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E-learning Acceptance Model in the Post-Pandemic World

ABSTRACT

The article analyses the determinants of the adoption of e-learning in higher education in the aftermath of the COVID-19 pandemic. In the article I will show the peculiarities of the educational market in Poland, which are due to the geographical location of Poland, its membership in the EU, and its proximity to the countries of the former USSR and the related phenomena. In the analysis, I used the Technology Acceptance Model and adapted it to the specifics of the Polish education system. The survey was conducted in 2023 on a sample of more than 1000 students at one of the private universities located in Poland's capital. I analyzed the relationships between the latent variables (perceived usefulness, ease of use, attitudes toward technology and behavioral intention, and current use of remote learning) and external variables (age, labor activity, mode of study, and nationality). The strongest relationship emerged between the perceived ease of use of remote learning and the perceived usefulness of remote learning. The strength of the relationship between demographic variables and the perceived usefulness of remote learning is negligible.

KEYWORDS: online learning; remote learning; e-learning in higher education; post-COVID reality; perceived ease of use; perceived usefulness

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INTRODUCTION

Kumar et al. (2019) found that e-learning is not simply a temporary trend that is affecting colleges and universities, but that it is beginning to become a new norm for education. Okano et al. (2023) stated that online distance learning creates significantly more value and minimizes the use of resources, so it is an economical innovation. The COVID-19 pandemic has increased the pace of change connected with transition to e-learning. Taking advantage of the experience of providing online studies during the COVID-19 pandemic, a number of universities in Poland continue to offer remote education. However, some universities returned to the traditional methods of instruction. The Polish tertiary education market is unique compared to other countries in Central and Eastern Europe. The 1990s brought a dramatic expansion of private higher education in Poland (Antonowicz et al., 2017; Kwiek & Szadkowski, 2018). Poland boasts the most developed system of non-public tertiary education in Europe (Dobbins & Knill, 2009). An important factor that had a major impact on higher education in the 1990s was the large number of people entering the labor market without a university degree. Career opportunities of those people were limited, as senior positions in the public sector and large public enterprises were often formally restricted to those with a university degree. As a result, these individuals became interested in furthering their education. Most of these were full-time employees who were interested in part-time study because of their work commitments (Antonovich et al., 2017). In Poland, the percentage of part-time students is very high – 35.7% of the total number of students in the 2021/2022 academic year (Central Statistical Office of Poland, 2022). According to the analyses carried out by Alexander (2006), it seems that the strength of the educational motivation of part-time studying adults is very high in this group. As a result of that motivation, the respondents entered into a difficult educational path (which required considerable financial resources, sometimes borne by the entire family). This demonstrates that education has become a valued asset for them. Without it, they would be unable to find their place in today's ever-changing and increasingly difficult reality – both civilizational and social. Poland is also seen as a gateway to the European Union for young people from former Soviet countries such as Ukraine and Belarus, as well as from Asia and Africa. They can legally enter the workforce by studying in Poland. Also, compared to the countries that were part of the European Union before 2004, also known as the "Old Union", the cost of living in Poland is much lower. Studies show that the possibility of legal employment is the main motivation for Ukrainians to study in Poland (Kapera, 2017). At the time of the survey, the war in Ukraine was still in progress, and some students have been conscripted. Some of them do not have the opportunity to come to Poland. The lockdown associated with the COVID-19 pandemic led to a deterioration of the situation faced by consumers. Rising inflation, growing unemployment, and a decrease in their purchasing power (Estrada, 2021) became a reality worldwide, but also directly in Poland, which is the subject of this analysis (Staniszewski, 2022). In Poland, there are additional problems related to economic uncertainty resulting from the war in Ukraine, such as the depreciation of the Polish zloty against the euro, the US dollar, rising energy prices, and others. All of this leads to a decline in household purchasing power (Arak & Miniszewski, 2022). The worsening financial situation also affects students (Polish Bank Association, 2022). Many of them find it difficult to make a living in a foreign city. For them, remote learning is often a solution to financial difficulties.

The purpose of this article is to answer the following question: what are the variables that influence the intensity of utilizing online education among university students in the post-COVID-19 reality? For this purpose, the author used the technology acceptance model (TAM) proposed by Davis et al. (1989) adapting it to the specifics of Polish conditions. The article opens with a literature review on the factors related to university students' perceptions of distance learning and their behaviors related to participation in online classes. Further, I present the assumptions of my own study of 1,025 students enrolled in one of the universities in the Polish capital, Warsaw. In the section that follows, I reposition the reconstructed model using SmartPLS. The article closes with conclusions and indications for future research.

Literature review

Davis et al. in their technology acceptance model, distinguished four latent variables that influence the acceptance of technology as expressed in its use: the perceived usefulness (PU) of a technology, its perceived ease of use (PEOU), attitude toward technology (ATT), and behavioral intention (BI). Perceived usefulness and perceived ease of use are separate measures. The former variable is defined as the prospective user's subjective probability that using a specific application system will increase his or her job performance within an organizational context, while the latter is defined as the degree to which the prospective user expects the target system to be free of effort (Davis et al., 1989, p. 985). Behavioral intention refers to the person's subjective probability that he or she will perform some behavior (Fishbein & Ajzen, 1975, p. 288). In addition, the model includes extraneous variables to describe the subjects and their influence on the acceptance of a given technology (Davis et al., 1989). I proposed the following external variables in the technology acceptance model: respondents' age, employment situation, mode of study and nationality. In my recent study (Szopiński & Bachnik, 2022) on the use of distance learning by students of a Polish university, I found that the nationality of the students determines the evaluation of online studies and the frequency of participation in online courses. My other study (2023) shows that age, students' labor activity, and the field of study influence the evaluation of the situation in which learning takes place remotely. In contrast, a study by López et al. (2023) shows that variables such as gender and age, among others, influence the adoption of remote learning. Accordingly, the author proposed the following research hypotheses:

H1. Students' age affects the perceived usefulness of remote learning.
H2. Mode of study affects the perceived usefulness of remote learning.
H3. Students' nationality affects the perceived usefulness of remote learning.
H4. Students' labor activity affects the perceived usefulness of remote learning.

According to TAM's assumptions, perceived ease-of-use positively influences perceived usefulness and attitude toward using technology (Davis, 1989). In the course of research on the acceptance of remote learning, we found that this relationship between perceived ease of use and perceived usefulness is not clear-cut. Studies by Kaewsaiha and Chanchalor (2021), Yao et al. (2022), Alyoussef (2023), Muñoz-Carril et al. (2021), Jiang et al. (2021), Huang et al. (2020), Saleh et al. (2022), Goh and Wen (2020), Natasia et al. (2022) on acceptance of remote learning show that perceived ease-of-use positively influences perceived usefulness. Studies by Alassafi (2022), Chang et al. (2017), and Akman and Turhan (2015) on remote learning demonstrate that there is no relationship between perceived ease of use and perceived usefulness. Research by Alassafi (2022), Huang et al. (2020), Saleh et al. (2022), Akman and Turhan (2015), Al-Hattami, H. M. (2023), Ramírez-Correa et al. (2015) confirm the impact of perceived ease of use on attitude toward e-learning technology. However, the study by Natasia et al. (2022), Shyu and Huang (2011), Ho et al. (2020), Chahal and Rani (2022), and Ly et al. (2023) do not confirm this relationship. Accordingly, I propose two research hypotheses:

H5. Perceived ease of use affects perceived usefulness of online learning.
H6. Perceived ease of use affects attitude towards online learning.

According to the assumptions of TAM, perceived usefulness positively influences attitude toward technology and behavioral intention of using the technology (Davis, 1989). This is supported by the results of numerous studies (Akman & Turhan, 2015; Chang et al., 2017; Cheng, 2015; Jiang et al., 2021; Mohammadi, 2015; Shyu & Huang, 2011). According to them, perceived usefulness has a positive impact on behavioral intention of using e-learning. García et al. (2019) finds the same relationship for m-learning. In contrast, the findings of Park (2009), Huang et al. (2020), Natasia et al. (2022) and Mailizar et al. (2021) do not confirm the relationship between perceived usefulness and behavioral intention to use e-learning. The findings of Akman and Turhan (2015) and Shyu and Huang (2011) confirm the relationship between perceived usefulness and attitudes toward using e-learning. Accordingly, I propose the following two research hypotheses:

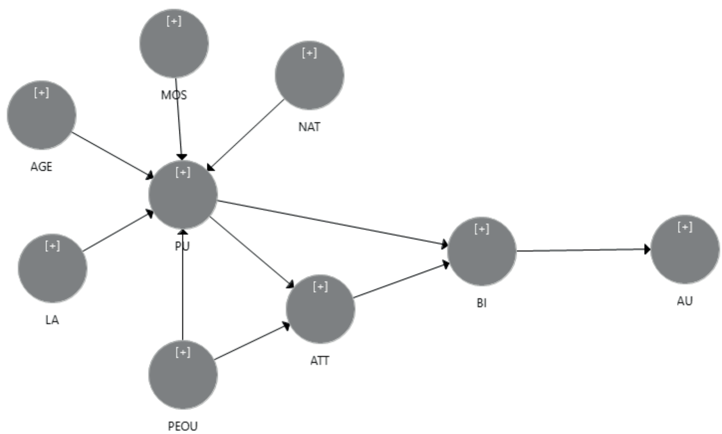
H7. Perceived usefulness affects the attitude toward online learning.
H8. Perceived usefulness affects the behavioral intention to use online learning.

According to TAM, attitude toward technology affects behavioral intention of using a technology, while behavioral intention affects the use of a technology (Davis, 1989). From a study by Mailizar et al. (2021), Ramírez-Correa et al. (2015), Mohammadi, (2015), Ly et al. (2023), and Al-Hattami (2023) show that attitude toward e-learning has a positive effect on behavioral intention of using e-learning among students. However, the study by Peng et al. (2023) shows that attitude toward online learning positively influences the use of online learning. In contrast, the studies by Agudo-Peregrina et al. (2014), Ramírez-Correa et al. (2015), Mohammadi, (2015), Zhang et al. (2008) show that behavioral intention to use e-learning systems affects students' use of e-learning. Accordingly, I propose the following two research hypotheses:

> **H9.** Attitude towards e-learning has a positive effect on behavioral intention of using e-learning among students.
> **H10.** Behavioral intention of using e-learning among students affects their actual use of e-learning.

Figure 1 contains a conceptual model showing the proposed technology acceptance model with external factors.

Figure 1. The conceptual model.



METHODS

The aim of this article is to address the question of what variables affect the intensity of use of e-learning among university students in the post COVID-19 reality. For this purpose, I used the technology acceptance model proposed by Davis et al. (1989) adapting it to the specifics of Polish conditions. The survey was conducted in March and April 2023 among students of a Polish private university. The survey included 1,025 students studying exclusively remotely and those studying in blended mode, where lectures are delivered online and practical classes are conducted on the university campus (via MS Teams). To invite students to participate in the survey, the system administrator e-mailed them information about the study and a link to the online questionnaire to the e-mail addresses provided by the students upon registration. Table 1 shows the characteristics of the sample. Among the respondents, almost 60% were those who studied in blended mode, while the rest studied exclusively in remote mode. Nearly 85% of the respondents combined work and study. Most of them studied part-time. The research group encompassed a wide range of ages and study programs, both Poles and persons from the former USSR.

Table 1. Characteristics of the sample.

Form of classes	***N***	**%**
Some classes held at the university and some held online	585	57.07
All classes online	440	42.93
Labor activity	***N***	**%**
Employed	156	15.22
Unemployed	869	84.78
Mode of study	***N***	**%**
Full-time	343	31.8

Part-time	682	63.3
Level of education	***N***	**%**
Long-cycle Master's degree	320	31.2
Undergraduate studies	548	53.5
Supplementary master's degree program (2 years)	157	15.3
Gender	***N***	**%**
Female	537	52.4
Male	488	47.6
Field of study	***N***	**%**
Computer science	105	10.2
Economic science	312	30.4
Legal and political science	122	11.9
Psychology	378	36.9
Philology	45	4.4
Other	63	6.1
Country of origin	***N***	**%**
Poland	868	84.7
Former USSR countries	157	15.3
Age (years)	***N***	**%**
≥ 24	618	57.3
25–29	127	11.8
30–39	156	14.5
40+	124	11.5

As variables affecting the intensity of participation in remote classes, I adopted the variables proposed by Davis et al. (1989) adjusted for online learning such as perceived usefulness of using remote learning (PU), perceived ease of use of remote learning (PEOU), attitude toward remote learning (ATT), behavioral intention related to the use of remote learning (BI) and actual use of remote learning (AU). In addition, the model included variables such as students' age (AGE), mode of study (MOS), labor activity (LA), and nationality (NAT). Variables such as PU, PEOU, ATT, BI, and AU are latent variables consisting of the items that describe them. Each item was rated by respondents on a 5-point Likert scale, from 1 (*completely disagree*) to 5 (*completely agree*). Table 2 lists the items describing the above latent variables.

Table 2. Scale items.

Dimension	**Items**
Attitude toward technology	ATT_1. By studying remotely, I lose the opportunity to interact with other students
	ATT_2. By studying remotely, verification of students' knowledge (exams, test) is fictitious
	ATT_3. The need to sit in front of a computer for long periods of time makes distance learning tiring for me
	ATT_4. Remote learning makes you lazy
	ATT_5. Remote learning is difficult for me due to poor Internet connection quality
	ATT_6. Remote learning makes it difficult for me to focus on the material being taught by the instructor
	ATT_7. Remote learning demotivates me to learn
	ATT_8. I have a positive attitude toward remote learning
	ATT_9. Studying remotely allows me to save significant amounts of money
	ATT_10. Remote learning allows me to later listen to recorded classes
	ATT_11. Learning remotely allows me to do different things at the same time (e.g., work and study)
Current usage	Actual_use1. I diligently participate in all remote classes
	Actual_use2. I regularly listen to recordings of remote classes

Behavioral intention	BI1. If I decide to go to a university in the future, I will first consider studying remotely BI2. I will encourage others to choose remote studies BI3. The ability to study remotely will be a factor in the future that may determine my decision to study in a particular field
Perceived ease of use	PEOU1. I find the online learning platform easy to use PEOU2. It took me little time to fully understand how to use the online learning platform PEOU3. The online learning platform makes it easy for me to gain knowledge PEOU4. I learned very quickly how to use the online learning platform PEOU5. Learning through the online learning platform is not difficult for me PEOU6. Online learning platforms allow me to easily interact with others (teacher and/or other students) PEOU7. Online learning platforms allow me to easily exchange files with the instructor (uploading and downloading) PEOU8. The online learning platform works without technical problems
Perceives usefulness	PU1. Online learning platform adds value to learning activities PU2. I find the online learning platform very helpful in gaining knowledge PU3. The learning mechanism provided by the online learning platform makes the learning process smoother PU4. The online learning platform helps me get useful information when I need it PU5. The online learning platform helps me to learn more effectively PU6. The online learning platform is more useful than traditional classroom teaching methods

The age variable was described on a 4-point scale (in years): 1 = ≤ 24; 2 = 25–29; 3 = 30–39; and 4 ≥ 40. Variables such as mode of study, labor activity and nationality were recorded as binary variables. In the case of mode of study, 0 meant full-time study and 1 meant part-time study. In the case of labor activity, 0 referred to unemployed individuals, and 1 to those who studied and worked at the same time. In the case of nationality, 0 indicated Polish citizens, and 1 represented persons from the former Soviet Union countries. I used the Partial Least Square Structural Equation Modeling (PLS-SEM) technique with the SmartPLS software to verify the relationships between the analyzed variables (Ringle et al., 2015).

RESULTS

The results for reliability and validity along with factors loadings for the remaining items are presented in Table 3. First, I examined the indicator loadings (λ). It is generally advisable for factor loadings to be greater than 0.708 indicating that more than 50% of the variance in a single indicator can be explained by the corresponding latent variable (Hair et al., 2019). A loading of 0.5 or 0.6 may still be acceptable if an additional indicator exists in the block for comparison basis (Chin, 1998). I removed from further analysis factor loadings below 0.7. Next, I assessed internal consistency reliability using composite reliability (CR) and Cronbach's alpha. Higher values generally indicate higher levels of reliability (Hair et al., 2019). Then, I assessed the convergent validity of each construct measure. Convergent validity is the extent to which the construct converges in order to explain the variance of its items. The metric used for evaluating a construct's convergent validity is the average variance extracted (AVE) for all items on each construct. In order to calculate the AVE, one has to square the loading of each indicator on a construct and

Table 3. Item loading, reliability, and validity.

Items	λ	Alpha	CR	AVE	R^2	VIF
ATT_1	0.750					1.964
ATT_2	0.822					2.502
ATT_3	0.869					3.056
ATT_4	0.879	0.929	0.943	0.704	0.537	3.481
ATT_6	0.891					4.031
ATT_7	0.900					4.256
ATT_8	0.749					1.769
AU_1	0.897	0.740	0.885	0.794	0.398	1.527
AU_2	0.885					1.527
BI_2	0.956	0.907	0.956	0.915	0.715	3.217
BI_3	0.958					3.217
PEOU_1	0.800					3.189
PEOU_2	0.750					2.691
PEOU_3	0.842					2.193
PEOU_4	0.812	0.901	0.919	0.619		3.844
PEOU_5	0.801					2.055
PEOU_7	0.770					1.918
PEOU_8	0.728					1.674
PU_1	0.904					3.838
PU_2	0.931					4.879
PU_3	0.909	0.940	0.955	0.808	0.533	3.709
PU_4	0.863					2.812
PU_6	0.886					3.125

compute the mean value. The minimum acceptable AVE is 0.50 or higher—an AVE of 0.50 or higher indicates that the construct explains 50 percent or more of the variance of the items that make up the construct (Hair et al., 2011; Sarstedt et al., 2021). The last column contains Variance Inflation Factor values. The smallest possible value for VIF is 1, which indicates the complete absence of collinearity. Typically, in practice there is a small amount of collinearity among the predictors. The Variance Inflation Factor value should be less than 5 (Akinwande et al., 2015; Hair et al., 2011). The structural model in PLS can be evaluated using coefficient of determination R^2. It measures the variance which is explained in each of the endogenous constructs, and is therefore a measure of the model's explanatory power. The R^2 ranges from 0 to 1, with higher values indicating a greater explanatory power (Hair et al., 2019). For perceived usefulness, $R^2 = 0.533$. This means that variables such as LA, MOS, AGE, NAT and PEOU explain 53.3% of the variation in the perceived usefulness variable. In contrast, for the actual use of remote learning $R^2 = 0.398$. In the case attitude toward remote learning $R^2 = 0.537$. The behavioral intention variable is best explained by exogenous variables. Variables such as perceived usefulness and attitude toward remote learning explain more than 70% of the variation of that variable.

Next, I assessed discriminant validity, which is the extent to which a construct is empirically distinct from other constructs in the structural model. In order to assess the discriminant validity, I used the HTMT criterion. The HTMT is defined as the mean value of the item correlations across constructs (i.e., the heterotrait–heteromethod correlations) relative to the (geometric) mean of the average correlations for the items measuring the same

Table 4. Discriminant validity: HTMT criterion.

	ATT	AU	BI	PEOU	PU
ATT					
AU	0.701				
BI	0.825	0.770			
PEOU	0.518	0.624	0.647		
PU	0.776	0.761	0.872	0.709	

construct (i.e., the monotrait–heteromethod correlations) (Hair et al., 2019). The results are presented in the Table 5. All HTMT values are below 0.90, which means that discriminant validity has been established between each two constructs. Table 5 shows cross-loadings for all the items. Cross-loading helps answer the

Table 5. Discriminant validity: Cross loadings.

	ATT	AU	BI	PEOU	PU
ATT_1	**0.750**	0.424	0.556	0.372	0.519
ATT_2	**0.822**	0.454	0.590	0.395	0.589
ATT_3	**0.869**	0.456	0.624	0.470	0.608
ATT_4	**0.879**	0.519	0.633	0.390	0.600
ATT_6	**0.891**	0.510	0.656	0.475	0.623
ATT_7	**0.900**	0.517	0.666	0.452	0.639
ATT_8	**0.749**	0.530	0.715	0.531	0.687
AU_1	0.531	**0.897**	0.576	0.483	0.559
AU_2	0.510	**0.885**	0.548	0.486	0.574
BI_2	0.721	0.598	**0.956**	0.612	0.763
BI_3	0.736	0.609	**0.958**	0.598	0.781
PEOU_1	0.260	0.349	0.366	**0.800**	0.429
PEOU_2	0.233	0.296	0.328	**0.750**	0.364
PEOU_3	0.664	0.595	0.722	**0.842**	0.783
PEOU_4	0.264	0.326	0.356	**0.812**	0.411
PEOU_5	0.473	0.435	0.518	**0.801**	0.564
PEOU_7	0.342	0.386	0.450	**0.770**	0.510
PEU_8	0.413	0.435	0.502	**0.728**	0.553
PU_1	0.653	0.566	0.698	0.603	**0.904**
PU_2	0.678	0.620	0.748	0.638	**0.931**
PU_3	0.671	0.563	0.742	0.661	**0.909**
PU_4	0.570	0.527	0.643	0.628	**0.863**
PU_6	0.709	0.574	0.787	0.617	**0.886**

following question: Does any indicator correlate more strongly with the other constructs than with its own construct (Kock, 2015)? All the factors-loadings measuring particular constructs loaded higher on that construct and loaded lower on the other constructs, which confirms the discriminate validity of the constructs.

After assessing discriminant validity, the hypotheses were verified. Table 6 shows the verified hypotheses on the direct relationships between the analyzed variables. Hypothesis H1 on stochastic independence between students' age and perceived usefulness of remote learning: AGE → PU ($\beta = 0.109$, $t = 4.699$, $p < .001$) was supported. Hypotheses 2 and 3 were also supported. The mode of study and nationality differentiated the perceived usefulness of remote learning: MOS → PU ($\beta = 0.162$, $t = 5.836$, $p < .001$), NAT → PU ($\beta = 0.086$, $t = 3.266$, $p = .001$). In contrast, students' labor activity did not affect the perceived usefulness of remote learning: LA → PU ($\beta = -0.003$, $t = 0.120$, $p = .905$). Thus, hypothesis H4 was rejected. The perceived ease of use of remote learning differentiated the perceived usefulness. PEOU → PU ($\beta = 0.684$, $t = 31.077$, $p < .001$). Hypothesis 5 was supported. However, Hypothesis 6 was not supported. The perceived ease of use of remote learning differentiated attitudes toward remote learning: PEOU → ATT ($\beta = 0.035$, $t = 0.780$, $p = .435$). The analysis shows that perceived usefulness influenced the attitude toward remote learning and behavioral intention: PU → ATT ($\beta = 0.707$, $t = 17.921$, $p < .001$), PU → BI ($\beta = 0.539$, $t = 13.939$, $p < .001$). Thus, Hypotheses 7 and 8 were supported. Attitude toward technology influences behavioral intention: ATT → BI ($\beta = 0.367$, $t = 9.506$, $p < .001$). Thus, Hypothesis 9 was supported. Hypothesis 10 was also supported. Behavioral intention affects the actual use of remote learning; BI => AU ($\beta = 0.631$, $t = 28.071$, $p < .001$). After confirming the above relationships, I considered their relevance. I assessed the effect size of the predictor construct by using f^2. The effect size is a measure used to assess the relevant impact of a predictor construct on an endogenous construct. According to

Cohen (1988, pp. 412–414) the f^2 value of 0.02 or more is define a small effect, the value of 0.15 gains a medium effect, and the value of 0.35 or more is described to have a large effect. Analyzing the data in Table 6, it is evident that for the four identified relationships there was a large effect size (PEOU → PU; PU → ATT; PU → BI; BI → AU). There was a medium effect size for the relationship between attitude toward remote learning and behavioral intention. There was a small effect size for the two relationships identified (MOS → PU; AGE → PU). For others relationships the endogenous construct showed no effect on the exogenous variable.

Table 6. Summary of verified hypotheses devoted to direct relationship.

		β	t	p	f^2
H1	AGE → PU	0.109	4.699	.000	.021
H2	MOS → PU	0.162	5.836	.000	.033
H3	NAT → PU	0.086	3.266	.001	.012
H4	LA → PU	-0.003	0.120	.905	.000
H5	PEOU → PU	0.684	31.077	.000	.985
H6	PEOU → ATT	0.035	0.780	.435	.001
H7	PU → ATT	0.707	17.921	.000	.550
H8	PU → BI	0.539	13.939	.000	.471
H9	ATT → BI	0.367	9.506	.000	.220
H10	BI → AU	0.631	28.071	.000	.662

DISCUSSION AND CONCLUSION

The survey was conducted in the aftermath of the pandemic, when many universities returned to on-campus teaching. The university in this study decided to allow students to study fully online or in a blended mode. Of all the correlations identified, the strongest relationship was found between perceived ease of use and perceived usefulness of remote learning, and between perceived usefulness and attitudes toward remote learning. However, it turned out that perceived ease of use did not affect attitudes toward remote learning at all. The Technology Acceptance Model was developed more than 30 years ago. During this time, many problems associated with the difficulty of operating computer programs have disappeared or been minimized. Perhaps surprisingly, the perceived ease of use of remote learning is strongly influenced by changes in perceived usefulness. Simultaneously, this relationship among all the analyzed relationships is the strongest. Online learning platforms are now more intuitive and they are less demanding to use on a day-to-day basis. Examples include e-learning platforms, which have now gained more intuitive user interfaces, their developers have simplified navigation. Today, most people have access to a personal computer, laptop, smartphone, or tablet. Online learning programs allow the use of various devices and offer mobile apps, making it much easier to access educational materials. In addition, broadband connections have become more widespread, allowing websites and online educational content to load faster. This, in turn, has contributed to the easier use of online learning platforms. The first versions of online learning platforms had incomparably poorer real-time communication capabilities for users or the potential to integrate with other external tools. There was no means for students to edit documents, work in groups, share files, and communicate with each other. In 2022, in the EU countries, the percentage of people using the Internet was 80–90% (Eurostat, 2023). According to the data for 2021, the percentage of citizens using the Internet was 85.4% in Poland, 79.2% in Ukraine and 86.9% in Belarus (The World Bank, 2023). In terms of the relationship between the perceived ease of use and the perceived usefulness of remote learning, the results of my study confirm the findings of Alyoussef (2023), Jiang et al. (2021), Kaewsaiha and Chanchalor (2021), Muñoz-Carril et al. (2021), Yao et al. (2022), and stand in opposition to the findings of Akman and Turhan (2015), Alassafi (2022), Chang et al. (2017). The results of my research are also contrary to those of López et al. (2023). These authors say that adoption of online education depends on individual factors such as age, income, digital skills. In my case, the characteristics of the respondents had very little effect on the behavior surrounding remote learning.

My study stands out for several unique reasons. First, I focus on surveying students from a variety of backgrounds, as opposed to other studies that often focus on a specific field of study. This multi-directional approach allows for more general insights and identification of differences in how different groups of students perceive and use remote learning. Second, my study focuses on analyzing the use of post-pandemic remote learning. It is not based on a hypothetical situation, but examines students who actually have the opportunity to study remotely when many universities have already abandoned online teaching. Unlike many other studies that have focused on the pandemic period, when remote learning was introduced as a response to COVID-19 restrictions, my goal is to understand how students continue to use this form of learning after the crisis has subsided. This provides important insights into students' long-term perspectives and opinions on remote learning. In addition, my study focuses on the specific conditions of education in Poland, which makes it unique. There is a large percentage of part-time students, a developed private market for higher education, and a significant influx of people from the former USSR countries, especially from Ukraine. This special nature of education in Poland may influence students' experiences and perspectives on remote learning. Therefore, my study provides valuable information about the Polish education system and contributes to a better understanding of the challenges and benefits of remote learning in this context. The particularities of the Polish education market are also the result of the country's geographical location. Poland borders the former Soviet Union, and as a result of the conflict in Ukraine, we are seeing a significant influx of Ukrainian students coming to Poland in search of educational opportunities. One of the main reasons why these students choose Poland is the possibility of finding legal employment during their studies. This has a significant impact on the education market in Poland and the trend was evident even before the war in Ukraine. Emigration was driven by a variety of reasons, including economic factors, corruption, the unstable situation in Ukraine, and the geographic and cultural proximity to Poland (Paszkowicz & Hrynenko, 2019). Consequently, my study adds to a broader understanding of the Polish education market and its situation, considering the impact of country's geographical location and cultural and linguistic peculiarities. Analyzing the use of remote learning in the context of this specific situation allows a better understanding of the adaptation and experiences of both Polish and non-Polish students.

Limitations and further research

The research was carried out at one university in Poland. The sample included participants from Eastern European countries such as Poland, Ukraine, and Belarus. Evaluations of remote learning may depend on the prevalence of Internet use among respondents, their nationality, their field of study, or the platform they use. It might be worthwhile to conduct a survey of acceptance of the use of remote learning on different continents, considering students in fields such as fine arts or medical fields which require direct doctor–patient interactions. The surveyed students used a single, specific remote learning platform. Acceptance of remote learning is also likely to vary depending on the specific learning platform used.

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