DEMATEL Analysis to Determine the Factors Affecting Indian Academicians Dropout in MOOCs

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Abstract: This paper aims to identify the factors influencing academician's dropout in MOOCs. The factors investigated were personal, social and academic factors. We adopted DEMATEL method, also known as multi criteria decision making model. A total of 7 experienced instructors were invited for determining the level of influence on among each factor. Out of eight factors, six factors were adopted from existing literature and they were distributed into three dimensions namely personal, social and academic factors. Assessment criteria and peer support were also added to this factor as per the suggestion from the experts. The study identified four core factors that directly influence the academician's dropout in Massive open online courses; the major factors were family pressure, social interaction, feedback and course structure, and other factors such as motivation, skills and abilities, peer support. Assessment criteria are considered to have indirect effect on influencing academicians' dropout in MOOCs.

Keywords: Online Learning, MOOCs, DEMATEL, Higher Education, Online Learning Environment

1. Introduction

Massive open online courses emerged as an alternative mode of learning for the students, academicians and working professionals during and post pandemic. The Moocs reduces the hindrances of geographical locations and provides access to the world class learning resources. In developed countries the MOOCs are adopted by students in bigger Nos as they eliminate huge travel costs and tuition fees. Whereas in the developing countries such as Africa, Thailand, and Asian countries the adoption of MOOCs were typically very low, the reasons for low adoption are huge digital divide, non-availability of infrastructure and lack of awareness. Studies conducted by Khalil and Ebner, (2014) showed that hefty volume of data and deficiency of motivation influence the customers to drop the MOOCs. In the process of learning the technology has started to play a major role, as a result there is a paradigm shift in the course design methods, the courses are now designed as per the learner preferences instead of instructor preferences.

Indian Government encouraged learning from MOOCs by launching a platform Called SWAYAM, and a step further it also directed the universities to accept the credits from credible online courses. It encouraged the Indian Universities to increase their presence in

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the MOOCs platform. Indian students, professional and academicians responded positively and enrolled for the online courses.

Despite the customer friendly interface with other unique features the customer retention is very low in MOOCs. The previous studies by Greene et al. (2015), de Freitas et al. (2015) focused on the factors influencing for dropouts on single MOOC. This paper aims to investigate on the factors that influence academicians to dropout from MOOCs by Academicians. The existing literature review revealed that 12 factors are influencing individuals to drop the course in the between. The current paper divided the factors in to personal, social, academic categories. The division of factors were supported by the Bonk et al. (2018), Gütl et al. (2014) and Josek et al. (2016).

2. Literature review

In this subdivision the author reviews the existing literatures to understand the factors that has positive relationship with dropout in MOOCs. Factors such as time, internal motivation and course design influence students to discontinue from MOOCs (Zheng et al., 2015). Previous studies by Yang et al. (2013) and Rostaminezhad et al. (2013) showed that lack of social interaction would also lead to increase the dropout trends in the online setup of education. In addition to the existing literature on the dropout behavior of students, Shapiro et al. (2017) identified additional factors such as prior skills, course duration and individual abilities also influences the students to drop from online education system.

The study by Hone & El Said, (2016) stated that student's perception has a positive relationship with the student's retention with the mediating influence of perceived effectiveness of MOOCs content. The study also showed that lack of interaction with instructors may lead to negative retention rate. Additionally, the study also briefed on the demographic factors that influence the MOOCs subscription. Moreover the study concluded that only 32.2% of the students completed course. However this study was done in the University of Cairo, located in Egypt. Thus it opens up the scope for study to be made in India.

2.1. Personal Factors

Henderikx et al., (2017) stated that the impact of personal differences on MOOCs is high compared to the distance learning system. Khalil and Ebner (2014) stated that lack of skills and experience are also key indicators of influencing students to drop out from MOOCs. In the year 2015 Greene et al. (2015) showed that the attrition rate was very high with the category of students who had no prior experience with MOOCs platform compared to the students who had experience with the MOOCs. The existing literature review indicates that personal characteristics compromising previous academic and professional capability are directly linked to student’s dropout. Family support plays a vital role in students dropout decision, the study by Josek et al. (2016) proved that family support is directly proportional with student’s dropout in MOOCs. Students who get positive support from the family are tend to be complete the course and students with high family pressure with is likely to dropout from MOOCs. The study by Hone & El Said, (2016) further investigated the impact of prior experience, academic skills and abilities on dropout of academicians in MOOCs. It was found that academic skills and prior experience were positively influencing students to dropout from MOOCs.

2.2. Course Factors

The existing literature justifies the strong relation between the course-related factors and students\ learner’s dropout from MOOCs. Students complete the course that supports students with the course supplies and assignments on the digital platform (Adamopoulos, 2013). Further, the study conducted by Al-Samarraie, (2019) stated that advanced/challenging content and the long duration of the course will have a negative influence on the students completing the courses online.

Lee and Choi (2011) used a literature review method to determine the impact of course design and organization support on the student’s dropout decisions. As a step further Greene et al. (2015) and Jordan (2015) explored the relationship between learner's commitment, course duration, and dropout decision. It was concluded that there is a positive relationship between low commitment, prolonged courses, and dropout decisions. Thus, the prolonged courses are difficult to complete and lead to an increase in dropout. As an extension to the existing research on commitment and dropout decisions, the commitment level was very low on the courses that were offered free of cost. Thus, student's low commitment was a consequence of the pricing factor, the courses that were offered at free of cost had low commitment thus leading to high dropout (Aldowah et al. 2019). The free-of-cost courses may influence learners to enrol without much thinking or act impulsively while enrolling in the course. The key determinant to enrol in the course is to enhance the job skills, if the courses are prolonged and not challenging learners will intend to discontinue from a course before the completion. The working professional who enroll in the course for job development and skill enhancement, may not intend to learn something they already know and engage in something which is not challenging, thus, leading to an increase in attrition rate from MOOCs.

2.3. Social Factors

The previous studies have investigated the role of social factors in influencing students to complete the course. Lu et al. (2017), Whitehill et al. (2017) and York and Richardson (2012), states that A continuous interaction between students, content, peers, and instructors will assist the students to increase the knowledge on the concepts, students with minimum interaction with instructors and peers are high likely to discontinue from the online courses. Furthermore, students who join in groups or when students join together they are less likely to drop out from the MOOCs, students who joins with intention to build networks and change the carrier are also less likely to discontinue from the MOOCs Kizilcec and Schneider (2015). According to Adamopoulos (2013), the help and support earned from relatives, friends, or co-workers/peers can have a direct impact on students' propensity to finish online courses. According to Park (2007), an online course's high dropout rate can be attributed to an absence of social support in terms of encouraging and inspiring students to complete the course. In the similar manner in this study Peer support and Social interaction are categorized with social factors. Hone & El Said, (2016) aimed to study the role of social interaction, social presence and social support in influencing dropout behaviour of the students. The study concluded that social support and social presence were the directly influencing the student’s dropout in MOOCs. Hence there is no existing study done specifically to understand the factors affecting academician’s dropout in MOOCs, this study will fill that uncovered gap.

3. Methodology

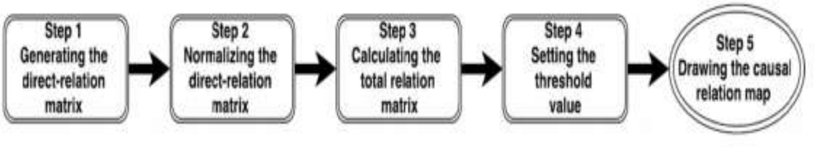
This study has adopted a practical approach to investigate and determine the key factors and casual relationships influencing academician’s dropout MOOCs. DEMATEL method plays a vital role by establishing the cause-and-effect relationship model. Geneva Battelle Institute was the first to implement DEMATEL in the year 1971, built using the principle called graph theory, to develop an envisioned structural method of complex causal relationships (a causal–effect) using matrixes and diagrams to display the interdependence link ships among factors in the model (Dalalah et al. 2011). Researchers around the globe have considered this technique to find a solution for complex problems of social, educational, and technical subject areas (Golabeska, 2018). Furthermore, the DEMATEL analysis is known as one of the effective approaches for structural modelling, it is very effective in identifying the cause-and-effect relationship between the factors. In other words, it is used to determine the interdependence of the factors, besides, this method is effective in visualizing the interrelation between the factors in the multi-criteria decision-making field (Muhammad and Cavus 2017).

After an extensive literature review, we extracted the variables for personal, social, and academic factors. The data was collected through the questionnaire method using the convivence sampling method. The questionnaire was handed over to the respondents and the scale used in the questionnaire ranged from 0 to 4 (0 no influence, 1 very low influence, 2 low influence 3 high influence, and 4 very high influence). To collect the data, we identified 10 major institutions which were engaged in creating MOOCs and invited 15 instructors to take part in the survey but only 7 instructors responded with the willingness to take part in the survey. Respondents were requested to rate the influence of each factor on other factors. The judgment on this influence is based on teaching experience in MOOCs and other online training experiences. Cause and effect relationship model is coding the responses individually. The steps of the DEMATEL analysis are explained in brief below subsections.

3.1. Dematel

The DEMATEL approach represents the visual graph of the factors, cause group on X axis, an effect group below x axis. Relationship diagram was derived after identifying the D+R and D-R, D+R refers to the level of influence among factors and D-R refers to the influence relation between the factors. The formed diagram is used to represent a collection of complicated factor relationships in an easy-to-understand structural model. In vector D-R if the values are negative, those factors are effects or the factors that are influenced by other factors, and if the values are in positive those factors are cause factors or trigger factor (Gharakhani, 2012). Threshold value was calculated to continue further analysis by taking average of Total relation matrix. Steps in DEMATEL approach are explained in the below diagram.

Figure 1: An Illustration of steps of DEMATEL Method



Step 1: To Identify the direct relation matrix

The initial matrix was constructed based on the questionnaire that was filled by the Academic experts. The level of influence between the factors was determined by asking respondents to rate the influence of each factor on other factors. We began calculating the average matrix by estimating the value of column I and row (j) based on the degree of influence between these two Fs. The influence level among Fi on Fj is presented by the assumed value of $X^k_{ij.}$ As depicted in Equation 1, F* F matrix was built and the value 0 was assigned in circumstances where I = j. (Each response matrix xij k had all of its diagonal elements set to zero, indicating that there was no effect). H indicates the no of participants who were involved in this study. Table 1 presents the final direct relation matrix.

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

Table 1: Generating the direct relation matrix

Average	**F1**	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**
F1: Family Pressure	0.00	2.33	1.83	2.00	0.17	1.50	3.00	1.67
F2: Motivation	1.83	0.00	3.33	2.33	2.50	2.67	3.17	2.17
F3: Skills and Abilities	1.83	3.17	0.00	2.50	2.00	2.50	3.17	3.17
F4: Social Interaction	2.33	3.17	3.00	0.00	2.17	2.33	1.83	2.33
F5: Feedback	0.67	2.17	2.33	2.00	0.00	2.50	2.83	3.17
F6: Peer Support	1.17	2.67	3.00	1.67	2.00	0.00	1.50	1.83
F7: Assessment Criteria	1.50	3.67	2.83	1.83	1.83	3.00	0.00	3.33
F8: Course Structure	2.83	3.50	2.50	3.17	2.00	2.50	2.17	0.00

A high score shows a certainty that a larger enhancement in I is required to enhance j. The mean matrix A represents a factor's initial direct impact on and earn from different factors.

Step 2: Normalising the direct relation matrix

I step 2 we reduced redundancy in data groups between mean responses after obtaining the average matrix. F value for both rows and columns were estimated by using highest value S from both rows and columns. Matrix X is designed by dividing the r matrix A by the maximum value S, as shown in Eqs. (2) and (3).

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

$$X = \frac{A}{S} \qquad (3)$$

Table 2: Normalized matrix

Factors	**F1**	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**
F1: Family Pressure	0.00	0.11	0.09	0.10	0.01	0.07	0.15	0.08
F2: Motivation	0.09	0.00	0.16	0.11	0.12	0.13	0.15	0.10
F3: Skills and Abillities	0.09	0.15	0.00	0.12	0.10	0.12	0.15	0.15
F4: Social Interaction	0.11	0.15	0.15	0.00	0.10	0.11	0.09	0.11
F5: Feedback	0.03	0.10	0.11	0.10	0.00	0.12	0.14	0.15
F6: Peer Support	0.06	0.13	0.15	0.08	0.10	0.00	0.07	0.09
F7: Assessment Criteria	0.07	0.18	0.14	0.09	0.09	0.15	0.00	0.16
F8: Course Structure	0.14	0.17	0.12	0.15	0.10	0.12	0.10	0.00

Normalised initial direct relation matrix is represented in Table 2. It shows the total direct effect of criterion I on the other criteria, that is, determined by adding individual row 'I' of matrix A. Furthermore, each column reflects the total direct effects that formation j has received.

Step 3: Calculation of Total relation Matrix

The next followed by the normalisation of direct relation matrix is to determine the direct relation matrix. The calculation total relation matrix was as per the equation (4). In which identity matrix is referred by I, and direct relation matrix is represented by X.

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

Table 3: Total Relation Matrix

Factors	**F1**	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**
Family Pressure	0.26	0.52	0.47	0.41	0.29	0.42	0.49	0.43
Motivation	0.44	**0.58**	**0.67**	**0.54**	0.49	**0.60**	**0.63**	**0.59**
Skills and Abilities	0.45	**0.72**	**0.54**	**0.56**	0.48	**0.60**	**0.64**	**0.64**
Social Interaction	0.44	**0.68**	**0.64**	0.42	0.46	**0.56**	**0.56**	**0.57**
Feed Back	0.35	**0.61**	**0.58**	0.49	0.34	**0.54**	**0.56**	**0.58**
Peer Support	0.34	**0.57**	**0.55**	0.43	0.39	0.39	0.46	0.48
Assessment Criteria	0.43	**0.73**	**0.66**	**0.53**	0.47	**0.62**	0.50	**0.64**
Course Structure	0.49	**0.74**	**0.65**	**0.59**	0.48	**0.60**	**0.60**	0.51

Step 4: Identifying the threshold value

In this step four, threshold value is set to eliminate the minor effect to visualize the causal relation map with minimum complexity level, rather than using a threshold value in the total relation matrix T. The causal link map becomes more complicated as the threshold value increases or decreases. The threshold value is derived by taking a average of the total matrix T.

Step 5: Building relationship Model

In step five of DEMATEL analysis we build causal relationship map by adding up values in the total relation matrix of rows and columns distinctly and represented them as vector D and vector R as exposed in Equation (5). Vector D represents the degree of influential impact since it reflects both direct and indirect influence of I on all other factors. On the other hand, vector R reflects direct and indirect influence of all other factor on factor J. Casual relationship map is developed in 2D plan, for the same horizontal axis was set up by accumulation of both vectors D and R(D+R), it is named as 'Prominence'. Furthermore, this represents the importance of factor I and eliminates the assumption that it has a role/influence on every factor. Once the horizontal axis was set, next step was to determine vertical axis by subtracting D and R(D-R), it is named has 'Relation'. It expresses the net influence of factor I on the complete model. The causal relation map that is developed is represented in the figure 2.

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

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

Table 4: The effect and Net effect Matrix

Code	Factors	D	R	D+R	D-R	Impact
F1	Family Pressure	2.43	2.37	4.80	0.07	**Cause**
F2	Motivation	3.87	4.38	8.25	-0.51	**Effect**
F3	Skills and Abilities	3.94	4.05	7.98	-0.11	**Effect**
F4	Social Interaction	3.69	3.14	6.83	0.55	**Cause**
F5	Feed Back	3.44	2.89	6.34	0.55	**Cause**
F6	Peer Support	3.08	3.39	6.47	-0.31	**Effect**
F7	Assessment Criteria	3.67	3.54	7.21	0.14	**Cause**
F8	Course Structure	3.42	3.79	7.21	-0.38	**Effect**

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

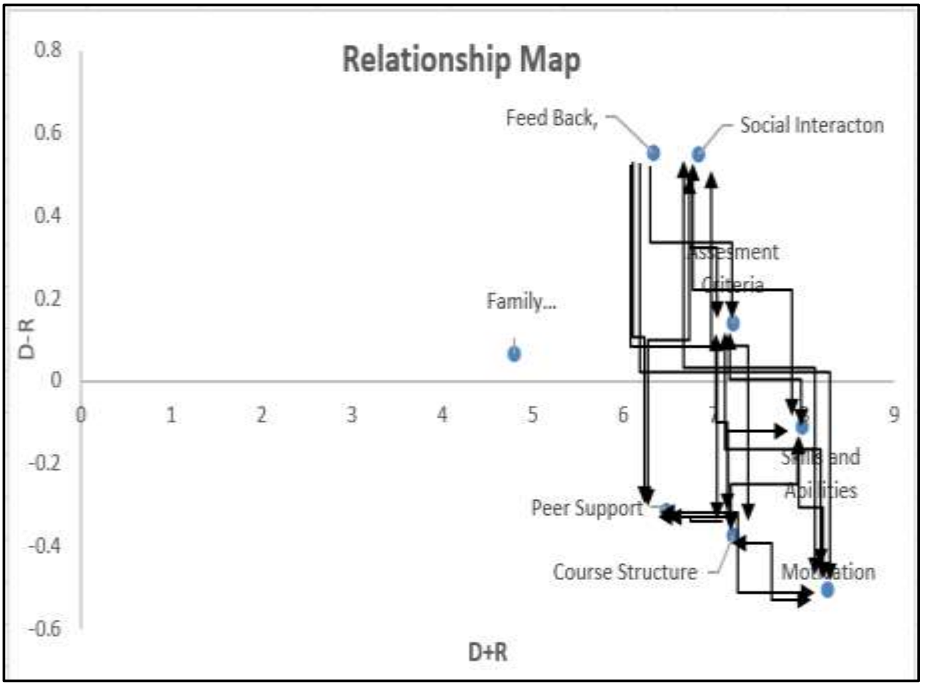
4. Results Discussion and Conclusions

MOOCs have been widely used to increase the students the skills and abilities. Along with the students even the academicians look towards MOOCs to increase their skill and abilities. The previous studies have listed various factors impacting dropout behaviour of the students from the MOOCs. Our literature review has shed light on the Personal, Social and Academic factors. The factors that are listed are personal factors (family pressure, motivation, skills and abilities), social factors (social interaction, peer support) academic factors (assessment criteria, feedback, course structure).

DEMATEL method was adopted to analyse the data from 7 instructors to determine the core factors and their relationship among other factors. Authors found multiple associations between the study factors. Furthermore, the method also identifies the significance of the factors by deriving the vectors. Relationship map depicts the relationship among the factors and determines the most influential factors. In the diagram, the line lines represent the direction of influencing relationship between the factors. In addition, the two arrows indicate mutual relationship between the two factors.

Vectors D and R helps to determine the influencing factors and least influencing factors, Causes are those factors whose D-R values are greater than Zero, and Effects are those factors whose D-R values are lesser than 0. Table 4 shows that family pressure, social interaction, feedback and assessment criteria are causes with (D-R>0). Motivation, skills and abilities, peer support, and course structure are effects with (D-R<0). Furthermore, the analysis can determine assessment criteria as the most influential factor that influences the academician's dropout in MOOCs (D+R= 7.21) followed by social interaction, feedback and family pressure respectively.

Figure 2: DEMATEL Relation Map



Family pressure (D+R= 4.7) is the most influencing factor in the personal factor variable, social Interaction (D+R=6.8) is the most influencing factor in the social factor variable and Assessment criteria (D+R=7.21) is the most influencing factor in the academic factor variable. Assessment criteria is the most influencing the factor that influences academician's dropout, further the online course designers are expected to give more importance while designing the assessments. Assessment criteria have a mutual relationship with feedback, course structure, motivation, and skills and abilities. Feedback has a mutual relationship with skills and abilities. Social Interaction has a mutual relationship between motivation, skills and abilities, assessment criteria, and course structure. Hence, we conclude that the social factors positively influence the personal factors and course factors. Furthermore, we can conclude that the course factors influence personal and social factors.

Feedback and Assessment criteria are influencing all the other factors except family pressure, social Interaction, and feedback. Hence, we can conclude that the course factor is the highly influential factor that influences the dropout of academicians from MOOCs.

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