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EXPLORING STUDENT READINESS TO MOOCS IN JORDAN: A STRUCTURAL EQUATION MODELLING APPROACH

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ABSTRACT

Aim/Purpose	The current study has been carried out to reveal students' readiness to utilize MOOCs at higher learning institutions in Jordan.
Background	Higher education institutions around the globe are shifting rapidly to reach learners worldwide by providing open education. In accordance with this universal effort, Jordan is committed to offering open access education that allows learners to access knowledge through the Internet and has launched one of the first Arabic "Massive Open Online Course" (MOOC) platforms in the Arabic region. Thus, students must be prepared and ready for this innovation in education. Nonetheless, MOOCs have been incessantly discussed and have faced wide criticism as an insufficient amount of research has been conducted on students' readiness to be involved in MOOCs. The level of tertiary students' preparation to utilize and attend MOOCs as a source of learning is unclear.
Methodology	Structural equation modeling (SEM) was used to test the proposed model of students' readiness for MOOCs. Convenience sampling was used to distribute a paper-based questionnaire to the students of three Jordanian universities during a period of four months from May to September 2019. Out of 700 distributed questionnaires, a total of 537 responses were returned giving a response rate of 76.7%. Out of the returned questionnaires, 69 responses were reported incom-

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plete as most of the questions (>80%) were left unanswered; these 69 questionnaires were eliminated from any further analysis. As a result, a total of 468 questionnaires were valid for statistical analysis.

Contribution This study aims to contribute to the existing literature by examining the perceptions of higher education students in Jordan toward MOOCs. The current study extends the continuing debate about MOOCs with respect to determining which factors influence students' readiness to participate in these courses. Specifically, this study investigates both the cognitive and psychological influential factors that determine the readiness of Jordanian students to adopt MOOCs. The proposed theoretical framework for this research is based on the work of Yu and Richardson, who developed the model of Student Online Learning Readiness (SOLR). SOLR is comprised of three forms of competency assumed to be important in examining students' readiness for online learning. Specifically, these competencies are (1) social competency represent skills, capabilities, and a sense of control, which is necessary for managing social situations and developing and sustaining relationships, (2) communication competency, "the ability of an individual to demonstrate knowledge of the appropriate communicative behavior in a given situation", and (3) technical competencies, "self-efficacy in technology". Furthermore, the research model includes an additional competency: self-management of learning, "the degree to which a student perceives himself/herself as being self-disciplined and is able to engage in a greatly autonomous learning setting."

Findings The results obtained from the SEM revealed that students' readiness to accept MOOCs in their learning is significantly influenced by four types of competency: social, technical, self-management of learning, and communication.

Recommendations for Practitioners Facilitators of MOOCs should take into account that technical competency can be enhanced by recognizing that technical competency related to online learning should be developed, taught, and constantly reinforced at every educational level as a life skill. Additionally, facilitators and developers of MOOCs should be prepared to find methods to support and inspire student participation, and to recognize the importance of learning skills in the MOOC environment. Furthermore, facilitators and developers of MOOCs should increase the social presence of fellow participants in MOOCs, which in turn facilitates the attainment of collaborative learning.

Recommendations for Researchers Researchers may use well-established theories related to investigating online learning usage in exploring students' readiness to use MOOCs.

Impact on Society A study like the current one would be beneficial for higher education institutions in Jordan to determine the key factors that influence students' readiness and in turn develop active strategies to address students' needs in order for them to adopt MOOCs.

Future Research Further studies may include additional factors to better measure students' readiness to use MOOCs. The additional factors can be revealed by utilizing a qualitative method. Thus, additional studies may employ a mixed-method approach (both quantitative and qualitative) to accurately identify additional factors that may influence student readiness to student readiness to MOOCs and to offer a more holistic understanding of readiness.

Keywords MOOCs, distance learning, MOOCs adoption, online learning, technological competency, self-regulate learning, MOOCs adoption

INTRODUCTION

Nowadays, higher education worldwide suffers from various challenges, such as sustainability concerns, increasing diversity of student population, and fragmented functionalities within higher education institutions (Zhou, 2016). However, the rapid growth and diffusion of ICTs may significantly alter the existing situation as ICTs offer new and diverse methods to deliver education (Lee, 2010). Consequently, the number of education providers who aim to have an impact on national and global levels has increased. A significant number of universities and colleges are developing and providing online programs and courses, offering more educational opportunities to learners. Thus, the availability of online courses/programs has increased considerably in terms of quantity and diversity.

The emergence of "Massive Open Online Courses" (MOOCs) is viewed as one of the most recent innovations in online learning (Zhou, 2016). MOOCs are considered the most recent evolutionary phase of open educational resources. Klobas et al. (2015, p.18) point out that MOOCs represent recent ICT developments in online/distance education; however, the MOOC market remains in its early stages, and "a sustainable configuration of individual, institutional, and commercial providers is yet to emerge." They also state that, despite there being a huge number of learners worldwide that have joined MOOCs, little knowledge is available about learners' "experience … what they learn, what works, and what does not work" (p. 19).

MOOCs are described as online distance-learning courses that are open to learners who register, and one MOOC might include thousands of learners (Gameel & Wilkins, 2019). Jansen and Schuwer (2015, p. 4) refer to MOOCs as "online courses designed for a large number of participants, that can be accessed by anyone, anywhere as long as they have an internet connection, are open to everyone without entry qualifications, and offer a full/complete course experience online for free." MOOCs are described as follows: massive – large enrolled student population (thousands); open – free and not limited to location, age, time etc.; online – entirely functioning digitally through the internet; and course content – not just restricted to depository of educational materials, but also includes instructor's guidance and a schedule of structured syllabi (Sokolik, 2014).

MOOCs enable educational institutions to deliver their courses through cloud-based hosting capacity, providing functionality and scale, while institutions deliver their courses with material and reputational value. MOOCs as an innovation differ slightly from traditional online courses. Indeed, MOOC platforms enhance educational quality around the world. This is demonstrated by the huge numbers of enrolled students and the proliferation of courses in diverse fields of study at basically no charge at all for students. Therefore, Selwyn et al. (2015) state that MOOCs have been extensively recognized as an innovation to transform learning in higher education. According to Fook et al. (2017, p.94), students in MOOCs are allowed "to arrange their own time and pace in attending online classes." Compared with the delivery formats of traditional online courses, students who attend MOOCs are involved in a real self-instructional device (Cole & Timmerman, 2015). Participants are exposed to a diversity of media that can be utilized to freely share learning. Hence, it has been found that MOOCs can expand students' motivation in learning (Bremer, 2012). With their features of self-organization, openness and scalability, the popularity of MOOCs has dramatically increased during the past few years. In addition, MOOC platforms such as edX and Coursera attract millions of learners and offer them thousands of courses taught by well-recognized universities such as MIT and Harvard. According to the latest report from Shah (2018), the number of MOOCs has grown dramatically in 2018 as the total number of enrolled learners worldwide reached 101 million, a 30% increase compared to 2017. Additionally, more than 900 universities worldwide offer approximately 11,400 MOOCs with roughly 2000 new courses added in 2018.

The use of MOOCs in higher education arouses wide debates, especially in developing countries, as to whether MOOCs can meet learners' requirements and whether these courses can expand the enrolment rates in developing countries as they have in Western countries. According to Rai and Chunrao (2016), while the emergence of MOOCs in higher education is recognized as a positive trend, the attractiveness of these courses as part of student learning is shrinking. Zhou (2016) argues that MOOCs can offer an opportunity to learners who are looking for high-quality education from top-ranked and well-known higher education institutions in developed countries, and such courses can offer considerable autonomy, which learners recognize as tempting. On the other hand, various concerns are observed with respect to the usage of MOOCs in higher education. For instance, the lack of standardization and inflexibility of MOOCs may certainly decrease the learners' passion to participate in MOOCs. Furthermore, it has been argued that MOOC providers may struggle to provide courses that are vastly varied in content and that consider the different levels of available resources or prior knowledge, and the multiplicity of motivations for and purposes of learning (Che et al., 2016).

The increasing enrollment rates in MOOCs around the globe encourage many scholars to highlight the importance of examining learners' readiness to engage in these courses (Gameel & Wilkins, 2019). The current generation of MOOCs is seen as appealing to learners from diverse countries, and many studies have been conducted to investigate learners' readiness to adopt MOOCs for online education (Subramaniam et al., 2019; Zhou, 2016). However, these studies focused on learners' actual usage of MOOCs provided by universities in the same country and, so, are insufficient to address the pre-adoption perceptions and readiness of students, especially in countries such as Jordan, where MOOCs are still in their infancy. While several studies have investigated e-learning (Al-Adwan, et al., 2013; Al-Adwan & Smedley, 2012) and m-learning (Al-Adwan, Al-Adwan, & Berger, 2018; Al-Adwan, Al-Madadha, & Zvirzdinaite, 2018), very little is known about higher education students' readiness for MOOCs in Jordan. The incorporation of MOOCs in higher education represents an effective strategy to enhance teaching and learning quality in Jordan. Additionally, as a new mode of delivering higher education, MOOCs can lead to an increase in positive competition in both teaching and learning among Jordan's academics and offer viable opportunities to deliver global online learning. To date, a very limited number of studies (Abu-Shanab & Musleh, 2018) have been conducted to explore higher education students' readiness for MOOCs in Jordan. A study like the current one would be beneficial for higher education institutions in Jordan to determine the key factors that influence students' readiness and in turn develop active strategies to address students' needs in order for them to adopt MOOCs. After this introduction, the significance of the study will be presented and then the process of developing the proposed framework will be explained. The next section will outline the research methodology. Afterwards, data analysis and findings are presented, followed by a section that discusses the research's findings and highlights practical implications. Finally, conclusions, limitations and future work are introduced in the last section

SIGNIFICANCE OF THE STUDY

While MOOCs in developed countries are successfully implemented and radically increasing every year, the situation in developing countries, especially in Arab countries such as Jordan, is different. In Jordan, MOOCs are still in their infancy in terms of student enrollment, the participation of universities, and the diversity of courses.

The increased usage of the internet in Arabic countries has triggered various initiatives regarding open online education deployment (Sallam, 2017). Primarily, individual initiatives began to record videos that explained a variety of educational materials and these videos were uploaded onto the YouTube platform. Over the years, these individual initiatives have turned into a more organizational strategy. According to Pappano (2012), 2012 was announced as the year of MOOCs around the globe. The spread of the remarkable MOOC phenomenon has been witnessed worldwide, and the Arab region was influenced by this global trend. The year of 2013 witnessed the launch of the Rwaq platform as the first MOOC platform in the Arab region to provide fully Arabic MOOCs (Brahimi & Sarirete, 2015; Sallam, 2017). Later, in 2014, in Jordan, the "Queen Rania Foundation for Education and Development" and edX officially announced the launch of the Edraak platform (edX, 2013). Since then, Arab countries have had a number of MOOC initiatives, but these did not gain enough popularity to become as widespread as the Edraak and Rwaq platforms. MOOCs are viewed as a new trend in online learning, however knowledge and familiarity with such new trend of online learning is very low in developing countries, such as Arabic countries, compared to developed countries. So far, limited systematic research has been conducted to examine the factors and competencies that influence student decisions to enroll in MOOCs. Various scholars have investigated students' learning experiences by examining students' actual posts within MOOCs (Cole & Timmerman, 2015; Fianu et al., 2018). Although such studies offer a holistic understanding of the beliefs of active MOOC students, they fail to explain the opinions of students who are considering whether to register for MOOCs. Based on very narrow empirical evidence, some scholars (Bremer, 2012; Fang, 2015) have proposed that MOOCs attract self-motivated students who perceive MOOCs as useful. This study aims to contribute to the existing literature by examining the perceptions of higher education students in Jordan toward MOOCs. The current study extends the continuing debate about MOOCs with respect to determining which factors influence students' readiness to participate in these courses. Specifically, this study investigates both the cognitive and psychological influential factors that determine the readiness of Jordanian students to adopt MOOCs.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK DEVELOPMENT

Nowadays, it has been argued that most students can use technology easily because they are considered digital natives (Yilmaz, 2017). Such an assumption is occasionally interpreted as showing that most students are prepared for online learning. Yet this proposition can be questioned. Indeed, it is true that most students are digital natives and, thus, are more ready to use technology than students in the past. For example, almost all students have the knowledge required to use search engines, share materials on social platforms, and send e-mails at a basic level. Nonetheless, these basic skills and knowledge might be insufficient due to the complexity of digital environments. The proposed theoretical framework for this research is based on the work of Yu and Richardson (2015), who developed the model of Student Online Learning Readiness (SOLR). SOLR is comprised of three forms of competency assumed to be important in examining students' readiness for online learning. Specifically, these competencies are communication, technical, and social competencies with classmates and with instructors. Competencies refer to people's capabilities or abilities and beliefs about their capability or ability. Myllyla and Torp (2010) state that social competencies represent skills, capabilities, and a sense of control, which is necessary for managing social situations and developing and sustaining relationships. Larson et al. (1978, p. 16) define communication competencies as "the ability of an individual to demonstrate knowledge of the appropriate communicative behavior in a given situation," while Heo (2011, p. 61) refers to technical competencies as "self-efficacy in technology."

The proposed research model (see Figure 1) includes the three types of competency (communication, social, and technical) of Yu and Richardson's (2015) SOLR. These types are applicable to the MOOC environment, considering the fact that a MOOC is viewed as an online course with further characteristics (massive and open). Furthermore, the proposed model incorporates one additional competency: self-management of learning.

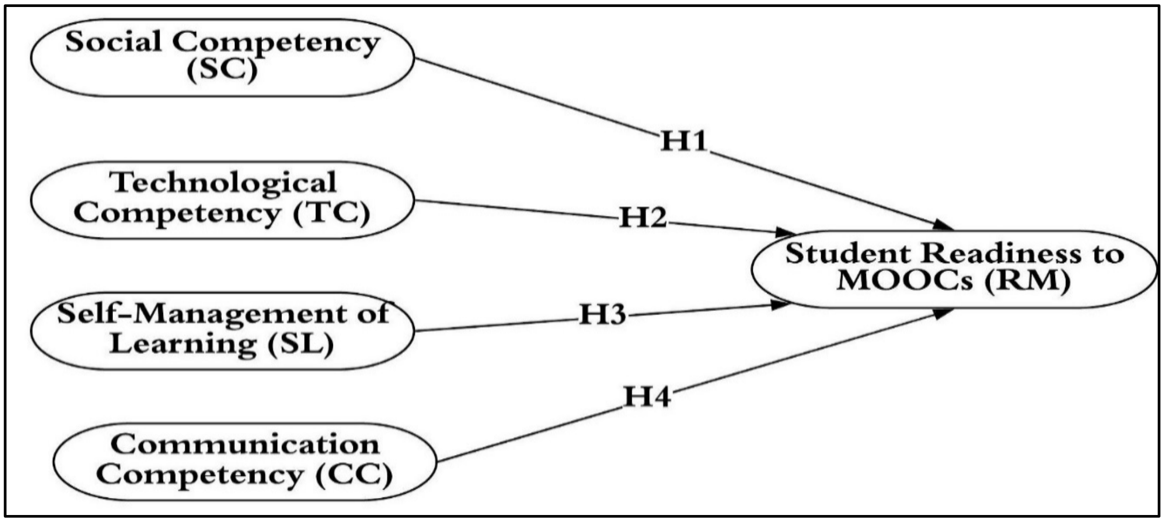


Figure 1: Research Model

SOCIAL COMPETENCY

The significance of social competencies for learners' academic achievement in the distance learning environment is evident (Subramaniam et al., 2019; Yu, 2018). Online learning students are required to actively participate in learning activities and to form communities (Bigatel et al., 2012). The online learning environment (such as MOOCs) is challenging in its nature in that students can become socially isolated due to the lack of interaction with others (Shen et al., 2013). Wise and Cui (2018) point out that lack of social interaction is often considered a factor that compromises learning experiences and outcomes in MOOCs. Learning is not just viewed as an intellectual activity but is also recognized as a social activity.

According to Shen et al. (2013), compared to online learning environments, the drop-out rates among students in traditional learning environments is low. One of the main reasons for such high rates of drop-out in online learning environments is the lack of social interaction. Specifically, the lack of interaction with instructors and classmates means online students are required to be self-motivated to accomplish their learning activities, and this can lead students to feel isolated. As a result, the lack of sufficient social interaction and social presence is considered a key challenge for taking and passing courses online (Akcaoglu & Lee, 2016). Tinto (1975), the developer of the student integration model (SIM) in the environment of traditional learning (face-to-face), argues that academic integration and social integration are the most important aspects for student retention in higher education. This also holds true in online learning environments. Social integration reflects the quality of students' relationships with classmates and instructors. On the other hand, academic integration refers to the academic performance of students and their level of intellectual development. High degrees of both academic and social integration mean students have resilient institutional and goal commitments, and therefore they tend to remain on their courses.

Students' academic achievement in online education is found to be highly correlated with various dimensions of self-efficacy (Shen et al., 2013). Cho and Jonassen (2009) state that online self-efficacy with respect to social interaction consists of two main aspects: (1) self-efficacy to interact with instructors and (2) self-efficacy to participate in an online community. Furthermore, they point out that students who possess high self-efficacy in participating in an online community and interacting with instructors are expected to utilize active interaction tactics, such as responding, reflecting and writing.

H1: *Social competency has a positive influence on student readiness to MOOCs.*

Technological Competency

With respect to technical competency, various studies in the literature have highlighted the significant role of technological self-efficacy in students' achievements in online education (Watulak, 2012; Yu & Richardson, 2015). Without adequate technological skills, students risk being unable to resolve technology-related problems during online classes, which may affect their access to learning materials and interaction with classmates and instructors. Online and distance learning has become widely technological, and new technologies are quickly incorporated into online learning programs. All forms of online and distance learning (e.g., electronic, mobile, ubiquitous learning) require learners to be adaptive and users of internet technologies. Consequently, learners are expected to possess and develop technological skills and competencies (Özbek, 2015). Some of these competencies are considered prerequisites for online courses, including having access to the internet and the computer hardware and software required to log in to online courses. However, having internet access and essential hardware and software does not guarantee that learners are able to utilize them effectively. Thus, there are other important technological competencies required for online learning, such as computer literacy/skills, being comfortable with technology for educational purposes, the ability to use communication and collaboration tools, and the ability to use ICT to research, store, analyze, and share information. In terms of computer literacy/skills, a set of computer/technological competencies and skills has been cited in the literature as the key skills that learners should develop when involved in online learning. These skills include the use and navigation of online educational settings, course management systems, internet, e-mail, word processors (such as MS Word) and e-learning management systems (Bork & Rucks-Ahidiana, 2013; Özbek, 2015). These competencies are necessary for learners to perform essential activities in online learning settings, such as following the course syllabus and submitting homework/assignments. Moreover, possessing adequate technological competencies facilitates learners' interactions with online learning systems software, which in turn leads increased efficiency in terms of dealing with the content, media, and course management systems (Stapa, 2009).

H2: *Technological competency has a positive influence on student readiness to MOOCs.*

Self-management of Learning Competency

Self-management of learning refers to the degree to which students perceives themselves as being self-disciplined and are able to engage in a greatly autonomous learning setting (Al-Adwan, Al-Adwan, & Berger, 2018). According to S. Yang (2013), students in online learning environments are physically separated from their classmates and instructors, which requires students to self-manage their education and learning and it is vital that students control their own learning. Consequently, online learning exclusively relies on self-direction and self-management. These key beliefs have been remarkably underlined as "resource-based" or "flexible" learning, which demand students to interact with several materials and sources, autonomously from instructors, providing the freedom to search for information that is most appropriate for their learning style (Al-Adwan, Madadha, & Zvirzdinaite, 2018). Students with high self-management abilities are expected to engage with online learning activities more effectively than those who lack the abilities required for self-regulated learning. Thus, students' self-management of learning competencies is viewed as a key determinant of student readiness to MOOCs.

H3: *Self-management of learning competency has a positive influence on student readiness to MOOCs.*

Communication Competency

Communication competency reflects the capability of students to share and transfer information through written or oral formats (Subramaniam et al., 2019). Communicating in online learning environments requires more effort than communicating with classmates and instructors in offline learning environments. This is because of the absence of body language in online learning. The use of facial expressions and body language in offline environments can significantly facilitate students' communication and deliver their ideas and messages effectively to classmates and instructors. In the same vein, active learning is closely connected to both interaction and communication. Petress (2008) points out that active learning reflects active engagement of students in their education as a participating and encouraged partner in the learning process. Active learners efficiently apply what they have learned. Active learning can be labeled as engaged learning due to the necessity of interaction, whether this interaction be student–student, student–content or student–instructor. Student–instructor interaction establishes an environment that motivates students to efficiently understand educational materials and content (Su et al., 2005). Student–student interactions may occur between one student and other student or with many students in group settings, with/without the real-time presence of an instructor; various studies demonstrate that this form of interaction is an important experience and learning resource (Su et al., 2005). Empirical evidence indicates that students essentially prefer student–student interactions, irrespective of the delivery mode (G. E. Moore et al., 2016). According to M. G. Moore (1989, p. 2), student–content interaction is referred to as "the process of intellectually interacting with content that results in changes in the learner's understanding, the learner's perspective, or the cognitive structures of the learner's mind."

H4: *Communication competency has a positive influence on student readiness to MOOCs.*

METHODOLOGY

PROCEDURES AND SAMPLING

The focus of this study is on Jordanian students in higher education institutions. Therefore, the participants in this study were current university students in Jordan; students were recruited from two private universities and one public university. Convenience sampling was used to distribute a paper-based questionnaire to the students of the three universities during a period of four months from May to September 2019. Consequently, out of 700 distributed questionnaires, a total of 537 responses were returned, of which 69 responses were reported incomplete as most of the questions (>80%) were left unanswered; these 69 questionnaires were eliminated from any further analysis. As a result, a total of 468 questionnaires were valid for statistical analysis. Table 1 shows the respondents' characteristics.

Table 1: Participants' Profile

Demographic	N	%
Gender		
Male	290	62%
Female	178	38%
Age		
18-25	294	63%
26-35	139	30%
>35	45	7%
Academic Program		
Bachelor's	375	80%
Master's	72	15%
PhD	21	5%
"Access to a PC/Laptop/Tablet"	422	90%

Demographic	N	%
"Have a smartphone"	468	100%
"Access to a steady Internet connection"	390	83%
"I have enrolled in a MOOC"	23	5%
"I plan to enroll in a MOOC"	269	57%

MEASURES

Previous research was used to develop an adapted paper-based questionnaire to assess university students' readiness for MOOCs. Tyupa's (2011) back-translation process was employed to translate the questionnaire's items into Arabic with a five-point Likert scale ranging from "1 = strongly disagree" to "5 = strongly agree". In the first part of the questionnaire, participants were instructed to provide their demographic information. The second part included questions related to the proposed factors that may influence students' readiness for MOOCs. All items (see Table 2) in this part were adapted and modified from previous literature (Al-Adwan, Al-Adwan, & Berger, 2018; Subramaniam et al., 2019; Yu & Richardson, 2015) to fit the context of MOOCs. A panel of experts (academics and other researchers) was employed to evaluate the questionnaire in terms of readability, clarity, and how appropriately each item measured its theoretical construct. Accordingly, the panel's feedback was analyzed, and the measurement items were consequently adapted. Afterwards, a pilot study with 50 students was carried out as an attempt to initially ensure the reliability of the questionnaire instrument. The test of Cronbach's alpha confirmed that all constructs acquired adequate internal consistency as the values of Cronbach's alpha exceeded the minimum cut-off value of 0.7 (Hair et al., 2016).

Table 2: Questionnaire items

Technical Competency (TC)	TC1: "I am able to download useful resources from the Web"
	TC2: "I communicate through emails to connect to others".
	TC3: "I am able to access digital library".
	TC4: "I use social medias to connect to others".
	TC5: "I am able to collaborate with others through online forums / discussions".
Self-management of Learning (SL)	SL1: "I have high expectations for doing well in my studies".
	SL2: "I set up my learning goals and study plan independently".
	SL3: "I manage my studies in accordance to my study plan".
	SL4: "I am independent in seeking for resources and completing my learning tasks".
Student Readiness to MOOCs (RM)	RM1: "I look forward to engage in MOOCs".
	RM2: "I can commit the time needed to complete a MOOC".
	RM3: "I would take up MOOCs if it is equivalent to a conventional course".
	RM4: "I am ready to enroll in a MOOC".
	RM5: "I like to learn more about MOOCs".
Communication Competency (CC)	CC1: "I am comfortable responding to other people's ideas".
	CC2: "I am able to express my opinion in writing so that others understand what I mean".
	CC3: "I am comfortable expressing my opinion in writing to others".
	CC4: "I give constructive and proactive feedback to others even when I disagree".

Social Competency (SC)	SC1: "I am able to pay attention to other students' social actions". SC2: "I am able to apply different social interaction skills depending on situations". SC3: "I am keen on meeting many new peers in my online course". SC4: "I am able to connect with others (peers and tutors) with ease".

DATA ANALYSIS

According to Lowry and Gaskin (2014, p. 7), although multiple regression analysis is ideal to deal with simple models (with few independent and dependent variables) such as the research model of this study, this technique offers limited modeling capabilities such as assessing the goodness "of the proposed (tested) model in comparison with the observed relationships contained in the data." Thus, structure equation modeling (SEM) was employed to test the research model. SmartPLS 3.2.7 software was utilized for data analysis. A preliminary analysis on the dataset indicated that there were no missing data or outliers. Data analysis in this study consisted of three stages. In the first stage, the model's goodness-of-fit indices were evaluated. The second stage was devoted to evaluating the measurement models. The last stage aimed to assess the structural model by performing a path analysis to test the proposed hypotheses (paths).

GOODNESS-OF-FIT (GOF) EVALUATION

Goodness of fit (GoF) indices were assessed in this stage to evaluate the proposed model performance. The indices were SRMR (standardized root mean square residual) and NFI (normed fit index), and the inferences of bootstrapped-based discrepancies were d_ULS (the unweighted least squares) and d_G (geodesic discrepancies) (Henseler et al., 2016). The examination demonstrated that the coefficient of SRMR was 0.053 (<0.08), and the value of NFI was 0.966 (>0.9), indicating acceptable fit estimates (see Table 3). The tests of discrepancies indicated that d_ULS < bootstrapped HI 95% of d_ULS and d_G < bootstrapped HI 95% of d_G. Consequently, the indices of goodness-of-fit were acceptable and satisfy the recommended rules of thumb, indicating that the data fit the model well (Henseler et al., 2016).

Table 3: Model Fit

Index	Saturated Model
SRMR	0.053
d_ULS	0.592
d_G	0.428
Chi-Square	893.014
NFI	0.966

MEASUREMENT MODEL ASSESSMENT

In this stage, a series of tests were performed to assess the reflective indicators' validity and reliability. In terms of the reliability tests, the indictor (item) loadings of each factor were examined. The recommended loadings should surpass the value of 0.708 (Hair et al., 2019). Additionally, both composite reliability (CR) and Cronbach's alpha (α) were evaluated to determine internal consistency reliability. As Hair et al. (2019) recommend, the estimates of both Cronbach's alpha and composite reliability should be ≥ 0.7 and < 0.95. As can be seen in Table 4, the standardized factor loading estimates for all items were acceptable, ranging from 0.75 to 0.93. Furthermore, all constructs had a composite reliability greater than the recommend value of 0.7, indicating a good internal consistency. All constructs had an acceptable coefficient of Cronbach's Alpha, ranging from 0.86 to 0.93. Construct validity was assessed by the means of convergent and discriminant validity. According to Hair et al. (2019), convergent validity determines the level to which "the construct converges in order to explain the variance of its items." The metric of AVE (average variance extracted) was employed to assess all constructs' convergent validity. As Table 4 demonstrates, the AVE for each construct was above the minimum acceptable coefficient of 0.5. Variance inflation factor (VIF) test was used to examine multicollinearity. Paul (2006), Kock (2015) and Montgomery et al. (2001) point out that if a VIF value exceeds five or ten, it is a clear indication of the presence of multicollinearity. Park (2015, p. 43) states that "practical experience indicates that if any of the VIFs exceeds 5 or 10, it is a sure sign that the associated regression coefficients are poorly estimated because of multicollinearity." As shown in Table 4, the VIFs values of the four independent variables were below the rules of thumb of 5 which approves the absence of multicollinearity.

Table 4: Construct Reliability and Validity

Construct	Item	Loading	Cronbach Alpha	Composite reliability	*AVE	VIF
Technical Competency (TC)	TC1	**0.88**	0.86	0.90	0.65	1.73
	TC2	**0.87**				
	TC3	**0.77**				
	TC4	**0.75**				
	TC5	**0.76**				
Self-management of Learning (SL)	SL1	**0.90**	0.90	0.93	0.76	1.31
	SL2	**0.91**				
	SL3	**0.82**				
	SL4	**0.88**				
Student Readiness to MOOCs (RM)	RM1	**0.84**	0.92	0.94	0.76	-
	RM2	**0.86**				
	RM3.	**0.90**				
	RM4	**0.87**				
	RM5	**0.88**				
Communication Competency (CC)	CC1	**0.86**	0.88	0.92	0.73	1.45
	CC2	**0.88**				
	CC3	**0.84**				
	CC4	**0.85**				
Social Competency (SC)	SC1	**0.88**	0.93	0.95	0.82	1.22
	SC2	**0.93**				
	SC3	**0.92**				
	SC4	**0.89**				

**AVE: "Average Variance Extracted", VIF "Variance inflation factor"*

Furthermore, cross-loadings of all constructs' items were examined to confirm convergent validity. Table 5 shows that each construct's items loaded more highly on the intended construct than any other construct. Thus, it can be concluded that convergent validity was present for all constructs.

Table 5: Cross-loading

Item	Communication Competency (CC)	Student Readiness to MOOCs (RM)	Social Competency (SC)	Self-management of Learning (SL)	Technical Competency (TC)
CC1	**0.86**	0.59	0.55	0.33	0.37
CC2	**0.88**	0.59	0.48	0.38	0.48
CC3	**0.84**	0.53	0.43	0.37	0.34
CC4	**0.85**	0.58	0.47	0.37	0.32
RM1	0.49	**0.84**	0.51	0.57	0.47
RM2	0.59	**0.86**	0.57	0.57	0.44
RM3	0.60	**0.90**	0.59	0.52	0.44
RM4	0.55	**0.87**	0.62	0.42	0.49
RM5	0.69	**0.88**	0.69	0.45	0.42
SC1	0.49	0.61	**0.88**	0.39	0.30
SC2	0.52	0.60	**0.93**	0.46	0.37
SC3	0.58	0.69	**0.92**	0.49	0.37
SC4	0.45	0.58	**0.89**	0.47	0.37
SL1	0.37	0.49	0.48	**0.90**	0.36
SL2	0.35	0.50	0.45	**0.91**	0.38
SL3	0.42	0.55	0.39	**0.82**	0.32
SL4	0.34	0.46	0.44	**0.88**	0.34
TC1	0.44	0.51	0.36	0.36	**0.88**
TC2	0.39	0.46	0.34	0.40	**0.87**
TC3	0.28	0.38	0.36	0.23	**0.77**
TC4	0.34	0.37	0.27	0.28	**0.75**
TC5	0.27	0.31	0.24	0.31	**0.76**

Discriminant validity was assessed based on Fornell and Larcker's (1981) and the HTMT (heterotrait-monotrait ratio) criteria. Hair et al. (2019) point out that discriminant validity determines the extent "to which a construct is empirically distinct from other constructs in the structural model." Two tests were performed to determine discriminant validity. First, the criterion of Fornell and Larcker, which proposes that the square root of a construct's AVE should be higher than the correlation of that same construct with any other construct in the structural model. As Table 6 shows, the abovementioned criterion was met. Henseler et al. (2015) state that this test suggests that a value of HTMT above 0.85 indicates that discriminant validity is absent. As demonstrated in Table 7, the criteria of HTMT was also satisfied.

Table 6: Discriminant Validity (Fornell & Larcker Criterion)

	Communication Competency (CC)	Student Readiness to MOOCs (RM)	Social Competency (SC)	Self-management of Learning (SL)	Technical Competency (TC)
CC	**0.85**				
RM	0.67	**0.86**			
SC	0.57	0.69	**0.90**		
SL	0.43	0.58	0.50	**0.87**	
TC	0.44	0.52	0.39	0.40	**0.81**

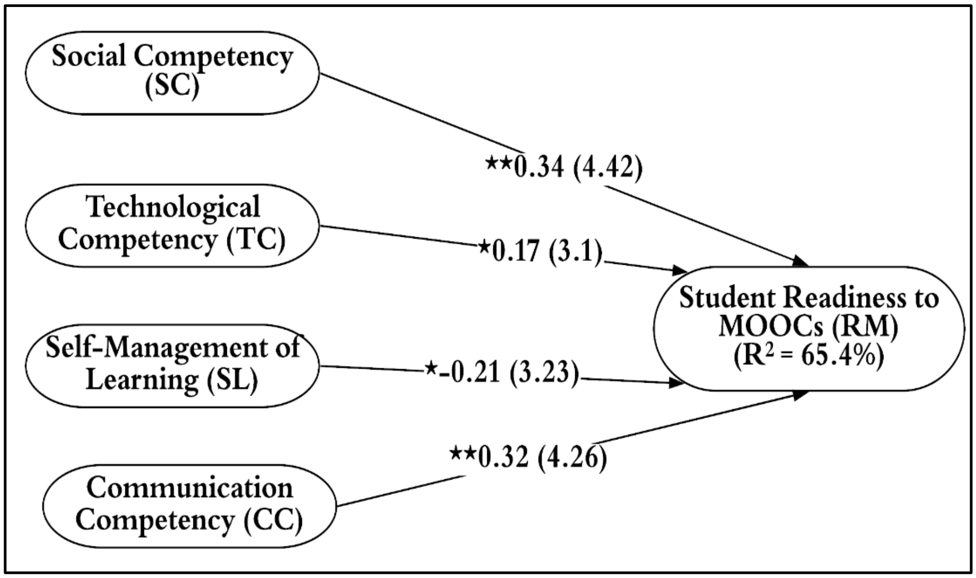
**The diagonal are the square root of AVE*

Table 7: Discriminant Validity (HTMT)

	Communication Competency (CC)	Student Readiness to MOOCs (RM)	Social Competency (SC)	Self-management of Learning (SL)	Technical Competency (TC)
CC					
RM	0.74				
SC	0.62	0.74			
SL	0.48	0.64	0.55		
TC	0.49	0.57	0.43	0.45	

Structural Model Assessment

The structural model was assessed based on three main stages: the coefficient of determination (R^2), predictive relevancy (Q^2), and the significance of path coefficients (Hair et al., 2019). R^2 measures the explanatory power of the structural model. Similar to MOOCs related studies (M. Yang et al., 2017), Figure 2 shows that the coefficient of R^2 is 0.654 for the construct of student readiness to MOOCs (RM). This suggests that the four independent latent variables in the theoretical model explain 65.4% of the variance in student readiness to MOOCs (RM), which is considered moderate explanatory power. The structural model in the current study explained 65.4% of the variance in the readiness of Jordanian students to adopt MOOCs, indicating that the model offered adequate explanatory power. The procedure of blindfolding was used to calculate the predictive relevancy (Q^2). Hair et al. (2019) point out that Q^2 should be >0. The value of Q^2 is 0.45, which indicates that the model gives a medium predictive relevancy. In terms of the evaluation of the models' paths, all paths are found to have significant coefficients. Specifically, social competency (β=0.34, *t*-statistic=4.42, *p*-value<0.01), technological competency (β=0.17, *t*-statistic=3.1, *p*-value<0.05) and communication competency (β=0.32, *t*-statistic=4.26, *p*-value <0.01) were found to have a positive influence on student readiness to MOOCs. On the other hand, self-management of learning (β=- 0.21, *t*-statistic=3.23, *p*-value<0.05) was found to have a negative impact on student readiness to MOOCs.



***p*-value<0.01, * *p*-value<0.05, numbers between parentheses show t-statistic for each path coefficient

Figure 2: Structural Model

DISCUSSION AND IMPLICATIONS

According to the findings, technical competency had a positive effect on students' readiness to adopt MOOCs. Such a finding is inconsistent with Subramaniam et al. (2019) who refer the insignificant effect of technical competency to the fact that the Malaysian students are "exposed to the Internet and are familiar with digital technology. While technical competency is necessary, students may perceive it as an inherent competency." Most of the participants (about 95%) in this study showed that they have adequate accessibility to various digital technologies (smartphone, PCs, laptops, tablets, etc.). Furthermore, the majority of participants reported that they have a steady internet connection (about 83%). Such figures suggest that the participants are reasonably familiar with digital technology and are exposed to the internet. Despite such high accessibility, exposure and familiarity with digital technology, the participants believe that technological competency related specifically to online educational purposes is necessary. Facilitators of MOOCs should take into account that technical competency can be enhanced by recognizing that technical competency related to online learning should be developed, taught, and constantly reinforced at every educational level as a life skill. Additionally, facilitators and developers of MOOCs should be prepared to find methods to support and inspire student participation and to recognize the importance of learning skills in the MOOC environment. Breslow et al. (2013) point out that participants with Bachelor's degrees or higher represent the largest category of participants in MOOCs. This strengthens the idea that a high level of technical competency, as might have been developed through prior educational attainment, is essential for students to succeed in their participation in a MOOC.

Contrary to Subramaniam et al. (2019), social and communication competencies were found to have significant and positive influences on student readiness to MOOCs. A MOOC is recognized as a collaborative learning environment, which requires students to possess socio-communication competencies to guarantee active participation. According to Milligan and Littlejohn (2017), one of the main motivations of MOOC students is forming social relationships with other learners. Therefore, Willis (2013) points out that improved socio-communication skills are fundamental for the success of collaborative learning in MOOC environments, in which the presence of learners' communities is recognized as an essential factor. Staubitz et al. (2015) state that the lack of social and communication skills among many learners is considered as a key concern that results in poor collaborative experiences. This highlights the fact that online interactions are different from face-to-face communication and thus require new competencies, which are often not taught. Facilitators and developers of MOOCs should increase the social presence of fellow participants in MOOCs, which in turn facilitates the attainment of collaborative learning. Kreijns et al. (2002) stress that group awareness is an essential element when it comes to collaboration in MOOCs. However, such awareness is difficult to attain without a proper social presence that allow learners to trace other group members' actions. Furthermore, MOOC providers and facilitators should bear in mind that synchronous communication has a great velocity of information by nature, and it also has a significant role in encouraging social presence. The increased level of social presence subsequently enhances trust and overall group cohesion, which then leads to improved group performance and a lessened perception of loneliness.

Inconsistent with the findings of Subramaniam et al. (2019) in the Malaysian context, self-management of learning is found to be a significant negative predictor of student readiness to MOOCs. Such result suggests that students who have autonomous learning capabilities will be keen to use MOOCs (the case of Subramaniam's et al. (2019) findings) than those with low autonomous learning capabilities (the case of this study). This may be caused by the nature of the educational culture in Jordan where students view educators as the main source of learning and thus well-structured and formal learning environments, such as classrooms, are still favorable for Jordanian students (Al-Adwa, Al-Madadha, & Zvirzdinaite, 2018). This finding has significance within the wider realm of education and learning policy, as it underpins the level of skills required for self-directed and independent learning. The open nature of MOOCs normally involves marginal direct interaction between the instructor and learners, which places the responsibility on learners to create and control their learning process. Consequently, learners are required to self-regulate their learning by monitoring and adjusting their actions and behaviors regarding their particular learning context. Littlejohn et al. (2016, p. 40) point out that, in MOOCs, "individuals must determine when, how and with what content and activities they engage." It has been demonstrated that, in online learning, learners with better self-regulated learning skills use more effective learning methods (Hood et al., 2015). Learners in online courses need to develop study skills and learning habits in order to avoid early dropouts. Such a situation is highly aggravated in the case of MOOCs, where support from instructors is scarce as they cannot address all requests for advice from learners. MOOC developers and designers should provide solutions that foster confidence and self-learning abilities, especially for learners with little or no experience in online learning. Such practice would enable learners to participate effectively and follow the pace in MOOC environments.

Offering self-learning mechanisms that provide personalized planning and tips would effectively support learners during their learning in MOOCs. For instance, Gutiérrez-Rojas et al. (2014) point out that time and task management tools in the MOOC context can effectively help learners to have regular study periods, take short breaks, identify prioritized tasks, and find alternative subjects. In addition, students should be encouraged and trained by higher education educators and administrators to be independent and self-regulating in their learning processes. This requires educators to change their style of teaching to be more oriented towards self-management in learning.

CONCLUSION

Higher education students need to possess a certain set of competencies in order to succeed in MOOCs. Thus, this research aimed to assess students' readiness and competence to utilize MOOCs. To achieve this objective, this study adapted the SOLR model to predict student readiness to MOOCs among Jordanian students. The proposed model investigated four competencies in predicting student readiness to MOOCs: (1) social competency, (2) technical competency, (3) self-management of learning competency, and (4) communication competency. The findings demonstrated that social, communication, and technical competencies had significant positive influences on student readiness to MOOCs. These competencies acted as facilitators of student readiness to MOOCs. On the other hand, self-management of learning competency had a negative influence on student readiness to MOOCs. Thus, special attention should be paid to the negative impact of self-management of learning on student readiness to MOOCs. Identifying the reasons for the low level of self-management of learning among students allows MOOC developers and senior management in higher education institutions to address the actual problems associated with student readiness to MOOCs. Specifically, senior management can use the items that have been used to measure the construct of self-management of learning to expose the causes behind students' low level of autonomous learning.

This study is subjected to a number of limitations. Although 65.4% of the variance in the readiness to use MOOCs is explained, the rest of the variance remains unexplained, perhaps due to the fact that factors were missed from the research model. Further studies may include additional factors, such as learners' self-efficacy (Gameel & Wilkins, 2019) and motivation for online learning (Ally et al., 2019), to better measure students' readiness to use MOOCs. Moreover, additional factors can be revealed by utilizing a qualitative method. Thus, additional studies may employ a mixed-method approach (both quantitative and qualitative) to accurately identify additional factors that may influence student readiness to MOOCs, and to offer a more holistic understanding of readiness (Al Adwan, 2017). The data of this study were collected from participants at three universities in Jordan, which indicates a potential sampling bias. Thus, the generalizability of the results of this study might be threatened by such a sampling process, although several samples from different programs and majors were included. Further research may include a larger sample size from additional universities to enhance the generalizability of the findings. The generalizability or transferability of this study's findings the finding to other countries than Jordan may also be a limitation. Thus, more studies can utilize this study's model and examine if there are any differences.

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