

A Model to Categorize Students' Perception on Endorsing Massive Open Online Courses

Dr. Anand Sasikumar

Assistant Professor-Operations, SDM Institute for Management and Development, Mysuru-570011, Karnataka
India

Email: anand@sdmimd.ac.in

Dr. Mousumi Sengupta

Professor-OB & HR, SDM Institute for Management and Development, Mysuru-570011
Karnataka, India

Email: mousumi@sdmimd.ac.in

Abstract

Open distance learning (ODL) is a comprehensive approach to extend access to standard learning and enable students to be independent learners which leads to improvement in success and better participation in an open and symbiotic environment. Massive open online courses (MOOCs) are courses that are intended for infinite involvement and open access through the internet. Though there are several inherent benefits of MOOCs, it is observed that the collective adoption of MOOCs is still very slow. An Analytic hierarchy process (AHP) methodology is used to prioritize the importance of factors inducing the decision of students to adopt MOOCs. The model mainly considers three factors and subsequently eight sub-factors are considered for classification. The data was obtained from 200 students by using convenience sampling and the results of the study suggest that scholastic recognition, enhancement of skill, and affordability are critical factors that B-school students take into consideration while taking up MOOCs courses.

Keywords: Open distance learning, Massive open online courses, B-schools

1. Introduction

E-learning or online education has been showing significant growth across the globe during the past few decades due to its distinctive influence on socio-economic development (Keqiang, 2017; Dvorakova et al., 2023). One such type of online platform which has lately obtained interest is Massive Open Online Courses (MOOC). MOOCs are offered through numerous platforms such as Udemy, Khan Academy, Canvsa network, Coursera, and so on. The feature of MOOC is that it is designed in such a way that an enormous number of participants across the globe are given opportunities to attend free online courses without any prior conditions for admission (Abu-Shanab & Musleh, 2018). Institutions in developing countries are shifting from the traditional model of higher education to methodologies adopting Open distance learning (ODL) systems (Musangafi et al., 2015). The United Nations Educational, Scientific and Cultural Organization (UNESCO) plays an active role in strengthening the position of ODL through the broadening of knowledge transfer systems and inspiring cooperation among professional organizations and distance teaching institutions (Ghosh et al., 2012). It has been observed in many studies that, MOOCs can augment the accessibility to quality education and decrease the education costs to a great (Shrivastava & Shrivastava, 2023; Chen et al., 2021). The outburst of the COVID-19 pandemic which was one of the first of its kind over the past 100 years, caused severe harm and threatened the lives of humans. Beginning of 2020, it was something unique happened in the history of universities worldwide. Most of the universities switched over from offline mode to online mode of education to prevent the spread of the virus (Yang & Lee, 2021). This was also one of the reasons there was a great demand for open online courses. Despite the advantages, the providers of MOOCs are faced with a learner attrition rate. The completion of MOOCs is around 10% (Gregori et al., 2018). Researchers have felt that limited self-regulated learning aspects, lack of computing skills, clashes with other students during the discussion, and a sense of isolation are reasons for low completion rate (Hew & Cheung, 2014; Shapiro et al., 2017).

Though there are several studies conducted on the adoption of MOOCs in developing countries like China (Ma & Lee, 2019), Pakistan (Khan et al., 2018), Jordan (Abu-Shanab & Musleh, 2018), not many studies have been conducted in the Indian context, especially in the education sector (Gupta, 2019; Yadav & Gupta, 2020). In this context, the present study attempted to apply the AHP technique to prioritize the factors that are important from the student's perceptive in adopting MOOC courses, post-COVID-19.

2. Literature review

Various platforms offer MOOC courses, namely Coursera, edX, Udacity, jMOOC, Futurelearn, MiriadaX, France universit_e num_rique (FUN), Iversity, Venduca, XuetaangX, and others (Tella et al., 2021). The popularity of MOOC courses is increasing and can attract and stimulate a huge number of learners from diverse cultural backgrounds, knowledge, and skill levels (Tella et al., 2021). Since several universities are offering more MOOC courses, the trainers are broad basing the locations to adapt to the MOOC content to allow students to enroll in MOOCs and connect via video lectures. Since 2008, MOOC channels have become a revolution in open and distance education, that has grew fame and acceptance, due to the increasing presence of MOOC providers (Hakami, 2018; Mulik et al., 2016; Ouyang et al., 2017; Shah, 2016; Wu & Chen, 2017).

2.1. MOOC adoption :

MOOC adoption can be divided into four categories (Hakami et al., 2017): learner-related factors; institution and instructor-related factors; platform and course-related factors; and perception of external control/ facilitating conditions. Learner-related factors emphasize personal motivations namely academic, job relevance, and social influence. The reputation of the institute and interaction with the teacher is described by institution and instructor-related factors. The perception of external control/facilitating situations explains the extent to which a person perceived the existence of organizational and technical resources, supporting the use of the MOOC platform. In a similar line, based on the content analysis, one can note total 34 factors, which are significant for adoption of MOOC (Olugbara & Letseka, 2019), such as, Perceived usefulness , Perceived ease of use , Intention , Motivation , Engagement , Enjoyment , Interactivity , Openness, University/institution's reputation , Skills, Collaboration, Assessment , Pedagogy , Attitude , Performance expectancy , Effort expectancy , Social influence , Facilitating condition , Service quality , System quality , Course quality , Instructional design quality , Sustainability , Professional and personal development , Lifelong learning , Mimetic pressure , Normative pressure , Perceived effectiveness , Participation , Satisfaction , Computer self-efficacy , Learners support , Technology , and, Self-regulation .

2.2. Facilitating features/ characteristics of MOOC for students' adoption :

Many studies have been conducted to identify factors leading to the adoption of MOOCs (Goel et al., 2023; Rungruang et al., 2023). Authors (Gao & Yang, 2015) have used the TAM model for examining the learner's adoption of MOOCs. They observed that ease of use, perceived usefulness, and representational pressures were the primary factors linked with learners' intent of taking up the course. The continuance behavior of learners in MOOCs course was described with the help of expectation-confirmation theory(ECT) (Alraimi et al., 2015). Some of the other factors include *willingness, intrinsic motivation, free course advantage, perceived reputation, cultural support* (Hakami, 2018; Hakami et al., 2017; Lambert, 2020), Openness, enjoyment, awareness, academic background, experience, and expectation (Alraimi et al., 2015; Liyanagunawardena et al., 2015; Milligan et al., 2013; Pundak et al., 2014; Radford et al., 2014; Rosell-Aguilar, 2013). Research (Mohapatra & Mohanty, 2017) have emphasized the fact that from an Indian perspective, learner skills, affordability, and availability are influencing factors for MOOCs adoption. A comprehensive collective framework including the task-technology-fit(TTF) model, social motivation, and self-determination theory to inspect the factors affecting.

2.3. Hindering features/ characteristics of MOOC for students' adoption :

The main barriers to adopting MOOCs adoption among students were the lack of basic subject knowledge, level of education, and lack of prior understanding with MOOCs (Semenova & Rudakova, 2016). A study (Abu-Shanab & Musleh, 2018) reasoned that social impact and perceived worthwhileness in terms of location and timeline have a substantial effect on the intent to adopt MOOCs. They observed that social recognition, perceived competence, and perceived relatedness were the key predictors of MOOC adoption intention.

3. OBJECTIVE AND METHODOLOGY

3.1. Objective

The present study attempted to apply the AHP technique to prioritize the factors that are important from the student's perceptive in adopting MOOC courses, post-COVID-19. In order to do so, In the light of the existing literature review, the authors interacted with four categories of stakeholders, who may act as catalyst or has experience in the context of MOOC adoption by the students: teachers, Software professionals, students and management representatives of the institutions, offering MOOC courses. Based on the same, three factors have been identified (further divided into certain sub-factors).

3.2. Factors for MOOC adoption, for the purpose of the present study :

. Based on the same, three factors have been identified (further divided into certain sub-factors). The details are presented below:

Factor 1: Advantages of MOOC – Researchers (Rogers, 2003; Hakami et al., 2017) have found that, learners' intentions to adopt the specific technology or innovation are significantly influenced by their perceptions of the benefits of MOOC. The advantages of MOOC has been further divided into three sub-factors: enhancement of skill, Increase in knowledge repository , and affordable

- Enhancement of skill – Contrary to the classroom learning, through MOOCs, students learn independently and their problem solving skills, decision making ability, and self-management become enhanced (Calonge & Shah, 2016).
- Increase in knowledge repository - As pointed out by few researches (Ma & Lee, 2019; Wu & Chen, 2017), MOOCs facilitate in developing the knowledge repository, which may even kindle interest among students, for further persuasion of study, even if the physical learning material is not easily available (Zhou, 2016).
- Affordable – MOOCs are cost-effective in comparison to the classroom-dependent courses (Ma & Lee, 2019).

Factor 2: MOOC attributes / property – MOOCs' typical characteristics, such as, size, openness, autonomy, and affiliations with prestigious academic institutions, are indeed beneficial for the students (Alraimi et al., 2015; Hakami et al., 2017). This factor can further be sub-divided into three sub-factors, such as, access without restriction, Freedom to learn at own pace, and, Image of the institution.

- Access without restriction – research opined that (Barclay & Logan, 2013), MOOCs are accessible to the registered learners, all the time, using any compatible system. Students can download MOOC learning content, which can be used even after completion of the course (Wu & Chen, 2017; Ma & Lee, 2019).
- Freedom to learn at own pace - MOOCs provide freedom to the to complete the course at their own pace (Khan et al., 2018). Students have the flexibility to learn as and when they are comfortable, which are possible in the traditional teaching techniques (Sun et al., 2018).
- Image of the institution – An institution's reputation is very crucial for a student, while deciding on course enrolment (Bourke, 2000), keeping in mind the credibility of the course in future.

Factor 3: Impetus from society / Social stimulation - MOOC certificates, awarded by the institutions of repute, are recognized by the society as an achievement of the learner, by itself (Bragg, 2014). Thus, such courses are of high demand from the students.

- Scholastic recognition - The acceptance of MOOC certificates / diplomas for pursuing higher studies, is another aspect, the students consider while deciding about the MOOC courses. Benefits, such as credit adjustment or time-off, may be very useful (Wu & Chen, 2017).
- Acceptance from corporate - The industry's acceptance of MOOC certificates boosts students' employability, thus, enhancing the willingness and motivation for MOOC learning (Khan et al., 2018; Wu & Chen, 2017).

3.3. Technique used for analysis :

The present study adopts one of the popular methods of multicriteria-decision making (MCDM), which is the Analytic hierarchy process(AHP). AHP is a decision-making method for categorizing influencing factors in different circumstances (Saaty, 1980). The methodology allows the person deciding to construct complicated problems in the form of a hierarchy or a set of combined levels. AHP methodology has been effectively adopted in the context of several types of situations (Şahin et al., 2019; Hoque et al., 2019; Saranya & Saravanan, 2020; Piprani et al., 2020). The AHP methodology represents complex problems in the form of multi-level structures. The first level is the goal, followed by criteria, sub-criteria and finally leading to the set of alternatives (Etlanda & Sutawidjaya, 2022). The main objective of the present study is to prioritize the importance of factors inducing the decision of students to adopt MOOCs, the framework of the model consists of three levels. The model consists of goals, factors, and sub-factors which are represented in the form of a hierarchical model. The model consists of three factors and eight factors which are presented in Figure 1.

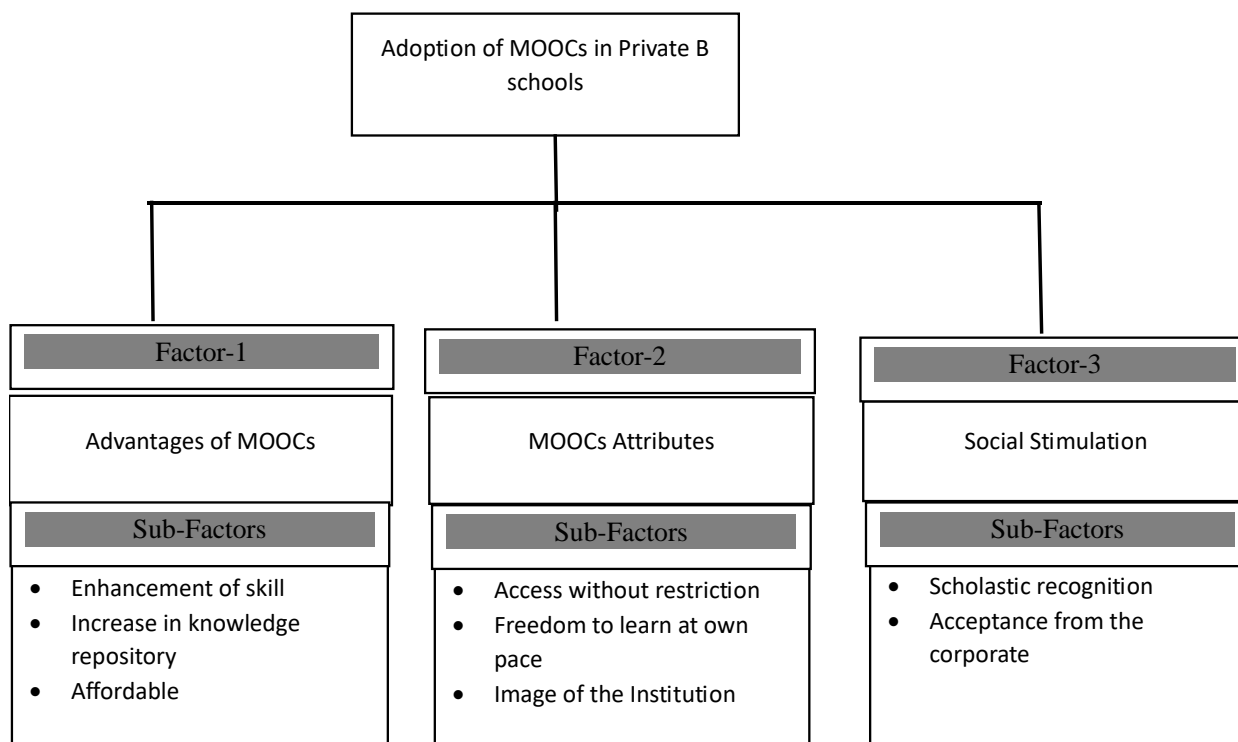


Figure 1: The AHP Model for MOOCs Adoption in Private B-schools

There are no decision alternatives as the main aim of the model, is to categorize the factors about student's perspective in selecting MOOCs courses in private business schools. Once the AHP framework is built, the weights of each factor/sub-factors are computed by conducting pairwise comparisons of factors and sub-factors.

3.4. Sample, tool:

The current study makes use of a convenience sampling technique and 200 students from four prominent B-schools based in Karnataka, India, were selected. A valid questionnaire (Saaty, 1980) was distributed among the students to capture the pairwise comparisons.

4. Data analysis

4.1. Key steps of the AHP methodology :

They are illustrated below :

1. Defining the main problem
2. Expand the goals of the problem or contemplate all actors, objectives, and outcome.
3. Determine the conditions that affect the behavior.
4. Construct the problem in a hierarchy of different levels to establish goals, criteria, sub-criteria, and alternatives.
5. Compare each element in the corresponding level and calibrate them on the numerical scale. This requires $n(n-1)/2$ comparisons, where n is the number of elements with the consideration that diagonal elements are equal or 1 and the other elements will simply be the reciprocals of the earlier comparisons.

6. Find the maximum Eigenvalue, consistency index CI, consistency ratio CR, and normalized values for each criterion/alternative.

7. If the maximum Eigenvalue, CI, and CR are satisfactory then the decision is taken based on the normalized values; else the procedure is repeated till these values lie in a desired range.

Table 1: Saaty’s Rating Scale

Intensity of Importance	Description
1	Equal Importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2,4,6,8	For compromise between the above values

4.2. Pairwise comparison of matrices:

As mentioned earlier, the AHP model discussed here works based on pairwise comparison of matrices. First, a pairwise comparison of the main factors concerning the goal is computed. This is followed by pairwise comparison of sub-factors concerning the factors. Since there are 200 respondents, there were 200 pairwise comparisons concerning the goal and sub-factors. The responses from individuals were aggregated using the concept of geometric mean. The studies (Aczél & Roberts, 1989; Forman & Peniwati, 1998; Adamcsek, 2008) reveal that have confirmed that geometric mean is a better technique for aggregation than the arithmetic mean due to its ability to fulfill the reciprocity requirement which is one of the conditions which should be satisfied if AHP technique is employed for decision making. The calculations are presented in Tables 2,3,4 and 5.

Table 2: Pairwise comparison of factors with respect to the Goal

Adopting MOOCs	Advantage of MOOCs	MOOCs Attributes	Social Stimulation
Advantage of MOOCs	1	2.92	1.86
MOOCs Attributes	0.34	1	0.402
Social Stimulation	0.54	2.49	1

Table 3: Pairwise comparison of sub-factors with respect to Advantages of MOOCs

Advantages of MOOCs	Enhancement of Skill	Increase in Knowledge repository	Affordable
Enhancement of Skill	1	2.96	1.80
Increase in Knowledge repository	0.34	1.00	0.34
Affordable	0.56	2.96	1.00

Table 4: Pairwise comparison of sub-factors with respect to MOOCs Attributes

MOOCs Attributes	Access without restriction	Freedom to learn at own pace	Image of the Intuition
Access without restriction	1	4.43	7.97
Freedom to learn at own pace	0.2	1	3.93
Image of the Intuition	0.11	0.25	1

Table 5: Pairwise comparison with of sub-factors with respect to Social Stimulation

Social Stimulation	Scholastic recognition	Acceptance from the corporate
Scholastic recognition	1	5.42
Acceptance from the corporate	0.18	1

Once the pairwise comparison of factors is done, the normalized matrix of the respective matrices is computed. The normalized values are obtained by dividing each element in the matrix by the respective column totals. In the AHP technique, the opinions made by the respondents have to go through a consistency test. If for a particular comparison matrix, the consistency test has failed, which indicates there are contradictions in the judgments made by the respondents. In such cases, the opinions made by the respondents are reviewed again. The following steps are used to perform the consistency test.

- The consistency ratios (CR) of the comparison matrices are calculated using the following formula
 $CI = (\lambda_{max} - n) / (n - 1)$
 Where CI = consistency index, λ_{max} is the principal eigen value, n = the order of the matrix or the number of criteria considered.
 If CI = 0, means expert's judgement satisfy consistency.
 If CI > 0, means the experts have conflicting judgements.
 If $CI \leq 0.1$, means there is reasonable level of consistency (Boateng et al., 2016).
 $CR = CI / RI$.
 The principal eigen value λ_{max} obtained by using the formula :
 $\lambda_{max} = \sum_{j=1}^n T_j PV_j$
 Where n = Number of criteria.
 T_j = Total of the relative importance values in the column corresponding to the j^{th} criterion
 The random consistency index (RI) is obtained from Table 6.
 The normalized matrices of the respective matrices are presented in Tables 7 to 10.

Table 6: Random Consistency Table

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

Table 7: Normalized weights of pairwise comparison of factors with respect to MOOCs Adoption

MOOC Adoption	Advantages of MOOCs	MOOCs attributes	Social Stimulation	PV
Advantages of MOOCs	0.53	0.46	0.57	0.52

MOOCS attributes	0.18	0.16	0.12	0.15
Social Stimulation	0.29	0.39	0.31	0.33
$\lambda_{max} =$	3.03	CI	0.01	
RI	0.58	CR	0.02	

Table 8: Normalized weights of factors with respect to Advantages of MOOCs

Advantages of MOOCs	Enhancement of Skill	Increase in the Knowledge Repository	Affordable	PV
Enhancement of Skill	0.53	0.43	0.57	0.51
Increase in the Knowledge Repository	0.18	0.14	0.11	0.14
Affordable	0.29	0.43	0.32	0.35
λ_{max}	3.05	CI	0.02	
RI	0.58	CR	0.04	

Table 9: Normalized weights of factors with respect to MOOCs attributes

Mooc Attributes	Access without restriction	Freedom to learn at own pace	Image of the Instuition	PV
Access without restriction	0.76	0.78	0.62	0.72
Freedom to learn at own pace	0.15	0.18	0.30	0.21
Image of the Instuition	0.08	0.04	0.08	0.07
λ_{max}	3.03	CI	0.02	
RI	0.58	CR	0.03	

The consistency ratios of all Tables 7 to 9 are less than 10 %. Therefore, eigenvectors/ weights are acceptable. Consistency tests are not conducted when the number of criteria is less than or equal to 2(Table 10). The final results indicating the global weights are calculated and the respective ranks of the sub-factors are presented in Table 11.

Table 10: Normalized weights of factors with respect to Social Stimulation

Social Stimulation	Scholastic recognition	Acceptance from the corporate	PV
Scholastic recognition	0.84	0.84	0.84

Acceptance from the corporate	0.16	0.16	0.16
-------------------------------	------	------	------

Table 11: Calculated Weights of the Main factors and Sub factors

Main factors	Weights		Local	Global	Rank
Advantages of MOOCs	0.52	Enhancement of Skill	0.51	0.26	2
		Increase in the Knowledge Repository	0.14	0.07	5
		Affordable	0.35	0.18	3
MOOCs attributes	0.15	Access without restriction	0.72	0.11	4
		Freedom to learn at own pace	0.21	0.03	7
		Image of the Institution	0.07	0.01	8
Social Stimulation	0.33	Scholastic recognition	0.84	0.28	1
		Acceptance from the corporate	0.16	0.05	6

5. RESULTS AND DISCUSSION

In line with previous researches (Gupta, 2019), Based on the AHP model, we can infer that within the main factors, "Advantages of MOOCs" is a strong influencing factor (weight =0.52) among students in adopting MOOC courses, supporting the earlier research (Hakami et al., 2017; Khan et al., 2018; Rekha et al., 2023; Dvorakova et al., 2023; Goel et al., 2023). Social stimulation (weight =0.33) is another factor that comes next, which encourages students in taking up MOOC courses. This is followed by MOOCs attributes (Weight =0.15).

The results signify the fact that the main impetus among students to adopt courses is the advantages offered by MOOCs course. This confirms the fact that students of Business schools are influenced by the tangible and intangible benefits of MOOC courses. Recognition is one aspect that students are looking for while pursuing MOOCs courses. This supports the existing literature (Abu-Shanab & Musleh, 2018; Alraimi et al., 2015; Bragg, 2014). Most of the MOOCs courses are well accepted and carry considerable value, this will, in turn, inspire students to take up courses extended by MOOCs platforms. The attributes of MOOCs are the least factor and do have not much influence among students in adopting MOOCs courses. This indicates that students, though MOOCs course offers flexible deadlines and fewer restrictions, have less impact while choosing courses.

If we analyze the sub-factors of the main factor (Advantages of MOOCs) which has the highest weight, it can be observed that enhancement of skill is more acceptable by students (weight =0.51) followed by affordability (weight =0.35) of the courses. This implies that students value the enrichment of knowledge and financial viability as critical factors while selecting MOOC courses. If we evaluate the factors within "social stimulation", Scholastic recognition (weight =0.84) is considered of greater value among the students, supporting earlier research (Wu & Chen, 2017) than acceptance from the corporate (weight =0.16). However, this is contrary in today's scenario, where students are looking for challenging careers.

Finally, the global weights help us in determining the overall ranks of the sub-factors. It can be observed that Scholastic recognition (global weight = 0.84) followed by Enhancement of skill (global weight= 0.51) and Affordable (0.35) are three utmost features that B-school students take into consideration while opting for MOOCs courses. This confirms the fact that students are looking for flexible ways of improving their knowledge and recognition, supporting the earlier research (Rogers, 2003; Zhou, 2016). This means that students emphasize more on value which is gained by knowledge and if the courses are offered at an affordable price by esteemed and respected universities, they get motivated to take up the courses, as earlier researches proposed (Ma & Lee, 2019).

6. CONCLUSION

The main objective of the study was to categorize the factors which influence students in private business schools in adopting MOOCs courses. The study used the AHP methodology and considered 3 main factors and eight factors for prioritizing the factors. It can be inferred from the results that students pay great importance to the features offered by MOOC courses and the enhancement of knowledge which they acquire when they take source courses. This supports other studies in India (Rekha et al., 2023; Shrivastava & Shrivastava, 2023) and abroad (Albelbisi et al., 2023; Alturki & Aldraiweesh, 2023; Rungruang et al., 2023). Social acceptance is also another driving force for the adoption of MOOCs courses. The results of the study indicate that Private B -Schools should design courses in such a way that they can include a few MOOC courses as part of their academic curriculum. This will expose students to courses that are more practical oriented and which is the need of the hour. Efforts should be initiated by B-schools to make such courses mandatory and provide necessary encouragement in the form of funding a part of their course fees. The study is confined to four prominent B-schools in Karnataka and this can be further extended to other B-schools in South India, for developing a comprehensive generic framework for B-schools. These studies can be validated by using techniques like Fuzzy AHP which might be better suitable for gauging experiences and judgments of humans which are represented by linguistic and vague patterns.

REFERENCES

1. Abu-Shanab, E. A., & Musleh, S. (2018). The adoption of Massive open online courses. *International Journal of Web-Based Learning and Teaching Technologies*, 13(4), 62–76. <https://doi.org/10.4018/IJWLTT.2018100104>
2. Aczél, J., & Roberts, F. S. (1989). On the possible merging functions. *Mathematical Social Sciences*, 17(3), 205–243. [https://doi.org/10.1016/0165-4896\(89\)90054-1](https://doi.org/10.1016/0165-4896(89)90054-1)
3. Adamcsek, E. (2008). The analytic hierarchy process and its generalizations. Eötvös Loránd University.
4. Alraimi, K. M., Zo, H., & Ciganek, A. P. (2015). Understanding the MOOCs continuance: The role of openness and reputation. *Computers and Education*, 80, 28–38. <https://doi.org/10.1016/j.compedu.2014.08.006>
5. Barclay, C., & Logan, D. (2013, December). Towards an understanding of the implementation and adoption of massive online open courses (MOOCs) in a developing economy context. In *Proceedings of the Annual Workshop of the AIS Special Interest Group for ICT in Global Development*, 6.
6. Bourke, A. (2000). A model of the determinants of international trade in higher education. *Service Industries Journal*, 20(1), 110–138. <https://doi.org/10.1080/02642060000000007>
7. Bragg, A. B. (2014). MOOCs: Where to from here? *Training and Development*, 41(1), 20.
8. Calonge, D. S., & Shah, M. A. (2016). MOOCs, graduate skills gaps, and employability: A qualitative systematic review of the literature. *International Review of Research in Open and Distributed Learning*, 17(5), 67–90. <https://doi.org/10.19173/irrodl.v17i5.2675>
9. Etlanda, K. A., & Sutawidjaya, A. H. (2022). Analysis of pump factory supplier selection criteria using AHP method (Pt. XYZ Jakarta).” *Eur. Journal of Business and Management Research*, 7(1), 280–286.
10. Forman, E., & Peniwati, K. (1998). Aggregating individual judgments and priorities with the analytic hierarchy process. *European Journal of Operational Research*, 108(1), 165–169. [https://doi.org/10.1016/S0377-2217\(97\)00244-0](https://doi.org/10.1016/S0377-2217(97)00244-0)
11. Gao, S., & Yang, Y. (2015). Exploring users’ adoption of MOOCs from the perspective of the institutional theory.
12. Ghosh, S. et al. (2012). Open and distance learning (ODL) education system: Past Present and future—A systematic study of an alternative education system.
13. Gregori, E. B., Zhang, J., Galván-Fernández, C., & Fernández-Navarro, Fd. A. (2018). Learner support in MOOCs: Identifying variables linked to completion. *Computers and Education*, 122, 153–168. <https://doi.org/10.1016/j.compedu.2018.03.014>
14. Gupta, K. P. (2019). An application of AHP for students’ perspectives on adopting MOOCs. *Management Science Letters*, 9(13), 2327–2336. <https://doi.org/10.5267/j.msl.2019.7.022>
15. Hakami, N. A. (2018). An investigation of the motivational factors influencing learners’ intentions to continue using Arabic MOOCs [Thesis]. Faculty of Physical Sciences and Engineering, School of Electronics and Computer Science, University of Southampton.

16. Hakami, N. et al. (2017). Motivational factors that influence the use of MOOCs: Learners' perspectives. In Proceedings of the 9th International Conference on Computer Supported Education (pp. 323–331) (CSEDU. 2017).
17. Hoque, M. A. A., Tasfia, S., Ahmed, N., & Pradhan, B. (2019). Assessing spatial flood vulnerability at Kalapara Upazila in Bangladesh using an analytic hierarchy process. *Sensors*, 19(6), 1302. <https://doi.org/10.3390/s19061302>
18. Hruška, R., Průša, P., & Babić, D. (2014). The use of AHP method for selection of supplier. *Transport*, 29(2), 195–203. <https://doi.org/10.3846/16484142.2014.930928>
19. 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. <https://doi.org/10.1016/j.edurev.2014.05.001>
20. Keqiang, L. (2017). Innovation in open and distance learning (ODL) system in India: The need to remove systemic barriers, *Ennovate*, 4(15) (pp. 1–9).
21. Khan, I. U., Hameed, Z., Yu, Y., Islam, T., Sheikh, Z., & Khan, S. U. (2018). Predicting the acceptance of MOOCs in a developing country: Application of task-technology fit model, social motivation, and self-determination theory. *Telematics and Informatics*, 35(4), 964–978. <https://doi.org/10.1016/j.tele.2017.09.009>
22. Ma, L., & Lee, C. S. (2019). Investigating the adoption of MOOC s: A technology–user–environment perspective. *Journal of Computer Assisted Learning*, 35(1), 89–98. <https://doi.org/10.1111/jcal.12314>
23. Mohapatra, S., & Mohanty, R. (2017). Adopting MOOCs for affordable quality education. *Education and Information Technologies*, 22(5), 2027–2053. <https://doi.org/10.1007/s10639-016-9526-5>
24. Mulik, S., Yajnik, N., & Godse, M. (2016). Determinants of acceptance of massive open online courses. In *IEEE Eighth International Conference on Technology for Education, India, 2016* (pp. 124–127). IEEE. <https://doi.org/10.1109/T4E.2016.032>
25. Musingafi, M. C. et al. (2015). Challenges for open and distance learning (ODL) students: Experiences from students of the Zimbabwe Open University. *Journal of Education and Practice*, 6(18), 59–66.
26. J. K. S. Al-Safi, A. Bansal, M. Aarif, M. S. Z. Almahairah, G. Manoharan and F. J. Alotoum, "Assessment Based On IoT For Efficient Information Surveillance Regarding Harmful Strikes Upon Financial Collection," 2023 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2023, pp. 1-5, doi: 10.1109/ICCCI56745.2023.10128500.
27. Tidake, Vishal & Mazumdar, Nilanjan & Kumar, A. & Rao, B. & Fatma, Dr Gulnaz & Raj, I.. (2023). Sentiment Analysis of Movie Review using Hybrid Optimization with Convolutional Neural Network in English Language. 1668-1673. 10.1109/ICAIS56108.2023.10073750.
28. M. A. Tripathi, R. Tripathi, F. Effendy, G. Manoharan, M. John Paul and M. Aarif, "An In-Depth Analysis of the Role That ML and Big Data Play in Driving Digital Marketing's Paradigm Shift," 2023 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2023, pp. 1-6, doi: 10.1109/ICCCI56745.2023.10128357.
29. M. Lourens, A. Tamizhselvi, B. Goswami, J. Alanya-Beltran, M. Aarif and D. Gangodkar, "Database Management Difficulties in the Internet of Things," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 322-326, doi: 10.1109/IC3I56241.2022.10072614.
30. Abd Algani, Y. M., Caro, O. J. M., Bravo, L. M. R., Kaur, C., Al Ansari, M. S., & Bala, B. K. (2023). Leaf disease identification and classification using optimized deep learning. *Measurement: Sensors*, 25, 100643.
31. Ratna, K. S., Daniel, C., Ram, A., Yadav, B. S. K., & Hemalatha, G. (2021). Analytical investigation of MR damper for vibration control: a review. *Journal of Applied Engineering Sciences*, 11(1), 49-52.
32. Abd Algani, Y. M., Ritonga, M., Kiran Bala, B., Al Ansari, M. S., Badr, M., & Taloba, A. I. (2022). Machine learning in health condition check-up: An approach using Breiman's random forest algorithm. *Measurement: Sensors*, 23, 100406. <https://doi.org/10.1016/j.measen.2022.100406>
33. Ouyang, Y., Tang, C., Rong, W., Zhang, L., Yin, C., & Xiong, Z. (2017). Task-technology fit aware expectation-confirmation model towards understanding of MOOCs continued usage intention. *Proceedings of the Annual Hawaii International Conference on System Sciences*. <https://doi.org/10.24251/HICSS.2017.020>
34. Piprani, A. Z., Jaafar, N. I., & Mohezar Ali, S. (2020). Prioritizing resilient capability factors of dealing with supply chain disruptions: An analytical hierarchy process (AHP) application in the textile industry. *Benchmarking*, 27(9), 2537–2563. <https://doi.org/10.1108/BIJ-03-2019-0111>
35. Rogers, E. M. (2003). *Diffusion of innovations*. Free Press.
36. Shah, D. (2016). By the numbers: MOOCs in 2016. <https://www.classcentral.com/report/mooc-stats-2016/>
37. Saaty, T. L. (1980). *The analytical hierarchy process*. McGraw-Hill.
38. Shapiro, H. B., Lee, C. H., Wyman Roth, N. E., Li, K., Çetinkaya-Rundel, M., & Canelas, D. A. (2017). Understanding the massive open online course (MOOC) student experience: An examination of attitudes, motivations, and barriers. *Computers and Education*, 110, 35–50. <https://doi.org/10.1016/j.compedu.2017.03.003>

39. Şahin, T., Ocak, S., & Top, M. (2019). Analytic hierarchy process for hospital site selection. *Health Policy and Technology*, 8(1), 42–50. <https://doi.org/10.1016/j.hlpt.2019.02.005>
40. Saranya, T., & Saravanan, S. (2020). Groundwater potential zone mapping using analytical hierarchy process (AHP) and GIS for Kancheepuram District, Tamil Nadu, India. *Modeling Earth Systems and Environment*, 6(2), 1105–1122. <https://doi.org/10.1007/s40808-020-00744-7>
41. Siemens, G. (2013). MOOCs: How did we get here. Society for Learning Analytics Research [Presentation].
42. Tella, A., Tsabedze, V., Ngoaketsi, J., & Enakrire, R. T. (2021). Perceived usefulness, reputation, and Tutors' advocate as predictors of MOOC utilization by distance learners: Implication on library Services in Distance Learning in ESwatini'. *Journal of Library and Information Services in Distance Learning*, 15(1), 41–67. <https://doi.org/10.1080/1533290X.2020.1828218>
43. Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, 67, 221–232. <https://doi.org/10.1016/j.chb.2016.10.028>
44. Yang, Q., & Lee, Y. C. (2021). The critical factors of student performance in MOOCs for sustainable education: A case of Chinese universities. *Sustainability*, 13(14), 8089. <https://doi.org/10.3390/su13148089>
45. Zhou, M. (2016). Chinese university students' acceptance of MOOCs: A self-determination perspective. *Computers and Education*, 92–93, 194–203. <https://doi.org/10.1016/j.compedu.2015.10.012>
46. Yadav, A., & Gupta, K. P. (2020). Investigating Students' Intentions to adopt MOOCs: An Application of technology acceptance model (TAM). *Journal of General Management, (Research)*, 7(1).
47. Boateng, P., Chen, Z., & Ogunlana, S. O. (2016). A dynamic framework for managing the complexities of risks in megaprojects. *Int. J. Management Research*, 1(5), 1–13. <https://doi.org/10.47127/ijtmr.v1i5.38>
48. Olugbara, T. C., & Letseka, M. (2019). Exploring factors influencing the adoption of massive open online courses for open distance learning.
49. Lambert, S. R. (2020). Do MOOCs contribute to student equity and social inclusion? A systematic review 2014–18. *Computers and Education*, 145, 103693. <https://doi.org/10.1016/j.compedu.2019.103693>
50. Liyanagunawardena, T. R., Lundqvist, K. Ø., & Williams, S. A. (2015). Who are with us: MOOC learners on a FutureLearn course. *British Journal of Educational Technology*, 46(3), 557–569. <https://doi.org/10.1111/bjet.12261>
51. Milligan, C. et al. (2013). Patterns of engagement in connectivist MOOCs. *MERLOT J. Online Learn. Teach.*, 9(2), 149–159.
52. Pundak, D., Sabag, N., & Trotskovsky, E. (2014). Accreditation of MOOCs. *European Journal of Open, Distance and E-Learning*, 17(2), 117–129. <https://doi.org/10.2478/eurodl-2014-0023>
53. Radford, A. W. et al. (2014). The employer potential of MOOCs: A survey of human resource professionals' thinking on MOOCs. http://www.rti.org/pubs/duke_handbook-final-03252014.pdf
54. Rosell-Aguilar, F. (2013). Delivering unprecedented access to learning through podcasting as OER, but who's listening? A profile of the external iTunes U user. *Computers and Education*, 67, 121–129. <https://doi.org/10.1016/j.compedu.2013.03.008>
55. Semenova, T. V., & Rudakova, L. M. (2016). Barriers to taking massive open online courses (MOOCs). *Russian Education and Society (Russian ed)*, 58(3), 228–245. <https://doi.org/10.1080/10609393.2016.1242992>
56. Rekha, I. S., Shetty, J., & Basri, S. (2023). 'Students' continuance intention to use moocs: Empirical evidence from India. *Education and Information Technologies*, 28(4), 4265–4286. <https://doi.org/10.1007/s10639-022-11308-w>
57. Shrivastava, A., & Shrivastava, A. (2023). Decoding and designing massive open online courses (moocs). *Interactive Technology and Smart Education*, 20(1), 89–105. <https://doi.org/10.1108/ITSE-08-2021-0146>
58. Albelbisi, N. A., Al-Adwan, A. S., & Habibi, A. (2023). A qualitative analysis of the factors influencing the adoption of MOOC in higher education. *Turkish Online Journal of Distance Education*, 24(2), 217–231. <https://doi.org/10.17718/tojde.973956>
59. Alturki, U., & Aldraiweesh, A. (2023). 'An empirical investigation into students' actual use of moocs in Saudi Arabia higher education. *Sustainability*, 15(8), 6918. <https://doi.org/10.3390/su15086918>
60. Rungruang, S. et al. (2023). Factors affecting decision making to study massive online open course (MOOC) for bachelor degrees in Bangkok. *Asia Pacific Journal of Religions and Cultures*, 7(1).
61. Goel, P., Raj, S., Garg, A., Singh, S., & Gupta, S. (2023). Peeping in the minds of moocs instructors: Using fuzzy approach to understand the motivational factors. *Online Information Review*, 47(1), 20–40. <https://doi.org/10.1108/OIR-04-2021-0205>
62. Dvorakova, K., Emmer, J., Janktová, R., & Klementová, K. (2023). The influence of remote learning environment and use of technology on university students' behavioural engagement in contingency online learning. *Tuning Journal for Higher Education*, 10(2), 271–300. <https://doi.org/10.18543/tjhe.2327>
63. Chen, Y., Ding, D., Meng, L., Li, X., & Zhang, S. (2023). Understanding consumers' purchase intention towards online paid courses. *Information Development*, 39(1), 19–35.