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PARTICIPATION IN MASSIVE OPEN ONLINE COURSES: THE EFFECT OF LEARNER MOTIVATION AND ENGAGEMENT ON ACHIEVEMENT

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PARTICIPATION IN MASSIVE OPEN ONLINE COURSES: THE EFFECT OF LEARNER MOTIVATION AND ENGAGEMENT ON ACHIEVEMENT[2]

Massive open online courses (MOOCs) are a relatively new format of distance education which has become popular among students, faculties, employees and others. Regardless of the fact that MOOCs are a widespread phenomenon, they face some challenges including high dropout rates, low levels of student-teacher interaction, low representation of poor and less educated learners, issues with data processing and data analysis for creating predictive models. In our study, we look more closely at the last issue, while creating a model describing the relationship between the motivation, engagement, and achievement of MOOC participants. We use a database which consists of trace data and survey data from students of 20 online courses launched on the Coursera platform in 2014–2015 at the Higher School of Economics. Our research shows that for modelling the relationship between factors and achievement of MOOC students, it is necessary to transform the interval dependent variable into an ordinal one. To evaluate the relationship between motivation, engagement, and achievement, we used mediation analysis with ordinal logistic regression. The research shows that academic motivation of MOOC learners has an indirect effect on their achievement. The level of engagement acts as a mediator of this relationship. At the same time, intrinsic motivation plays an alternative role in the MOOC format compared to a traditional course format. Intrinsic motivation decreases the likelihood of getting a higher score from the second week of the course.

Keywords: MOOC, Coursera, motivation, intrinsic motivation, engagement, achievement
JEL codes: I21, I29

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Introduction

Modern higher education is becoming more accessible because of the spread of massive open online courses (MOOCs). This is a relatively new format of distance education, whose characteristics arise from its definition: it is open to everyone, free, massive and offered by universities through online platform such as Coursera, edX, Udacity. MOOCs have become not only a means to personal development but also the equivalent of full-time courses. Some universities offer students the opportunity to replace some offline courses with online ones taught by professors of other institutions. According to Babson Survey Research Group, 28% of American students took at least one online course in 2014. Moreover, the share of students who participated in online learning has increased by 19% since 2002[3].

Regardless of the fact that MOOCs are a widespread phenomenon, they face some challenges. The first issue is high dropout rate among registered learners [Ramesh et al., 2013; Kolowich, 2013; Parr C., 2013; Jordan 2014]. Studies show that the probability of successful completion of the course is affected by student characteristics, course parameters and the platform on which the course is offered [see for example, Adamopoulos, 2013; Dillahunt et al., 2014]. The second issue is the massive participation in MOOCs, which results in the low involvement of teachers and their assistants in communication with learners. Moreover, this communication may be hindered by the differences among registered participants [Daradoumis et. al., 2013]. Other issues are connected with the relatively high price for creating a MOOC [Morrison, 2014] and low representation of poorer, less educated participants in the body of MOOC students [Schmid et. al., 2015]. Despite official declarations by the heads of the large online platforms that MOOCs give the opportunity for such groups of people to get access to higher education [Koller, 2012], in fact it turns out that MOOCs are mostly used by those who have at least a bachelor's degree. Another issue is connected with data processing and data analysis for creating predictive models. While researchers have access to big data, including all the information about student activity on the platform, they run into some difficulties working with such data. The first problem is related to what type of data researchers use for creating their models. For instance, if only trace data is used, then some characteristics of registered students (such as motivation, background, socio-economic status) are not taken into account, reducing the predictive power of the models. If researchers employ either data from forum activity or survey data then results of the study are restricted by sample. Another issue is that the distribution of the quantitative dependent variable (for example, number of posts in the forum discussion or grade) is not similar to any known density. This distribution is strongly skewed to the left because of the prevalence of zero scores [Lamb et al., 2015]. This distribution is caused by the fact that the

[3] Official website of Research Group: http://www.onlinelearningsurvey.com/

majority of participants do not demonstrate any activity after registering for the course. To solve this problem it is possible to employ Poisson regressions, but in most cases, it is not appropriate since there is also a significant proportion of students who are distinguished by high activity and get high grade at the end of the course.

In studies to find predictors of the achievement of MOOC students, the overrepresentation of zero values within distribution of the dependent variable has to be dealt with. In our research, we look more closely at this problem and show how to overcome it. Another focus of our research is to estimate the effect of motivation of MOOC participants on their achievement, controlling for the level of engagement. Studies of the traditional course format show that student achievement is the result of psychological characteristics, intelligence, self-control, self-efficacy, insistence, metacognitive skills, learning strategies, and academic motivation [Komarraju et al., 2009; Pintrich, De Groot, 2009; Lepper et al., 2005; Vallerand, Bissonnette, 1992]. Students with extrinsic motivation get lower grades compared to students with intrinsic motivation who use meaningful learning strategies, demonstrate more insistence in their studying, and try to solve more difficult tasks [Vallerand, Bissonnette, 1992; Goldberg, Cornell, 1998; Mitchell, 1992]. Moreover, meta-analysis of the effect of external rewards on intrinsic motivation has shown a strong and stable negative effect [Deci et al., 1998]. However, after controlling for such parameters as cognitive engagement, self-efficacy and self-regulation, academic motivation ceases to have a direct impact on achievement [Pintrich, De Groot, 2009].

Findings of research on the MOOC format have demonstrated a significant correlation between achievement and some individual student characteristics and a relationship between achievement and student activity. A lack of willingness, self-direction and self-discipline were critical factors that impacted student success in MOOCs [Chang et al., 2015]. Phan et al. [2016] showed that learners whose reasons for registration for the course were earning a certificate, gaining skills, and improving professional practice have more chance of completing the course successfully. However, a significant correlation between learner performance and motivation for enrolment was not found in an earlier work [Breslow, 2013]. Furthermore, the majority of studies of MOOCs have shown a significant impact of learner activity on their achievement. The main factors of engagement, which correlate with the total score, are overall time spent on the learning process [Xu, Yang, 2016], cumulative time spent watching videos [Balakrishnan, Coetzee, 2013; Qiu et al., 2016], time spent on assignments [Qiu et al., 2016], the average quiz score in week 1 and assignment performance in week 1 [Jiang et al., 2014]. Some researchers construct an index of activity based on general information about student interaction with course resources. For example, a quantitative “Information Processing Index” (IPI) was created by

Sinha et al. [2014] by operationalizing video watching. It was shown that students who rewatch videos and watch a larger proportion of them are less likely to dropout.

The majority of MOOC studies focus on determining the influence of motivation or engagement on achievement. In our research, we evaluate what kind of effect motivation has on achievement controlling for the level of engagement. In other words, we show whether motivation has a direct influence on achievement or whether engagement acts as a mediator of this relationship. Moreover, we define whether intrinsic motivation plays the same role in MOOCs as in traditional classes (i.e. whether students with intrinsic motivation get higher grades compared to students with extrinsic motivation). Our study has two research focuses: the first one is solving the problem of distribution of MOOC students' grades, the second is estimating the impact of motivation on achievement controlling for the level of engagement. The findings show, first, what method should be used to overcome the problem of the distribution of interval dependent variable (in our case achievement), and second, whether academic motivation has the same effect on achievement in MOOCs and traditional course format. We use a database which includes trace data and survey data from students of 20 online courses, launched on Coursera in 2014–2015 at the Higher School of Economics (HSE). The majority of courses are devoted to economics, but there are some social science, humanities and math-intensive courses.

Theoretical model

There are several theoretical models simulating the student learning process, and showing the factors of dropout and success in class [see, for example, Tinto, 1975; Bean, Metzner, 1985; Carroll, 1989]. We use the theoretical model of Rovai [2003] which combines the essential elements of the Tinto, and Bean and Metzner frames, and is devoted to the online learning process. The Rovai model includes four groups of elements, where two groups are input student characteristics (for example, socio-demographic characteristics, educational background, time management skills, skills for computer-based interaction), and two groups are related to the learning process and indicate the external and internal factors of participation (for example, academic and social integration, learning and institutional commitment, student needs, level of satisfaction and stress). We use a shortened version of the Rovai model, because we had no data concerning external factors (information about finances, family responsibilities, hours of employment etc.), student skills, and student needs. Moreover, we exclude from our research model factors of academic and social integration to avoid reducing our research sample to those who participated in the forum discussion. We concentrate our model on individual student characteristics and such internal factors of learning process as the level of engagement (see Figure 1).

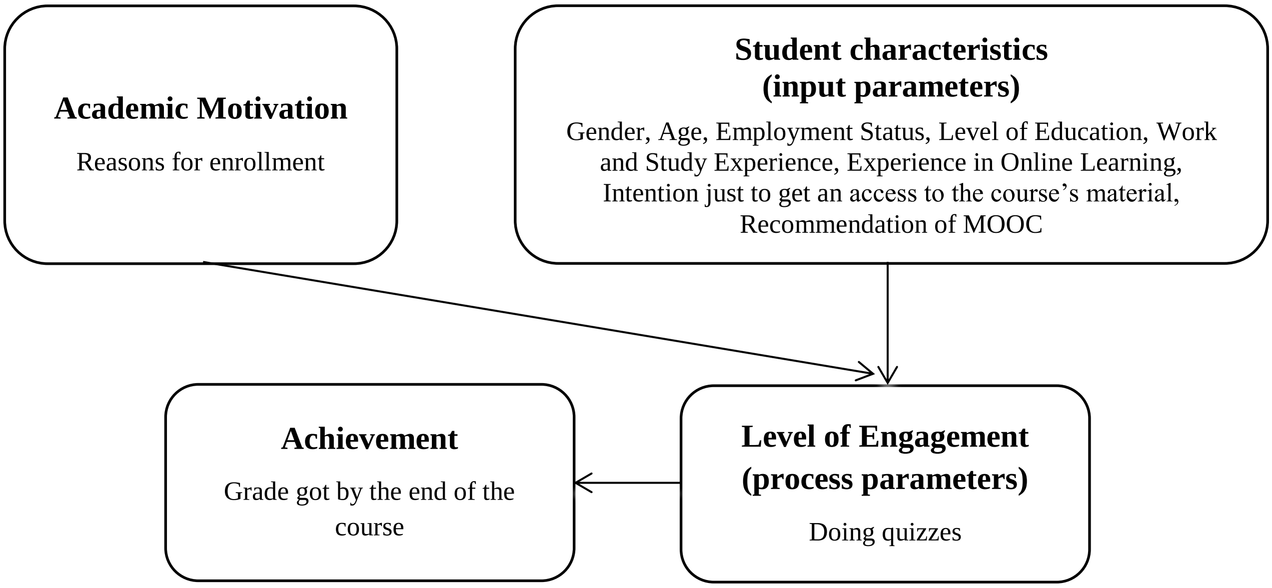

Figure 1 – Theoretical model of research

We assume that the achievement of MOOC students depends on their individual characteristics, academic motivation and level of engagement. However, we assume that academic motivation of MOOC students has an indirect effect on their achievement as has been shown in studies of the traditional course format. We test our theoretical model using regression analysis.

Distribution of dependent variable and method to deal with it

Before employing regression analysis we looked at the distribution of our dependent variable which is the final grade. The second figure shows that the majority of participants got zero (74% of students from 20 online courses). The distribution of grades including zero is not similar to any known distribution. Therefore we excluded all zero values to find out whether the distribution looks more like any known distributions. Zero values can be either an indicator of a lack of any activity during the course (so called "structural zero" [Lamb et al., 2015]), or the inability of the student to complete any tasks successfully. In our case, we consider the zero value as structural and exclude it from further analysis. The third figure shows that we still have a deal with a distribution which is strongly skewed to the left and has some rise to the right. Figures 2 and 3 show distribution of grades among all students of 20 online courses at HSE on Coursera[4].

[4] Our general population includes 391 882 participants

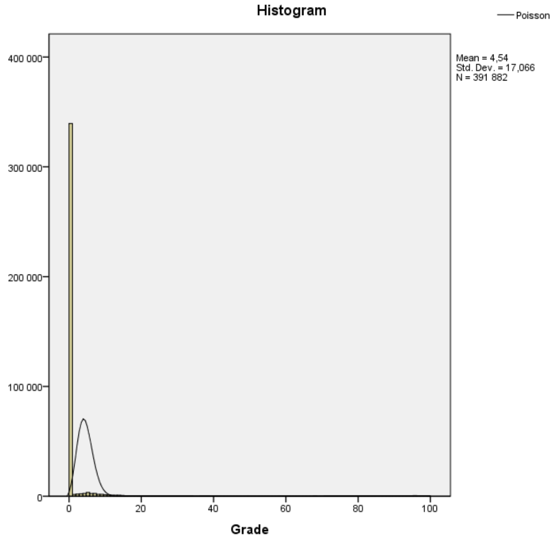

Figure 2 – Distribution of final grades got by MOOC students including zero values

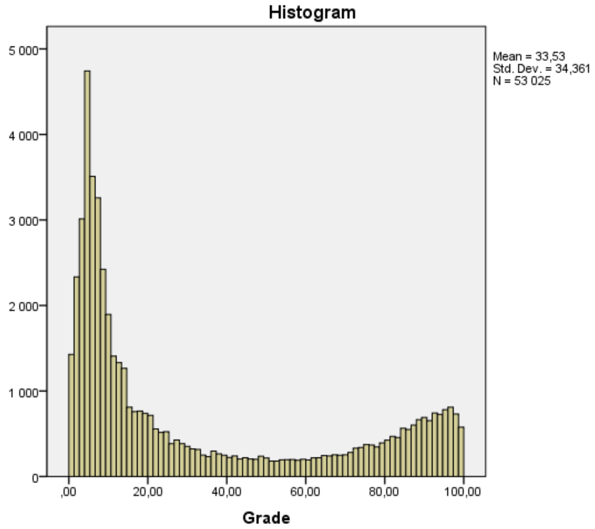

Figure 3 – Distribution of final grades got by MOOC students without zero values

However, since our second research goal is to determine the effect of motivation on achievement controlling for the level of engagement we limited the general population to the sample of those students who participated in surveys (because we derived information about academic motivation from survey data). The surveys were conducted before the start of each online course. The same questionnaire was sent to each student registered for any of the 20 courses. It included questions about motives for enrolment, educational background, socio-demographic characteristics, and employment status. The sample was 19 720 MOOC students who completed the survey. Figure 4 shows that the distribution of grades among participants of survey remains the same: it is skewed to the left and has a rise to the right.

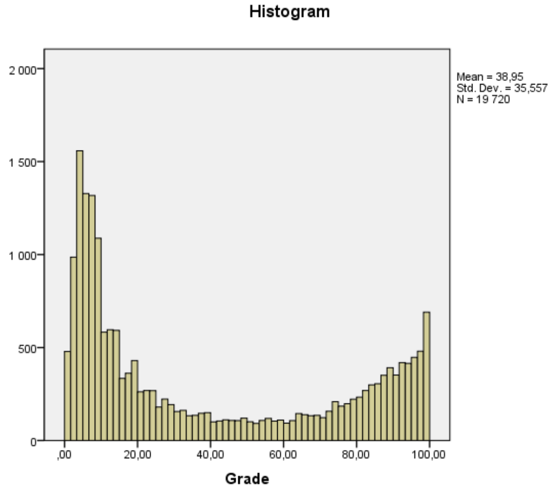

Figure 4 – Distribution of final grades got by MOOC students without zero values who completed the survey

To deal with the problem of the distribution of the interval dependent variable we transformed it into an ordinal one marking out 3 categories: a grade lower than 20 points, a grade between 20 points and 80 points, and a grade higher than 80 points. This division catches the grade variation. Thus, we replace the interval dependent variable with an ordinal one, and exclude students who got a zero grade considering it a structural zero.

Data and methods of analysis

In order to determine whether engagement can be a mediator of the relationship between motivation and achievement we need to perform several steps of mediation analysis with ordinal logistic regressions which are indicated in Figure 5 [MacKinnon, 2008]. The first step is to determine the influence of the independent variable (motivation) on the dependent variable (achievement). The second step is to find the relationship between the independent variable and the mediator (engagement) which may mediate the relation between dependent and independent variables. The last step is to include in the model the dependent variable, the independent variable and the mediator. If the coefficient of independent variable falls but remains statistically significant, then the model demonstrates partial mediation. If the coefficient is not statistically significant, then the model demonstrates full mediation. At the last step, we include student characteristics (socio-demographics characteristics, educational background, experience in online learning[5]) in the model.

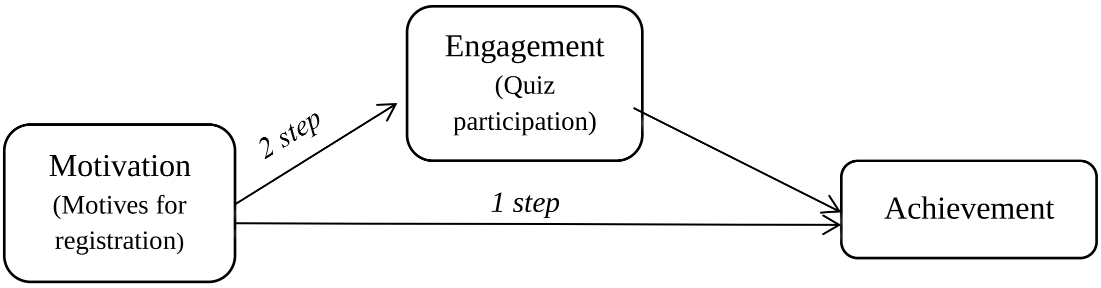

Figure 5 – Steps of mediation analysis

To measure the motivation of MOOC students a question about the reasons for registration for the course was used. The question about motives was included in the questionnaire of pre-surveys. An index of motivation was constructed on the basis of this question according to the methodology proposed in [Vallerand, Bissonnette, 1992; Grolnick, Ryan, 1987; Ryan, Connell, 1989]. A specific weight reflecting the degree of frustration of autonomy need was assigned for each type of motives. A positive index value captures the extent of intrinsic motivation, and a negative index value indicates the extent of extrinsic motivation.

[5] Indicators of student characteristics which we include in analysis are listed in Figure 1.

The average value of the motivation index is 4, which means that the MOOC students in the research sample registered for the course for the sake of interest and some external reasons (standard deviation is 2.7). We measure participant motivation before the course. We do not have the appropriate data to measure their motivation during the course.

To measure the level of engagement we used trace data about quiz participation. The choice of this parameter is based on the fact that quiz participation can be a good indicator of the level of student activity during the course as it shows their intention to complete the course successfully. For example, if participants watch online lectures we cannot define whether they have such an intention. However, if participants do quizzes, it indicates that they want to follow the course schedule and to get a grade. Our variable "quiz participation" is dummy one so the correlation between grades in quizzes and achievement does not equal 1. The score for each quiz was transformed into the dummy variable, and we used five dummy variables for "quiz participation" which indicate participation in half of the quizzes. The majority of MOOC students in the sample did the quiz in the first week (93%) and the quiz in second week (65%). There is also decline in the proportion of students who did quizzes during the course. For example, 38% of students did quiz in the fifth course week.

We used the ordinal variable as an indicator of achievement described above. In our research sample, 56% of MOOC students got a grade below 20 points, and 20% got a grade higher than 80 points.

Student characteristics were derived from survey data. In the sample, the average age of MOOC students is 31 (standard deviation is 10). 45% of students are female. 97% of students work or study at universities, and have a bachelor's or master's degree (45% and 29% respectively). Half of students do not have study experience in the field of study, and 75% do not have work experience in the field of study. 62% of students have experience in online learning. 87% of MOOC students in our sample did not register just to get access to the course material and 79% registered for the course without any recommendation. 97% of students did not buy a Signature Track[6]. More information about variables is presented in Table 1.

Table 1. Information about variables of the research model

Names of variables	Information about variables
Group_achievement	Ordinal variable with 3 categories [0 –student, who got a grade lower than 20 points, 1 – student, who got a grade higher than 20 points and lower than 80 points, 2 – student, who got a grade higher than 80 points]
Index of motivation	Interval variable from -9 to 9, where «-9» is a great extent of extrinsic motivation and «9» is a great extent of intrinsic motivation
Fact quiz1, fact	Dummy variables with 2 categories [0 – student didn't do quiz of the

[6] A Signature Track is a Certificate of course completion which proves learning via Coursera

quiz2, fact quiz3, fact quiz4, fact quiz5	first/second/third/fourth/fifth weeks of the course, 1 – student did quiz of the first/second/third/fourth/fifth weeks of the course]
Age	Interval variable
Gender Male	Dummy variable with 2 categories [0 – female, 1 – male]
Work, study	Dummy variable with 2 categories [0 – student doesn't work or study, 1 – student works or/and studies]
Education	Ordinal variable with 7 categories [1 – student doesn't complete 9 grades, 2 – student has compulsory education, 3 – student has complete general education, 4 – student has initial/secondary professional education (college), 5 – student has bachelor's degree, 6 – student has master's degree, 7 – student has higher education and science degree]
Study experience	Dummy variable with 3 categories [1 – student doesn't have a study experience in the field of study, 2 – student is self-studied in the field of study, 3 – student has a diploma or certificate in the field of study]
Work experience	Dummy variable with 3 categories [1 – student doesn't have a work experience in the field of study, 2 – student has a short term work experience in the field of study, 3 – student has a long term work experience in the field of study]
Experience in MOOC	Dummy variable with 2 categories [0 – student doesn't have an experience in online learning, 1 – student has an experience in online learning]
In Signature Track	Dummy variable with 2 categories [0 – student didn't buy a Signature Track, 1 – student bought a Signature Track]
Intention	Dummy variable with 2 categories [0 – student doesn't have the intention to get an access to the course's material without completing the course to get a certificate, 1 – student has the intention to get an access to the course's material without completing the course to get a certificate]
Recommendation	Dummy variable with 2 categories [0 – nobody recommended to take part in this course, 1 –somebody recommended to take part in this course]

Results

At the first step of our analysis we examined the relationship between motivation and achievement. There is a statistically significant relation between the two variables. Thus, the odds of getting a higher grade (being entered for a higher group) decrease by 0.98 for each unit increase in the motivation index. However, although the model shows well goodness of fit and is better than the model with intercept, it can explain just 0.01% of the variation of the dependent variable.

If we conduct the same analysis using a sample with participants who got a zero score and higher, then we find that the model has bad goodness of fit and it is even worse than the model with intercept. Therefore we exclude participants with zero scores from the sample.

At the second step, we examined the relationship between motivation and the mediator, employing logistic regressions (because our dependent variable has two categories). The results of all five models show a statistically significant relation between the two variables. At the same time, if intrinsic motivation has a positive effect on the participation in the first quiz then, in all other cases, it has a negative effect.

Since the relation between the independent variable and the mediator is statistically significant as does the relation between the independent and dependent variables, we conducted mediation analysis. We included in our model the index of motivation, the mediator, and individual characteristics of students, such as age, gender, employment status, educational background, work and study experience.

The model shows that simultaneously including the mediator and the independent variable in one equation leads the independent variable (motivation) to lose its significance. Thus, the motivation of MOOC students has an indirect effect on achievement, and the level of engagement acts as a mediator. Participation in quizzes leads to increased odds of getting a higher grade. Moreover, the model shows a statistically significant causal relationship between achievement and such student characteristics as gender, educational background, study experience and experience in online learning, and intention to complete the course successfully (see Table 2). Experience in MOOCs, a lack of or brief study experience in the field of course, the purchase of a Signature Track, and lack of intention to just get access to the course material increase the odds of getting a higher grade. Whereas, a level of education which is lower than a bachelor's and master’s degree, decreases odds of getting a higher grade. There were some curious results about the relation between study experience and achievement. In some research it has been shown that students who have previous course experience and subject knowledge have more chance of completing the course successfully [Phan et al., 2016; Waite et al., 2013; Breslow, 2013]. In our case, we found the opposite. It can be assumed that students who have a certificate or a degree in the field of the online course may be less interested in successfully completing the course, because they have already the formal conformation of their knowledge. Nevertheless, students with higher education and online learning experience are better prepared to learn and acquire information by means of an online course.

Table 2. Coefficients of ordinal logistic regression model

		Coefficient	SE	Wald	df	Sig.	Exp
Threshold	Group_achievement [1]	-4.128	0.199	430.409	1	<0.001	0,016
	Group_achievement [2]	-1.124	0.193	34.056	1	<0.001	0,325
	Index of motivation	0.005	0.008	0.444	1	0.505	1,005
	Fact quiz1 [0]	-0.346	0.169	4.198	1	*0.040*	*0,708*
	Fact quiz2 [0]	-1.252	0.111	126.746	1	*<0.001*	*0,286*
	Fact quiz3 [0]	-1.839	0.084	482.497	1	*<0.001*	*0,159*
	Fact quiz4 [0]	-1.575	0.064	605.662	1	*<0.001*	*0,207*
	Fact quiz5 [0]	-2.376	0.064	1360.754	1	*<0.001*	*0,093*
Control variables	Age	0.001	0.002	0.092	1	0.762	1,001
	Intention [0]	0.143	0.070	4.155	1	*0.042*	*1,154*
	Gender Male [0]	-0.124	0.043	8.444	1	*0.004*	*0,883*
	Work, study [0]	0.040	0.122	0.106	1	0.745	1,041
	Recommendation [0]	-0.060	0.053	1.296	1	0.255	0,942
	Education [1]	-1.158	0.370	9.788	1	*0.002*	*0,314*
	Education [2]	-0.853	0.222	14.749	1	*<0.001*	*0,426*
	Education [3]	-0.427	0.104	16.946	1	*<0.001*	*0,652*
	Education [4]	-0.578	0.127	20.715	1	*<0.001*	*0,561*
	Education [5]	-0.340	0.080	17.982	1	*<0.001*	*0,712*
	Education [6]	-0.290	0.082	12.635	1	*<0.001*	*0,748*
	In Signature Track [0]	-0.646	0.098	43.641	1	*<0.001*	*0,524*
	Work experience [1]	-0.042	0.097	0.185	1	0.667	0,959
	Work experience [2]	-0.030	0.101	0.086	1	0.769	0,970
	Study experience [1]	0.213	0.056	14.400	1	*<0.001*	*1,237*
	Study experience [2]	0.210	0.059	12.571	1	*<0.001*	*1,234*
	Experience in MOOC [0]	-0.169	0.044	14.548	1	*<0.001*	*0,845*

Note. Italic typeface denotes statistical significance at $p < 0.05$. Dependent variable – ordinal variable with 3 categories, where 0 – grade lower than 20 points, 1 – grade higher than 20 points and lower 80 points, 2 – grade higher 80 points. The model shows well goodness of fit, and it explains 71% of variation of dependent variable.

Summary

Our study has two research focuses: to describe in detail the distribution of the grades of MOOC students and to solve the distribution problem; and to evaluate the effect of motivation on the achievement of MOOC students controlling for the level of engagement in order to assess whether academic motivation plays the same role in MOOCs and in the traditional course format. The database includes trace data and survey data from students of 20 online courses, launched on the Coursera platform in 2014–2015 at the HSE.

The distribution of the MOOC students' grades is not a normal distribution, since the majority of registered students do not show any activity on the course. It is strongly skewed to the left, and majority of scores are zero. We restrict our sample to those whose grade is higher than zero to get a better visualization of the distribution. However, it is still skewed to the left and has a rise to the right. This distribution is not similar to Poisson or negative binomial distribution. To deal with the problem we transformed the dependent variable to an ordinal one with three categories, which captures the variation in grades, and excluded from our research sample a group of students who got a zero value, considering these to be "structural zeros". Another method to overcome the problem of distribution is to create an index of activity separating "structural zeros" from the zeros of those students who unsuccessfully participated in the MOOC. However, to create this method we need to have the appropriate data on student activity in dates. In our case, we faced the problem of incomplete data. Therefore we defined all zeros as "structural zeros".

In the second part of the research, we estimated the effect of motivation on achievement controlling for the level of engagement by conducting a mediation analysis with ordinal logistic regression. The results show that the relationship between the motivation of MOOC students and their achievement is mediated by the level of engagement. Thus, motivation acts as indirect predictor of achievement in the MOOC format as in the traditional course format. However, intrinsic motivation ceases to play the role that it does in the traditional course format. Intrinsic motivation increases the likelihood of getting a higher grade only in the first week of the course. In all the following weeks, intrinsic motivation leads to a decreasing probability of getting a higher grade. Thus, in the MOOC format extrinsic motivation encourages students to complete the course successfully.

Moreover, our model showed a statistically significant causal relationship between achievement and some individual MOOC student characteristics such as gender, educational background, study experience, experience in online learning, and intention to complete the course successfully. Our research confirms that a MOOC is not an appropriate format for all registered students, and it is most suitable for students with higher education, with experience in online learning and who have the intention to complete the course. Although our research shows gender has in impact on achievement, in other research this relationship has not been found [Adamopoulos, 2013; Breslow et al., 2013]. We assume that this effect is specific to our sample.

In further research, it is necessary to include in the model a more comprehensive variable capturing the level of engagement, and an indicator of motivation measured both in the middle of the course and at the end of the course.

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