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The mediating role of students' ability to adapt to online activities on the relationship between perceived university culture and academic performance

JEL Classification: *I21; I23; M21*

Keywords: *online academic activities; engagement; e-learning academic performance; adaptability; PLS-SEM*

Abstract

Research background: The COVID-19 pandemic has affected higher education globally and disrupted its usual activities, according to differing perspectives. The ability to adapt to online activities was an important factor for many researchers during the pandemic period.
Purpose of the article: In this article, the authors are studying the ability of the students to adapt to online activities, and also the direct and indirect effect on their academic performances.
Methods: The data was collected with a questionnaire and the respondents are students from Romanian Universities. The analysis was made with an econometric model by using the PLS-

SEM methodology. The goal of the paper was to find and analyse the factors used to perform academic online activities during the pandemic period.
Findings & value added: The results of the paper validate the research hypotheses formulated in the introductory part and confirm that the students' academic performances are a direct result of many factors, such as: system parameters, personal demand, personal commitment, and regulatory environment. The identification of the exogenous variables with significant impact on the students' performances through online activities could help the management of the universities to implement the positive aspects and to reward them for their efforts while preventing from resilience to change. The higher education system has to acknowledge that flexible online learning opportunities are needed by students to fit their coursework around their employment and family responsibilities.

Introduction

The COVID-19 experience changed and challenged the current business models with a direct impact on education. Strongly connected with the new economic digitalized word, the online teaching switched to a new paradigm of education. The new paradigm has created patterns hardly to be changed in the next few years. Apparently disappointed by the lack of the in-person Teacher, students found out the unlimited opportunities of online learning, while the teachers discovered the unexplored online resources for teaching and research.

Online activities at the university level are a topic covered in a variety of literature, and the phrase is frequently used as a catch-all for concepts like web or online learning. The distinctions between these ideas are determined by the features of the kind of educational material employed, the means used to communicate the educational information, or the manner of interaction between the student and the teacher (Baber, 2020; Elmer *et al.*, 2020; Muthuprasad *et al.*, 2021). This assignment is challenging, and research done to date shows a discrepancy between students' online behaviour and their projected success (Cerezo *et al.*, 2016; Li & Tsai, 2017; Çebi & Güyer, 2020). This issue needs to be addressed, and this article makes progress in that direction.

This article is analysing the situation of Romanian universities and develops an econometric model to quantify the impact of online academic activities on students' performance level based on the adaptability to the new paradigm. Identifying the drivers of increasing the academic performance through the online system is essential for the university management board, in order to capitalise on the main issues, such as the degree of involvement in online activities and reward opportunities, to increase motivation and reasonable evaluation. In March 2020, university teaching and learning moved to the online platforms, which were substantially improved to respond firstly to the higher number of users and, secondly, to the various needs related to teaching, assessment, and evaluation methods

Initially perceived as a new short-term tool, the online system became the normality in the unprecedented reality with unexpected consequences and unlimited resources. The opportunities and vulnerabilities of the online educational system are still under exploration and the results are still incipient. Top world universities have invested millions of dollars in infrastructure to capture the new perspectives of the online system that will increase competition among programmes, internationalization trends and partnerships in business-oriented education.

By including all of these ideas in the current growing setting and disclosing the model variables to study the advantages of e-learning in the pandemic period, the most significant theoretical contribution of the study may be highlighted. Many prior papers have analysed the indicators that affect the implementation of e-learning in a variety of scenarios (Abbad, 2021; Fazil & Rupert, 2016; Hossein, 2015; El-Masri & Tarhini, 2015; Mehta *et al*., 2019). Whether online academic activities would continue after the pandemic and how this change might affect the international system of education are topics of discussion throughout the world.

From an international perspective, an important study (Yao *et al*., 2022) was a base study in designing this manuscript (Yao *et al*., 2022). This study sought to determine if students who began using internet resources for their studies during the pandemic would continue to do so. The respondents were five hundred students enrolled in eight universities in the Henan region. The method used for data analysis was PLS-SEM. The findings of this paper have proved that self-awareness does not significantly affect how valuable online academic activities are considered by users who want to continue using them. Additionally, the college students' perspectives on utilizing the online system activities may directly affect their continuous intention. The econometric model also explains the influence of self-awareness on the tendency to continuously use the online learning activities. Given the high importance of this topic in the international research, the current paper emphasizes the case of Romania and completes the research gap with a valuable contribution.

This article's main goal is to evaluate if the online teaching and learning paradigm is consistent with academic performance in the new academic paradigm influenced by Zoom, Internet platforms and applications. The data was collected with a questionnaire distributed to university students in Romania, and a structural equation model with PLS methodology was used for data analysis. The structure of the paper follows the general format of any academic paper starting with concepts and literature review, then research hypothesis and methodology, afterwards the results and discussion part, and finally the conclusions. The key research hypothesis addressed in this article are: Personal demand (PD) has a significant impact on the ability to adapt to online activities (AS); The use of the = parameter system (SP) has a significant impact on the ability to adapt to online activities (AS); Regulatory environment (RE) has a significant impact on the ability to adapt to online activities (AS); The personal commitment to online activities (PC) has a significant impact on the ability to adapt to the online system (AS); The ability to adapt to the online system (AS) has a significant impact on the academic performance of students (AP); The student's ability to adapt to online activities has a mediator role between the exogenous variables PD, SP, RE and PC and the endogenous variable academic performances of students (AP).

Literature review

The new literature related to the COVID-19 implications in the educational sector distinguishes between online education, online teaching, e-learning, etc. According to Yang and Huang, there is general agreement that there are considerable differences between the various concepts in terms of the complexity of educational ideas (2021). However, most authors agree that the simple transfer of knowledge via Internet is not enough for online education manifestation and there are some "novel endeavours" to support the achievement of this process.

Online learning is a demanding environment where students must assume complete responsibility for their education. It is frequently learner-centred and demands a significant amount of self-motivation (Xu & Jaggars, 2013; Luo *et al.*, 2021; Meşe & Sevilen, 2021; Doan, 2022). This type of communications has been widely used in blended courses and offers new pedagogical possibilities and comprehensive levels of involvement in the classroom.

It had already been used in universities before the pandemic period, referring mostly to the asynchronous mode of sharing course materials and discussions (Kozakowski, 2019; Jung *et al.*, 2021). According to Seok (2007), "e-learning" is the methodology for modern education in the twenty-first century. This allows online students to live far away from school and balance their education with other commitments such as job or family.

Given the fact that student academic performance has increased, it seems reasonalbe to infer that online dialogue can promote collaborative learning and information acquisition. For instance, Federmeier *et al.*

(2020), pioneers in the study of the function of language in cognition, asserted that conceptual acquisition required a collaborative effort and constructive dialogue. While this appears to make sense in principle, practical evidence supporting the positive effects of online activities is limited. Cheng *et al.* (2011) discovered that the amount of discussion board postings that students made over the semester was substantially correlated with their final scores in an online class. True learning dialogue in the online medium, on the other hand, requires students to reflect and read in order to participate.

Lately, online learning has facilitated the creation of a new type of educational process, attracting a huge number of stakeholders and students, in which they interact directly with systems or applications rather than teachers. Nonetheless, there are some obstacles in assessing students' performance holistically from many perspectives. There has been much debate about whether online education would eventually replace in-person teaching and take over as the primary delivery method for education. Although there are many good arguments for the Internet benefits for teaching, research, and knowledge exchange, Dhawan (2020), Jung *et al.* (2021) and Philip *et al.* (2021) recognized that online learning is not a panacea.

People were forced to stay at home in 2020 as the COVID-19 pandemic grew. Many organizations, companies, and colleges throughout the world asked their employees to work remotely (Bolisani *et al.*, 2020; Pollák *et al.*, 2021). To be able to prevent disruptions brought on by pandemics like COVID-19, Kazancoglu *et al.* (2022) focused on supply networks that are resilient and sustainable globally. The research assumptions were analysed using a PLS model with 200 responses gathered from businesses with intricate supply chains. The connection between the global supply chains' flexibility, agility, and responsiveness was discovered as a novel outcome. However, in order to keep up with technological advancements and online education, flexibility was the keyword for most colleges that instantly turned to online learning platforms to continue the educational process.

It has been determined that there is a glaring knowledge gap concerning the significant obstacles and factors of e-learning during the COVID-19 pandemic, because there is no consensus on the fundamental issues and variables that impact the usage of e-learning systems at this time. In a study that was published in Education and Information Technologies, interviews were conducted with 31 e-learning system specialists and 30 students from six universities in Saudi Arabia and Jordan. The study's objectives were to identify the significant problems with the current e-learning systems and to look into the key elements that encourage their use in the COVID-19 pandemic. The respondents identified the following factors as the most significant influences on the use of e-learning systems that universities should consider in the future: cultural considerations, technology, self-efficacy, e-learning system quality, and trust elements (Almaiah *et al*., 2020).

An intriguing study looked at the variables affecting the desire of the college students to pursue online learning during the COVID-19. The researchers received information from 109 students who were enrolled at one of Indonesia's institutions and completed an online survey. SEM methodology and SMART PLS 2.0 M3 were used for analysing the data. Results showed that the proposed model was effective in revealing the reasons why Indonesian university students relied so heavily on online learning systems during the COVID-19 pandemic. It was shown that the attitude of university students to using online learning systems during the pandemic was the key determinant of their motivation to do so (Mailizar *et al*., 2021).

Abumalloh *et al.* (2021) used a survey that was collected from students at a University from Dammam, Saudi Arabia, to analyse the anticipated benefit of web education during the pandemic. On 179 usable replies, PLS-SEM was used. Study's results showed that the pull effect is a key factor in deciding whether or not to transition to online learning and enjoy its advantages. This study's pull effect is based on how users perceive the online learning environment and social isolation policies. Additionally, it demonstrates how crucial system security is in order to avoid impeding knowledge sharing within an e-learning system.

Universities had to swiftly adjust to new circumstances because the majority of nations did not have particular regulations for online activities: implement online teaching and assessment strategies, identify a universal channel of communication with students, and create an online learning platform (Chayomchai, 2020; Păunescu & Mátyus, 2020; Owusu *et al.*, 2021). Students had to adjust to new environmental situations and technologies that were not the same as those in the usual university offline classes. Particularly, these unfamiliar surroundings may be uncomfortable and affect the students' academic performance. These novel circumstances, in particular, can be upsetting and affect students' academic performance in several ways. Thus, the objective of this paper is to examine the impact of several variables on academic performances of the students in online courses during the COVID-19 pandemic.

Empirical state of the art

Avcı and Ergün (2022) conducted a recent study that looked at the learning management system activities of online students and how those activities affected their information literacy, engagement, academic success. 65 bachelor students enrolled in an online "Computer Literacy" course made up the study's participants. The collected data was subjected to cluster analysis, and participation levels were split into two categories: low and high participation. The multivariate analysis of variance (MANOVA) showed that student engagement and academic achievement might be significantly influenced by LMS involvement levels. Moreover, an important outcome is that technology and interface features affect the way students interact with one another and participate in class. Another study by Tsai *et al.* (2021) supports the idea that students' views of involvement and learning results were most positively rated in highly interactive courses.

As more students migrate to online learning, especially after COVID-19, the demand for adaptable online activities that meet students' desire to be able to study anywhere, at any time, will increase (Crawford *et al.*, 2020). A mixed-method design was used in research by Sugden *et al.* (2021) to explore students' interactions with online activities. They used learning analytics, surveys, qualitative interviews, and focus groups (FG) approaches to give a thorough evaluation of the use and engagement in the learning activities by the students. The main findings show that students engage in study sessions using different devices to fit study time around job and family obligations. These results collectively demonstrate the necessity for flexibility, mobility, and device compatibility in the design of online activities in the future.

Six proxy variables were examined, building on the models outlined in the literature review: personal demand, system parameters, regulatory environment, individual commitment, capability of adapting to online activities, and academic performance. Table 1 reveals the number of items used for each formative variable and the corresponding references in the literature.

Research hypothesis development

To be able to predict academic performance is essential for offering high-quality education. The literature has developed a number of techniques for utilizing data to predict academic achievement by analysing the influence of the factors affecting academic success (Ahmad *et al.*, 2018; Cao *et al.*, 2018; Kassarnig *et al.*, 2018; Liu *et al.*, 2018; Qu *et al.*, 2018; Yao *et al.*, 2019; Akram *et al.*, 2019). For instance, Wang *et al.* (2015) used passive sensing data and student self-reports from their smartphones to predict academic progress. Based on data from submitted assignments, Akram *et al.* (2019) predicted the academic success of students enrolled in a blended learning course.

Other researchers claim that the degree of structuring in the course impacts students' performance (Stein, 2004). Encouraging views about technology and an independent learning style affect student satisfaction in online learning, according to Drennan *et al.* (2005). Since students who believe they haven't had enough access to their professors are also less happy with the activities, Fredericksen *et al.* (2006) contend that the interaction between the student and the teacher is the most crucial component of online learning. Jung *et al.* (2002) , however, claim that students' performance was shown to be more significantly correlated with the level of student-student connection than with the level of involvement with the teacher. They discovered that learners who worked with one another had the best academic results.

Shukor *et al.* (2014) suggested a study to evaluate the quality of online learning through students' cognitive participation in response to the growing popularity of online learning across all educational levels. The respondents of the questionnaires were students at the Universiti Teknologi Malaysia. The results of this study have demonstrated that just two factors — information sharing and posting of sophisticated messages — accounted for students' online cognitive involvement.

More recently, Gonzalez *et al.* (2020) analysed how the learning performances of the students in higher education was impacted by the COVID-19 limitations. Their findings show that online instruction improved students' academic achievement by helping them establish more reliable study habits and boost their productivity.

Additionally, Adnan and Anwar (2020) investigated what Pakistani college students thought about online education. Students believe that because the majority of students in impoverished countries do not have internet access, it is difficult for online classrooms to achieve the desired academic results. Other COVID-19 pandemic impacts include slower response times, a decline in traditional classroom interactions, and a lack of direct interactions with professors. Additionally, university administration previously worked under intense pressure and was abruptly required to incorporate online activities, which led to stress and burnout (Parmar *et al.*, 2022).

The noteworthy findings from Haider and Al-Salman (2020) have revealed that most students believe that face-to-face interaction is important in improving their academic accomplishment, and a great percentage considers that the number of e-learning assignments leads to confusion, dissatisfaction, and poor performance.

Additional research on the impact of internet conversations show the factors that influence student engagement behaviour. Information overload, instructional tasks, content and materials, and student roles are among the factors that affect students' participation in online conversation (Ma *et al.*, 2014). Moreover, there has been little investigation on the impact of collaboration-related characteristics on students' engagement in online discussions. Additionally, it has been shown that social ability, which measures how well kids can use their social environment's resources to achieve goals, affects collaborative work (Laffey *et al.*, 2006).

In order to enhance the process of decision-making in universities, Edu *et al*. (2021) examined the variables influencing student transfer to online education (STOE) in Romania. They have discovered direct and negative correlations between five factors: the online platform, the functioning of the platform, demographics, the amount of enrolment, the location.

Five statistical hypotheses were constructed in the context of the literature review to create a regression model of the mediating role of students' capacity to adapt to online activities between perceived university culture and academic achievement:

H$_1$: *Personal demand (PD) has a direct impact on the ability to adapt to online activities (AS).*

H$_2$: *The use of the parameter system (SP) has a significant impact on the ability to adapt to online activities (AS).*

H$_3$: *Regulatory environment (RE) has a direct impact on the ability to adapt to online activities (AS).*

H$_4$: *The personal commitment to online activities (PC) has a significant impact on the ability to adapt to the online system (AS).*

H$_5$: *The ability to adapt to the online system (AS) has a positive impact on the academic performance of students (AP).*

Hypothesis 5 incorporates the relationship between the independent variables and academic performance and formulates the mediation model, which is formulated in Hypothesis 6.

H$_6$: *The student's ability to adapt to online activities has a mediator role between the independent variables PD, SP, RE and PC and the students' academic performances (AP).*

The creation of the structural model will be aided by the description of the exogenous and the endogenous variables in the section that follows.

Following a structural equation modelling (SEM) analysis, the structural model will be put to the test and validated.

Research method

This study aims to corroborate the conceptual model via the use of structural equation modelling and econometric analysis of data gathered via questionnaire. Using a quantitative analysis, the paper also evaluates the impact of the econometric model on the academic performance of students during the pandemic period, represented by personal commitment, personal needs, regulatory framework, and system variables.

The respondents of the questionnaire were the university students in Romania. The population represents all Bachelor, Master and Doctorate students, and the respondents were chosen using a non-probabilistic sample approach, because of the social distancing measures enforced by the pandemic conditions generated by COVID-19.

The authors employed a survey based on a questionnaire containing both closed-ended and open-ended questions to assess all six study hypotheses. The collection of the data was organized between February 1st, 2021 and April 30th, 2021. The usual problem of the respondents' reluctance to fill in the questionnaire was an important issue, in order to avoid this situation, the authors deleted all personal data, and statistics were presented in an aggregate way.

According to Kadam and Bhalerao (2010), in the case of an unknown population, the sampling volume should consist of at least 1,068 respondents with a margin of error of 3% and a confidence interval of 95%. In our research, the sample consisted of 1,447 questionnaires, out of which 1,410 were valid and 37 incomplete, which meanst that the rate of response was 97.44%. Although the non-responses rate was low, the authors reduced non-responses bias by asking simple questions, using the best possible distribution method for the audience, providing an incentive for the respondents in terms of telling them that they will have access to the aggregate answers of the survey, reminding them from time to time to answer the survey and asking for feedback. The incomplete questionnaires were removed from the analysis. For the response options, a 7-point Likert scale was used, and the answers were ranged from 1 (very little) and 7 (very much). The pre-testing step of the questionnaire ensured the appropriateness of the language, format, etc.

The sample distribution (the number of students per cycle) is available in Table 2.

According to the table, the sample consisted of 1,410 students from the universities, classified by gender, age, cycle and residence, the questionnaire containing 30 open-ended, close-ended, and mixed questions.

The questionnaires also include demographic questions (gender, age, degree, residence, professional status, etc.) in order to have a broader picture of the respondents.

Exogenous and endogenous variables interact to generate the structure of the model's variables. The exogenous variables are defined in Table 3, while the dependent variables could be seen in Table 4.

In the conceptual model, the formative variables will be the exogenous variables presented in Table 3, while the reflexive variables will be the endogenous variables in Table 4. Thus, all constructs of the exogenous variables are formative, while the constructs of the endogenous variables are reflexive.

The structural model (Figure 1) resulting from the exogenous and endogenous variables has been defined above.

In the next chapter, we will test and validate the structural model.

The analysis of the impact of indicators of the online academic activities on the academic performance was made through a quantitative model. All six research hypotheses were tested using the PLS-SEM methodology, and the analysis was made using the Smart PLS 3.3. statistical software (Ringle *et al.*, 2015). The motivation of using SMART-PLS instead of CB-SEM (Covariance Based SEM) was that the first one is less sensitive to the multicollinearity issues, small samples, and asymmetric distributions and is more robust. Also, when using CB-SEM methodology, the residuals' correlation could be followed by problems of identification which could be solved by using unrealistic condition that the error term is 0. On the other hand, PLS-SEM methodology does not have any identification issues if the residuals are correlated (Falk & Miller, 1992). Other reasons for choosing PLS-SEM methodology are: exploratory research objective/ predictive purposes, non-normality assumptions, analysing reflective and formative constructs and the number of interaction terms (Roldán & Sánchez-Franco, 2012; Balcerzak & Pietrzak, 2016; Szostek *et al.*, 2020, 2022a; 2022b).

Results

The level of significance of the variables in the structural model was checked before proceeding to the proposed analysis, meaning of internal consistency, reliability and validity of data. Hence, the "Dillon-Golsteins' ρ" and "Cronbach's Alpha" coefficients were computed (Tenenhaus *et al.*, 2005). The calculated values are displayed in Table 5.

Table 5 indicates that the variance inflation factor (VIF) values are between 1 and 5, and, according to Hair *at al.* (2013), it means that multicollinearity is not present in the model. Moreover, the coefficients of the formative variables are between 0.7 and 1, which proves that all independent variables of the model are significant.

According to Nacaskul (2017), the convergent validity of the formative variables also needs to be analysed. Figure 2 displays the correlation coefficients between the latent variables and their constructs.

The Average Variance Extracted (AVE) method might be used to run the discriminant validity test. Fornell and Larcker (1981) assert that the square roots of the coefficients of correlation between the exogenous variables must be bigger than the AVE indicator values for the construct variables in order for the discriminant validity to be supported. As a result, the values from Table 8 support the model's discriminant validity.

According to Sarstedt *et al.* (2014), from the measurement model, we should delete the constructs with coefficients less than 0.5. Consequently, we will eliminate the following constructs: pd_3, pd_4, sp_2 and pc_2 in the measurement model 1. After this exclusion procedure, we will run again the PLS-SEM analysis and obtain the second model.

Figure 3 shows that all coefficients of the latent variables are greater than 0.5. Hence, we can conclude that all constructs are statistically significant and that the measurement model 2 is valid.

Figure 3 also reveals the coefficients of determination (R^2). Hence, we note that about 72.4% of the variability of the endogenous variable AP is interpreted by the variability of the independent variables PD, SP, RE and PC, while 64.8% of the variability of the endogenous variable AS is explained by the independent variables PD, SP, RE, and PC.

The direct effects analysis

We will firstly analyse the direct effects between the four independent variables of the model and the dependent variable AS, and between AS and its successor AP. We also analyse the size of the effect (f^2). All these results are presented in Table 6.

The model parameters t-test and the standard error (SE) were generated by the Bootstrap Test methodology with 5,000 resamples (Nitzl *et al.*, 2016). These values were used for validating the statistical hypotheses formulated in the introductory section. Bootstrapping allows the calculation of indirect and direct effects, related bias corrected confidence intervals (BCI) and t-statistics, as well as the distribution of sample estimate precision measures.

In Table 6, the results of the testing of the statistical hypotheses H_1-H_5 are presented.

From the first line of the above table, we notice that PD has a positive direct effect on AS ($\beta = 0.285$; $p < 0.001$). Moreover, according to to Rosenthal *et al.* (1994), the size of the effect of one exogenous variable on the endogenous variable is given by the modification of R^2 if the exogenous variable is excluded from the model. Thus, we can see that the size of the effect of the exogenous variable PD on the endogenous variable AS is moderate ($f^2 = 0.109$; $p < 0.01$). This indicates the importance of personal demand of students in their ability to adapt to online academic activities.

The second row of Table 6 reveals that the endogenous variable SP has a significant and direct impact on the endogenous variable AS ($\beta = 0.212$; $p < 0.01$). Also, we can see that there is a low size effect of SP on AS ($f^2 = 0.098$; $p < 0.05$). This means that the role of system parameters on the students' ability to adapt to online academic activities is low.

Also, given that the explanatory variable RE has a significant and direct impact on the explained variable AS ($\beta = 0.218$; $p < 0.01$) and that the level of the direct effect of RE on AS is average ($f^2 = 0.108$; $p < 0.05$), we can state that the regulation environment plays an important role on the students' ability to adapt to online academic activities.

Also, we notice that the exogenous variable PC has a strong and positive impact on the endogenous variable AS ($\beta = 0.311$; $p < 0.001$). Also, the size effect of PC on AS is average ($f^2 = 0.198$; $p < 0.01$), so we can say that the personal commitment of students is an important factor of their ability to adapt to online academic activities.

Thus, from the last line of the above table we notice that the coefficient between AS and AP is positive and significant ($\beta = 0.412$; $p < 0.001$). Thus, we conclude that the ability to adapt to online teaching activities is an important factor of students' performance. Moreover, the reflexive variable, namely "Online evaluation of teaching activities carried out, compared to the face-to-face version, was better", has a high value, which reveals that this is an important indicator of the academic performance of students during online activities.

Mediation analysis

The direct effects between AS and the other four independent variables (PD, SP, RE and PC) and one dependent variable (AP) were tested in the previous chapter. Now we will test the direct effects of the four independent variables on the dependent variable AP, as well as the mediation role of AS on PD, SP, RE, PC and AP. The direct effects and indirect effects of AS as the mediator results, obtained by using the bootstrap procedure, can be seen in Table 7.

From the first line of the above table, we could see that PD has a significant and positive direct effect on AP ($\beta = 0.181$; $p < 0.05$). Also, the indirect effects of AS ($\beta = 0.078$; 95% BCI = [0.050; 0.101] reveal that AS is a mediator between the variables PD and AP. Thus, the academic performances of students are greater when students are investing in their personal demands.

We also notice that SP has a direct and significant effect on AP ($\beta = 0.387$; $p < 0.001$), while the indirect effect on AS is also significant ($\beta = 0.120$; 95% BCI = [0.090; 0.150]). Thus, we conclude that AS is a mediator between the SP and AP variables, which means that if universities are investing in IT equipment for students to carry out their academic activities, students' performances would increase.

Given that the direct effect of RE on AP is significant ($\beta = 0.218$; $p < 0.01$) and that the indirect effect with mediator variable AS is also significant ($\beta = 0.131$; 95% BCI = [0.106; 0.156]), we state that AS mediates between the RE and AP variables. This means that the performance of students in their online academic activities will be stronger if universities invest in their regulatory frameworks.

Finally, the direct effects of PC on AP ($\beta = 0.285$; $p < 0.001$) and the indirect effects through AS ($\beta = 0.216$; 95% BCI = [0.165; 0.267]) are both strong and significant, so we could conclude that AS is a mediator between PC and AP. This underlines the fact that the personal commitment of students with their online academic activities would increase their performance.

Hence, hypothesis H_6 is confirmed.

Besides the model fit assessment, we would also like to evaluate the strength of the partial mediation. Partial mediation should be also analyzed when performing mediation analysis, so it will be helpful to acknowledge future information on the mediation part. A useful approach is to rate between the indirect effect to the total effect. This indicator is also known as the Variance Accounted For (VAF) value. This indicator reveals which part of the variance of the endogenous variable is determined by the mediation process. Variance accounted for is defined as:

$$VAF = \frac{a\ x\ b}{a\ x\ b + c'} \tag{1}$$

where:
a direct path between A and B;
b direct path between B and C;
c' direct path between A and C;
A and C variables;
B the mediator between A and C.

We will calculate the VAF for the mediator variables, using the path coefficients from Figure 3. Hence, we obtain the results in Table 9.

Hair *et al.* (2014) considers that if VAF > 80%, then we have full mediation, if 20% ≤ VAF ≤ 80% we have partial mediation, and if VAF < 20% then we do not have any mediation. From Table 9, we see that all VAF values are between 20% and 80%, so we conclude that we have partial mediation.

Discussion

The results are in line with other recent economic papers which argue that personal demand, system parameters, and personal commitment have a direct impact on students' performances (Zhang *et al.*, 2020; Kim *et al.*, 2019), but denies that regulatory environment has a positive impact on students' academic performances (Alghamdi *et al.*, 2020). Our findings also confirm other recent studies which demonstrate that the capacity to adapt to online activities has a mediating impact on formative factors and academic success (Lu & Cutumisu, 2022).

On the other hand, the methodology proposed by the authors of this paper is slightly different from other methodologies used in other recent academic papers. For instance, Cataldo *et al.* (2021) used PLS-PM methodology to check the consistency of the econometric analysis to forecast for discrete cases, while the authors of this paper used PLS-SEM, as it was described in the Methodology section. Another paper by Gimeno-Arias and Santos-Jaén (2022) is also using PLS-SEM methodology, but on a smaller sample, as the data were collected from a questionnaire with 172 respondents. Moreover, Palacios-Manzano *et al.* (2021) are analysing the effect of corporate social responsibility (CSR) on the financial performances with a model which has three independent variables and one dependent variable, which is less than the number of variables used by the authors of this paper. This leads to the conclusion that the academic performances of undergraduate and graduate students in Romania during the pandemic period is a result of several factors and was related to their ability to adapt to online courses.

Hence, we can affirm that personal demand, system parameters, regulatory environment, and personal commitment of students are determining factors in terms of the ability to adapt to online courses, which is also a mediator to their academic performances.

The challenges of COVID-19 are mainly related to the erosion of socialization and relational functions on the grounds of "*commodification and marketization*" of universities. The "*post-coronial*" high education institution will need to combine face-to-face and web learning activities to respond actively to the future needs of the society (Eringfeld, 2021). According to Agasisti and Soncin (2021), a student-centred strategy and significant community involvement would further assure student continuity, faculty support, and the redesign of services for administrative personnel. Discovering the most appropriate balance between on-campus and online will be the most relevant challenge for the future strategy of the post-pandemic university.

Our results confirm the hypotheses formulated in the Research hypothesis development section, stating that the online academic performances of the students are based on a few indicators, like system parameters, personal demand, personal commitment and regulatory environment. Additionally, there is a mediating effect between the endogenous and exogenous variables due to the capacity to adapt to online academic activities.

Conclusions

The paper shows that academic performance is the direct and essential result of several indicators' intersection, such as *regulatory environment, personal commitment, personal demand, and system parameters.* The analysis of the impact of online academic activities on academic performance was made through a quantitative model and the research hypotheses were validated. The conclusions of this analysis could be useful for other universities, other education authorities, teaching staff and students, public authorities for the smooth transition of the process of educational system to the new online paradigm model. Moreover, this study completes the international research environment with the case of Romania.

A possible limitation of the study could come from the small number of the formative and reflexive variables of the model, as well as the small number of respondents. In addition, the subjective answers of students when filling in the questionnaire could be seen as another limitation. Future study might address these issues by expanding the quantity of formative and reflexive factors, including open-ended questions in the questionnaires, and by recruiting more participants. Further research could incorporate in the model certain macroeconomic variables. In addition, future studies could analyse the students' changes in their performance due to the pandemic situation.

All educational institutions had to shut down due to the COVID-19 virus quick spreading. Therefore, approaches to helping students who stayed at home to finish their education were required. Numerous initiatives have encouraged online study during the lockdown period in order to sustain the educational process. All these developments in online education have greatly aided in guiding students to comply with lockdown procedures. Decision-makers may benefit from this experience by using virtual platforms and technology more frequently in the future. The study findings could be used by universities to analyse students' performance during online academic activities and see whether there are any positive effects that could be incorporated in the academic activities even after the pandemic is over.

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Annex

Table 1. Scales of measurement

Formative variable	Number of items	References in the literature
Personal demand (PD)	4	Chemers *et al.* (2001); Shaha *et al.* (2015).
System parameters (SP)	3	Alkış and Temizel (2018); Broadbent (2017).
Regulatory environment (RE)	3	Alghamdi *et al.* (2020); Pardo *et al.* (2016).
Personal commitment (PC)	3	Ma *et al.* (2014); Edu *et al.* (2021).
Ability to adapt to the online system (AS)	4	Laffey *et al.* (2006); Akram *et al.* (2019); Liu *et al.* (2018); Sahebi *et al.* (2018).
Academic performance (AP)	4	Langford *et al.* (2014); Faught *et al.* (2017).

Table 2. Sample distribution

	Number of students
Bachelor	750
Master	580
Ph.D.	80
Total	1,410

Table 3. Exogenous formative variables

	1. Personal demands (PD)
pd_1	The importance of spending free time with friends and family.
pd_2	Level of education: Bachelor, Master, graduate studies.
pd_3	Living expenses during online activities compared to the previous period.
pd_4	The importance of benefiting from higher education.
	2. System parameters (SP)
sp_1	The importance of using adequate equipment for online activities.
sp_2	The importance of access to information for online activities.
sp_3	Computer skills have a great importance for developing academic activities in the online system.
	3. Regulatory environment (RE)
re_1	A regulatory framework is important in order to develop academic activities in the online system.
re_2	The academic specificity facilitates the online system activities.
re_3	Online courses are facilitated by the existence of a protocol.

Table 3. Continued

	4. Personal commitment (PC)
pc_1	The existence of a proactive attitude towards online courses.
pc_2	The existence of pressure or stress when it comes to daily activities.
pc_3	The existence of a negative attitude towards online courses, such as anxiety and isolation.

Table 4. Dependent reflexive variables

	1. Ability to adapt to the online system (AS)
as_1	Accessibility of the online platforms.
as_2	Interaction with colleagues and professors.
as_3	Interaction with the non-academic university staff.
as_4	Accessibility of services within the university.
	2. Academic performance (AP)
ap_1	By using information technology, attendance at teaching activities has increased.
ap_2	The pandemic caused by COVID-19 may adversely affect graduation.
ap_3	The volume and quality of online work.
ap_4	Online evaluation of teaching activities was better, compared to the face-to-face version,.

Table 5. Measurement model evaluation

Variables	Cronbach's Alpha	Dillon Golsteins' rho	Composite Reliability	AVE**	VIF*
PD	0.886	0.721	0.712	0.725	2.414
SP	0.821	0.764	0.719	0.825	1.935
RE	0.789	0.698	0.748	0.712	1.846
PC	0.748	0.689	0.723	0.705	1.753

Note: *AVE = Average Variance Extracted. *VIF=Variance Inflation Factor.

Table 6. Statistical hypotheses results

Hypothesis	Coefficients (β)	Standard Error (SE)	t-value	f^2	Decision
H_1: PD → AS	0.285***	0.079	2.567	0.109**	Accepted
H_2: SP → AS	0.212**	0.068	2.812	0.098*	Accepted
H_3: RE → AS	0.218**	0.075	2.758	0.108**	Accepted
H_4: PC → AS	0.311***	0.127	3.215	0.198**	Accepted
H_5: AS → AP	0.412***	0.185	3.107	0.205***	Accepted

Note: β = standardized coefficients; SE = standard error; f^2 = effect dimension; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 7. Direct and indirect hypotheses results (H_6)

Structural effects	Direct effects	Indirect effects. MV: AS		
		Coefficients	Lower 95%	Upper 95%
PD→ AP	0.181*	0.078*	0.050	0.101
SP→AP	0.387***	0.120*	0.090	0.150
RE→AP	0.218**	0.131**	0.106	0.156
PC→AP	0.285***	0.216***	0.165	0.267

Note: *p < 0.05; **p < 0.01; ***p < 0.001; MV = mediation variable.

Table 8. The correlation matrix of the latent variables

Latent variables	AVE	The square root of the correlation coefficients between latent variables			
		PD	SP	RE	PC
PD	0.885	1			
SP	0.869	0.634	1		
RE	0.817	0.681	0.534	1	
PC	0.752	0.585	0.489	0.542	1

Table 9. VAF values with AS mediator

Indirect effects with AS mediator	VAF value (%)
PD→ AP	64.87
SP→AP	33.04
RE→AP	44.76
PC→AP	61.51

Figure 1. Conceptual model

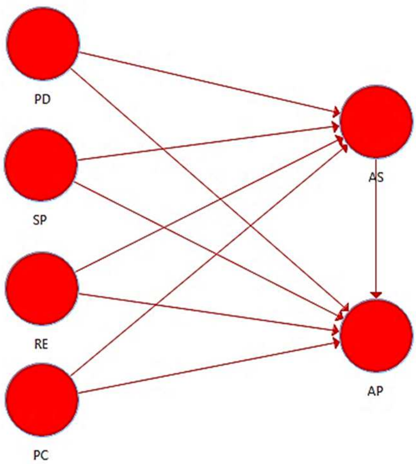

Figure 2. Measurement model 1

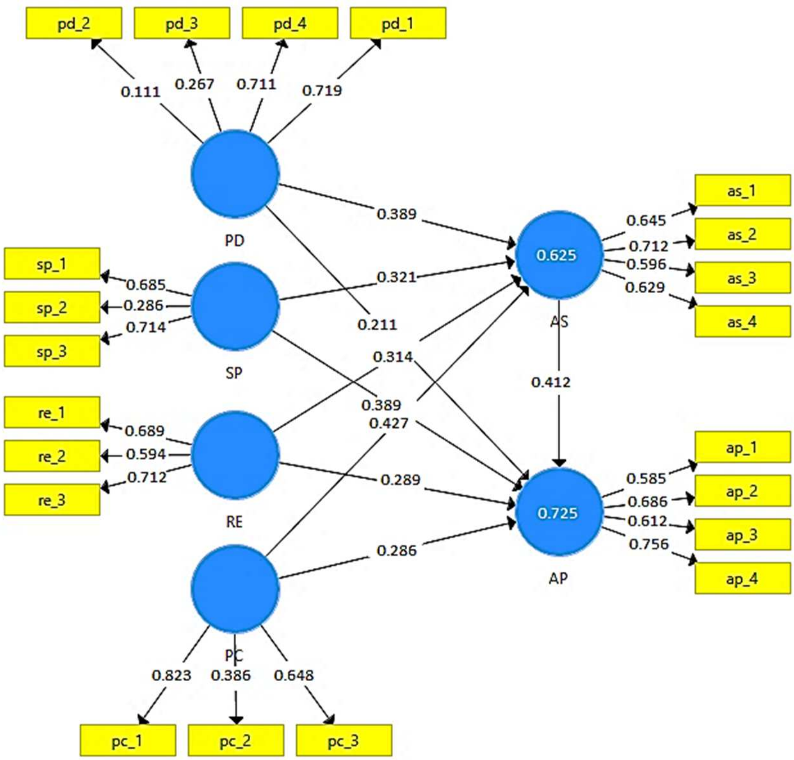

Figure 3. Measurement model 2