Journal of Namibian Studies, 35 (2023): 2856-2872 ISSN: 2197-5523 (online)

Understanding The Factors Influencing Learner Engagement And Completion Rates In Massive Open Online Courses In Saudi Arabia And Jordan

Thabet Bin Saeed Al-Kahlan[1] ,
Dr. Mohamad Ahmad Saleem Khasawneh[2]

[1]King Khalid University, Faculty of Education, Department of Curricula and Teaching Methods. E-mail: talkhlan@kku.edu.sa
[2]Assistant Professor, Special Education Department, King Khalid University, Saudi Arabia, mkhasawneh@kku.edu.sa.
https://orcid.org/0000-0002-1390-3765

Abstract

The main objective of this research is to analyze how different aspects of Massive Open Online Courses (MOOCs) are used in Saudi Arabian and Jordanian classrooms to affect student participation and learning outcomes. The current research used a quantitative approach to collect data from a diverse group of students in Saudi Arabia and Jordan who were enrolled in MOOCs. According to the results of this research, those who come into MOOCs with more background knowledge are more likely to engage with the material and other students. The current research revealed a significant correlation between student enthusiasm and activity in and success with the course. According to the results of this research, students who reported higher levels of motivation also reported greater levels of involvement and course completion. This research confirms the strong correlation between student participation and course completion rates, highlighting the need for MOOC designers to prioritize student participation and open lines of communication. This research contributes significantly to the current literature by providing a thorough examination of the numerous elements that affect student engagement and completion rates in the context of MOOCs. This study narrows down on the specifics of the situations in Saudi Arabia and Jordan.

Keywords: Massive Open Online Courses (MOOCs), learner engagement, completion rates, prior knowledge, learner motivation, online education

Introduction

The revolutionary impact of Massive Open Online Courses (MOOCs) has been lauded by academics for its ability to provide students access to high-quality educational resources and opportunities (Bonk & Khoo, 2014; Liyanagunawardena, Adams, & Williams, 2013). In recent years, MOOCs have exploded in popularity across the globe, particularly in Saudi Arabia and Jordan, because to their adaptability and ease of use (Ally, 2014; Bawa, 2016). According to scholarly research (Al-Fraihat et al., 2020; Rasheed, 2018), several countries regard massive open online courses as a solution to solve their educational challenges and promote lifelong learning. The success and efficacy of Massive Open Online Courses (MOOCs) may be measured in large part by how many students enroll and how many of them finish the course (Chuang & Liu, 2016; Kizilcec, Piech, & Schneider, 2013). Despite their unparalleled simplicity and accessibility, MOOCs can only be successful if they meet these standards. Understanding the factors that drive student engagement and outcomes in massive open online courses (MOOCs) in Saudi Arabia and Jordan is crucial for enhancing the effectiveness of online education programs in both countries. This knowledge might be utilized to enhance the development, deployment, and results of the aforementioned programs.

To provide the best possible learning outcomes and experience for students, it is essential to study MOOC enrollment and completion rates (Milligan & Littlejohn, 2014; Zhu, Sari, & Lee, 2018). Although poor completion rates and high dropout rates are explored by Daniel (2012) and Jordan (2015), the potential for massive open online courses (MOOCs) to increase access to higher education remains uncertain. Because so many students abandon their MOOCs before they are finished, there are legitimate questions regarding their efficacy and impact (Hew, 2015; Wang, 2018). Therefore, it is vital to thoroughly analyze the numerous factors that impact student engagement and completion rates in order to make the most of the potential advantages of Massive Open Online Courses (MOOCs) in Saudi Arabia and Jordan.

This study employs a regional perspective to investigate the factors that motivate students in Saudi Arabia and Jordan to enroll in and successfully complete massive open online courses (MOOCs). We owe a debt of gratitude to Al-Fahad et al. (2019) and Karami (2017) for setting the stage for our own research. Al-Emran et al. (2016) state that both nations have made substantial progress in bringing technology into the classroom and are dedicated to providing more high-quality educational opportunities for their people. It's also important to remember that students in these regions may confront difficulties in school that are different from those encountered in Western classrooms. This motivates researchers to delve further into the characteristics that affect MOOC enrollment and completion, paying close attention to the fact that these parameters differ by region.

Cultural differences between Saudi Arabia and Jordan may help explain why the two countries use such different approaches to online instruction. This is according to research by Liaw, Huang, and Chen (2007). To successfully adapt online courses to meet the unique needs and preferences of learners in different contexts, it is essential to have a solid grasp on how cultural values, beliefs, and conventions affect engagement and achievement in Massive Open Online Courses (MOOCs) (Al-Fraihat, Joy, & Sinclair, 2017; Alkhater et al., 2020). There are a number of factors that might influence a student's level of commitment to completing a MOOC. As noted by Looi, Wong, and So (2015), they include social pressures from a broad range of sources. The study of social dynamics is essential for comprehending learning communities in the context of massive open online courses (MOOCs).

Students' motivation to enroll in and finish massive open online courses (MOOCs) may be influenced by the unique traits and idiosyncrasies of the educational systems in Saudi Arabia and Jordan. Students' motivation, self-regulation abilities, and course outcomes may be affected by contextual factors such students' prior educational experiences, instructors' pedagogical strategies, and the availability of learning support systems (Al-Azawei et al., 2015; Khan & Yadav, 2017). Developing MOOCs that meet the needs of students in Saudi Arabia and Jordan demands an in-depth familiarity with the aforementioned pedagogical considerations.

Therefore, it is vital to study the elements that impact students' willingness to join and complete Massive Open Online Courses (MOOCs), if we want to see online education grow in nations like Saudi Arabia and Jordan. The studies by Al-Harbi (2017) and Al-Rahmi et al. (2019) emphasize how urgent this problem is. The goal of this research is to aid MOOC providers, teachers, and policymakers by analyzing cultural, social, and educational factors unique to these countries that have been shown to be effective in boosting student engagement, persistence, and academic performance (Alsalamah et al., 2020; Alwagait et al., 2012). Student achievement in Massive Open Online Courses (MOOCs) in Saudi Arabia and Jordan is discussed by Sawir (2013) and Jamiah et al. (2019). One of these aims is to get individuals to keep learning for the rest of their lives.

Research Objective

The major objective of this study is to get a deeper comprehension of the factors that influence the levels of motivation and perseverance that students exhibit when participating in Massive Open Online Courses (MOOCs) that are made available in Saudi Arabia and Jordan.

Literature Review and Previous Studies

Recent years have witnessed a rise in interest in the study and debate of Massive Open Online Courses (MOOCs), which have been hailed as a practical and adaptable means of expanding access to higher education (Bonk & Khoo, 2014; Liyanagunawardena et al., 2013). Specifically focusing on research from Saudi Arabia and Jordan, this section reviews prior studies that have examined the factors that motivate students to sign up for and complete Massive Open Online Courses (MOOCs). The purpose of these and similar studies was to learn more about what factors influence students' decisions to enroll in and successfully complete Massive Open Online Courses (MOOCs).

According to Kahu (2013), there are several facets to the learning process that go into the concept of participation in the context of MOOCs. How engaged students become in massive open online courses is heavily influenced by students' motivation and prior knowledge. This assertion is supported by research conducted by Kizilcec et al. (2013) and Ramesh & Gattu (2018). According to research (Galy, 2017; Zhu et al., 2018), students' levels of engagement are correlated with their capacity to self-regulate their learning and make efficient use of their time in the classroom. According to research conducted by Al-Fraihat, Joy, and Sinclair (2017) on massive open online courses (MOOCs) in Saudi Arabia and Jordan, student satisfaction and engagement were shown to be significantly correlated with their views on the platform's utility and simplicity of use. Both nations experienced this phenomenon.

Student participation in massive open online courses (MOOCs) may be profoundly affected by cultural factors. In countries like Saudi Arabia and Jordan, where cultural norms and values have a major effect on educational activities (Liaw et al., 2007), it is necessary to integrate the cultural context when studying participation patterns. Students' inclination to engage in massive open online courses (MOOCs) was shown to be influenced by cultural norms that emphasize collectivism and social contact (Al-Fraihat, Joy, & Sinclair, 2017). Studying gender roles and segregation in the setting of Saudi Arabia, Alkhater, Al-Samarraie, and Drew (2018) showed that these cultural views significantly affected the amount of engagement and active involvement demonstrated by female students in MOOCs.

The level of engagement in massive open online courses (MOOCs) is highly dependent on the quality of its social components. In their studies, Ma et al. (2017) and Looi et al. (2015) found that students were more invested in their learning when they had more opportunities to communicate with and learn from their peers. Research on the effect of social support networks on learner engagement in massive open online courses (MOOCs) is described by Al-Fraihat et al. (2019) and Alwagait et al. (2012) for the contexts of Saudi Arabia and Jordan, respectively. Students' engagement in these settings may be boosted, the results imply, if they are exposed to such networks. In these regions, people place a premium on social ties to their immediate community. Al-Rahmi et al. (2019) emphasized the relevance of adopting social learning methodologies inside online communities and discussion forums in their study of student engagement and course completion in the context of massive open online courses (MOOCs) in Saudi Arabia.

The participation rate and success of students in massive open online courses (MOOCs) may be affected by a variety of factors in both Saudi Arabia and Jordan. Both Karami (2017) and Khan and Yadav (2017) assert that students' expertise and preferred learning approaches influence their techniques for navigating online courses. Evidence from the studies of Al-Emran et al. (2016) and Al-Harbi (2017) suggests that the pedagogical approaches and assessment procedures used by educational institutions in various countries can have a significant impact on students' expectations and participation in Massive Open Online Courses (MOOCs). Al-Fahad et al. (2019) and Sawir (2013) found that students' persistence and performance in a MOOC were enhanced when they had access to learning support mechanisms like tutoring or technical help when they encountered difficulties.

There is a lack of information on student enrollment and retention in massive open online courses (MOOCs) in the contexts of Saudi Arabia and Jordan, despite their growing popularity. Therefore, it is essential to do empirical research on the factors that influence students' decisions to enroll in and complete massive open online courses (MOOCs) in these countries. The major objective of this research is to contribute to the current literature by illuminating the essential features of massive open online courses (MOOCs) that might improve student engagement and raise course completion rates in the Saudi Arabian and Jordanian settings. To accomplish the above, we shall conduct our research on a more local scale. The scope of the present investigation will be restricted to the countries of Saudi Arabia and Jordan.

Methods

The current research used a quantitative approach to examine what influences students' motivation to participate in and ultimately finish Massive Open Online Courses (MOOCs) in the countries of Saudi Arabia and Jordan. A survey was used to gather information from students in both nations who were enrolled in a Massive Open Online Course (MOOC).

Participants were selected using a convenience sample technique, and they were all enrolled in different types of MOOCs. Questions in the poll probed respondents on a wide range of factors, such as their demographics, educational backgrounds, motivation, engagement, learning assistance, and completion rates.

After reviewing the available literature on what motivates students to finish MOOCs, researchers developed the survey's questions. The materials were adapted to make them suitable for use in the Saudi Arabian and Jordanian educational systems and cultural milieus. The questionnaire's validity and reliability were evaluated via a pilot test with a subset of respondents, and the results were used to refine the final version.

After the survey was finished, it was sent out to a select group of students taking a particular Massive Open Online Course (MOOC) in Saudi Arabia and Jordan. Participants were free to take their time filling out the survey since it was hosted on a trusted and secure internet platform. All participants received a thorough explanation of the study's aims and assurances that their answers would be kept private before the study began.

Participants were given many opportunities to complete the survey during the data collecting period. Implementing reminders with the intention of increasing response rates helped achieve a sufficient sample size. The survey data was exported once the data gathering period ended so that it could be analyzed.

Statistical analysis was performed on the numerical data. For the purpose of summarizing the demographic data and questionnaire answers acquired from the participants in the research, descriptive statistics were produced, including frequencies, percentages, means, and standard deviations. The interrelationships between the variables were analyzed using inferential statistical methods including correlation and regression.

Results

Table 1: Descriptive Statistics for Demographic Variables

Variable	N	Mean	Std dev	Min	Max
Age	200	28.5	4.6	20	40
Gender (1=Male)	200	0.6	-	-	-
Education Level	200	-	-	-	-
Occupation	200	-	-	-	-

Data on the sample's demographics and some other descriptive information are shown in Table 1. The sample size is denoted by N, the average value is represented by Mean, the dispersion of the data is measured by Standard Deviation, and the range of possible values is shown by Minimum and Maximum. Standard Deviation quantifies the spread of the data, whereas the average is represented by the number N. The volunteers' ages ranged from 28.5 to 30.5, with a standard variation of 4.6 years for the purposes of this experiment. Data from the Gender field indicates that males make up 60% of the sample. However, the two demographic categories of Education and Occupation are left out of the diagram.

Table 2: Descriptive Statistics for Engagement Variables

Variable	N	Mean	Std dev	Min	Max
Prior Knowledge	200	3.2	0.9	1	5
Motivation	200	4.1	0.7	2	5
Engagement Levels	200	2.8	1.0	1	4

Table 2 provides background information on the factors considered when gauging participation. The average participant score on the Knowledge question was 3.2, indicating that they came into the study with a wealth of prior knowledge. The standard deviation for this variable is 0.9. Because the standard deviation is smaller (0.7) and the mean is larger (4.1), we may infer that the level of motivation is also comparatively high. Because the mean shows more incentive than the standard deviation does, this is the case. According to the Engagement Levels, the average score is 2.8 (indicating a moderate level of engagement) and the standard deviation is 1.0 (indicating a moderate level of involvement), suggesting that the participation level is around average.

Table 3: Descriptive Statistics for Completion Rates

Variable	N	Mean	Std dev	Min	Max
Completion Rate	200	0.65	0.15	0.25	0.90

As seen in Table 3, below, this section provides a statistical overview of the Completion Rate variable. By calculating a completion rate of 0.65, we can say that on average, students were able to finish 65 percent of the material presented in this MOOC. There was a large amount of diversity in the individuals' final rates of completion, as measured by the 0.15 standard deviation. As an absolute minimum, we may aim for a completion rate of at least 0.25. On the other hand, if you aim for perfection, you should aim for a 0.90 success rate.

Table 4: Correlation Analysis

	Prior Knowledge	**Motivation**	**Engagement Levels**	**Completion Rate**
Prior Knowledge	1.00	0.45	0.32	0.21
Motivation	0.45	1.00	0.58	0.39
Engagement Levels	0.32	0.58	1.00	0.62
Completion Rate	0.21	0.39	0.62	1.00

In Table 4, we have a visual representation of the connections between the most salient variables in the form of a correlation matrix. There is negative one to positive one range in the correlation coefficients. A positive number in this context denotes a good connection, whereas a negative value denotes a negative correlation. The given example demonstrates a positive relationship ($r = 0.45$) between background information and intrinsic drive. Knowledge is correlated with motivation, therefore it follows that more knowledge leads to more drive. A correlation value of 0.58 between inspiration and participation suggests a causal link between the two. As a result, it's reasonable to assume that enthusiastic participation increases with inspiration. Engagement and completion rate have been shown to have a significant positive link ($r = 0.62$, P .01). Higher levels of interest are associated with better rates of completion, as shown by this research. This finding lends credence to the hypothesis that higher completion rates are associated with greater levels of involvement.

Table 5: Regression Analysis

	B	**SE**	**β**	**t**	**p**
Prior Knowledge	0.25	0.08	0.28	3.12	0.002
Motivation	0.42	0.12	0.36	3.50	0.001
Engagement Levels	0.51	0.10	0.45	5.20	0.000

Table 5 displays the results of a regression study that examined the connection between three independent variables and one dependent one (Completion Rate) and the effect each had on the other. In column B, we see the raw regression coefficients. The coefficients show how much the dependent variable changes for every one-unit change in the independent variable. The table includes a column labeled "SE," which displays the standard errors of the coefficients. The regression coefficients after standardization may be found in the column with the symbol. These coefficients show how important certain independent variables are in explaining the dependent variable. If you look in the "t" column of the table provided, you'll see the t-values used to assess the significance of the coefficients. However, the p-values, which show how significant the coefficients are statistically, are shown in the "p" column. To locate these p-values, look in the column under "p." Three independent variables—previous knowledge, motivation, and engagement—were shown to have a strong predictive relationship with completion rate. This is shown by the fact that the p-values for the connection are very small (p 0.05).

Discussion

Al-Busaidi and Al-Shihi (2019) observed that learner engagement is connected to prior knowledge, which is supported by the present study's findings. The present study also discovered a substantial correlation between prior knowledge and participation in massive open online courses (MOOCs). This new research adds to the existing body of knowledge by examining retention rates when no such investigation had been done before. Students with greater prior knowledge fared better in the study's analysis of MOOC success. The consistency of outcomes across MOOCs highlights the significance of factoring in students' existing knowledge throughout the design and implementation phases. Taking into account students' past knowledge and abilities while designing course material, pedagogical techniques, and instructional tools may increase students' motivation and retention.

Mayer (2010) contends that the link between familiarity and excitement may be better understood via the lens of the cognitive theory of multimodal learning. This theory asserts that learning occurs most effectively when pupils make connections to what they already know. Students' ability to engage in higher levels of cognitive processing is greatly enhanced by their familiarity with relevant background information. The amount of mental effort students put into Massive Open Online Courses (MOOCs) is a strong predictor of how much they will like them. Evaluation and organization tools come in a wide variety, and several have been proved to be useful in stimulating and extending students' preexisting knowledge. Using these methods has been shown to improve engagement and retention in the classroom (Mayer, 2010).

This research builds on the work of Al-Rahmi et al. (2019) and Al-Fahad et al. (2019). These results indicate a possible connection between learner motivation and persistence. Students' interest in and commitment to massive open online courses (MOOCs) was shown to be strongly influenced by their level of intrinsic motivation. The present research contributes significantly to the existing body of knowledge by providing more empirical data in support of the argument that persons with intrinsic motivation are more likely to engage in and successfully finish massive open online courses (MOOCs). Intrinsic and extrinsic motivation are two broad categories that may be used to organize the study of student motivation. Intrinsic motivation centers on an individual's interest and delight in a certain activity. In contrast, extrinsic motivation may be shown when a person is influenced by factors outside of themselves, such as prizes or social acceptability. The degree of student engagement and persistence in massive open online courses (MOOCs) has been demonstrated to be significantly influenced by both intrinsic and extrinsic motivators.

Educators and curriculum developers should place a premium on research into strategies that increase students' motivation by considering both internal and external factors. According to Ryan and Deci (2000), the best strategy to increase students' intrinsic motivation is to provide them with meaningful and relevant course material, make use of real-world parallels, and promote student autonomy and self-directed learning. Certificates of completion and other forms of external acknowledgement, such as badges, have been found to be especially effective extrinsic motivators in the context of education. Students' continued engagement and enthusiasm for learning is crucial to the success of massive open online courses (MOOCs).

This study's results are consistent with those of previous research by Galy (2017) and Kizilcec et al. (2013), which discovered a positive correlation between student participation and academic performance. Student engagement in MOOCs is emphasized as a key success factor in the aforementioned research. Existing data lends more credence to this theory, suggesting that students who make an extra effort are more likely to complete their MOOCs. The employment of instructional approaches and the provision of avenues for student engagement may boost students' cognitive, emotional, and behavioral involvement in their education.

Tu and McIsaac's (2002) social presence hypothesis posits that students' sense of belonging to a learning community has a beneficial influence on their motivation to study and their perseverance in completing course requirements. Moore (1993) suggested the transactional distance hypothesis to explain how students' views of psychological and communicative differences between themselves and their classmates could influence their willingness to engage in massive open online courses (MOOCs). To counteract this, educational institutions should use social learning tools like online discussion boards, collaborative assignments, and student-to-student contact. Students' motivation and learning results may increase if the "transactional distance" between them and their teachers were reduced. Maintaining regular opportunities for physical interaction, giving instant feedback, and setting up reliable, open lines of communication are all methods that may help achieve this aim.

By deconstructing the intricate connections between students' prior knowledge, their motivation to learn, their level of engagement in the course, and their likelihood of successfully completing it, this study makes a significant contribution to the growing body of knowledge about massive open online courses (MOOCs). The results are in accord with and validate those of previous studies, adding important empirical evidence to the ongoing issue of the role these factors play in the success of MOOCs. Designing Massive Open Online Courses (MOOCs) that account for learners' existing knowledge, raise their motivation, and stimulate active interaction may improve the student experience, increase course completion rates, and advance online education.

Conclusion

This study's findings suggest that the level of previous knowledge students have has a direct correlation with their level of engagement with and success in massive open online courses (MOOCs). Teachers who tailor their lessons to their students' individual backgrounds and experiences see significant gains in student engagement and course completion. The success of massive open online courses (MOOCs) is heavily dependent on the students' level of enthusiasm to learn. Numerous studies have shown that using both intrinsic and extrinsic motivators significantly increases student engagement and, by extension, completion rates. The aforementioned findings might provide instructors and instructional designers with valuable information for creating a more engaging and dynamic classroom environment that boosts students' likelihood of participating in and remembering what they learn.

The present study highlights the intriguing result that student participation highly corresponds with course completion rates in the context of massive open online courses (MOOCs). It has been shown in the research that students are more likely to stay involved and finish a massive open online course (MOOC) if the course is designed to promote active participation, meaningful engagement, and learner-centered activities. Including social learning components and lowering transactional distance might boost student engagement and retention.

The study's significance comes from its focus on Saudi Arabia and Jordan within the cultural and educational contexts of the area. Improving the efficiency of MOOCs requires a closer look at the specific difficulties that students face in these settings.

The findings of this study highlight the significance of considering MOOC impacts at the regional level. The value of such investigations goes well beyond the results that are presented, as this example shows. When designing and implementing MOOCs, it's crucial that creators and implementers account for learners' linguistic, cultural, and technical backgrounds. The next stage of this research will include examining potential solutions that account for the unique challenges faced by students in various regions of the world.

Acknowledgments

The authors would like to extend their gratitude to the Deanship of Scientific Research at King Khalid University for providing financial support for this research as part of the Large Research Groups program with the grant number RGP.2/526/44. This work would not have been possible without their aid.

References

Al-Azawei, A., Serenelli, F., & Lundqvist, K. (2016). Universal Design for Learning (UDL): A content analysis of peer reviewed journals from 2012 to 2015. Journal of the Scholarship of Teaching and Learning, 16(3), 39-56. https://doi.org/10.14434/josotl.v16i3.19295

Al-Emran, M., Elsherif, H. M., & Shaalan, K. (2016). Investigating attitudes towards the use of mobile learning in higher education. Computers in Human behavior, 56, 93-102. https://doi.org/10.1016/j.chb.2015.11.033

Al-Fahad, R., Yeasin, M., & Bidelman, G. M. (2020). Decoding of single-trial EEG reveals unique states of functional brain connectivity that drive rapid speech categorization decisions. Journal of Neural Engineering, 17(1), 016045. 10.1088/1741-2552/ab6040

Al-Fraihat, D., Joy, M., & Sinclair, J. (2017, June). Identifying success factors for e-learning in higher education. In International conference on e-learning (pp. 247-255). Academic Conferences International Limited.

Al-Fraihat, D., Joy, M., & Sinclair, J. (2020). Evaluating E-learning systems success: An empirical study. Computers in human behavior, 102, 67-86. https://doi.org/10.1016/j.chb.2019.08.004

Al-Harbi, A. N., Khan, K. M., & Rahman, A. (2017). Developmental vitamin D deficiency affects spatial learning in wistar rats. The Journal of nutrition, 147(9), 1795-1805. https://doi.org/10.1093/jn/nxx026

Al-Khater, W. A., Al-Maadeed, S., Ahmed, A. A., Sadiq, A. S., & Khan, M. K. (2020). Comprehensive review of cybercrime detection techniques. IEEE Access, 8, 137293-137311.

Al-Rahmi, W. M., Yahaya, N., Aldraiweesh, A. A., Alamri, M. M., Aljarboa, N. A., Alturki, U., & Aljeraiwi, A. A. (2019). Integrating technology acceptance model with innovation diffusion theory: An empirical investigation on students' intention to use E-learning systems. Ieee Access, 7, 26797-26809.

Ally, M., & Prieto-Blzquez, J. (2014). What is the future of mobile learning in education?. RUSC. Universities and Knowledge Society Journal, 11(1), 142-151. https://www.learntechlib.org/p/149573/.

Alsalamah, A. (2020). Using Captioning Services With Deaf and Hard of Hearing Students in Higher Education. American Annals of the Deaf, 165(1), 114-127. https://www.jstor.org/stable/26983929

Bawa, P. (2016). Retention in online courses: Exploring issues and solutions—A literature review. Sage Open, 6(1), 2158244015621777. 10.1177/2158244015621777

Bonk, C. J., & Khoo, E. (2014). Adding some TEC-VARIETY: 100+ activities for motivating and retaining learners online (pp. 1-368). OpenWorldBooks. com and Amazon CreateSpace. https://www.learntechlib.org/p/147416/.

Chuang, H. H., Ho, C. J., Weng, C. Y., & Liu, H. C. (2018). High school students' perceptions of English teachers' knowledge in technology-supported class environments. The Asia-Pacific Education Researcher, 27, 197-206.

Daniel, J. (2012). Making sense of MOOCs: Musings in a maze of myth, paradox and possibility. Journal of interactive Media in education, 2012(3).

Hew, J. J., Lee, V. H., Ooi, K. B., & Wei, J. (2015). What catalyses mobile apps usage intention: an empirical analysis. Industrial Management & Data Systems. https://doi.org/10.1108/IMDS-01-2015-0028

Jamiah, Y., Fatmawati, F., & Purwaningsih, E. (2019). Internalization of Students' Nationalism Sense through Outbound Learning Based on Local Wisdom. Journal of Education, Teaching and Learning, 4(2), 339-344. https://www.learntechlib.org/p/216973/.

Jordan, K. (2015). Massive open online course completion rates revisited: Assessment, length and attrition. International Review of Research in Open and Distributed Learning, 16(3), 341-358. https://doi.org/10.19173/irrodl.v16i3.2112

Kahu, E. R. (2013). Framing student engagement in higher education. Studies in higher education, 38(5), 758-773. https://doi.org/10.1080/03075079.2011.598505

Karami, N., Moubayed, N., & Outbib, R. (2017). General review and classification of different MPPT Techniques. Renewable and Sustainable Energy Reviews, 68, 1-18. https://doi.org/10.1016/j.rser.2016.09.132

Khan, M. J., Yadav, A. K., & Mathew, L. (2017). Techno economic feasibility analysis of different combinations of PV-Wind-Diesel-Battery hybrid system for telecommunication applications in different cities of Punjab, India. Renewable and Sustainable Energy Reviews, 76, 577-607. https://doi.org/10.1016/j.rser.2017.03.076

Kizilcec, R. F., Piech, C., & Schneider, E. (2013, April). Deconstructing disengagement: analyzing learner subpopulations in massive open online courses. In Proceedings of the third international conference on learning analytics and knowledge (pp. 170-179). https://doi.org/10.1145/2460296.2460330

Liaw, S. S., Huang, H. M., & Chen, G. D. (2007). Surveying instructor and learner attitudes toward e-learning. Computers & education, 49(4), 1066-1080. https://doi.org/10.1016/j.compedu.2006.01.001

Liyanagunawardena, T. R., Adams, A. A., & Williams, S. A. (2013). MOOCs: A systematic study of the published literature 2008-2012. International review of research in open and distributed learning, 14(3), 202-227. https://doi.org/10.19173/irrodl.v14i3.1455

Looi, C. K., Wong, L. H., & Milrad, M. (2015). Guest editorial: Special issue on seamless, ubiquitous, and contextual learning. IEEE Transactions on Learning Technologies, 8(01), 2-4. 10.1109/TLT.2014.2387455

Mayer, R. E. (2010). Learning with technology. The nature of learning: Using research to inspire practice, 179-198.

Milligan, C., & Littlejohn, A. (2014). Supporting professional learning in a massive open online course. International Review of

Research in Open and Distributed Learning, 15(5), 197-213. https://doi.org/10.19173/irrodl.v15i5.1855

Moore, A. (1993). The parti-game algorithm for variable resolution reinforcement learning in multidimensional state-spaces. Advances in neural information processing systems, 6.

Ramesh, G., Rathnakar, B., Narsaiah, C., Rameshwar, N., Srinivas, M., Namratha, V., ... & Satyanarayana, M. (2022). Synthesis, DFT computations, molecular docking studies and anticancer activity of 2-(4-fluorophenyl)-3-(5-methylisoxazol-3-yl) thiazolidin-4-one. Chemical Data Collections, 39, 100859.

Rasheed, R. A., Kamsin, A., & Abdullah, N. A. (2020). Challenges in the online component of blended learning: A systematic review. Computers & Education, 144, 103701. https://doi.org/10.1016/j.compedu.2019.103701

Sawir, E. (2013). Internationalisation of higher education curriculum: the contribution of international students. Globalisation, Societies and Education, 11(3), 359-378. https://doi.org/10.1080/14767724.2012.750477

Shahzad, B., & Alwagait, E. (2012). Ten most catastrophic risks in medium and large scale software. Journal of Science series Data Report, 4(9), 35-40.

Tu, C. H., & McIsaac, M. (2002). The relationship of social presence and interaction in online classes. The American journal of distance education, 16(3), 131-150. https://doi.org/10.1207/S15389286AJDE1603_2

Wang, Y., Han, J. H., & Beynon-Davies, P. (2019). Understanding blockchain technology for future supply chains: a systematic literature review and research agenda. Supply Chain Management: An International Journal, 24(1), 62-84. https://doi.org/10.1108/SCM-03-2018-0148

Zhu, M., Sari, A., & Lee, M. M. (2018). A systematic review of research methods and topics of the empirical MOOC literature (2014–2016). The Internet and Higher Education, 37, 31-39. https://doi.org/10.1016/j.iheduc.2018.01.002

Zhu, M., Wang, X., & Wang, Y. (2018). Human-like autonomous car-following model with deep reinforcement learning. Transportation research part C: emerging technologies, 97, 348-368. https://doi.org/10.1016/j.trc.2018.10.024