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Massive Open Online Courses as an Improvement in Education for Countries in Transition: Case of Bosnia and Herzegovina

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Abstract

With the rapid progress in technology and the advancement in learning systems, E-learning has become the topic of many studies in the last several decades. The success of a society is based on education; those who have a better educational system prosper and develop faster. The schooling systems of countries that are in transition are facing many problems. Due to the complex governing structure, the reforms of the education system are very slow thus researchers opt for an alternative to traditional education. The goal of this research is to examine what tiger intention to use online-courses and the current barriers that exist. This researcher aims to answer the following questions. "What are the main factors affecting the intention to use online-courses? For this research four variables have been developed (Performance Expectancy, Effort Expectancy, Social Influence, and Motivation) and their influence on students' behavioural intention to use MOOCs was measured. Moreover, in the main model of the study, five variables (Age, Gender, Experience, Language Barriers, and Level of Education) were used as controlling (moderating) variables. The research used a quantitative method where data has been collected using surveys that have been done among high school and university students. Regression analysis was used to test hypotheses and the main findings showed that all four variables have an influence on students and their intention to use MOOCs. The findings of the study show that performance expectancy and device consistency have an influence on MOOC use intentions. Facilitating environments, instructional consistency, and MOOC use purpose all influence MOOC use. MOOC use intention was found to be influenced by social impact and effort expectationsand further, this study has confirmed that motivation impacts behavioural intention to use MOOCs. The study finally concluded that the universities must have systems and tools in place to encourage students to use MOOCs. At all stages of education, tech skills instruction should be included in the curriculum. MOOC designers must use the best teaching and learning methods to ensure that

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MOOCs have good instructional content, as well as ensure that the sites and learning materials are in excellent quality.

Keywords: massive open online courses, online learning, e-Learning, Bosnia and Herzegovina's education, universities, schools.

1. Introduction

Education is the most important segment in the evolution of the nation, countries with good educational systems are growing faster and it is one of the critical impacts on the growth of the economy (Seltzer, Bently, 1999; Coates, 2013). It gives people proper skill, knowledge, information, and technique to know their rights and obligations toward country, nation, society, family. Unfortunately, a clear disadvantage of proper education is found in developing courtiers (Barber et al., Rizvi, 2013; Tett, 2018).

To balance these factors various innovations have been launch one of them is e-Learning. E-Learning is defined by the European Commission as the "consumption of the internet to increase the quality of learning by giving access and resources to the larger masses". E-Learning enables distance sharing and distant collaboration (Dominici, Palumbo, 2013), which is a very important fact in reaching masses all over the country.

A segment of e-learning that is growing very fast is MOOCs. It can be defined as distance offered courses that can take a large number of students (Lin et al., 2015). MOOCs had a huge acceptance from the time they were launched. It is considered as one of the curtail change that was needed in education (Weissmann, 2018; Chafkin, 2018).

MOOCs raised the discussion of the potential extension of Higher Education to all, where it would be accessible to any student with an internet connection around the globe (Yuan et al., 2018; Valenza, 2018).

Despite the reality that MOOCs are rapidly increasing mode of education programs with the ability to provide access to world-class teaching and educational opportunities across social and geographical boundaries, retention rates are typically poor. (figures of 10 percent retention are widely cited) (Roca et al., 2006).While research is beginning to look into the reasons for the low retention rates, most studies concentrate on a single MOOC as a case study (Lee et al., 2009; Blin, Munro, 2008) or look at intent to complete rather than actual behavior (Alraimi et al., 2015). However, there are some elements that could be considered barriers in students' learning processes while using E-learning platforms, such as reduced motivation, delayed feedback or support because teachers are not always accessible when students need help while learning, or feelings of alienation due to the lack of presence of classmates (Hughes, 2009; Coman et al., 2020). Because of these difficulties, adapting existing MOOCs is difficult, and users can be hesitant to accept MOOCs. As a result, the effectiveness of a MOOC will be determined by whether or not users are willing to follow it, which is determined by a number of factors such as performance expectancy, commitment expectancy, social influence, and motivation, as well as their impact on students' behavioural intention to use MOOCs (Wang et al., 2009). Consequently, some other determinants such as age, gender, experience, language barriers, and educational attainment are significant for user intention to use MOOC. Very few research has been done to examine the factors, that influencing users' intentions to adopt MOOCs, as well as the impact of disparities in age, gender, experience, language barriers, and level of education on MOOC acceptance.Current studies in this field are narrowly focused on some specific subjects such as satisfaction (Name, et al., 2014), motivation (Hew, Cheung, 2014), or the success rate of students only (Levy, 2007). Therefore this study is to see what inspires tiger's users to take online courses and what obstacles they face. The main objective of the study was to see whether experiential variables affected people's intention to take online courses, in order to aid designers in creating more successful MOOCs.

2. Literature review

UNESCO World Educational in 1998 reported that "New possibilities are emerging which already show a powerful impact on meeting basic learning needs, and it is clear that the educational potential of these new possibilities has barely been tapped". Communication and information technology has shown the potential to transform the role of teachers and education. Developed nations are leading in online learning, intensive competition, globalization, a new form of the classroom, revolution of the information technology, sharing and transferring knowledge is the difference between old and new economy (Stricker et al., 2011). To understand where was the country in transition stands, we need to understand B&H. War which lasted from 1992 to 1995 devasted the country leaving it with the Dayton agreement where there is Federation of B&H, Republika Srpska, and District Brcko. Complex structure made many issues in education. Curriculums are not harmonized; every party is introducing the changes by themselves, with no joint intention to improve education. The statistic shows that 38 % of the population in B&H has just elementary education, 52.5 % secondary education only 9.5 % has a higher education (Stricker et al., 2011; Bašić, 2018). E-learning in Bosnia and Herzegovina is mainly left to the individuals to make effects, with no help of society, institutions, or government. Being so careless about this big opportunity also created large masses unfamiliar with the system that can improve the quality and lower the spending on traditional education. Agency for the statistic in Bosnia and Herzegovina 2.5 billion per year is spent on education. But the result is more than ineffective (Ibrahimović, 2015). On another side, Bosnia and Herzegovina is a country that has no problem in transferring digital information. According to (Global Digital Report, 2018) 74 % of people in B&H are internet users. In a study done by Chaushi, Chaushi, and Ismaili (Tyler-Smith, 2006) on the western Balkan region, they concluded that the technical aspect of e-learning is implemented as in private as in public universities where 72 % have LMS system where the material for the courses has been uploaded.

E-learning is the process of creating and designing learning environments using information and computer technology and systems (Horton, 2006). E-learning, according to Elmarie Engel Brecht, is a term that uses electronic media such as the internet, CDs, cell phones, and even television which provide distance learning and teaching (Engelbrecht, 2005). In a brief, E-learning is the process of transmitting information and education through the use of different electronic devices (Koohang et al., 2005), and the term is best understood when it is placed within a framework in which technology is used to satisfy people's desire to learn and develop (Cohen, Nycz, 2006). It is often seen as the paradigm of traditional education. Time and place (Croxton, 2014) is no longer an obstacle for people to gather information and cultivate knowledge (Aparicio et al., 2014). The central point of learning has been changed, from teacher to student, and the possibility that was previously unthinkable such as to use some platforms and to learn new things are today available (Felice, 2009; Yanaze, 2006; Coleman, 2012). D. Zhang et. al. (Zhang, Nunamaker, 2003) confirmed that e-learning students performed better than the group without having any online learning. Various online tools are used in the E-learning phase in higher education. Many terms, such as Computer-mediated learning (Anaraki, 2004), Web-based training, E-learning systems, and Learning Management Systems, have been used to describe online learning over time. Regardless of their names, all of these systems use the Internet and have certain features that enable registration, evaluation of learners' and teachers' activities as well as facilitating lecture delivery and interaction between students, their peers, and teachers (Costa et al., 2012). Forums, which enable asynchronous student-teacher communication and collaboration, web conferences, which allow video, audio, and written communication, and chat, which allows users to send messages and receive responses in real time are among the most critical features of online learning platforms (Cacheiro-Gonzalez et al., 2019). As a result of the incorporation of e learning; education has recently undergone major changes. One of these innovations is the introduction of MOOCs, or massive open online courses. Many organizations such as Coursera, Udacity, and EDX launched MOOCs in 2011, and they embodied significant new advances in education (Alhazzani, 2020). MOOCs are open accessible online courses in which anyone can participate normally for free. Participants are advised to use additional materials such as textbooks in addition to conventional course material such as recorded lectures to help their self-directed studies. Some MOOCs often provide structured and unstructured interactivities, such as video conferencing tools and forums between students, teachers, and experts, as well as immediate feedback during fast quizzes and assignments (de Jong et al., 2020). MOOCs are organized into "modules" or "courses" that are normally spread out over a set period of time and allow students to work through the material at their own pace. (Pilli et al., 2016) Despite the tremendous growth rate of MOOCs and a high rate of enrolments, participation in the MOOCs after enrolment, as well as completion of the courses has been criticized widely (Porter, 2015). A survey of 316 users of three major MOOC platforms based in the United States (Coursera, EdX, and Udacity) was conducted to determine their intention to continue with MOOCs. They discovered that perceived credibility, perceived transparency, perceived utility, perceived pleasure, and user satisfaction all had a major impact on intention.

The emphasis on purpose to use rather than actual completion is a drawback of this review, which had the advantage of looking at experience through various MOOC platforms and courses (Alraimi et al., 2015). Users' intention to use online learning systems in the future is measured by their satisfaction, which is determined by their perception of system quality (Chiu et al., 2005). The decision to continue using online learning systems is positively linked to system quality (Ramayah et al., 2010). Students' behavioral intentions to use online learning course websites are influenced by their perceptions of system quality (Chang, Tung, 2008). According to the literature, the major factors that impact the educational process through e-learning are individual motivation, environmental characteristics, ease of use, system factor, individual factors, usefulness, network externality factor, social factor, student interface, content, learning community, and customization are the main parameter for acceptance of e-learning systems (Vaughan, 2001; Nawal, 2012; David, Bagozzi, Warshaw, 1992; UNESCO, 1998). From the review of the literature, The research model was built using the following variables: performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and usage behavior. Furthermore, five variables (age, gender, experience, language barriers, and level of education) were used as controlling (moderating) variables in the study's research model.

2.1. Development of the Research model

To decide the rate of technology adoption, Alraimi et al. proved that the most frequent factor is performance expectancy. Venkatesh et al. defined performance expectancy as a “degree to which a person believes that using a particular system would enhance his or her job performance”. Further Venkatesh et al. defined five constructs: Perceived usefulness (TAM/TAM2, C-TAM-TPB); Extrinsic motivation (MM); Job-fit (MPCU); Relative advantage (IDT); Outcome expectation (SCT); On this grounds the first hypothesis was developed:

H1: Performance expectancy (perceived usefulness) positively influences the usage of MOOCs.

Wu et al. explained that a significantly important segment of technology acceptance is the factor of ease of use. Evaluating MOOCs based on the fact “perceived ease of use” is accessing the system designed to be learner-friendly. Creating a learner-friendly design need to be considered and people with a variety of skills need to be able to operate with the system. The goal should be easy to use and useful for learners. Effort expectancy is defined as the “degree of ease that individuals think they will have when using an information system” (Venkatesh et al., 2003). Three constructs are crucial for the existing model of effort expectancy: Perceived ease of use (TAM/TAM); Complexity (MPCU); Ease of use (IDT). Therefore, the following hypothesis is developed.

H2: Effort expectancy (easy of usage) has a positive influence on the usage of MOOCs.

Khan, Hameed & Khan, discovered that individuals are easily influenced to use new online technology if their peers, colleagues, friends, relatives, and others are using it. Brahmasrene & Lee, (Brahmasrene, Lee, 2012) encourages students to use communication tools as much as it is possible during the courses, the effect increased social participation among students which led to a bigger commitment to continue e-learning. The conclusion was that social ability affects positively student’s intention to use e-learning. A student enrolled with friends is more likely to be engaged with course material (Kizilcec, Schneider, 2015), and drop out from MOOCs are less likely (Onah et al., 2014). Social engagement via large online group has a positive effect on a student to finish the course (Kizilcec, Schneider, 2015) and small group engagement face-to-face positively affect MOOCs learning (Li et al., 2001).

Venkatesh et al. referred that social influence can be explained as "the degree to which an individual perceives that important others believe he/she should use the new system". (UTAUT) the unified theory of acceptance explained that social influence is strongly predicting behavioral intention (Venkatesh et al., 2003). Base on the theoretical background the following hypothesis has been established.

H3: Social Influence has a positive effect on the intention to use MOOCs.

The fundamental difference between traditional classroom-based instruction and MOOCs is motivation. Motivation can be described as the reason or a goal a person behaves in a certain manner. It is about what people believe is important (Ames, 1992).

Motivation is a psychological construct that is an important factor in learns’ aim to continue using MOOCs and to finish the course (Moore, 2013; Barba et al., 2016). It explains whether a person has the interest to be engaged in a certain activity. When it comes to learning motivation is conceptualized as enhances, maintains, or mediates cognitive development. It is intentional behavior (Brophy, 2004). Many researchers tried to understand deeper about motivation drives and goals that MOOCs learners have (Moore, 2013; Barba et al., 2016; Glynn, 2011; Zhou, 2016).

The following components influence a person to learn:

- Intrinsic motivation includes emotions that learning is delightful and intriguing (Glynn et al., 2011).
- Extrinsic motivation involves external factors for learning such as reward or punishment (Glynn et al., 2011).
- Personal relevance involves indications of the learner's goals (Duda, Nicholls, 1992).
- Self-efficacy indicates certainty that they can accomplish high results (Bandura, 2006).
- Self-determination indicates learners' beliefs about the control that they have over learning (Black, Deci, 2000).

Motivation plays important role in persistence and learning in any education environment. MOOCs learning are "voluntary learning", so motivation is especially important when it comes to the amount of time individuals spend learning and the effort intensity. Lei (Lei, 2010) studies also revealed that motivation to participate in MOOCs can be internal and external. "Internal can be curiosity and personal interests. External factors are the impact on the development of job competencies and reputation of the universities" (Milligan, Littlejohn, 2017; Wu, Chen, 2017).

H4: Motivation has a positive effect on the intention to use MOOCs.

2.2. Moderators

Previous studies indicated that individual expectation defers depending on age (Venkatesh et al., 2003). Age groups among MOOC learners are critical for learner-friendly features so students would not experience technical problems and they would feel that MOOCs are useful for their learning activities and goals (Younet al., 2018). Most of the learners are over 18-year-old students (Yousef et al., 2014), the average age of MOOC participants was 30 and greater (Rodriguez, 2012). The age of the participants was a significant factor for student success in an online program (Diaz, 2000).

H1a: Age moderates the relationship between performance expectancy and behavior intention to use MOOCs.

H2a: Age moderates the relationship between effort expectancy and behavior intention to use MOOCs.

H3a: Age moderates the relationship between social influence and behavior intention to use MOOCs.

H4a: Age moderates the relationship between motivation and behavior intention to use MOOCs.

Christensen and Alcorn (Christensen, Alcorn, 2014) discovered a gap in the gender of online learners only 36.5 % of MOOC participants were female. In a recent study, Halawa et al. (Halawa et al., 2014) confirmed this gender inequality in online learning. Macleod et al. (Macleod et al., 2015) did not agree with previous studies and proposed a theory that gender proposition in MOOCs courses often depends on the subject chosen. The further researcher explained that the Equine Nutrition course at the University of Edinburg had for instance 90 percent female audience while the AI course on MOOCs had only 15 percent, female students.

H1b: Gender moderates the relationship between performance expectancy and behavior intention to use MOOCs.

H2b: Gender moderates the relationship between effort expectancy and behavior intention to use MOOCs.

H3b: Gender moderates the relationship between social influence and behavior intention to use MOOCs.

H4b: Gender moderates the relationship between motivation and behavior intention to use MOOCs.

Diaz (Diaz, 2000) suggested that the profile of an online learner who has more life, work, academic experiences made the student better prepared for independent, self-directed study. Tyler-Smith (Tyler-Smith, 2006) and Diaz (Diaz, 2000) presented that more mature students with more life and work experience are more successful in online learning.

H1c: Experience moderates the relationship between performance expectancy and behavior intention to use MOOCs.

H2c: Experience moderates the relationship between effort expectancy and behavior intention to use MOOCs.

H3c: Experience moderates the relationship between social influence and behavior intention to use MOOCs.

H4c: Experience moderates the relationship between motivation and behavior intention to use MOOCs.

Language has a critical role in communicating and transferring knowledge. As Vygotsky (Vygotsky, 1978) explained that spoken or written language plays the important role in social, cognitive, and motivational factors. Further learners are coming from different cultural and social backgrounds so communication differs and plays important role in learning (Vygotsky, 1978; Lemke, 2001). Language mediates learning and it represents an important factor in transferring ideas, thoughts, and knowledge. Proper communication is crucial in correctly interpreting knowledge by learners (Lemke, 2001). Inappropriate use of language might lead to misunderstanding, miscommunication, and with that lower motivation of students (Vygotsky, 1978) and higher dropout.

In online education, English has become an international medium for communication among learners that do not speak the same native language. Many MOOCs courses are just in English and there are a lot of non-native English speakers that are taking courses in that language (Altbach, 2014).

H1d: Language barrier moderates the relationship between performance expectancy and behavior intention to use MOOCs.

H2d: Language barrier moderates the relationship between effort expectancy and behavior intention to use MOOCs.

H3d: Language barrier moderates the relationship between social influence and behavior intention to use MOOCs.

H4d: Language barrier moderates the relationship between motivation and behavior intention to use MOOCs.

According to the article of Universities UK 2013, there are five groups interested in MOOCs. Vocational learners – professionals that want to maintain their knowledge or learn about new fields and develop their careers through lover cost independent learning models. Educators and researchers –To improve their work with the students or in the field, they are using MOOCs. Higher Education students – This category uses MOOCs as an addition to the courses that they have at the university. Hobby learners – Adults that are eager to learn something new, use the MOOCs system as an easily accessible material at low cost or for free. Prospective students – There is always a group of students that want to learn more. They one to explore a more different topic and work on themselves in different fields.

"Some other characteristics of students are as follows:

- Most of them are over 18-year-old students,
- The length of course schedule changes between 5-12 weeks,
- Educational videos might be on a specific course or a topic,
- The length of videos changes between 5-10 minutes,
- The language of most courses is English,
- Due to a high number of participants and the instructional approach (peer learning), assessment of participants are made through multiple-choice tests, online assessment tests, and peer assessment." (Yousef et al., 2014)

In research done by the Diaz (Diaz, 2000) and K. Tyler-Smith (Tyler-Smith, 2006) reported that despite the high level of education and carrier experience, participants in MOOCs often drop out.

H1e: Level of education moderates the relationship between performance expectancy and behavior intention to use MOOCs.

H2e: Level of education moderates the relationship between effort expectancy and behavior intention to use MOOCs.

H3e: Level of education moderates the relationship between social influence and behavior intention to use MOOCs.

H4e: Level of education moderates the relationship between motivation and behavior intention to use MOOCs.

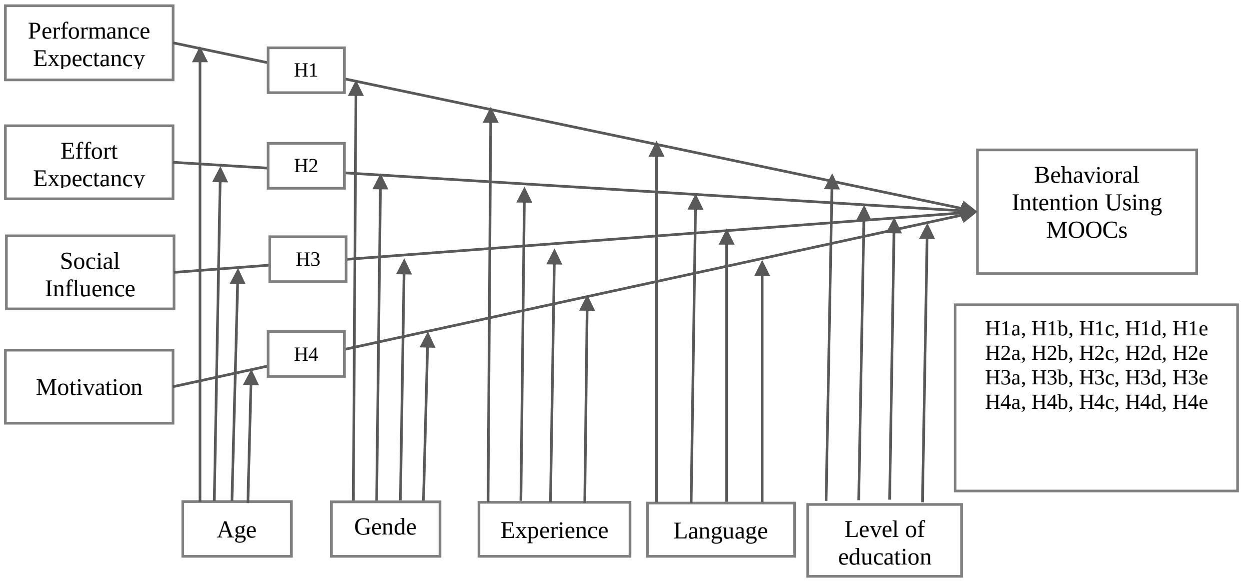

Fig. 1. Proposed Research Model

2. Methodology

Instrument Development

The research model included the above mentioned variables, each of which is measured with multiple items. To develop data validity, the items were adapted from the literature Straub, Boudreau, Gefen, 2004. The items have been revised to represent the MOOC environment and the possible outcome. The questions were reviewed by other researcher to ensure that they were relevant and understandable for respondents. The questions were updated in response to their feedback. The instrument was then validated with a pilot study. The instrument had strong validity, according to the results of an exploratory factor analysis.

Table 1. Model fit

	Saturated model	Estimated model
SRMR	0.071	0.072
d_ULS	2.687	2.705
d_G	0.737	0.734
Chi-square	2119.381	2100.068
NFI	0.744	0.747

Table 1 shows that that the Saturated model and the Estimated model have similar SRMR values (0.071 and 0.072, respectively), which indicates that there is a small difference between the two models. The goodness-of-fit statistics (d_ULS and d_G) are similar for both models, with the values being close to the recommended cut-off value of 2. The chi-square value of the estimated model (2100.068) is lower than the saturated model (2119.381), which indicates that the estimated model is a better fit for the data. The NFI (Normed Fit Index) value of the estimated model is higher (0.747) than that of the saturated model (0.744), indicating that the estimated model is a better representation of the data. Overall, the results suggest that the estimated model provides a good fit for the data and can be used to make inferences about the relationships among the variables in the model.

Table 2. Construct reliabiliry and validity – Overview

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Behavioral Intention Using MOOCs	0.889	0.891	0.924	0.753
Effort Expectancy	0.816	0.828	0.871	0.577
Motivation	0.89	0.891	0.919	0.694
Language	0.737	0.842	0.739	0.527
Performance Expectancy	0.862	0.863	0.901	0.645
Social Influence	0.758	0.775	0.838	0.514

The first column in Table 2 "Cronbach's alpha" is a commonly used measure of internal consistency. A value of 0.7 or above is considered to be good. In this table, all the values for the five constructs are above 0.7, which indicates a high level of internal consistency.

The second column, "Composite reliability (rho_a)," measures the reliability of a composite of multiple indicators. A value of 0.7 or above is considered to be good. In this table, all the values for the five constructs are above 0.7, which suggests that the composite indicators are reliable.

The third column, "Composite reliability (rho_c)," is another measure of composite reliability. Like rho_a, a value of 0.7 or above is considered good. All the values in this table are above 0.7, which indicates good reliability of the composite indicators.

The fourth column, "Average variance extracted (AVE)," is a measure of how much of the variance in a construct is explained by the indicators. A value of 0.5 or above is considered to be good. In this table, all the values for the five constructs are above 0.5, which indicates that the indicators are effectively capturing the variance in the constructs.

Overall, these results suggest that the five constructs are reliable and that the indicators used to measure them are capturing the variance in each construct effectively.

Table 3. Discriminal validity – Fornell – Lacker criterion

	Age	Behavioral Intention Using MOOCs	Effort Expectancy	Experience	Gender	Language	Level of Education	Motivation	Performance Expectancy	Social Influence
Age	1									
Behavioral Intention Using MOOCs	0.081	0.868								

Effort Expectancy	0.016	0.586	0.759							
Experience	-0.165	-0.36	-0.308	1						
Gender	-0.233	-0.07	-0.16	0.216	1					
Language	-0.042	0.273	0.196	-0.03	-0.061	0.654				
Level of Education	0.572	0.116	0.043	-0.052	-0.092	0.003	1			
Motivation	-0.02	0.657	0.647	-0.296	-0.133	0.357	0.024	0.833		
Performance Expectancy	-0.027	0.647	0.649	-0.289	-0.08	0.292	-0.007	0.726	0.803	
Social Influence	-0.004	0.456	0.422	-0.169	-0.127	0.402	0.011	0.543	0.459	0.717

This table presents the results of a discriminant validity analysis, which aims to assess whether the measures of different constructs are distinct from each other. The values in the table represent the correlation coefficients between the variables listed in the columns and rows.

According to the Fornell-Lacker criterion, discriminant validity is established if the average variance extracted (AVE) for each construct is greater than the square of the correlation between that construct and any other construct.

Measurement Instrument

Variables performance expectancy, effort expectancy, and social influence has been measured base on the UTAUT model developed by Venkatesh, Morris, Davis & Davids (Venkatesh et al., 2003) and the instrument developed by Davis (Davis, 1989). Questions have been adjusted for this study. UTAUT framework was tested on 215 respondents. So, this research should contain a sample of no less than 215.

Motivation would be measured using a specifically designed questionnaire of accessing motivation for online learning. It provides a more focused view on the Online learning enrolment intentions. The questionnaire includes five scales: intrinsic motivation, self-determination, self-efficacy, career motivation, and grade motivation. Self-determination indicates learners' beliefs about the control that they have over learning. The fifth scale was not included it is less relevant in the MOOCs environment of learning. "The reliability of the motivation questionnaire, determined by Cronbach's alpha, was 0.94. For each scale, Cronbach's alpha was: 0.73 for intrinsic motivation, 0.90 for self-determination, 0.90 for self-efficacy, and 0.94 for career motivation (Black, Deci, 2000)".

Data collection and analysis

For this study quantitatively data has been collected through 487 surveys. The population is people from Bosnia and Herzegovina with the main simple of high school and university students. While measuring variables 5-level scale has been used in such order: Strongly Agree; Agree; Neutral; Disagree; Strongly Disagree. Quantitative data is measured using SPSS software. Data screening and factor analysis was carried out in SPSS. Partial Least Squares (PLS) was used to perform structural model analysis. PLS was chosen because of the exploratory nature of this study.

3. Results

The demographics of this study were as follows. Gender, 44,1 % are male while 55.9 % are female. Ages 28.2 % participants are from 14-18 years old, 63.9 % are 19-25, 7.8 % 26 or older. The education level of respondents was 60 % high school. 28.7 bachelor degree and 22 % master degree, 0.8 % have a doctorate. Many MOOCs programs are in English so the participants were asked about the level of their English and 87 % responded that they understand English well to be able to follow an online course.

Hypotheses were tested using regression and analyzed by software SPSS. "Multiple regression is an extension of simple regression or bivariate because it allows two or more independent variables to be examined" (Vaughan, 2001). Through regression, we analyze all the variables together and we take into consideration interactions or overlaps of the independent variables. This method is often considered when it is needed to find out how much variance independent variable can be explained by the independent variables. Also, this is showing which independent variables is the best predictor of outcomes.

In the main model hypothesis H1–H4 were tested whether performance expectancy, effort expectancy, social influence, and motivation are affecting the behavioral intention of the user to use MOOCs. Positive influence represents a strong intention to use MOOCs and negative influence represents that those factors are not directly impacting the intention of users to use MOOCs.

Table 4. Regression Analyses – Impact of Independent Variables on Behavioural Intention

Model	R	R Square	Adjusted R Square	Std. An error of the Estimate	Change Statistics					
					R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.713[a]	.508	.504	.61714	.508	124.644	4	482	.000	2.066
a. Predictors: (Constant), Performance Expectancy, Social Influence, Effort Expectancy, Motivation										
b. Dependent Variable: Behavioural Intention										

From Table 4, we can see the estimated change in the dependent variable for a unit change of the independent variables, R = .713. Following is the coefficient of determination R^2 = .508 that represents as the Hear et al. (2013) explained "measure of the proportion of the variance of the dependent variable about it mean that is explained by the independent variables". The adjusted coefficient of determination (adjusted R2 = .504) will be used in the comparison of the two models proposed. That is telling us that 50.4 % of the variance and the dependent variable are explained by the independent variable. The standard Error of the Estimate is .61714. Durbin-Watson is 2.066 that indicate the level of autocorrelation which is acceptable.

Table 5. Analyses of Variance

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	189.889	4	47.472	124.644	.000[b]
	Residual	183.576	482	.381		
	Total	373.465	486			

a. Dependent Variable: Behavioural Intention

b. Predictors: (Constant), Performance Expectancy, Social Influence, Effort Expectancy, Motivation

In Table 5, we can see the standard error of the estimate that represents an estimate of the standard derivation of the actual dependent values around the regression line. Findings of the main model are significant and also F rate is presented which is 124.644.

Table 6. Regression Analyses Loadings

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.684	.160		4.269	.000		
	Social Influence	.105	.040	.100	2.639	.009	.704	1.420
	Motivation	.286	.050	.292	5.689	.000	.386	2.588
	Effort Expectancy	.193	.052	.163	3.698	.000	.522	1.914
	Performance Expectancy	.314	.055	.280	5.695	.000	.421	2.373

a. Dependent Variable: Behavioural Intention

The results presented in Table 6 show that hypothesis H1, H2, H3, H4 are supported. Performance expectancy (β = 0.314), effort expectancy β = 0.193, social influence (β = 0.105), and motivation (β = 0.286) influence behavioural intention to use the MOOCs. They are strongly significant with the level 0.01.

In the full model, we have the main hypotheses as well as moderators. As presented in Figure 2 secondary hypotheses represent moderators in this relationship. They are factors that potentially influence the existing relationship. Those factors are age, gender, experience, language, level of education.

In Table 7 we can see that the estimated change in the dependent variable for a unit change of the independent variables, R = .741 is higher than in the main model. We can also see the higher level of coefficient of determination (R^2 = .549) in the full model than in the main model and it represents that the dependent variable is better explained by the independent variables in the full model. Adjusted R Square is a just little bit higher than in our main model. If we look at the table and explanations in headings that follow the table, we can see which variables moderate the mentioned relationship. We can see the standard error of the estimate as well the significance level and F ratio of the full model.

Table 7. Regression Analyses – Relation between the dependent variable and independent variable with the moderating effect

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.741[a]	.549	.525	.60405

a. Predictors: (Constant), Moderator4e, Performance Expectancy, Moderator3d, Moderator3b, Moderator3c, Moderator2a, Moderator3a, Moderator2b, Social Influence, Moderator2c, Moderator1d, Moderator1c, Moderator3e, Moderator1a, Effort Expectancy, Moderator1b, Moderator2e, Moderator2d, Moderator4b, Motivation, Moderator4c, Moderator4d, Moderator1e, Moderator4a

Table 8 shows the standard error of the estimate, significance level as well as F radio of full model.

Table 8. The standard error of the estimate, significance level as well as F radio of full model

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	204.890	24	8.537	23.397	.000[b]
	Residual	168.575	462	.365		
	Total	373.465	486			

a. Dependent Variable: Behavioral Intention

b. Predictors: (Constant), Moderator4e, Performance Expectancy, Moderator3d, Moderator3b, Moderator3c, Moderator2a, Moderator3a, Moderator2b, Social Influence, Moderator2c, Moderator1d, Moderator1c, Moderator3e, Moderator1a, Effort Expectancy, Moderator1b, Moderator2e, Moderator2d, Moderator4b, Motivation, Moderator4c, Moderator4d, Moderator1e, Moderator4a

Table 9. Regression Analyses – Loadings

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.724	.171		4.227	.000
	Performance Expectancy	.283	.056	.252	5.029	.000
	Effort Expectancy	.209	.055	.177	3.821	.000
	Social Influence	.131	.040	.125	3.267	.001
	Motivation	.272	.052	.278	5.253	.000
	Moderator1a	-.031	.054	-.034	-.561	.575
	Moderator1b	-.044	.044	-.049	-.990	.323
	Moderator1c	-.099	.047	-.106	-2.137	.033
	Moderator1d	-.073	.042	-.091	-1.738	.083
	Moderator1e	.031	.057	.035	.554	.580
	Moderator2a	-.103	.049	-.107	-2.108	.036
	Moderator2b	-.048	.041	-.053	-1.180	.239
	Moderator2c	.050	.041	.052	1.208	.228

	Moderator2d	.014	.038	.018	.364	.716
	Moderator2e	.122	.049	.135	2.508	.012
	Moderator3a	-.025	.042	-.028	-.598	.550
	Moderator3b	.013	.036	.015	.370	.711
	Moderator3c	.004	.037	.004	.101	.920
	Moderator3d	.021	.033	.029	.643	.521
	Moderator3e	.028	.039	.033	.718	.473
	Moderator4a	.136	.061	.145	2.240	.026
	Moderator4b	.040	.048	.044	.831	.406
	Moderator4c	.042	.048	.046	.882	.378
	Moderator4d	-.071	.044	-.090	-1.595	.111
	Moderator4e	-.186	.064	-.191	-2.919	.004
a. Dependent Variable: Behavioural Intention						

Considering the results presented in Table 9. We can see that this factor moderates the relationship between effort expectancy and behavioural intention to use MOOCs as well as the relationship between motivation and behavioural intention to use MOOCs. It does not infect other relationships. We can conclude that we accept H2a and H4a as a secondary hypothesis another hypothesis (H1a, H3a) is not confirmed.

If we look at the relationship between the independent and dependent variables in Table 9 we will see that gender does not moderate any relationship. Thus, all secondary hypotheses that gender influence the relationship between performance expectancy, effort expectancy, social influence, and motivation on the behavioural intention of users to use MOOCs (H1b, H2b, H3b, H4b) are not confirmed.

When it comes to the factor of how experience influences the relationship between variables as it can be seen from Table 9 we can confirm secondary hypothesis H1c but there is no significant moderating effect of these factors on the relationship between effort expectancy, social influence, and motivation (H2c, H3c, H4c).

Language does not moderate any relationship. All secondary hypotheses (H1d, H2d, H3d, H4d) are not confirmed.

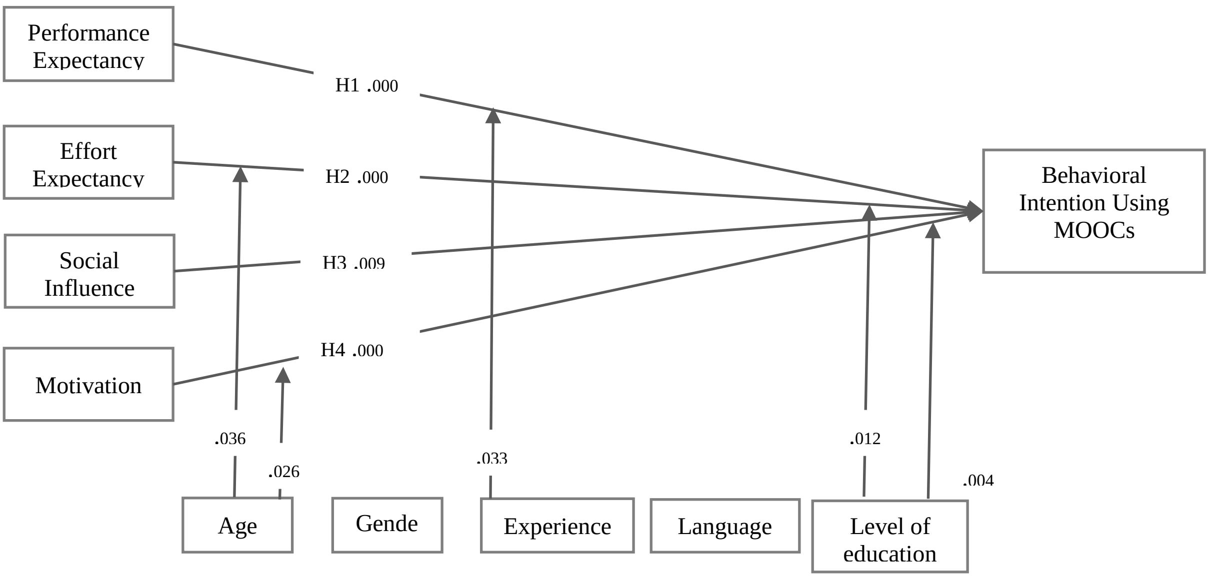

Fig. 2. Loading of the individuals

Considering Table 9 level of education as a secondary hypothesis influences the relationship between effort expectancy and behavioural intention of using MOOCs at 0.05 (H2e), and also a relationship between motivation and level of education .004 (H4e). Thus, other secondary hypotheses (H1e, H2e, H3e, and H4e) are not confirmed.

Once all results are obtained and diagnostic analyses are performed to ensure that the overall model meets the regression assumptions and that no observations have undue influence on the results. Several assumptions about the relationship between the dependent and independent variables that affect the statistical procedure used for multiple regression are made. Assumptions were examined in four areas:

1. Normality of the error term distribution
2. The linearity of the phenomenon measured
3. Homoscedasticity

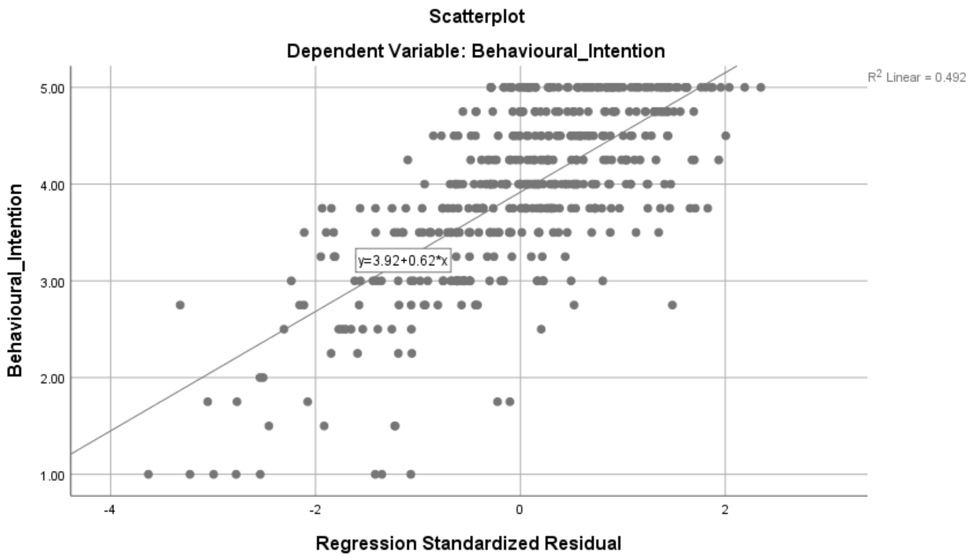

Fig. 3. Homoscedasticity

On Figure 3 we can see a consistent pattern which means that we have homoscedasticity.

Table 10. Multicollinearity

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	Performance Expectancy	.421	2.373
	Effort Expectancy	.522	1.914
	Social Influence	.704	1.420
	Motivation	.386	2.588
a. Dependent Variable: Behavioral Intention			

We can see from the Table 10 that Variable Inflation Factor are less than 3 and all tolerance values are higher than 0.10 this indicates that there are no multicollinearity issues. O'brien (2007) explained that values which are strong indicators of multicollinearity issues are less than 0.10.

All performed analyses showed that the overall model meets the regression assumptions

4. Discussion

E-Learning is still changing and evolving. It still has not reached its full potential but it is on the right way to bring crucial changes in education and our perception of education. This evolution was led by the institutions such as Cambridge, MIT, Harvard, and soon many other colleges aspired to provide MOOCs as part of their campus offerings. Unlike some popular platforms whose materials are not always available for reproduction. MOOCs are re-usable material developed by teachers and educators (Yuan, Powell, 2013). One of the main purposes of this research was to get a proper understanding of the MOOC phenomenon and to examine what factors would help Bosnians to learn more online. Data showed that 48.7 % of people had never finished an online course. This study helps us understand the factors which can improve this statistic. MOOC attendance after enrolment, as well as course completion, has been widely criticized (Porter, 2015). Coursera and EdX, two of the most popular MOOC sites, have typical completion rates of less than 13 % of those who registered for the course prior to its launch. The completion rates of some MOOCs are as poor as 4 % or 5 % (Jordan, 2014).The intention of Acceptance of MOOCs is influenced by a number of factors, including performance expectations, effort expectations, social impact, and motivation, which were all studied variables. MOOC use is also affected by the users' age, gender, experience, language barriers, and level of education, according to the report. The first study variable performance expectancy is significant at level 0.01; therefore it is affecting behavioural intention to use the MOOCs. The degree to which a person believes that using the MOOCs would enhance his or her job performance is an important factor in deciding to use MOOCs. The study results authenticate those of (Dečman, 2015; Wang et al., 2009; Pynoo et al., 2011), who found that success expectancy has a major impact on usage intention. This demonstrates that students believe that regular participation in the MOOC will improve their academic performance.The effort expectancy (easy of usage) has a positive influence on the behavioural intention of users to use MOOCs. We accept this hypothesis at the level of 0.01, which is highly significant. This may be because students value the MOOC's utility and learning over the effort required to complete it. Learning is seen as an activity that needs effort, as opposed to conventional technology systems that are mostly built to increase efficiencies and therefore reduce effort. This result is in the line with (Wang et al., 2009) who indicates that effort expectancy had a significant influence on individual intention to use m-learning. This means that the majority of users think m-learning systems should be easy to use. Juinn and Tan (Tan, 2013) also reported that the facilitating conditions have a significant influence on MOOC usage. As a result, these universities must have the required structures and resources to encourage students to use MOOCs.The study investigates the social influence factors on MOOC acceptance and it has been confirmed to have a positive impact on the behavioural intentions of students. It means social interaction accepting the MOOCs is very important. Hypothesis H3 has been confirmed at a significant level of .01. Bosnia is a high context culture so social segments can contribute to better MOOC adoption. Students like to study with their peers and they care what society thing about them. The finding relating to perceived competence is in line with the hypothesis that any student's competence is vital for the development of behavioural intentions. It can be concluded that students are influenced to use new online technology if their peers, colleagues, friends, relatives, and others are using it. Wung et al., reported that Social influence have a major impact on m-learning user intentions. The role of social factors should be recognized by M-learning practitioners and educators. Users can begin to persuade their colleagues and friends to adopt an m-learning system once they have become familiar with it. As a result, m-learning educators will encourage m-learning to potential early adopters, who are more likely than others to have a high degree of personal innovation in IT (Agarwal, 1998). Further, this study has confirmed that motivation impacts behavioural intention to use MOOCs. This hypothesis is accepted at a significant level at 0.01. Motivation to participate in MOOCs learning is crucial from the fact that this type of studying is not obligatory and it depends on any person to commit time and energy to search for the knowledge. Motivation is one of the most important factors that can prevent a student from completing MOOCs (Yuan et al., 2018). We have confirmed all four main hypotheses, besides them, we had secondary hypotheses (Age, Gender, Experience, Language, and Level of education). An assumption has been made that those 5 factors would moderate the relationship with the main model and the main variables. Previous research explained that the intention of students to use MOOCs is influenced by attitude, enjoyment, usefulness, and subjective norm (Nawal, 2012). It has been confirmed that performance expectancy, effort expectancy, social influence, and motivation all those factors are influencing the intention of users to use MOOCs. In secondary hypotheses, age is moderating the relationship between effort expectancy and behavioural intention also between motivation and behavioural intention. Experience in moderating the relationship between performance expectancy and behavioural intention. At last but not least level of education is moderating relationships between performance expectancy and behavioural intention as well as the relationship between motivation and behavioural intention. Similar findings were reported by (Wang et al., 2009). If the user believes that the system is useful, he or she will be interested in learning using MOOCs. David, Bagozzi, & Warshaw (David et al., 1992) were also using this factor trying to access to whether users might be willing to spend time and effort learning a new interface to be able to perform needed functions. So, if the students see the usefulness of e-learning, the acceptance of using it is increasing. Language does not moderate any relationship. This research has proved that 80% of the respondents do not have a problem with the following courses in the English language. This emphasizes the importance of MOOC designers to ensuring that MOOCs are of high quality. It can do so by ensuring that the site launches quickly, is simple to use, navigate, and visually appealing, and that easy access and interactive technologies are used. These results point to additional variables that could be investigated further through further research with MOOC participants. In addition, more in-depth qualitative research is recommended for identifying emerging problems that impact learner intention to use MOOCs.

5. Conclusion

MOOCs provide new opportunities and creativity in education by allowing institutions and scholars to explore new online learning models and emerging approaches in teaching and learning at a national and international level by making learning more open, versatile, affordable, and free or low-cost to learners who are interested in learning.This research provides an understanding of MOOCs in Bosnia and Herzegovina with a view to identify the factors affecting MOOCs users' intention to use MOOCs. The findings show that performance expectations and device efficiency influence MOOC use intention. Facilitating environments, educational consistency, and MOOC user intention all influence MOOC uses. MOOC use intention was found to be significantly influenced by social influence and effort expectations, and this research also indicated that motivation influences behavioural intention to use MOOCs.The study Finally find that the universities should implement programs and resources to enable students to participate in MOOCs at all stages of education. Technical professional development should be included in the curriculum. MOOC designers should use the best teaching techniques, as well as ensuring that the sites and learning materials are of excellent quality, to ensure that MOOCs provide appropriate learning.

This research is bringing the theories about the factors that influence the behavioural intention of using online courses. It also discovered many other topics and problems where the next researchers can focus. It can be a base for many upcoming theories about e-learning in Bosnia and Herzegovina. This research showed a factor that influences students and their intention to use MOOCs but before they can have any intention, they need to be educated that they can update their knowledge using MOOCs. Conducting this study just quantity data have been used for this research, it can be extended by qualitative data. Adding focus groups. The fact that can help to obtain a wide range of options is running focus groups with university staff and students. Another reason is a time limitation, longer research would have a bigger amount of data, and with that more accurate findings.

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