.71**	0.63	0.60	0.59	**0.71**	0.57	0.49
Prior experience	**F2**	**0.67**	0.52	**0.71**	**0.67**	0.63	**0.69**	0.63	0.59	0.57	**0.71**	0.56	0.49
Social interaction	**F3**	0.63	0.59	0.60	**0.67**	0.61	**0.68**	0.59	0.59	0.57	**0.69**	0.56	0.46
Social presence	**F4**	0.64	0.59	**0.70**	0.58	0.62	**0.69**	0.62	0.60	0.58	**0.70**	0.57	0.47
Course design	**F5**	0.65	0.59	**0.71**	**0.67**	0.56	**0.72**	0.63	0.62	0.59	**0.70**	0.57	0.44
Content difficulty	**F6**	0.62	0.53	0.65	0.61	0.61	0.56	0.56	0.57	0.52	0.65	0.52	0.41
Commitments	**F7**	0.59	0.53	0.63	0.59	0.56	0.64	0.49	0.54	0.52	0.64	0.51	0.42
Course time	**F8**	0.56	0.53	0.63	0.58	0.57	0.63	0.57	0.47	0.50	0.63	0.51	0.40
Feedback	**F9**	0.57	0.52	0.64	0.62	0.58	0.64	0.56	0.54	0.46	0.63	0.51	0.42
Motivation	**F10**	0.62	0.58	**0.70**	**0.67**	0.61	**0.68**	0.62	0.59	0.58	0.61	0.56	0.47
Social support	**F11**	0.55	0.50	0.59	0.56	0.54	0.59	0.54	0.51	0.49	0.61	0.42	0.41
Family work	**F12**	0.43	0.38	0.48	0.45	0.39	0.43	0.44	0.39	0.37	0.50	0.38	0.27

The values in bold represents the highest value for each column and row

Step 4: setting the threshold value

To be able to visualize the causal relation map with reasonable complexity level, we had to set a threshold value $\boldsymbol{p}$ to eliminate the smaller effect rather than using threshold value in the total relation matrix $\boldsymbol{T}$. Whenever the threshold value increase or decrease, the causal relation map become more complex. In this study, the threshold value was obtained by summing the mean and the standard deviation of the values in the total matrix $\boldsymbol{T}$.

Step 5: drawing the causal relation map

To draw the causal relation map, we had to sum up values in rows and columns of the total relation matrix separately, which named as a vector **D** and vector R respectively as in Eq. (5). **D** vector represents all direct and indirect influence given by factor ***i*** to all other factors, and so **D** can be called the degree of influential impact. On the other hand, vector R represents both direct and indirect impact received by factor j from all other factors, which is denoted as R (the degree of influenced impact). In order to produce the causal relation map in **2D** plan; the horizontal axis was determined by adding **(D + R)** and named 'Prominence' which shows the importance of the factor *i* and the rule that *i* plays in the whole model. In addition, the vertical axis was acquired by subtracting **(D − R)**, named 'Relation', which represents the net effect of factor **i** that has on the model. Based on the result of **D** and **R** from Eqs. (6) and (7), we were able to map the causal relation from **(D + R)** and **(D − R)** as shown in Table 6.

$$T = \left[t_{ij}\right]_{n\times n} \quad i,j = 1, 2, \ldots, n \tag{5}$$

$$D = \sum_{j=1}^{n} t_{ij} \tag{6}$$

Table 6 The effect and net effect of the dropout factors

Code	Factors	R	D	D + R	D − R	Impact
F1	Academic skills and abilities	7.49	7.1	14.59	0.39	Cause
F2	Prior experience	7.44	6.46	13.90	0.98	Cause
F3	Social interaction	7.25	7.74	14.99	− 0.49	Effect
F4	Social presence	7.37	7.35	14.72	0.02	Cause
F5	Course design	7.47	6.95	14.42	0.52	Cause
F6	Content difficulty	6.83	7.66	14.49	− 0.83	Effect
F7	Commitment	6.66	6.89	13.55	− 0.23	Effect
F8	Course time	6.57	6.61	13.18	− 0.04	Effect
F9	Feedback	6.69	6.35	13.04	0.34	Cause
F10	Motivation	7.27	7.77	15.04	− 0.50	Effect
F11	Social support	6.32	6.25	12.57	0.07	Cause
F12	Family/work circumstance	4.91	5.15	10.06	− 0.24	Effect

$$R = \sum_{i=1}^{n} t_{ij} \tag{7}$$

Noting that the DEMATEL method was originally constructed based on the concept of graph theory, a graph can be associated with a number of nodes connected through edges. In the total matrix $\mathbf{T}$ for each element t_{ij}, we identified the factor x_i as a dispatch-node while x_j was identified as a receive-node. By doing so, we treated the total matrix $\mathbf{T}$ as set of n^2 pair ordered elements, and then we divided every subset of $\mathbf{T}$ into two sets (ordered dispatch-node set and ordered receive-node set). We also assumed the cardinality of a dispatch or receive node as m and the frequency of any element x_i as k where the probability of any element x_i measured by $p_i = \frac{k}{m}$. In this study, the cardinal number of an ordered set $\mathbf{X}$ is referred to as $\mathbf{C}(x)$ to represent the number of elements included in the set to which the cardinal number in set $\mathbf{X}$ was identified as $N(x)$ (the number of different elements included in the set).

Results and discussion

Although MOOCs have been widely accepted in most higher education institutes as a way to help students access learning resources at anytime and anywhere, but the high rate of dropout in MOOC platforms remain a subject of concern for educational decision makers, instructors, system developers, and MOOC platform providers. Our review of previous studies shed light on 12 potential factors that may affect student dropout in MOOCs, which categorized under—personal factors (academic skills and abilities, prior experience, and family/work circumstances), social factors (social interaction, social presence, and social support), course factors (course design, content difficulty, commitments, course time), and academic factors (feedback and motivation). Then, the DEMATEL method was used to analyze data collected from 17 instructors in order to identify the core factors and conduct relationships analysis. The overall results showed the potential impact of certain factors on student dropout in MOOCs. We found several associations between the studied factors. Based on the causal relation diagram or map (see Fig. 3), one can see the most important (prominent) factors of dropout in MOOCs and the most important relationships amongst these factors. Here, the interrelated lines between the factors indicate the direction of the relationship from the influencing factor to the affected one. However, the two-way arrows (double-sided) indicate the mutual influence between these factors. The most important dropout factors were social presence (F4), academic skills and abilities (F1), course design (F5), prior experience (F2), and social support (F11) with the values of 14.72, 14.59, 14.42, 13.90, and 12.72, respectively. Our results showed that family/work circumstances (F12), course time (F8), and commitments (F7) were the least important criteria with values of 10.06, 13.18, 13.55, respectively. Contrary to the importance of criteria, course design (F5) and prior experience (F2) were net causers, whereas content difficulty (F6) was the net receiver in accordance with the value of difference (r–c, shown in Table 6).

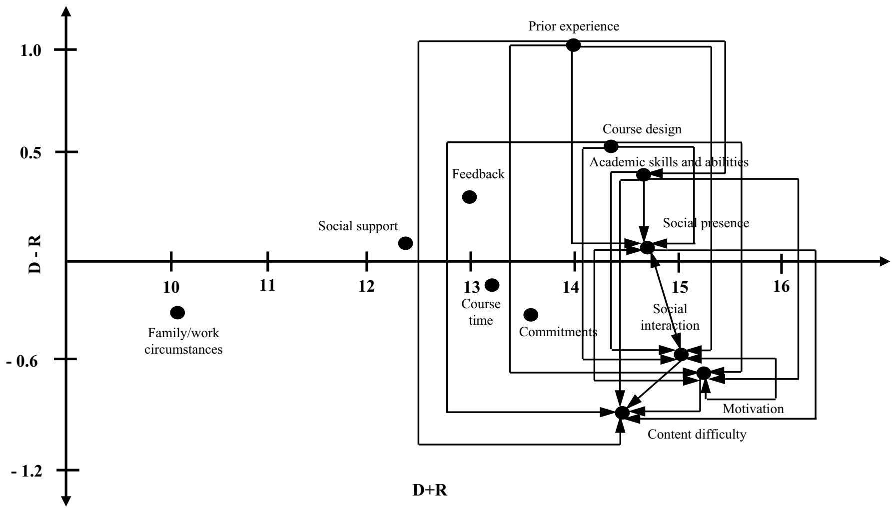

Fig. 3 The DEMATEL map

However, other factors, such as social presence (F4), academic skills and abilities (F1), social interaction (F3), and motivation (F10) were net causers and receives. According to Fontela and Gabus (1976), given the interdependence of factors, much attention should be paid to the cause factors group and their influence on the effect factors group. If the factor is not linked with any other factors, such as social support and feedback, course time, commitment, and family/work circumstances, it means that their cause/effect is independent from other factors.

The findings indicated that causal factors of student dropout in MOOCs were prior experience and academic skills, and therefore more attention should be given by decision-makers to these factors. This finding adds to the work of previous studies (e.g., Greene et al. 2015; Hone and El Said 2016; Khalil and Ebner 2014; Shapiro et al. 2017; Yamba-Yugsi and Lujan-Mora 2017) by demonstrating the effect of students' academic skills/abilities and their prior experience on the dropout rate in MOOCs. Moreover, this study found that both motivation and social interaction factors can play a secondary role in affecting students' decision to drop from the course (indirect effect). This result is in contrast with many previous studies (Adamopoulos 2013; El Said 2017; Eriksson et al. 2017; Hone and El Said 2016; Kim et al. 2017; Yang et al. 2013; Zheng et al. 2015) that have reported motivation and social interaction are two main factors that influence students' decisions to drop online courses. However, these two factors were found to be strongly associated with other core factors. Similarly, the complexity or difficulty of the course content was found in many studies to be associated with students' dropout rates (El Said 2017; Eriksson et al. 2017; Halawa et al. 2014; Liu et al. 2014; McMahon 2013; Willging and Johnson 2009; Zheng et al. 2015). Yet, we found that content difficulty can potentially affect online students' dropout through its association with other core factors such as course design, academic skills, prior experience, and social presence.

In addition, content difficulty, motivation, commitments, social interaction, and social presence factors were found to be associated with students' academic skills and prior experience in MOOCs. This findings is supported by Wang and Baker (2015) who stated that students prior experience is an essential element for students to be able to complete MOOC courses. This is also evident from the work of Barak et al. (2016) who emphasized that student prior experience with MOOCs and their academic skills play significant roles in promoting their motivation and commitment towards the course. Although prior studies (e.g., Clow 2013; Onah et al. 2014; Yang et al. 2013, 2014) have emphasized on the importance of family and work circumstances in influencing individual's decision to dropout from online courses, there was no significant influence of these factors found in this study. This result is in line with Lee et al. (2013) who confirmed that family and work circumstances have no significant impact on student dropout in online courses.

Moreover, several studies reported that a high dropout rate from MOOC courses, averaged 95% of course participants, was due to issues related to the design of these courses. Accordingly, the quality of MOOC course design needs more attention by instructional designers and developers to increase its effectiveness (Yousef et al. 2014), thus enabling students to complete the online course (Adamopoulos 2013). The result also showed that the difficulty of course content, motivation, and social interaction to be associated with the course design factor, which supports the argument made by Gütl et al. (2014) that student dropout from online courses can be due to several factors including course design issues, which may significantly affect students' overall motivation and communication with peers. For example, when students find the content to be challenging, they are more likely to dropout from the course especially when support or prompt feedback is not provided by the instructor (Bonk et al. 2018; Park and Choi 2009). Thus, if the design of MOOC courses is compatible with students' experiences, students are likely to appreciate the course and the instruction, and, therefore, the relationship between course design and other personal factors can be expressed as inter-correlation rather than as one-sided dependence.

Students' academic skills/abilities, prior experience, and the course design were found to be linked to their social presence and social interaction. In general, the low communication and social interaction among students themselves and between students and instructors was found to occur in association with MOOC learners' dropout behavior, which supports previous studies on how poor communication may lead students to dropout of online courses (Eriksson et al. 2017; Yang et al. 2013). Yang et al. (2014) emphasized that lack of communication is one of the key factors contributing to higher dropout rates in MOOC platforms, which, in turn, may affect students' motivation and social interaction with the course content. According to Kizilcec and Schneider (2015), different motivational goals of students and their interaction level with the course can predict their dropout intention in MOOCs (Barak et al. 2016). Our findings are consistent with other previous studies which emphasized that MOOC participants who were engaged in significant interactions with peers are less likely to drop from the course (Ferguson and Clow 2015; Halawa et al. 2014; Jordan 2014; Onah et al. 2014). Meanwhile, our findings showed that social factors (presence and interaction) are linked to each other in terms of their relationship to students' decision to dropout. This can be attributed to the fact that MOOCs include learners who are not only unfamiliar with each other but also come from different academic and cultural backgrounds, making the communication and social interaction very difficult (Barak et al. 2016). As such, MOOC designers should focus on the strategies that stimulate students' social interaction and increase the peer communication, such as student-led facilitation strategies, rather than focusing on instructor facilitation strategies in order to overcome the challenges of instructor-dominated facilitation and to enhance the sense of community, thus encouraging student participation in online courses. This is because embedding specific facilitation strategies within the MOOC discussion will help students generate innovative ideas and take an active role in related decisions (Baran and Correia 2009). Moreover, MOOC designers should provide diverse communication platforms for the learners who desire to be part of a community of people with similar interest (Barak et al. 2016). In addition, promoting work group and competitive activities in the MOOC platform can potentially encourage students to communicate with their peers to solve complex learning problems (El Said 2017; Zheng et al. 2015). Supported by Yang et al. (2013), our findings also revealed that social support provided for students is a key factor influencing students' decision to continue or drop the course. According to Park and Choi (2009), students are more likely to drop online courses if when they do not receive proper encouragement and support from their instructors, peers, family, and institution regardless of their academic skills and backgrounds. Moore and Fetzner (2009) reported that social support provided to learners through online social interaction and communication has contributed to high course completion rates. Therefore, more research should be conducted to examine how students in MOOC courses can be further supported to help them gain the educational benefits so that they have the confidence and motivation to complete the course (Zhenghao et al. 2015).

Furthermore, our findings revealed that feedback was also found to influence students' dropout decision, which can be attributed to the fact that in MOOC environments, it is very difficult to provide individual feedback to all students enrolled in one or more classes. Hone and El Said (2016) and Jordan (2015) have declared that feedback is a crucial factor that may cause students to dropout a course, while Halawa et al. (2014) emphasized on how feedback can be an important indicator of student dropout in MOOC platforms. Thus, it is anticipated that higher education institutions may consider the benefits of introducing new regulations or a change of practice by the instructors to provide timely feedback that reflect the massive and open nature of MOOC courses. In conclusion, our findings emphasize the importance of instructors' perceptions when assessing student dropout or success in MOOCs. This does not mean that it should replace students' views with the instructors' views, but rather complement it.

Implications and future works

The use of the DEMATEL method helped in examining the relationship between the different factors affecting students' decision to dropout of MOOCs, which can help higher education decision-makers to recognize the most influential factors on dropout rate in MOOC environment, thus taking early measures to reduce that rate. Based on the findings, only six factors out of twelve were found to have a significant impact on students dropping the course, these were: academic skills and abilities, prior experience, social presence, course design, feedback, and social support. While other factors such as social interaction, course content, commitment, course time, motivation, and family/work circumstances were found to be primarily associated with the core factors. The relationships between the core and seconder factors are interrelated and have an effect on each other.

However, there were some unavoidable limitations in this study. For example, this study was limited to 17 instructors who accepted to participate in this study. It was difficult to find instructors who are both experts and experienced in teaching with MOOCs, and therefore future studies may involve a large and more diverse heterogeneous sample to model cause-and-effect relationships between the identified dropout factors. In addition, future studies may also consider examining students' views, particularly to establish the causality between the factors affecting their dropout in MOOCs and compare the results from the two views (instructors and students). Furthermore, future works may also consider investigating demographic characteristics of different types of users, as this may offer additional insights to the findings of the current study. Other decision-making-related approaches such as fuzzy cognitive maps or analytical hierarchical processes can be also applied to find the causal relations of other different factors that were not included in the study.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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