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THE EFFECT OF ONLINE EDUCATION ON THE ACADEMIC PERFORMANCE OF STUDENTS DURING COVID-19 PANDEMIC: EVIDENCE FROM KAZAKHSTAN

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ABSTRACT

Purpose of the research. This study explores COVID19-imposed online education at one of the universities in Kazakhstan to understand whether and in what way it has affected students' academic performance.

Methodology. We use several methodologies, such as the principal component analysis, the nearest-neighbour propensity score matching and the latent variable multilevel model.

Originality / value of the research. To the best of our knowledge, this is the first attempt to estimate the effect of COVID19-imposed online teaching on academic performance in Kazakhstan.

Findings. Though our data suggest that the students exposed to online education had slightly lower academic performance than the earlier cohort of similar students who studied in class, this result is not statistically significant. In fact, for both cohorts of students, their past academic performance reflecting their academic abilities and attitudes, such as university entry test score and past accumulative GPA, matter much more than the mode of study. However, we found out that certain technical variables which characterise the "quality" of Zoom® sessions affect students' academic performance. Specifically, using a smartphone instead of a personal computer to enter a class conducted in Zoom® negatively affects students' achievement. Some other characteristics also produce expected effects though they turned out to be statistically insignificant possibly due to aggregation and a small dataset.

Keywords: COVID19-imposed online teaching, academic performance, Kazakhstan.

INTRODUCTION AND MOTIVATION

A sudden COVID-19 outbreak caused "the largest disruption of education systems in human history, affecting nearly 1.6 billion learners in more than 200 countries" [1, p. 133]. Kazakhstan was not an exception. On March 13, 2020, two first coronavirus cases were registered in the country. After three days, the lockdown was announced across the country, and universities and schools suddenly switched to online teaching and learning that continued for the whole 2020/21 academic year. Similarly, with other countries, education institutions in Kazakhstan were not prepared for such a dramatic change and adapted to it with varying performance depending on their capabilities and facilities' availability. Zoom® was commonly used by Kazakhstan's HEIs for online teaching over the whole period, and some universities have invested in licensed full versions of it. We use the Zoom® data collected by the private university located in the capital city linked with the administrative data from the same university to address the following research question: What was the effect of online education on students' academic performance?

Online learning, though was not widely spread before the COVID-19 outbreak, has obvious advantages over the traditional learning mode for the learners. Murgatrotd identifies such benefits associated with online learning as its accessibility, affordability, flexibility, and its aptitude to maximize the learning potential of students [2]. However, transit to online teaching and learning, which is beneficial for learners, teaching staff and educational institutions, requires time for an adjustment. Thus, the effectiveness of the urgent switch to massive online mode due to the lockdown is broadly questioned all over the world.

How effectively universities have adapted to online learning depends on their resources and "the expertise and exposure to ICT" [3]. In Kazakhstan, it is a huge diversity in education institutions with regards to the above-listed. While some universities have advanced facilities and experience in employing learning management systems, others substantially lag behind. However, even the most advanced universities still had a very limited experience in using online teaching itself, and, more importantly, students, likewise in other parts of the world, were not prepared for that as well.

It is important to note that students in many countries around the world have experienced issues with an Internet connection and access to digital devices [1]. In poorer countries, this sort of disruption had affected even the higher education students. This was the case for Kazakhstan as well, where, in 2019, only somewhat more than 75 per cent of the country's population had access to the internet connection [4]. The limited internet access is particularly harsh in remote areas due to the country's large geographical size. Additionally, the speed of the internet connection is poor: according to the data collected by the private British company Cable.co.uk, Kazakhstan appears among the countries with the slowest internet connection in the world [5]. This likely contributed to the decreased quality of the online classes and students' academic performance during the online learning imposed by the pandemic restrictions. Specifically, the study exploring students' perception of online teaching during the COVID-19 outbreak in 40 UK medical schools found out that poor internet connection and family distraction are the most common barriers to using online teaching platforms [6]. In turn, the latter is reasonably more pronounced in poorer countries with worse living arrangements and larger families, which is likely the case for Kazakhstan at least in the context of comparisons with the developed world. Even in our data collected by a university with a relatively rich student body, not all students had their own personal computers and tablets and had used their smartphones for learning instead. It is reasonable to believe that this was an obstacle to the effective study process.

Another possible negative effect of online learning might be induced by a lack of interaction with teachers for consultation and with peers [7; 8; 9]. Data collected via a semi-structured survey with students exposed to online learning experience during the pandemics at a university in Jordan revealed that many of them report "lack of motivation, understanding of the material, decrease in communication levels […] and their feeling of isolation" [10]. One might challenge to explain the phenomenon of a lack of understanding of the material and motivation, however, this is what is broadly reported by educators around the world, and possibly might be attributed to a lack of experience of students in online learning and interaction with the peers. Inability to benefit from possible positive peer effects during studying online could potentially be harmful. It is well-known that exposure to an academic environment with abler peers helps students to unlock their own potential and improve academic performance, and vice versa [11; 12; 13; 14]. Therefore, the peer-effect during the COVID19-related online teaching might potentially have both positive and negative effects. One way or another, communicating with peers is an important part of the learning process and limiting it likely cause disappointment. Additionally, the pandemic itself and strict quarantine regulations possibly induced psychological issues at least in some learners. Several psychological studies suggest that students exposed to sudden online teaching during the outbreak massively experienced anxiety, mood changes, boredom and low self-control and other psychological effects negatively affecting their wellbeing, partially as a result of deficiency of interpersonal communication, partially due to being "locked up" at home [15; 16; 17; 18].

The unique natural experiment of massive online teaching, which the whole world has conducted involuntarily, spawned much research exploring its effect on various aspects of a teaching process and possible policy implications. However, to the best of our knowledge, there is a lack of such research in Kazakhstan, at least quantitative research. With this study, we aim to partially fill this gap. The goal of the study is to understand whether the COVID-19 outbreak imposed online teaching affected students' academic performance in Kazakhstan. To answer this research question, we scrutinise the data on academic performance, various technical characteristics of the online classes conducted via Zoom® and the demographics of 61 higher education students exposed to online teaching during the COVID-19 outbreak. With this data, we exploit two methodologies. The first one is propensity score matching allowing to match students affected by online teaching with the similar cohort of other students who had the same set of courses before the COVID-19 outbreak and then compare their academic performance. The second technique focuses on the group of students affected by online teaching to estimate the effect of the Zoom® sessions' technical characteristics – duration of a Zoom® session, connection errors, use of PC vs. smartphone, audio and video latency and locality – on students' performance.

The paper is organised in the following way. In the next section, we start with the description of the dataset. It is followed by the section explaining our methodology and empirical strategy. Finally, we provide the results, possible misinterpretations and concluding remarks to the study.

MAIN PART

Data. We employ the data collected by a relatively more expensive English-teaching private university in Kazakhstan. The Zoom® classes participation technical data is merged with the administrative data recorded by the university Registrar Office.

It is a dataset on 61 senior undergraduate students representing four majors (specialities) who attended classes for 53 subjects during the Autumn semester of 2020/21 academic year via Zoom®. The semester lasts for 15 weeks starting from September of 2020.

Our units of observation are the Zoom® sessions. The initial dataset consists of 11,346 such entries – each time a student entered Zoom® for a class during the semester. Each of them is described by various technical characteristics for each session derived from Zoom®. Based on the principle component analysis, we selected the most important of them, as listed in table 1.

Table 1 – Technical characteristics for each Zoom® session

duration	minutes spent in Zoom® for each session
device	device type used to enter a Zoom® session (PC, smartphone or tablet)
network	type of network connection used to enter a Zoom® session (wi, cellular, wired)
network connection error	a Zoom® session ended due to network connection error
audio latency	audio latency (delay) in milliseconds (ms)
screen latency	screen latency (delay) in milliseconds (ms)
Note – compiled by the authors	

We linked the Zoom® classes data with the data on the students' demographics: major, year of study, whether a student is a publicly funded scholarship holder, the language of instruction at a secondary school, university entry centralised test (Unified National Test – UNT) score, past accumulative university GPA, a locality (city, town or a village) where a student has attended Zoom® classes from. Finally, we merged this data with the students' academic performance data that is measured by three midterms' grades and the final grade for each subject.

Table 2 depicts the distribution of the students by their majors and the number of entries for each of them. The majority of the students involved in COVID19-imposed online teaching majored in Finance and Business Management. There are fewer students with a major in Accounting and Economics.

Table 2 – Distribution of students by majors

Major	Number of students	Number of entries
Accounting	12	2637
Business Management	22	3696
Economics	3	582
Finance	24	4431
Note – compiled by the authors		

On average, each student has attended six subjects per semester (varying from two to eight). On average, each student has entered 186 Zoom® sessions per semester (varying from 30 to 297) spending 1707 minutes in Zoom®. This accounts for about 30 Zoom® sessions per subject during the semester, or two sessions per week consistent with the university timetable (one lecture and one seminar class).

Table 3 presents the list of subjects taken by the students. It is a variety of them starting with the foreign languages, broader subjects such as "Critical Thinking" or "The Art of Programming", and specialised major-related subjects.

Table 3 – List of subjects

1	Audit	28	Investment Management
2	Brand Management	29	Kazakh
3	Business Communications	30	Labour Law
4	Business Ethics	31	Macroeconomics
5	CFA Ethics and Professional Standards	32	Macroeconomics 2
6	Compensation Management	33	Managerial Accounting
7	Corporate and Business Law	34	Microeconomics
8	Critical Thinking	35	Microeconomics 2
9	Digital Marketing	36	Operations Management
10	Econometrics	37	Organizational Behaviour
11	Entrepreneurship	38	Performance Management
12	Event Management	39	Principles of Accounting
13	Financial Accounting 1	40	Principles of Economics
14	Financial Accounting 2	41	Principles of Leadership
15	Financial and Tax Reporting	42	Principles of Finance
16	Financial Management	43	Professional English
17	Financial Risk Management	44	Professional Kazakh
18	Fixed Income Securities	45	Public Relations
19	French	46	Research Methods
20	Fundamentals of International Relations	47	Statistics
21	German	48	Strategic Management
22	Hotel Management	49	Strategic Marketing
23	Human Resource Management	50	Tax Law of the Republic of Kazakhstan
24	Innovation Management	51	Taxation
25	Integrated Marketing Communications	52	The Art of Programming
26	International Business	53	Valuation
27	International Economics		
Note – compiled by the authors			

Students have entered Zoom® classes from 33 different localities representing nearly all provinces of the country, as figure 1 suggests where these localities are shown by bubbles with the size of a bubble representing the number of Zoom® sessions attended. The largest share of the sessions was attended from the capital city where the university is located, though there were some students studying from a very remote area.

Figure 1 – Students' location
Note – compiled by the authors

Empirical strategy

Propensity Score Matching. We employ two empirical strategies. The first one is an OLS regression regressing students' academic performance indicator – subject final grade – on students' characteristics effectively comparing the students affected by online teaching with the similar cohort of other students who had the same set of courses before the COVID-19 outbreak. For simplicity, we further refer to the affected cohort as "post-COVID" students and the previous unaffected cohort – as "pre-COVID" students.

We merged the post-COVID students' data with the sample of the pre-COVID students who attended the same courses taught by the same lecturers in the Autumn semester 2019/20 (n=153). Then we matched pre- and post-COVID students based on observed characteristics (major, scholarship holder status, language of instruction at a secondary school, university entry test score, GPA, gender) and a subject with the nearest-neighbour propensity score matching with replacement [19; 20; 21]. Finally, we run the OLS model explaining the students' final grade per subject with a dummy variable for the post-COVID semester on a matched sample.

Pre-COVID and post-COVID students do not differ by their characteristics even before matching as table 4 suggests.

Table 4 – T-test for main class characteristics before and after the COVID-19 outbreak

Variable	Autumn 2019/2020	Autumn 2020/21	Welch Two Sample t-test of difference-in-means: p-value
University entry test score (out of 140)	94.30	92.86	0.4203
GPA (out of 4.0)	2.74	2.77	0.4373
Share of scholarship holders	0.13	0.12	0.7849
Share of male students	0.32	0.31	0.7208
Share of students whose language at school was Kazakh	0.27	0.27	0.9023
Note – compiled by the authors			

Pre-COVID and post-COVID students' final grades do not differ either – Figure 2.

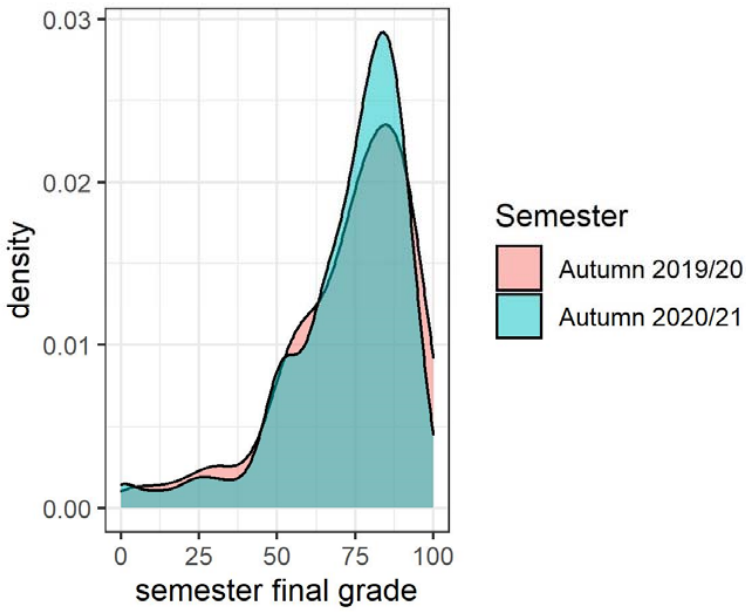

Figure 2 – Density plot for the semester final grade
Note – compiled by the authors

Nonetheless, with matching we ended up with the smaller data set of 374 observations:
- 347 student-subject observations for the post-COVID semester;
- 27 student-subject observations for the pre-COVID semester.

We run OLS on both matched and unmatched samples.

Since most of the explanatory variables (major, scholarship holder status, language of instruction at a secondary school, university entry test score, GPA and gender) are "aggregated" at a higher (student) level we perform OLS with standard errors clustered at a student level as one of the options.

Thus, we estimate two subsequent models:
- *Nearest-neighbour propensity score matching:*

$$D_i = \alpha_0 + \alpha' X_i, \tag{1}$$

Where, D_i – semester (pre-COVID or post-COVID);

X_i – vector of the students' observed characteristics (course or subject, major, scholarship holder status, language of instruction at a secondary school, gender, UNT score, past accumulative GPA).

Data on only those courses where the same instructor has been teaching in both semesters were employed.
- *OLS:*

$$Y_i = \beta_0 + \beta_1 D_i + \beta' X_i, \tag{2}$$

Where, Y_i – subject final grade;

D_i – semester (pre-COVID or post-COVID);

X_i – vector of the students' observed characteristics (course or subject, major, scholarship holder status, language of instruction at a secondary school, gender, UNT score, past accumulative GPA);

β_1 – is the main coefficient of interest.

Latent variable multilevel model. The model seeks to estimate the effect of the Zoom® sessions' technical characteristics – duration of a Zoom® session, connection errors, use of PC vs. smartphone, audio and video latency, locality – on students' performance during the COVID19-imposed online teaching.

Since the main explanatory variables are observed at a Zoom® session-level and the academic performance is observed at an aggregate level (midterms that included several sessions each), we use a latent variable multilevel model [22]. To ensure more data points, we use midterm grades corresponding to a specific timeframe and link them with the Zoom® sessions.

In a so-called multilevel micro-macro setting, one is keen to explain individual-level outcome (student-course grade) with the covariates observed both at a lower level (Zoom® session characteristics) and a higher level (student characteristics), which results in biased parameter estimates. We use a correction procedure proposed by Croon and van Veldhoven [22] producing the best linear unbiased predictors (BLUPs) for the group means. This effectively means that we aggregate the student-course grade and Zoom® session characteristics to a student level and adjust standard errors.

Thus, we estimate the following model:

$$Y_i = \alpha + \tau' Z_i + \beta' X_i, \tag{3}$$

Where, Y_i – subject midterms' grades;

Z_i – Zoom® session characteristics (type o device, network connection error, session duration, audio latency in ms, screen latency in ms, locality);

X_i – vector of the students' observed characteristics (course or subject, major, scholarship holder status, language of instruction at a secondary school, gender, UNT score, past accumulative GPA);

τ' – are the main coefficients of interest.

Regression results, discussion and concluding remarks. Table 5 displays the results of the OLS regression on the unmatched and matched sample. The outcome for the unmatched sample is shown for comparison reasons.

Table 5 – Regression results: OLS with matching

	Dependent variable: subject final grade					
	unmatched sample			matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
entry test score		0.072**	0.072**		0.081*	0.081
		(0.035)	(0.052)		(0.045)	(0.069)
past GPA		21.461***	21.461***		20.293***	20.293***
		(1.464)	(2.417)		(2.071)	(3.775)
scholarship holder: yes		-3.815*	-3.815		-8.256***	-8.256
		(2.122)	(4.835)		(2.877)	(8.046)
language: Russian		2.933**	2.932		4.082**	4.082
		(1.387)	(2.146)		(1.796)	(2.938)
gender: male		1.593	1.593		-0.609	-0.609
		(1.434)	(1.878)		(1.979)	(2.383)
Semester: Autumn 2020/21	0.012	-0.964	-0.964	-0.083	-1.964	-1.964
	(2.945)	(2.482)	(2.500)	(4.103)	(3.484)	(3.284)
major	no	yes	yes	no	yes	yes
subject	yes	yes	yes	yes	yes	yes
N	567			374		
Adjusted R2	0.301	0.538		0.309	0.510	
F Statistic	5.695***	11.978***		4.208***	7.480***	

Note – compiled by the authors.
Matching is performed with "MatchIt" package in R (Ho, Imai, King and Stuart, 2011).
Model (3) is computed with lm.cluster command from "miceadds" package in R (Robitzsch and Grund, 2021).
Robust standard errors are reported in parentheses.
Sign. codes: *p<0.1; **p<0.05; ***p<0.01

Our estimations suggest that academic performance somewhat dropped with the COVID19-imposed online teaching when we compare two groups of similar students studying the same set of subjects with the same lecturer, however, this result is not statistically significant: neither coefficient for a dummy variable "Semester: Autumn 2020/21" is statistically significant.

In fact, what matters for a current academic achievement – either before the outbreak or during it – is past academic achievement. One-unit increase in the entry test (UNT) score is associated with the 0.07 (for the unmatched sample) and 0.08 (for the matched sample) increase in the final grade. The past university cumulative GPA is even more important: one score higher GPA provides about 20-21 score increase in the semester mark. Surprisingly, students holding the scholarship have lower final grades for both matched and unmatched samples, however, significance vanishes with clustering standard errors. The same is with the language of instruction at a secondary school that suggests that students who studied in Russian perform somewhat better than those who studied in Kazakh. Notably, models controlling for all variables demonstrate rather a good fit explaining around a half variation in the subject final grade.

Table 6 presents the results of the latent variable multilevel model on aggregated data.

Table 6 – Regression results: Latent variable multilevel model

	Dependent variable: subject midterm grade	
	OLS with aggregate data	Latent variable multilevel model
entry test score	0.006	0.006
	(0.047)	(0.057)
past GPA	13.292***	13.292***
	(2.447)	(2.332)
scholarship holder: yes	1.034	1.034
	(3.426)	(3.519)
language: Russian	3.716*	3.716*
	(2.067)	(2.021)
gender: male	0.043	0.043
	(1.984)	(1.958)
device: PC	5.844**	5.844**
	(2.893)	(2.913)
network connection error: yes	-1.297	-1.297
	(6.898)	(7.129)
Zoom® session duration	0.020	0.020
	(0.037)	(0.032)
audio latency in ms	-0.001	-0.001
	(0.005)	(0.005)
screen latency in ms	-0.001	-0.001
	(0.006)	(0.006)
major	yes	yes
subject	yes	yes
locality	yes	yes
N	785	
Adjusted R2	0.076	
F Statistic	5.628***	
Note – compiled by the authors. Sign. codes: *p<0.1; **p<0.05; ***p<0.01		

Generally, the results are consistent with both the matching models and our expectations regarding the Zoom® sessions' technical characteristics, but mostly neither statistically nor economically significant.

With regards to the Zoom® sessions technical characteristics we can conclude the following:

- Using a PC vs. a mobile phone had increased academic performance and this result is significant even after controlling for all observed students' characteristics.

- Experiencing connection error slightly decreases the academic performance though not statistically significant.
- Students who spend more time in Zoom® have somewhat higher academic performance (statistically insignificant).
- Both audio and screen latency decrease academic performance (also statistically insignificant).

One should keep in mind that statistical significance might suffer from using a small dataset and data aggregation.

We must also emphasize that even by matching students we do not fully control for possible intervening effects. For example, lecturers might change their assessment strategies with online teaching; and since they have not been fully prepared to switch the teaching mode to online, this is not surprising.

Technical characteristics' effects might also be ambiguous. For example, "better" students might tend to use a PC versus a mobile phone. If this is the case, a higher grade might capture an effect of a better attitude rather than a device used by a student; and we cannot fully rule this out even after controlling for the past academic performance.

Our final remark is about the external validity of our study that might be questionable. The university under analysis is a relatively expensive, selective, and better-quality one. It also invested in online teaching somewhat better than an average university in Kazakhstan. Thus, what we observe with the data from this university might not be easily generalised to other HEIs in Kazakhstan and beyond. For example, worse-quality universities with poorer students might be stronger affected by the pandemic-related online teaching. Additionally, as Doucet et. Al. suggest, "different subjects and age groups require different approaches to online learning" [23]; therefore, the effect of online teaching could be different at universities with a wider range of subjects and specializations.

Despite its possible bottlenecks, our study still provides an objective and informative snapshot of the effect of online teaching on academic performance, at least locally.

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COVID-19 ПАНДЕМИЯСЫ КЕЗІНДЕГІ ОНЛАЙН-БІЛІМ БЕРУДІҢ ҮЛГЕРІМГЕ ӘСЕРІ: ҚАЗАҚСТАН КЕЙСІ

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АҢДАТПА

Зерттеу мақсаты. Бұл зерттеу Қазақстанның университеттерінің бірі мысалында COVID-19 пандемиясы кезінде онлайн оқытудың студенттерінің үлгеріміне әсері болды ма және қалай әсер еткенін зерттеуге бағытталған.

Әдіснамасы. Мақалада бірнеше әдістемелер қолданылды, атап айтқанда: негізгі компоненттерді талдау, бейімділік коэффициенті бойынша ұқсас параметрлік емес іріктеу әдісі және жасырын айнымалысы бар көп деңгейлі модель.

Зерттеудің бірегейлігі / құндылығы. Біздің білуімізше, бұл COVID-19 кезінде онлайн-оқытудың Қазақстанның жоғары оқу орындарындағы академиялық үлгерімге әсерін бағалаудың алғашқы әрекеті.

Зерттеу нәтижелері. Біздің деректеріміз онлайн білім алған студенттердің әдеттегі форматта оқыған студенттердің алдыңғы тобына қарағанда үлгерімі біршама төмен болғандығын көрсетсе де, бұл нәтиже статистикалық тұрғыдан маңызды емес болып шықты. Студенттердің екі тобы үшін олардың академиялық қабілеттері мен оқуға қатынасын көрсететін үлгерімнің алдыңғы деңгейі, атап айтқанда ҰБТ-ға түсу балы және алдыңғы жинақталған GPA сияқты көрсеткіштер оқу тәсіліне қарағанда (онлайн немесе әдеттегі) әлдеқайда маңызды. Сонымен бірге, Zoom® сессияларының «сапасын» сипаттайтын белгілі бір техникалық айнымалылар студенттердің академиялық үлгеріміне әсер еткенін анықтадық. Атап айтқанда, Zoom®-да өткізілетін сабақта жеке компьютердің орнына смартфонды пайдалану олардың үлгеріміне теріс әсер етті. Бірнеше басқа сипаттамалар да күтілетін әсерлерді көрсетті, бірақ олар статистикалық тұрғыдан маңызды емес болып шықты, мүмкін, біріктіру және пайдаланылған деректер жиынтығына байланысты.

Түйін сөздер: COVID-19 кезеңінде онлайн оқыту, академиялық үлгерім, Қазақстан.

ВЛИЯНИЕ ОНЛАЙН-ОБРАЗОВАНИЯ ВО ВРЕМЯ ПАНДЕМИИ COVID-19 НА УСПЕВАЕМОСТЬ: КЕЙС КАЗАХСТАНА

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АННОТАЦИЯ

Цель исследования. Данное исследование ставит целью изучить, повлияло ли и каким образом повлияло онлайн-обучение во время пандемии COVID-19 на успеваемость студентов в одном из университетов Казахстана.

Методология. Мы используем несколько методологий, а именно анализ основных компонентов, непараметрический метод отбора подобного по коэффициенту склонности и многоуровневую модель со скрытой переменной.

Оригинальность / ценность исследования. Насколько нам известно, это первая попытка оценить влияние онлайн-обучения вовремя COVID-19 на академическую успеваемость в вузах Казахстана.

Результаты исследования. Хотя наши данные свидетельствуют о том, что студенты, обучавшиеся онлайн, имели несколько более низкую успеваемость, чем предыдущая группа таких же студентов, обучавшихся в обычном формате, этот результат оказался статистически незначимым. Для обеих групп студентов предыдущий уровень успеваемости, отражающий их академические способности и отношение к учебе, а именно такие показатели как вступительный балл ЕНТ и предыдущий накопленный GPA, имеют гораздо большее значение, чем способ обучения (онлайн или обычный). Вместе с тем мы обнаружили, что определенные технические переменные, характеризующие «качество» Zoom® сессий, повлияли на академическую успеваемость студентов. В частности, использование смартфона вместо персонального компьютера на занятии, проводимом в Zoom®, негативно повлияло на их успеваемость. Некоторые другие характеристики также показали ожидаемые эффекты, хотя они оказались статистически незначимыми, возможно, из-за агрегации и небольшого используемого набора данных.

Ключевые слова: онлайн обучения во период COVID-19, академическая успеваемость, Казахстан.

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SOFT SKILLS OF BACHELOR DEGREE STUDENTS: ANALYSIS OF SOURCES BY GENDER FOR EMPLOYMENT

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ABSTRACT

Purpose of research. The aim of the research is to study the knowledge of students about soft skills (SS), the types and where SSare acquired. Determine necessary SSfor employment, according to students.

Methodology. The research methodology consisted in conducting a questionnaire survey among bachelor's students of universities of the Republic of Kazakhstan. In total, 215 students from 9 universities. Based on the literature review, the main areas of soft skills formation were identified – family, school and universities. SPSS software and Excel were used to analyze student responses. The analysis was also carried out in terms of gender.

Originality / value of the research – the employment of students, directly depends on their professional and soft skills; therefore, it is important to know what soft skills students of Kazakhstan universities have.

Research results – showed that Responsibility and Politeness are continuously developed in students, which are more intensively established in the family and further developed more actively in universities, than at schools. The main results of the study showed that students have a general understanding of the importance of SSin employment. Therefore, it was recommended to conduct a more detailed analysis of the skills acquired by students in passing certain disciplines.

Keywords: soft skills, employment, bachelor student, university.