Pakistan Journal of Distance & Online Learning
Volume: IX, Issue I, 2023, xx–xx

University Students' Perception of MOOCs based on MOOC Instructional Design Elements

Zainab Shahzadi Javed[1]

Zohra Nazeer[2]

Muhammad Umair[3]

Abstract

This study aimed to investigate university students' overall perception of MOOCs based on the instructional design elements of MOOCs. Due to the increase in enrollment in MOOCs, it is essential to understand students' general perception of them. Additionally, only a few studies have been conducted on MOOCs in developing countries. Given the latest trends in online learning, it is important to understand students' perception of MOOCs. Furthermore, MOOCs are one of the most talked-about and latest trends in e-learning. For this study, a quantitative research design was employed, and data were collected from 266 students studying in various universities in Pakistan, using a survey questionnaire. The data were analyzed using different statistical techniques. The results of this study indicated that each element of MOOC instructional design elicited a positive perception among students. Moreover, it was noticed that among all the elements of MOOC instructional design, active learning and meaningful connection demonstrated the strongest correlation with intended perception.

Keywords: *Massive Open Online Courses, Course Information, Course Resources, Active Learning, MOOCs*

[1] Iqra University. Karachi, Pakistan. Email: zainabfive@gmail.com
[2] Iqra University. Karachi, Pakistan. Email: zohranaz888@gmail.com
Email: cigdem.cigdem@yahoo.com
[3] Iqra University. Karachi, Pakistan. Email: umairchawdhary@gmail.com

Introductıon

Online learning is a rapidly growing trend in higher education. Massive Open Online Courses (MOOCs) are one of the fastest growing trends in e-learning. Unlike traditional classrooms, MOOCs can accommodate an unlimited number of students (Jordan, 2014a). Additionally, individuals from any part of the world can enroll and learn at their own pace (Hew, 2015). The concept of MOOC is not very old. The term was first introduced in 2008 by Stephen Downes and George Siemens (Littlejohn, 2013), based on connectivism. Connectivism is based on the principle that knowledge is distributed through people's engagement (Kop et al., 2011), and students learn when they socialize and share ideas with others.

Distance education is a well-known concept in Pakistan. In Asia, Allama Iqbal Open University was the first university to start distance education, and it currently has an enrollment of 13 million students (AIOU, 2016). As a developing country, Pakistan has enormous potential for MOOCs, as many students cannot afford to study at expensive and world-renowned academic institutions (Ahmed et al., 2017). EdX has 90,000 students from Pakistan, and its international regional office is located in Lahore (Ahmed, 2016). Furthermore, the indigenous domestic context of Pakistan lacks sufficient scholarly research on MOOCs, as highlighted by Qureshi (2019).

Despite the significant boost in MOOCs and the large number of enrollments in these courses, there is a very high dropout rate, with only as few as 10 percent of students successfully completing the MOOCs (Alraimi et al., 2015). According to Siddiqi (2015), a significant number of Pakistani students are enrolled in traditional universities that provide face-to-face education. However, the affordability and government recognition of distance learning institutions have increasingly attracted individuals to pursue education through distance education universities in Pakistan. Since the outbreak of COVID-19, online learning and MOOCs in Pakistan have been rapidly increasing. This study will help MOOCs and online course designers gain a better understanding of the factors that influence students' intention to successfully complete these courses without dropping out midway. Furthermore, having a comprehensive understanding of the elements of MOOC instructional design that students perceive as having a positive impact on their intention can assist educators in designing courses more effectively, ultimately reducing the dropout rate. This study will also be helpful for online course instructors in enhancing the engagement of their courses. In this way, the objective of this research is to identify the elements of MOOC instructional design (based on the model of engaging online students developed by Khe Foon Hew, 2014) that students perceive to have a positive impact. The model consists of six elements of instructional design. For this study, an additional element i.e. "students' perception" was included to measure students' perception of MOOCs in relation to the instructional design elements. This research aims to address questions related to various elements of MOOCs, specifically focusing on the instructional design elements of MOOCs.

Literature Review

Theoretical framework:

Khe Foon Hew (2014) developed a model for engaging students in online learning based on self-determination theory and the instructional design elements of MOOCs. According to this model, an effective online instructional design has six key elements: active learning, monitoring learning, making meaningful connections, promoting interaction, course information, and course resources. According to Hew, course information includes clear objectives, course duration, workload, language of instruction, course syllabus, any recommended background or prerequisites, and course requirements. Active learning involves utilizing strategies for active learning and self-assessment. Monitoring learning includes the use of weekly quizzes and exercises for practice. Making meaningful connections includes presenting real, illustrative examples and using assignments that require students to create games. Student interaction promotes effective engagement among students through discussion forums, enabling them to interact with both their peers and the course instructor. Course resources include the use of videos, simple language, up-to-date information, slides, and captions on videos (Hew, 2014).

MOOCs

Massive Open Online Courses, commonly known as MOOCs, can be defined as a form of structured online learning that allows for unlimited participation and open access through the web (Kaplan & Haenlein, 2016). These courses offer flexible completion options (asynchronous) and attract participants from diverse demographic backgrounds with varying motivations for enrolling in their programs (Chuang & Ho, 2016). There are two types of MOOCs: cMOOCs and xMOOCs. In order to promote collaborative learning processes and the development of networks among all MOOC learners, CMOOCs were designed. Because of the introduction of the so-called "connectivism" as a new theory in the first MOOC "Connectivism and Connective Knowledge" (CCK08), this MOOC was referred to as a CMOOC (Bozkurt, Kilgore & Crosslin, 2018). As opposed to traditional MOOCs, an XMOOC utilizes individual learning strategies or cognitive behavioral learning approaches with didactic or transmission models of teaching. XMOOCs may have limited openness, occasionally for profit, and place less emphasis on the co-construction of knowledge by the learners (Ichimura & Suzuki, 2017; Yousef et al., 2014). The service is primarily dedicated to the transmission of knowledge, which is achieved through video lectures, automated quizzes, reading materials, discussion forums, and assignments (Bates, 2020).

Hew and Cheung (2014) found in their study that students are motivated to participate in MOOCs for four main reasons: aspiring to acquire new knowledge, expanding their existing knowledge base, pushing their boundaries, and obtaining a certificate of achievement. Hew K. F. (2016) studied to understand the different factors behind the popularity of MOOCs. They have identified five factors, listed here in order of importance: (1) clear and problem-centric learning exposition, (2) instructor passion and ability, (3) active learning, (4) peer-to-peer interaction, and (5) utilization of helpful course resources.

Inadequate MOOC Instructional design and dropout

Previous research has identified a high dropout rate as a significant concern of MOOCs (Hew, 2015). Therefore, several studies have been conducted in the past to understand the reasons behind the high dropout rate among students. In this regard, many studies have explored social, personal, instructional design, and course-related factors that affect students' retention in MOOCs (Aldowah et al., 2020; Huang & Hew, 2017; Nordin et al., 2016; Rosé et al., 2014). Aldowah, Al-Samarraie, Alzahrani, and Alalwan (2019) identified six primary factors that directly influence and contribute to student dropout in MOOCs. The influencing factors were course design, academic abilities and skills, feedback, prior experience, social support, and social presence. There are several other factors that are mentioned, such as course time and difficulty, interaction, motivation, commitment, and family/work circumstances. These factors were found to play a secondary role in the dropout of students in MOOCs.

Literature also highlights the reasons for dropping out from MOOCs. The reasons mentioned are: monitoring mechanism, lack of guidance for learners, feedback, and consolidated material. It was also possible to propose models and methods to predict the dropout rate of MOOCs in other studies (Kloft, Stiehler, Zheng & Pinkwart, 2014). A study conducted by Margaryan, Bianco, and Littlejohn (2015) examined a sample of seventy-six randomly selected MOOCs. The findings of the study revealed that although these MOOCs demonstrated effective presentation and organization of materials, the quality of instructional design fell short of expectations. Specifically, these courses lacked the incorporation of problem-centered activities, and the collaborative learning experiences did not effectively engage students in the co-construction of knowledge. Additionally, the courses did not adequately address the learning needs of students and neglected to utilize learning analytics to enhance feedback on instructional design in MOOCs. Furthermore, some of the courses that were examined lacked authentic and reliable learning resources that were specific to the nature of MOOCs (Margaryan et al., 2015). Similarly, Jordan (2015) conducted a study that focused on the determinants of completion rates and dropouts in MOOCs. The research study examined various factors and identified that both course design and course length significantly influenced student attrition.

Aydın and Yazıcı (2020) found that students face issues related to content design in their study. Lack of feedback from instructors, low visual quality of videos, the excessive number of assignments, and the overwhelming number of courses were among the issues reported by the learners. Aydın and Yazıcı (2020) conducted an investigation to identify possible reasons. This study reported that students who started but dropped out of AKADEMA courses provided important and necessary suggestions for improving the course and keeping students engaged. Course length plays an important role in providing timely or delayed feedback. Due to long courses, insufficient timely feedback from the instructors among the content design-based reasons was noted the most.

Instructional design and MOOC retention

Factors related to the instructional design of MOOCs play a key role in retention (Romero-Rodríguez et al., 2020). For example, Huang and Hew (2017) found that the instructional design of MOOCs is an external factor that motivates students to continue learning, such as well-structured content and engaging material. Similarly, the course curriculum should align with the learning outcomes in order to facilitate better understanding and skill development among students (Paton, Fluck & Scanlan, 2018). The willingness and motivation of students in online courses increased when the course content was appealing, relevant, and of high quality (Bocchi, Eastman & Swift, 2004).

Student-teacher interaction and student-student interaction are important factors in MOOCs (Khalil & Ebner, 2014). Furthermore, a lack of interaction results in a loss of focus. Similarly, the lack of communication and unclear feedback from the instructor can result in student frustration (Brahimi & Sarirete, 2015). Therefore, the availability of the instructor is an important factor that needs to be considered in MOOCs (Hew & Cheung, 2014). Likewise, student-student interaction also plays a significant role. Sunar et al. (2016) found that the dropout rate in MOOCs decreases when students frequently interact with one another. In online learning, students' engagement could improve if the published material is replaced with videos created by the instructors, along with guided note-taking sheets for these videos (Hegeman, 2015).

MOOCs' instructional design plays a significant role in sustaining students in MOOCs and contributing to successful course completion. Deshpande and Chukhlomin (2017) conducted a study in which they surveyed 77 MOOC students on the influence of visual design, content, navigation, interactivity, accessibility, and self-assessment. They found that the content, accessibility, and interactivity of MOOCs significantly influenced students' motivation in MOOCs. Similarly, Khan et al. (2021) highlighted that critical factors such as course relevance, the instructor's role, and learning outcomes had a significant influence on MOOC participants' retention. Wang et al. (2023) also reported that improved course design could decrease the rate of student dropout. They found that improved course design increased interaction, which ultimately led to motivation.

Research Objectives

1. To explore the relationship between students’ intended perception and various elements of MOOC instructional design.

2. To find which element of MOOC instructional design contributes the most toward the students’ positive perception.

Hypotheses of the Study

Based on the above discussion, the following hypotheses of the study were proposed.
H1: There is a positive relationship between intended perception and course information of MOOCs.
H2: There is a positive relationship between intended perception and course resources of MOOCs.
H3: There is a positive relationship between intended perception and active learning of MOOCs.
H4: There is a positive relationship between intended perception and meaningful learning of MOOCs.
H5: There is a positive relationship between intended perception and meaningful connection of MOOCs.
H6: There is a positive relationship between intended perception and interaction of MOOCs.

Methodology

The researchers employed a quantitative approach for this study. Quantitative studies facilitate generalizations and provide a comprehensive view of the entire population (Queirós, Faria, and Almeida, 2017). For this study, the researchers utilized an instrument developed by Fesol et al., which was derived from Hew's (2015) model of effectively engaging students in online environments.

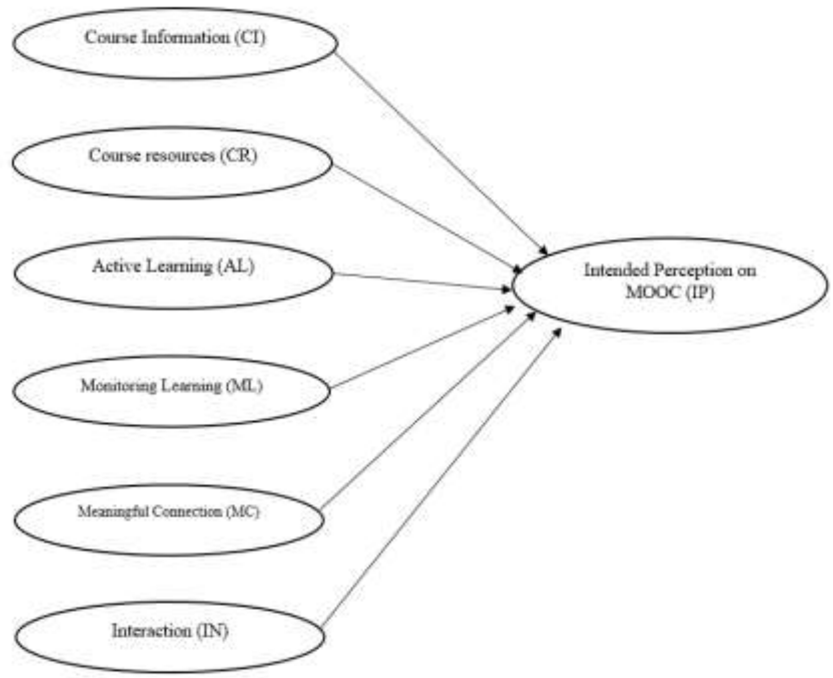

Figure 01. Model of MOOC instructional design elements (adopted from Fesol et al., 2017)

Population and sampling

This study aimed to examine university students' intended perception of MOOCs based on the elements of MOOC instructional design. The population consisted of university students who attended one or more MOOCs during their study program. Moreover, simple random sampling was selected as the appropriate sampling technique for this study, in which each case has an equal chance of being selected as a sample (Taherdoost, 2016). The questionnaire was devised using Google Forms. The survey questionnaire was then sent to the respondents via email and Facebook groups. Some of the responses were collected by giving a survey questionnaire to the participants. The data were collected from a sample of 266 university students enrolled in various universities in Karachi.

Research Instrument

The researchers in this study utilized an instrument created by Fesol et al., which was developed following Hew's (2015) model for effectively engaging students in online settings. The instrument has six dependent variables and one independent variable, and it employs a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Validity and Reliability of the research instrument

Educational researchers with expertise in the field were consulted to validate the questionnaire. They thoroughly examined the instrument and confirmed that its items aligned with the research objectives. As a result, both experts endorsed the validity of the tool.

To assess the internal consistency and reliability of instrument, we calculated instrument, Cronbach's alpha coefficient. According to Hair et al. (2017), if the Cronbach alpha is less than 0.60, the study data obtained through such a tool is considered poor. All the values were above 0.60 and therefore deemed acceptable (see table 1).

Table 01
Reliability

Variable	No. of Items	Cronbach’s Alpha
Course Information	2	.646
Course Resources	9	.85
Active Learning		4
Meaningful Learning	3	.77
Meaningful Connection		5
Interaction	5	.75
Intended Perception	3	.96
Overall	29	.9

Kaiser-Meyer-Olkin and Bartlett’s Tests of Sampling Adequacy

The Kaiser-Meyer-Olkin (KMO) test is used to ensure that the sample for collected data is adequate. The KMO test is used to determine whether there are enough items in each construct to form a valid group. According to Morgan et al. (2005), the KMO value must be greater than 0.5 to ensure that there are enough items to form valid groups. Table 2 shows that the

KMO value is 0.7, indicating that there are a sufficient number of items in each group.

Bartlett's test shows that the correlation matrix is substantially different from the identity matrix. A Bartlett's test probability value less than 0.05 indicates that the properties of the correlation matrix are different from the identity matrix. Table 3 shows that Bartlett's test criteria are fulfilled, as the probability value is less than 0.05, i.e., 0.000.

Table 02
Results of KMO and Bartlett's Test

Test	Chi-square value	Df	Sig. value
KMO Measure of Sampling Adequacy	0.839		
Bartlett's Test of Sphericity	5003.881	465	.000

Findings
Both descriptive statistics, including means and standard deviation, and inferential statistics, specifically t-tests, were utilized for data analysis. Descriptive and inferential statistics were used in the SPSS software to evaluate and interpret the correlation between students' intended perception (IP) and various elements of MOOC instructional design. These elements include Course Information (CI), which encompasses CI1 and CI2; Course Resources (CR), which comprise CR1, CR2, CR3, CR4, CR5, CR6, CR7, CR8, and CR9; Active Learning (AL), consisting of AL1, AL2, AL3, and AL4; Meaningful Learning (ML), incorporating ML1, ML2, and ML3; Meaningful Connection (MC), involving MC1, MC2, MC3, MC4, and MC5; Interaction, encompassing I1, I2, I3, I4, and I5; and finally, Intended Perception, consisting of IP1, IP2, and IP3. The results from Table 3 indicate that students have a positive perception of the different elements of MOOC instructional design.

Table 03
Descriptive analysis of scale for measuring intended perception and various elements of MOOC instructional design

Factor	N	Mean	Standard Deviation
Course Information	266	7.93	1.40

Course Resources	266	35.72	5.40
Active Learning	266	16.28	2.23
Meaningful Learning	266	12.03	2.09
Meaningful Connection	266	19.80	2.28
Interaction	266	19.35	3.60
Intended Perception	266	12.09	2.42

Correlation analysis

This study had two objectives: (1) to explore the relationship between students' intended perception and various elements of MOOC instructional design, and (2) to determine which element of MOOC instructional design contributes the most to students' positive perception. To achieve the objectives, a correlation analysis was conducted using the Pearson correlation coefficient. Various statistical analyses can be utilized to examine the relationship between variables, including correlation analysis, regression analysis, and factor analysis. However, for this particular study, correlation analysis is the most appropriate method. This approach aids in determining the strength and direction of the linear relationship between two variables (Cohen et al., 2013). Table 4 shows the corellation analysis between the intended perception and various elements of MOOCs

Table 04

Correlation between the intended perception and various elements of MOOCs

Factor	Mean	SD	[1]CI .276**	[2]CR .372**	[3]AL .413**	[4]ML .394**	[5]MC .412**	[6]I .229**	[7]IP
[1]CI	7.93	1.40	1						
[2]CR	35.72	5.40	.526**	1					
[3]AL	16.29	2.23	.419**	.474**	1				
[4]ML	12.03	2.09	.462**	.440**	.496**	1			
[5]MC	19.80	2.28	.429**	.579**	.499**	.358**	1		
[6]I	19.35	3.60	.355**	.369**	.352**	.284**	.330**	1	
[7]IP	12.09	2.42	.276**	.372**	.414**	.394**	.412**	.229**	1

**. Correlation is significant at the 0.01 level (2-tailed).

[1]CI=Course Information; [2]CR= Course Resources; [3]AC= Active Learning; [4]ML= Meaningful Learning; [5]MC=Meaningful Connection; [6]I= Interaction;[7]IP= [7]Intended Perception

Table 4 shows the relationship between students' intended perception and various elements of MOOCs instructional design. In order to achieve the objectives of this study, the relationship between intended perception and six different elements of MOOCs instructional design was investigated. The correlation analysis demonstrated a positive relationship between the intended perception and all six elements of MOOCs instructional design. Although all the elements of MOOC design are positively related, there is a medium to low correlation between intended perception and all the elements of MOOC instructional design. Active Learning (AL) has the highest positive correlation with intended perception, followed closely by meaningful connection (MC) with r values .413 and .412, respectively. While ML and CR have a weaker positive relationship compared to AL and MC, with correlation coefficients of 0.475 and 0.412, respectively. Conversely, CI and I demonstrate a weak positive relationship with the intended perception, as indicated by their small coefficients, with values of 0.276 and 0.229, respectively.

Overall, table 4 demonstrates that all the elements of MOOCs instructional design are positively related to intended perception of university students. University students are more likely to engage with massive open online courses when the course includes comprehensive cource information, relevant course resources, and provides enough opportunities for active learning, meaningful learning, meaningful connection and interaction. Moreover, it is evident from the findings of this study that active learning (AL) and meaningful connection (MC) contribute the most to students' positive perception.

Hypotheses testing

Table 05

Results of Hypotheses Testing

Hypotheses	R Square	T	P	F	Interpretation

H1 There is a positive relationship between intended perception and course information (CI)	0.075	4.650	0.000	21.624	Accepted
H2 There is a positive relationship between intended perception and course resources (CR)	0.138	6.494	0.000	42.175	Accepted
H3 There is a positive relationship between intended perception and active learning (AL)	0.171	7.363	0.000	54.213	Accepted
H4 There is a positive relationship between intended perception and Meaning learning (ML)	0.155	6.946	0.000	48.251	Accepted
H5 There is a positive relationship between intended perception and Meaning connection (MC)	0.170	7.328	0.000	53.693	Accepted

H6 There is a positive relationship between intended perception and interaction (I)	0.052	3.807	0.000	14.495	Accepted

The results of the hypothesis testing are presented in Table 5. A simple linear regression analysis was performed to evaluate the influence of each element of MOOC instructional design on university students' intended perception. The results demonstrated that hypotheses H1, H2, H3, H4, H5, and H6 are supported because the p-value for all cases is less than 0.05, which is the threshold value. The findings in Table 5 indicate that university students' intended perception (IP) is predominantly influenced by active learning ($t=7.363$, $p < .05$) as the strongest predictor, closely followed by meaningful connection ($t=7.328$, $p < .05$), meaningful learning ($t=6.946$, $p < .05$), course resources ($t=6.494$, $p < .05$), and course information ($t=4.650$, $p < .05$). Conversely, the interaction variable is identified as the weakest predictor of intended perception among university students ($t=3.807$, $p < .05$).

Discussion

This study had two objectives: firstly, to find the relationship between students' intended perception and various elements of instructional design in MOOCs, and secondly, to identify the element of MOOC instructional design that contributes the most towards students' positive perception. The significant findings obtained from this study are presented in this section and analyzed in relation to the existing body of literature on MOOCs.

The research study shows that course information, course resources, active learning, meaningful learning, meaningful connection, and interaction are the elements of MOOC instructional design that lead to a positive perception of students toward MOOC learning. Active learning, meaningful connection, and monitoring learning are elements of MOOC instructional design that contribute to a favorable perception of MOOCs and exhibit a notable association with intended perception. Conversely, interaction, course resources, and course information are elements of MOOC instructional design that display a comparatively weaker relationship with intended perception.

The findings are consistent with the available literature on MOOCs, indicating that well-structured content, engaging materials, and appealing and relevant course content motivate students to remain engaged in online courses. (Bocchi, Eastman, & Swift, 2004; Huang, B., & Hew, K. F., 2017). Similarly, active learning strategies increase student engagement and have a positive impact on students' learning when implemented effectively throughout the course (Khan et al., 2017). Furthermore, several studies have demonstrated that integrating active learning into online courses promotes student engagement (Shukor and Abdullah, 2019; Harrington & Floyd, 2012). This finding is also consistent with De Lange et al. (2003), who found that online discussion leads students to feel satisfied with the course.

Fesol et al. (2018) emphasized that incorporating active learning strategies within the MOOC course resulted in a favorable perception among students. Secondly, this research found that meaningful connection has a positive relationship with intended perception. This finding aligns with the recommendation proposed by Deng and Benckendorff (2021), which suggests that MOOC content should prioritize the inclusion of authentic learning contexts. Additionally, the instructional design of MOOCs should be tailored to promote the acquisition of knowledge that can be easily applied in real-world scenarios.

Fesol et al. (2018) found that meaningful connection in the MOOC leads to a positive perception of the students. Monitoring learning is found to be another element of MOOC instructional design that is significantly related to intended perception. Self-monitoring activities like weekly quizzes and assignments help learners to monitor their learning. This finding is consistent with Fesol et al. (2018), who found that monitoring learning and active learning are among the elements of MOOC instructional design that contribute to students' positive perceptions. According to Belousova et al. (2019), it is argued that an effective distance learning system should include mechanisms for students to self-monitor their educational progress. The research demonstrates that when students are aware of regular monitoring, they tend to engage with the subject matter more thoroughly and responsibly.

Conclusion

This paper intended to find University students' perception of MOOCs based on MOOC instructional design elements. In order to collect the data, a survey questionnaire was used consisting of 29 closed-ended questions based on the Likert scale. The responses were collected from 266 respondents. Once the data was collected, several statistical tools were applied. SPSS software was used to analyze data and find the outcomes. Firstly, the reliability of the instrument and each construct was tested, using SPSS. Later Descriptive and inferential statistics were used to evaluate and interpret the correlation between students' intended perception (IP) and various elements of MOOC instructional design.

The outcomes indicated that reliability is present The findings from this study indicate that Active learning, meaningful connection, and monitoring learning are among the elements of MOOC instructional design that lead to the positive perception of MOOCs and have a significant relationship with intended perception. Whereas, interaction, course resources, and course information are among the elements of MOOC instructional design that have a less significant relationship with intended perception.

For future research, it will be interesting to conduct a qualitative study to find students' perceptions of MOOCs based on MOOCs' instructional design elements to confirm findings from this study. It will also be interesting to compare the perception of Undergraduate and master's students' perception of MOOCs.

References

Ahmed, K. (2016, June 04). MOOCs on edX: a world of unlimited learning opportunities. MIT Technology. www.technologyreview.pk/mooc-s-on-edx-a-world-of-unlimited-learning-opportunities/

Ahmed, S. S., Khan, E., Faisal, M., & Khan, S. (2017). The potential and challenges of MOOCs in Pakistan: A perspective of students and faculty. *Asian Association of Open Universities Journal, 1*(1), 94-105.

AIOU. (2016, December 10). *Vice chancellor message*. www.aiou.edu.pk/vc_message.asp

Aldowah, H., Al-Samarraie, H., Alzahrani, A. I., & Alalwan, N. (2020). Factors affecting student dropout in MOOCs: A cause and effect decision-making model. *Journal of Computing in Higher Education, 32*(2), 429-454.

Alraimi, K. M., Zo, H., & Ciganek, A. P. (2015). Understanding the MOOCs continuance: The role of openness and reputation. *Computers & Education, 80*, 28-38.

Bates, A. W. (2020, March 09). Advice to those about to teach online because of the corona-virus. https://www.tonybates.ca/2020/03/09/advice-to-those-about-to-teach-online-because-of-the-corona-virus/

Belousova, V. I., Knysh, A. A., & Potorochina, K. S. (2019, May). Automation of intermediate remote education student control when teaching mathematics. In 1st International Scientific Conference" Modern Management Trends and the Digital Economy: from Regional Development to Global Economic Growth"(MTDE 2019) (pp. 583-589). Atlantis Press.

Bocchi, J., Eastman, J. K., & Swift, C. O. (2004). Retaining the online learner: Profile of students in an online MBA program and implications for teaching them. *Journal of education for Business, 79*(4), 245-253.

Bocchi, J., Eastman, J. K., & Swift, C. O. (2004). Retaining the online learner: Profile of students in an online MBA program and implications for teaching them. *Journal of education for Business, 79*(4), 245-253.

Bozkurt, A., Kilgore, W., & Crosslin, M. (2018). Bot-teachers in hybrid massive open online courses (MOOCs): A post-humanist experience. *Australasian Journal of Educational Technology, 34*(3). https://doi.org/10.14742/ajet.3273

Brahimi, T., & Sarirete, A. (2015). Learning outside the classroom through MOOCs. *Computers in Human Behavior, 51*, 604-609.

Chuang, I., & Ho, A. (2016). *HarvardX and MITx: Four years of open online courses--fall 2012-summer 2016*. Available at SSRN 2889436.

De Lange, P., Suwardy, T., & Mavondo, F. (2003). Integrating a virtual learning environment into an introductory accounting course: determinants of student motivation. *Accounting Education, 12*(1), 1-14.

Deng, R., & Benckendorff, P. (2021). What are the key themes associated with the positive learning experience in MOOCs? An empirical investigation of learners' ratings and reviews. International Journal of *Educational Technology in Higher Education, 18*(1), 1-28.

Deshpande, A., & Chukhlomin, V. (2017). What makes a good MOOC: A field study of factors impacting student motivation to learn. American *Journal of Distance Education, 31*(4), 275-293.

Fesol, S. F. A., Salam, S., & Bakar, N. (2018). *Wearable technology in education to enhance technical MOOCs*. CARNIVAL ON e-LEARNING (IUCEL) 2017, 220.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods. *Journal of the academy of marketing science, 45*, 616-632.

Harrington, S. J., & Floyd, K. S. (2012). Enhancing engagement and the value of the course to the student through course organization and active learning. *Online student engagement tools and strategies*, 15-17.

Hegeman, J. (2015). Using instructor-generated video lectures in online mathematics courses improves student learning. *Online Learning, 19*(3), 70-87.

Hew, K. F. (2015). Towards a model of engaging online students: lessons from MOOCs and four policy documents. *International Journal of Information and Education Technology, 5*(6), 425.

Hew, K. F. (2016). Promoting engagement in online courses: What strategies can we learn from three highly rated MOOCS. *British Journal of Educational Technology, 47*(2), 320-341.

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.

Huang, B., & Hew, K. F. (2017, April). Factors influencing learning and factors influencing persistence: A mixed-method study of MOOC learners' motivation. In *Proceedings of the 2017 International Conference on Information System and Data Mining* (pp. 103-110).

Ichimura, Y., & Suzuki, K. (2017). Dimensions of MOOCs for quality design: Analysis and synthesis of the literature. *International Journal for Educational Media and Technology, 11*(1), 42-49.

Jordan, K. (2014a). Initial trends in enrolment and completion of massive open online courses. *The International Review of Research in Open and Distance Learning, 15*(1), 133–160.

Jordan, K. (2015). Massive open online course completion rates revisited: Assessment, length and attrition. *The International Review of Research in Open and Distributed Learning, 16*(3), 341–358

Kaplan, A. M., & Haenlein, M. (2016). Higher education and the digital revolution: About MOOCs, SPOCs, social media, and the Cookie Monster. *Business horizons, 59*(4), 441-450.

Khalil, H., & Ebner, M. (2014). MOOCs completion rates and possible methods to improve retention-A literature review. *EdMedia+ innovate learning*, 1305-1313.

Khan, A. U., Khan, K. U., Atlas, F., Akhtar, S., & Farhan, K. H. A. N. (2021). Critical factors influencing MOOCs retention: The mediating role of information technology. *Turkish Online Journal of Distance Education, 22*(4), 82-101.

Khan, A., Egbue, O., Palkie, B., & Madden, J. (2017). Active learning: Engaging students to maximize learning in an online course. *Electronic Journal of e-learning, 15*(2), pp107-115.

Kloft, M., Stiehler, F., Zheng, Z., & Pinkwart, N. (2014, October). Predicting MOOC dropout over weeks using machine learning methods. In *Proceedings of the EMNLP 2014 workshop on analysis of large-scale social interaction in MOOCs* (pp. 60-65).

Kop, R., Fournier, H., & Mak, J. S. F. (2011). A pedagogy of abundance or a pedagogy to support human beings? Participant support on massive open online courses. *The International Review of Research in Open and Distributed Learning, 12*(7), 74-93.

Littlejohn, A. (2013). Understanding massive open online courses. *CEMCA EdTech Notes*, 1-12.

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

Nordin, N., Norman, H., Embi, M. A., Mansor, A. Z., & Idris, F. (2016). Factors for development of learning content and task for MOOCs in an Asian context. *International Education Studies, 9*(5), 48-61.

Paton, R. M., Fluck, A. E., & Scanlan, J. D. (2018). Engagement and retention in VET MOOCs and online courses: A systematic review of literature from 2013 to 2017. *Computers & Education, 125*, 191-201.

Qureshi, J. A. (2019). Evolution and Advancement in Massive Open Online Courses (MOOC) to Revolutionize Education Sector via Disruptive Technology: The Case of Pakistan. *Journal of Education and Educational Development, 6*(2), 219-234

Romero-Rodríguez, L.M.; Ramírez-Montoya, M.S.; Aguaded, I. (2020). Determining Factors in MOOCs Completion Rates: Application Test in Energy Sustainability Courses. *Sustainability, 12*(7), https://doi.org/10.3390/su12072893

Rosé, C. P., Carlson, R., Yang, D., Wen, M., Resnick, L., Goldman, P., & Sherer, J. (2014, March). Social factors that contribute to attrition in MOOCs. In *Proceedings of the first ACM conference on Learning@ scale conference* (pp. 197-198).

Shukor, N. A., & Abdullah, Z. (2019). Using learning analytics to improve MOOC instructional design. *International Journal of Emerging Technologies in Learning (iJET), 14*(24), 6-17.

Siddiqi, H. K. (2015). The need and prospects of distance education in higher education sector of Pakistan. *International Journal of English Language, Literature and Humanities, 2* (10), 579 – 594

Sunar, A. S., White, S., Abdullah, N. A., & Davis, H. C. (2016). How learners' interactions sustain engagement: A MOOC case study. *IEEE Transactions on Learning Technologies, 10*(4), 475-487.

Taherdoost, H. (2016). Sampling methods in research methodology; how to choose a sampling technique for research. How to choose a sampling technique for research (April 10, 2016). https://ssrn.com/abstract=3205035

Wang, W., Zhao, Y., Wu, Y. J., & Goh, M. (2023). Factors of dropout from MOOCs: a bibliometric review. *Library Hi Tech, 41*(2), 432-453.

Yousef, A. M. F., Chatti, M. A., Schroeder, U., & Wosnitza, M. (2014, July). What drives a successful MOOC? An empirical examination of criteria to assure design quality of MOOCs. In *2014 IEEE 14th International Conference on Advanced Learning Technologies* (pp. 44-48). IEEE.

Javed, Z.S., Nazeer, Z. & Umair, M. (2023). University students' perception of MOOCs based on MOOC instructional design elements. *Pakistan Journal of Distance and Online Learning, 9*(1), xx–xx.