# Exploring Factors Influencing the Adoption of Massive Open Online Courses for Open Distance Learning

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## Abstract

Open distance learning (ODL) is a holistic strategy to increase ubiquitous access to quality learning, empower students to become autonomous learners, improve student success and student engagement in an open and online collaborative effort. However, this effort requires an appropriate technology platform to promote effective ODL practices. Massive open online courses (MOOCs) have attracted a great deal of interest in recent years as an appropriate model for novel technology enhanced learning. However, despite the numerous intrinsic benefits of MOOCs, its ubiquitous adoption for ODL is still lagging. In an attempt to fill this gap, the overarching purpose of this study is to use a method based on the decision theory approach to select the most influential adoption factors of MOOCs to support student learning in an ODL environment. Content analysis has been deployed to identify factors that have been generally attributed in literature to influence the adoption of MOOCs. Numerous research papers, 190 on MOOCs and 301 on ODL, published between 2012 and 2019 as indexed by web of science and google scholar were examined. This paper presents the research results with a discussion on factors that can help to develop student support for ODL.

**Keywords:** Content analysis, Decision theory, Online courses, Open distance learning

## INTRODUCTION

Open distance learning (ODL) system around the world has shown a tremendous growth during the past few decades because of its unique contributions to socioeconomic development (Keqiang, 2017). It has become one of the most rapidly growing fields of education that countries around the world are adopting it to meet the demands of students (Dea Lerra, 2014). Many educational institutions, especially those in the developed countries are shifting from a purely campus model of higher education to that agglutinates with ODL model (Musingafi, Mapuranga, Chiwanza & Zebron, 2015). Great attention is given to ODL to meet the educational challenges of marginalised adult population with a view to providing novel alternative learning opportunities to the deprived (Dea Lerra, 2014). The United Nations Educational, Scientific and Cultural Organization (UNESCO) continues to strengthen the role of ODL in the diversification of educational delivery systems towards encouraging collaboration between professional bodies and distance teaching institutions (Ghosh, Nath, Agarwal & Nath, 2012). ODL offers affordable, flexible, accessible, convenient, cost-effective, quality and lifelong learning education to millions of students around the world (Bordoloi, 2018). However, it is facing a lot of challenges, ranging from high rates of dropout, low throughput, low acceptability of ODL students for higher degree studies in reputable conventional universities and difficulty faced by ODL graduates in getting lucrative employment in comparison with their counterparts from conventional universities (Keqiang, 2017).

Numerous initiatives were undertaken by ODL institutions to ameliorate these challenges. The initiatives focused on mediated technologies like synchronous and asynchronous video-tutoring, automatic formative assessment, virtual reality, artificial intelligence, emotion detection, learning analytics, social communication software and massive open online courses (MOOCs) (Sánchez-Elvira Paniagua & Simpson 2018). This study focuses on MOOCs, whose advent in 2012 has highlighted a potent substitute to improve education quality in an ODL environment (McAndrew & Scanlon, 2013). MOOCs can improve the quality of learning pedagogy, help accelerate collaboration, ensure social cohesion and promote sustainable growth (Nisha & Senthil, 2015). However, we cannot guarantee that MOOCs will mitigate all ODL challenges, without first unveiling the most influential factors that can help improve its adoption for ODL practices, which is the overarching purpose of this study. Indeed, the understanding of factors that would improve the adoption of MOOCs for ODL practices is a significant barometer for ODL institutions, software companies, educators, protagonists and evangelists to help overcome possible obstacles and eventually bridge the digital access chauvinism often experienced by marginalised communities (Ochieng, Olugbara & Marks, 2017).

## METHODS

### Content Analysis

Content analysis of published research papers on MOOCs between 2012 and 2019 has indicated that several factors are influencing the adoption of MOOCs for ODL. The process of content analysis involves a literature search of academic databases of web of science and google scholar using relevant search parameters. The reason for selecting the 2012 baseline for literature review is that it was the year that Coursera Company partnered with universities to offer MOOCs for extensive online learning (Hakami, White & Chakaveh, 2017a). The authors have reviewed several papers and those found unrelated to the study themes and methods were discarded because they add little contributions to the study purpose. After the initial screening, 110 papers were selected and 50 factors were generated. However, it was observed that a number of the identified factors, despite using different terms, semantically expressed the same factors and by removing duplications, 34 distinct factors were finally identified as shown in Table 1.

**Table 1: Factors Influencing the Adoption of MOOCs with Citing Authors**

| SN | Factor | Author |
|---|---|---|
| 1. | Perceived usefulness | Gamage, et al., 2015; Gao &Yang, 2015; Schrader et al., 2016; Sa et al.,2016; Hakami et al., 2017a; Hakami et al., 2017b; Ouyang et al., 2017; Yang et al., 2017; Al-shami et al., 2018; Mohamad & Abdul Rahim, 2018; Yang & Sun, 2018; Ma & Lee, 2019. |
| 2. | Perceived ease of use | Gao & Yang, 2015; Hakami, et al., 2017a; Yang et al., 2017; Al-shami et al., 2018. |
| 3. | Intention | Al-shami, Rashid & Aziz, 2018; Al-shami et al., 2018; Fianu et al., 2018; Al-Rahmi, et al., 2019. |
| 4. | Motivation | Milligan et al., 2013; Abeer & Miri, 2014; Davis et al., 2014; Hew & Cheung, 2014; Wen et al., 2014; Gamage et al., 2015; Morris et al., 2015; Zheng et al., 2015; Rai & Chun-rao, 2016; Hakami et al., 2017a; Li & Moore, 2018; Al-Rahmi, et al., 2019. |

| | | |
|---|---|---|
| 5. | Engagement | Hill, 2013; Kizilcec et al., 2013; Milligan et al., 2013; Waite et al., 2013; Anderson et al., 2014; Hew & Cheung, 2014; Nawrot & Doucet, 2014; Ferguson et al., 2015; Veletsianos et al., 2015; Phan et al., 2016; Al-Rahmi, et al., 2019. |
| 6. | Enjoyment | Davis et al., 2014; Alraimi et al., 2015; Hakami et al., 2017a; Mohamad & Abdul Rahim, 2018 |
| 7. | Interactivity | Alzahrani & Ghinea, 2012; Colone, 2013; Grunewald et al., 2013; Guo et al., 2014; Li et al., 2014; Lim et al., 2014; Mamgain et al., 2014; Gamage et al., 2015; Nisha & Senthil, 2015; Hone et al., 2016; Qiang et al., 2016; Kolås et al., 2016; Wong, 2016; Hakami et al., 2017a; Huang, et al., 2017; Huanghuang et al, 2017; Mohamad & Abdul Rahim, 2018; Yang & Sun, 2018; Al-Rahmi et al., 2019. |
| 8. | Openness | Liyanagunawardena et al., 2013; Siemens, 2013; Davis et al., 2014; Alraimi et al., 2015; Yousef et al., 2015; Shrader et al., 2016; Hakami et al., 2017a; Albelbisi et al., 2018. |
| 9. | University/institution's reputation | Alraimi et al., 2015; Yousef et al., 2015; Rai & Chun-rao, 2016; Hakami et al., 2017a. |
| 10. | Skills | Rosell-Aguilar 2013; Radford et al. 2014; Chang, et al 2015; Farrow et al., 2015; Liyanagunawardena et al., 2015; Yousef et al., 2015; Hakami et al., 2017a. |
| 11. | Collaboration | Milligan et al., 2013; Chang et al., 2015; Farrow et al., 2015; Gamage et al., 2015; Yousef et al., 2015; Barak et al., 2016; Wong, 2016; Zhou, 2016. |
| 12. | Assessment | Kulkarni et al., 2013; Piech et al., 2013; Sandeen, 2013; Admiraal, et al., 2014; Clarà & Barberà, 2014; Reilly et al., 2014; Admiraal et al., 2015; Gamage et al., 2015; del Mar Sánchez-Vera & Prendes-Espinosa, 2015; Raposo-Rivas et al., 2015; Yousef et al., 2015. |
| 13. | Pedagogy | Ahn, et al., 2013; Glance et al., 2013; Yuan & Powell, 2013; Bayne & Ross 2014; Gamage et al., 2015; Ferguson et al., 2015; Istrate & Kestens 2015;Toven-Lindsey et al., 2015. |
| 14. | Attitude | Nordin et al., 2015; Hakami et al., 2017a. |
| 15. | Performance expectancy | Nordin et al., 2015; Fianu et al., 2018; Mulik et al., 2018. |
| 16. | Effort expectancy | Nordin et al., 2015; Mulik et al., 2018. |
| 17. | Social influence | Nordin et al., 2015; Hakami et al., 2017a; Mulik et al., 2018. |
| 18. | Facilitating condition | Nordin et al., 2015; Fianu et al., 2018; Mulik et al., 2018. |
| 19. | Service quality | Yang et al., 2017; Albelbisi, 2019. |
| 20. | System quality | Yang et al., 2017; Albelbisi et al., 2018; Fianu et al., 2018. |
| 21. | Course quality | Butcher et al., 2013; Yousef et al., 2014; Gamage et al., 2015; Margaryan et al., 2015; Hone & El Said, 2016; Hood & Littlejohn, 2016; Jansen et al., 2016; Huang et al., 2017; Yang et al., 2017. |
| 22. | Instructional design quality | Amo, 2013; Downes, 2013; Young, 2013; Chen, 2014; Lin et al., 2015; Munoz-Merino et al., 2015; Littlejohn et al., 2016; Fianu et al., 2018. |
| 23. | Sustainability | Dellarocas & van Alstyne, 2013; Parr, 2013; Aparicio et al., 2014; Burd et al., 2014; Kalman, 2014. |
| 24. | Professional and personal development | Rosell-Aguilar, 2013; Radford et al. 2014; Chang et al., 2015; Farrow et al., 2015; Liyanagunawardena et al., 2015; Yousef et al., 2015. |
| 25. | Lifelong learning | Rosell-Aguilar, 2013; Pundak et al., 2014; Farrow, et al., 2015. |
| 26. | Mimetic pressure | Gao & Yang, 2015; Hakami et al., 2017a; Al-Shami et al., 2018. |
| 27. | Normative pressure | Al-shami et al., 2018. |
| 28. | Perceived effectiveness | Hone & El Said, 2016; Mulik et al., 2018. |
| 29. | Participation | Nisha & Senthil, 2015; Castaño-Garrido, et al., 2017; Chiu & Hew, 2018. |
| 30. | Satisfaction | Yang & Sun, 2018; Al-Rahmi, et al., 2019. |
| 31. | Computer self-efficacy | Fianu et al., 2018. |
| 32. | Learners support | Gamage et al., 2015. |
| 33. | Technology | Gamage et al., 2015. |
| 34. | Self-regulation | Ma & Lee, 2019. |

**Data Analysis**

During the planning of an ODL implementation in an education institution, planners, administrators, implementers, policy makers, academics and other stakeholders have to consider many important factors to arrive at the best choice that provides an optimum fit for their aspirations. However, one important issue that reduces the clarity of a planning decision is the failure of introspection of the essential factors that could guide an effective planning option. This study proposes the use of multiple criteria decision making (MCDM) approach based on the "technique for order of preference by similarity to ideal solution (Topsis)" (Hwang & Yoon, 1981) to analyse the data generated at the content analysis stage of the study. Factor selection was based on "factor citations" over a period of 8 years to help circumvent the challenges associated with introspection during an ODL decision making process. The analysis of factor citations is the examination of frequency of citations in published documents. The Topsis method works on the concept of selecting a factor with the minimum distance from the ideal solution ($A^+$) and maximum from the non-ideal solution ($A^-$). The ideal is a possible solution that contains maximum values for all the benefit and minimum values for all the non-benefit criteria. The non-ideal is a possible solution that includes minimum values for all benefit criteria and maximum values for all the non-benefit criteria. The method finds the most influencing factor that is the nearest to the hypothetically best solution and furthest from the worst solution concomitantly.

The choice of criteria weights is essential in the Topsis process to express the importance of criteria, which can be estimated subjectively or objectively. This study implements the Topsis method by employing the entropy technique for objective weight estimation. The weight estimation technique is based on the Shannon entropy to measure uncertainty in data. The entropy-Topsis has been used in this study because of its popularity for solving multiple criteria decision making problems in different application domains.

**RESULTS**

The process of identifying the most influential adoption factors of MOOCs for ODL is articulated in this study as MCDM problem and solved using the entropy-Topsis method. The statistics of an ideal solution ($A^+$), a non-ideal solution ($A^-$) and criteria weights (weight) are shown in Table 2. The uncertainty reflected by the criterion 1 (2012) is high, resulting in the smallest weight, but the uncertainty of criterion 3 (2014) is sufficiently low to provide information for the ranking of factors. Criteria 3, 2 and 5 are the most important with their weights 18.94%, 17.95%, 17.00% respectively.

**Table 2: Result of Ideals with Criteria Weights**

| **Statistic** | **2012** | **2013** | **2014** | **2015** | **2016** | **2017** | **2018** | **2019** |
|---|---|---|---|---|---|---|---|---|
| Ideal solution ($A^{+)}$) | 0.0036 | 0.0745 | 0.0763 | 0.0540 | 0.0796 | 0.0618 | 0.0383 | 0.0141 |
| Non-Ideal solution $A^-$ | 0.0018 | 0.0149 | 0.0153 | 0.0090 | 0.0159 | 0.0124 | 0.0096 | 0.0071 |
| Criteria Weight | 0.0108 | 0.1795 | 0.1894 | 0.1485 | 0.1700 | 0.1366 | 0.1112 | 0.0539 |

Table 3 shows the ranking of 34 factors with separation distance of each criterion from $A^+$ ($S^+$) and $A^-$ (**$S^-$**), the relative proximity of each factor to ideal solution (**$C^*$**) and the order of factor ranking (rank). The ranking result shows that interactivity and effort expectancy are the best and worst factors because they have the highest and lowest relative proximity respectively. In addition, interactivity, engagement, motivation, assessment, course quality and perceived usefulness are the top 6 factors that are deemed highly influential for planning the adoption of MOOCs for ODL implementation because they all have relative proximities above a threshold. The threshold (0.3960) is calculated as the sum of the mean (0.2337) and standard deviation (0.1623) of C*. The final selection of influential factors is relevant and it provides insight into the study purpose. Moreover, the study method provides significant results that can be of great help in planning, monitoring and evaluating the adoption of MOOCs for ODL implementation.

**Table 3: Result of Ranking Decision Factors**

| **SN** | **2012** | **2013** | **2014** | **2015** | **2016** | **2017** | **2018** | **2019** | **$S^+$** | **$S^-$** | **$C^*$** | **Rank** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1.** | **0** | **0** | **0** | **2** | **2** | **4** | **3** | **1** | **0.0950** | **0.0683** | **0.4181** | **6** |
| 2. | 0 | 0 | 0 | 1 | 0 | 2 | 1 | 0 | 0.1169 | 0.0280 | 0.1933 | 15 |
| 3. | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 1 | 0.1258 | 0.0296 | 0.1903 | 16 |
| **4.** | **0** | **1** | **4** | **3** | **1** | **1** | **1** | **1** | **0.0797** | **0.0723** | **0.4757** | **3** |
| **5.** | **0** | **4** | **3** | **2** | **1** | **0** | **0** | **1** | **0.0807** | **0.0792** | **0.4953** | **2** |
| 6. | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0.1132 | 0.0236 | 0.1728 | 17 |
| **7.** | **1** | **2** | **4** | **2** | **4** | **3** | **2** | **1** | **0.0432** | **0.1039** | **0.7065** | **1** |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 8. | 0 | 2 | 1 | 2 | 1 | 1 | 1 | 0 | 0.0883 | 0.0441 | 0.3331 | 11 |
| 9. | 0 | 0 | 1 | 2 | 1 | 1 | 0 | 0 | 0.1045 | 0.0310 | 0.2291 | 14 |
| 10. | 0 | 1 | 1 | 4 | 0 | 1 | 0 | 0 | 0.1024 | 0.0437 | 0.2989 | 12 |
| 11. | 0 | 1 | 0 | 4 | 3 | 0 | 0 | 0 | 0.0969 | 0.0617 | 0.3889 | 7 |
| **12.** | **0** | **3** | **3** | **5** | **0** | **0** | **0** | **0** | **0.0885** | **0.0783** | **0.4692** | **4** |
| 13. | 0 | 3 | 1 | 4 | 0 | 0 | 0 | 0 | 0.0989 | 0.0594 | 0.37**53** | 8 |
| 14. | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0.1220 | 0.0153 | 0.1114 | 26 |
| 15. | 0 | 0 | 0 | 1 | 0 | 0 | 2 | 0 | 0.1234 | 0.0212 | 0.1463 | 20 |
| 16. | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0.1245 | 0.0131 | 0.0000 | 34 |
| 17. | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0.1201 | 0.0180 | 0.1306 | 23 |
| 18. | 0 | 0 | 0 | 1 | 0 | 0 | 2 | 0 | 0.1234 | 0.0212 | 0.1463 | 20 |
| 19. | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0.1248 | 0.0142 | 0.1025 | 27 |
| 20. | 0 | 0 | 0 | 0 | 0 | 1 | 2 | 0 | 0.1220 | 0.0228 | 0.1574 | 19 |
| **21.** | **0** | **1** | **1** | **2** | **3** | **2** | **0** | **0** | **0.0811** | **0.0606** | **0.4279** | **5** |
| 22. | 0 | 3 | 1 | 2 | 1 | 0 | 1 | 0 | 0.0905 | 0.0539 | 0.3730 | 9 |
| 23. | 0 | 2 | 3 | 0 | 0 | 0 | 0 | 0 | 0.1026 | 0.0546 | 0.3474 | 10 |
| 24. | 0 | 1 | 1 | 4 | 0 | 0 | 0 | 0 | 0.1075 | 0.0419 | 0.2803 | 13 |
| 25. | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0.1130 | 0.0232 | 0.1700 | 18 |
| 26. | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0.1201 | 0.0180 | 0.1306 | 23 |
| 27. | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0.1274 | 0.0096 | 0.0699 | 29 |
| 28. | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0.1203 | 0.0186 | 0.1338 | 22 |
| 29. | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0.1201 | 0.0180 | 0.1306 | 23 |
| 30. | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0.1272 | 0.0119 | 0.0855 | 28 |
| 31. | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0.1274 | 0.0096 | 0.0699 | 29 |
| 32. | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0.1263 | 0.0090 | 0.0665 | 31 |
| 33. | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0.1263 | 0.0090 | 0.0665 | 31 |
| 34. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0.1290 | 0.0071 | 0.0520 | 33 |

## DISCUSSION

The overarching purpose of this study was to unveil the most influential adoption factors of MOOCs for ODL implementation using the entropy-Topsis method. The study results indicate that six factors among the 34 investigated can help promote student support for ODL implementation with MOOCs. These factors are interactivity, engagement, motivation, assessment, course quality and perceived usefulness. The interactivity of MOOCs provides an opportunity for students to seamlessly connect and interact with contents, other students, instructors and experts in various subjects. The engagement activity that is provided by MOOCs will mitigate the problem of students travelling long distances to regional centres. The video-lecture facility in MOOCs can motivate students to easily access a course content continuously and help them to understand study materials through graphical representations. The presentation of a course in MOOCs is clear and in the right length, which is an important attribute that helps motivate students to learn, improve knowledge, make their studies more meaningful and allow them to complete their courses as stipulated. The peer assessment resource of MOOCs can offer promising solutions to scale the grading process of assignments for a large set of students. The course contents in MOOCs are useful, well organised, high quality, interactive, relevant and up-to-date. The usefulness of MOOCs can offer a valuable source of knowledge that supports learning, enable the understanding of difficult curricula, improve student learning efficiency, foster sharing of knowledge and promote self-directed learning.

In general, the ubiquitous accessibility to MOOCs can remove education costs such as travelling time and money in an ODL environment. This study is imperative for theoretical and practical reasons. For theoretical aspect, it is the first study in this direction to the best of our knowledge that can open opportunities for further research. In practice, the study results could provide useful insights and help institutions, academics and other stakeholders who plan to adopt MOOCs for ODL implementation to be aware of how teaching can be best delivered to promote effective learning in an ODL environment.

## CONCLUSION

This study has presented the adoption factors of MOOCs for ODL implementation based on the relevant literature. The method of entropy-Topsis has been successfully applied to identify six most influential factors to guide the adoption of MOOCs for effective ODL implementation. The study results find that entropy-Topsis is able to apply a set of factors to help ODL planners, administrators, implementers, policy makers and academics to systematically choose a subset of factors to consider germane when planning for ODL implementation. However, there is still a very long way to go in this research direction and we call for further study to expand our knowledge. Finally, it is important to note that many of the references cited in the text are not listed in the bibliography list because of space limitations.

## BIBLIOGRAPHY


Abeer, W., & B. Miri, B. (2014). Students' preferences and views about learning in a MOOC. *Procedia - Social and Behavioral Sciences, 152,* 318-323.

Admiraal, W., Huisman, B., & Pilli, O. (2015). Assessment in massive open online courses. *Journal of e-Learning, 13*(4), 207-216.

Admiraal, W., Huisman, B., & Ven, M. Van de (2014). Self- and peer assessment in massive open online courses. *International Journal of Higher Education, 3*(3), 119-128.

Albelbisi, N., Yusop, F. D., & Salleh, U. K. M. (2018). Mapping the factors influencing success of massive open online courses (MOOC) in higher education. *Eurasia Journal of Mathematics, Science and Technology Education*, 14(7), 2995-3012.

Al-Rahmi**,** W., Aldraiweesh, A., Yahaya, N., Kamin, Y.B., & Zeki, A.M. (2019). Massive open online courses (MOOCs): Data on higher education. *Data in Brief,* 22, 118-125.

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

Al-Shami**,** S. A., Rashid, N., & Aziz, H. (2018). The adoption of MOOC utilization among undergraduate students in Universiti Teknikal Malaysia Melaka (UTeM). *Journal of Fundamental and Applied Sciences,* Special, 10(6S), 2634-2654.

Al-shami, S.A., Sedik, S., Rashid, N., & Hussin, H. (2018). An empirical Analysis of MOOC adoption from the perspective of institutional theory. *Journal of Advance research in Dynamical & Control Systems*, (10), Special Issue, 332-342.

Barak, M., Watted, A., & Haick, H. (2016). Motivation to learn in massive open online courses: Examining aspects of language and social engagement. *Computers & Education, 94,* 49-60.

Bordoloi, R. (2018) "Transforming and empowering higher education through open and distance learning in India". *Asian Association of Open Universities Journal,* 13 (1), 24-36,

Burd**,** E. L., Smith, S. P., & Reisman, S. (2014). Exploring business models for MOOCs in higher education. *Innovative Higher Education, 40*(1), 37-49.

Chang, R. I., Hung, Y. H., & Lin, C. F. (2015). Survey of learning experiences and influence of learning style preferences on user intentions regarding MOOCs. *British Journal of Educational Technology*, *46*(3), 528-541.

Chen, Y. (2014). Investigating MOOCs through blog mining. *The International Review of Research in Open and Distributed Learning*, *15*(2).

Chiu, T. K. F., & Hew, T. K. F. (2018). Factors influencing peer learning and performance in MOOC asynchronous online discussion forums. *Australasian Journal of Educational Technology, 34*(4), 16-28.

Clarà, M., & Barberà, E. (2014). Three problems with the connectivist conception of learning. *Journal of Computer Assisted Learning, 30*(3), 197-206.

Dea Lerra, M. (2014). The dynamics and challenges of distance education at private higher institutions in South Ethiopia. *Asian Journal of Humanity, Art and Literature*, 1(3), 137-150.

Dellarocas, C., & van Alstyne, M. (2013). Money models for MOOCs. *Communications of the ACM*, 56(8), 25-28.

del Mar Sánchez-Vera, M., & Prendes-Espinosa, M. P. (2015). Beyond objective testing and peer assessment: alternative ways of assessment in MOOCs. *International Journal of Educational Technology in Higher Education*, *12*(1), 119-130.

Farrow, R., Arcos, B. D. L., Pitt, R., & Weller, M. (2015). Who are the open learners? A comparative study profiling non-formal users of open educational resources. *European Journal of Open, Distance and E-Learning, 18*(2), 50-74.

Gamage, D., Fernando, S., & Perera, I. (2015). Quality of MOOCs: A review of literature on effectiveness and quality aspects. In Ubi-Media Computing (UMEDIA), 8th International Conference on (pp. 224-229).

Ghosh, S., Nath, J., Agarwal, S., Nath, A. (2012). Open and distance learning (ODL) education system: Past, present and future - a systematic study of an alternative education system. *Journal of Global Research in Computer Science*, 3 (4), 53-57.

Hakami, N., White, S., & Chakaveh, S. (2017a). Motivational factors that influence the use of MOOCs: Learners' perspectives - a systematic literature review. In Proceedings of the 9th International Conference on Computer Supported Education (CSEDU 2017), 2, (pp. 323-331)**.**

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.

Hone, K., & El Said, G. (2016). Exploring the factors affecting MOOC retention: A survey study. *Computers & Education, 98,* 157-168.

Huang, L., Zhang, J., & Liu, Y. (2017). "Antecedents of student MOOC revisit intention: Moderation effect of course difficulty," *International Journal of Information Management*, 37 (2), 84-91.

Hwang, C. L., & Yoon, K. P. (1981). Multiple attribute decision making: Methods and applications. New York: Springer-Verlag.

Jansen, D., Rosewell, J., & Kear, K. (2016). Quality frameworks for MOOCs. In: Open Educ. from OERs to MOOCs. Springer, Berlin, 261-281.

Kalman, Y. M. (2014). A race to the bottom: MOOCs and higher education business models. Open Learning: *The Journal of Open, Distance and e-Learning*, *29*(1), 5-14.

Keqiang, L. (2017). Innovation in open and distance learning (ODL) system in India: The need to remove systemic barriers. *Ennovate,* 4(15), 1-9.

Kulkarni, C., Wei, K. P., Le, H., Chia, D., Papadopoulos, K., Cheng, J., Koller, D., & Klemmer, S. R. (2013). Peer and self-assessment in massive online classes. *ACM Transactions on Computer-Human Interaction (TOCHI), 20*(6), 33.

Li, N., Verma, H., Skevi, A., Zufferey, G., Blom, J., & Dillenbourg, P. (2014). Watching MOOCs together: Investigating co-located MOOC study groups. *Distance Education*, *35*(2), 217-233.

Lim, C., Lee, J., & Lee, S. (2014). A theoretical framework for integrating creativity development into curriculum: the case of a Korean engineering school. *Asia Pacific Education Review, 15*(3), 427-442.

Lin, Y-L., Lin, H-W., & Hung, T-T. (2015). Value hierarchy for massive open online courses. *Computers in Human Behaviour, 53,* 408-418.

Littlejohn, A., Hood, N., Milligan, C., & Mustain, P. (2016). Learning in MOOCs: Motivations and self-regulated learning in MOOCs. *The Internet and Higher Education, 29,* 40-48.

Liyanagunawardena, T. R., Adams, A. A., & Williams, S. (2013). MOOCs: A systematic study of the published literature 2008-2012. *The International Review of Research in Open and Distance Learning, 14*(3), 202-227.

Liyanagunawardena, T. R., Lundqvist, K.O. & Williams, S. A. (2015). Who are with us: MOOC learners on a FutureLearn course. *British Journal of Educational Technology*, *46*(3), 557-569.

Ma, L., & Lee, C. S. (2019). Investigating the adoption of MOOCs: A technology-user-environment perspective. *Journal of Computer Assisted Learning,* 35:89-98.

Mamgain, N., Sharma, A., & Goyal, P. (2014). Learner's perspective on video-viewing features offered by MOOC providers: Coursera and edX. In *MOOC, Innovation and Technology in Education (MITE), IEEE International Conference on*, 331-336.

Margaryan, A., Bianco, M., & Littlejohn, A. (2015). Instructional quality of massive open online courses (MOOCs). *Computers & Education, 80*, 77–83.

McAndrew, P., & Scanlon, E. (2013). Open learning at a distance: Lessons for struggling MOOCs. *Article in Science,* 340, 1450-1451.

Milligan, C., Littlejohn, A., & Margaryan, A. (2013). Patterns of engagement in connectivist MOOCs. *MERLOT Journal of Online Learning and Teaching, 9*(2), 149-159.

Mohamad, M., and Abdul Rahim, M.K.I. (2018). Factors affecting MOOCS continuance intention in Malaysia: A proposed conceptual framework. *Journal of Humanities, Language, Culture and Business (HLCB),* 2(7), 61-72.

Musingafi, M.C.C., Mapuranga, B., Chiwanza, K., Zebron,S. (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.

Munoz-Merino, P., Ruiperez-Valiente, J., Alario-Hoyos, C., Perez-Sanagustin, M., & Delgado Kloos, C. (2015). Precise effectiveness strategy for analyzing the effectiveness of students with educational resources and activities in MOOCs. *Computers in Human Behaviour*, *47*, 108-118.

Nisha, F. & Senthil, V. (2015). MOOCs: Changing trend towards open distance learning with special reference to India. *DESIDOC Journal of Library & Information Technology*, 35(2), 82-89.

Nordin, N., Norman, H., & Embi, M. A. (2015). Technology acceptance of massive open online courses in Malaysia. Malaysian. *Journal of Distance Education,* 17(2), 1–16.

Ochieng, D. M., Olugbara, O. O., & Marks, M. M. (2017). Exploring digital archive system to develop digitally resilient youths in marginalised communities in South Africa. *The Electronic Journal of Information Systems in Developing Countries*, *80*(1), 1-22.
Phan, T., McNeil, S. G., & Robin, B. R. (2016). Students' patterns of engagement and course performance in a Massive Open Online Course. *Computers & Education, 95*, 36-44.
Pundak, D., Sabag, N., & Trotskovsky, E. (2014). Accreditation of MOOCS. *European Journal of Open, Distance and E-Learning*, *17*(2), 116-128.
Rai, L., & Chun-rao, D. (2016). Influencing factors of success and failure in MOOC and general analysis of learner behavior. *International Journal of Information and Education Technology, 6(4)*, 262-268
Raposo-Rivas, M., Martinez-Figueira, E., & Campos, J. A. S. (2015). A study on the pedagogical components of massive online courses. *Comunicar, 44*, 27-35.
Reilly, E. D., Stafford, R. E., Williams, K. M., & Corliss, S. B. (2014). Evaluating the validity and applicability of automated essay scoring in two massive open online courses. *The International Review of Research in Open and Distance Learning, 15*(5), 83-98.
Sa, J.H., Lee, J.M., Kang, T.W., & Gim, G.Y., & Kim, J.B. (2016). A study of factors affecting the intention of usage in MOOC. *Advanced Science and Technology Letters*, 160-163.
Sánchez-Elvira Paniagua, A., & Simpson, O. (2018). Developing student support for open and distance learning: The EMPOWER Project. *Journal of Interactive Media in Education*, X(X), 1-10.
Shrader, S., Wu, M., Owens-Nicholson, D., & Ana, K.S. (2016). Massive open online courses (MOOCs): Participant activity, demographics, and satisfaction. *Online Learning, 20*(2).
Veletsianos, G., Collier, A., & Schneider, E. (2015). Digging deeper into learners' experiences in MOOCs: Participation in social networks outside of MOOCs, notetaking and contexts surrounding content consumption. *British Journal of Educational Technology, 46*(3), 570-587.
Waite, M., Mackness, J., Roberts, G., & Lovegrove, E. (2013). Liminal participants and skilled orienteers: Learner participation in a MOOC for new lecturers. *Journal of Online Learning and Teaching*, *9*(2), 200-215.
Wong, B.T.M. (2016). Factors leading to effective teaching of MOOCs. *Asian Association of Open Universities Journal*, 11(1), 105-118.
Yang, M., Shao, Z., Liu, Q., & Liu, C (2017). Understanding the quality factors that influence the continuance intention of students toward participation in MOOCs*.* *Education Tech Research Dev,* 65:1195-1214.
Yousef, A. M. F., Wahid, U., Chatti, M. A., Schroeder, U., & Wosnitza, M. (2015). The effect of peer assessment rubrics on learners' satisfaction and performance within a blended MOOC environment. In *Proceedings of the CSEDU 2015 Conference*, 148-159.
Zhou, M. (2016). Chinese university students' acceptance of MOOCs: A self-determination perspective. *Computers and Education*, *92-93*, 194-203.