Education and Information Technologies
https://doi.org/10.1007/s10639-024-12639-6

How the support that students receive during online learning influences their academic performance

Juan José García-Machado[1] · **Minerva Martínez Ávila**[2] · **Nicoleta Dospinescu**[3] · **Octavian Dospinescu**[4]

Received: 17 June 2023 / Accepted: 21 March 2024

Abstract

In recent years educational institutions are increasingly using online learning and because of this trend it is necessary to investigate its impact on student academic performance. Although this topic has been addressed in different educational fields before, there is an objective justification for our approach. Thus, the reasoning behind this particular research is the fact that recent findings have shown that the academic performance of students using online education is affected by a series of motivating factors which can have an impact on their performance. The main goal of this paper is to highlight and analyze the mediating effect of intrinsic student motivation and student academic engagement and how they affect the relationship between the range of support, which students receive during their online learning and thus their academic performance. This study was conducted in two higher educational institutions in Mexico and Romania, with a sample of 822 students. The data was analyzed using a second generational PLS-SEM technique. The results confirm that the support students enjoy during online learning has no direct impact on their academic performance, unless it is fully mediated by their own intrinsic motivation and academic engagement. The influence of Gender was also analyzed, but it was not found to be a determining factor of academic performance in both higher educational institutions. These findings not only have theoretical and practical implications for students, teachers and education authorities, they also help us to broaden the field of knowledge in the e-learning environment.

Keywords Academic performance · Student support · Online learning · Intrinsic motivation · Academic engagement · Mediating effect

Extended author information available on the last page of the article

Published online: 10 April 2024

1 Introduction

The importance of students being supported during their learning experience has been analyzed before from different approaches in scientific literature but it requires further in-depth studies. Lee et al. (2011) consider that support for student learning can optimize students' experience and be a key element in the educational process. The guidance provided for students in their courses contributes decisively to their perception of the learning process. Three distinct categories of training support were identified: instructional support (from instructors), peer support (from fellow students) and a robust technical support (from academic staff and technical instructors, online support, etc.). The results of research conducted by Falloon (2020), Greenhow and Galvin (2020), Anthony et al. (2022) at different universities have shown that teachers should inform students and provide relevant details about the types of resources that are available to students and also guide them to easy access to that support.

The effect of a student's personal educational background is a key factor in terms of achieving the desired academic performance objective. Thus, Sánchez-Elvira Paniagua and Simpson (2018) discuss intrinsic motivation as a key factor underlying students' commitment to academic performance. The study conducted in Australia by Stone (2019) shows that, in general, the profile of students who study through the medium of online education is different from that of "classic" on-campus students. Hence, students, who choose the online approach, are usually older, more experienced, with important family responsibilities. As a result, motivational fundamentals differ depending on student profiles.

Chen (2005) analyzed academic engagement as the link between students' perception of the academic support, which they received, and the results they obtained in the educational process. The study highlighted an important aspect of this student perception of the support they received from parents, colleagues and teachers and how it was indirectly related to academic results. This relationship is mediated by one's own perception of academic commitment. Gasiewski et al. (2012) pointed out that the lack of academic engagement in the field of exact sciences is one of the determining factors of educational dropout. The results interestingly revealed that students tended to be more strongly involved in course activities if teachers were more open to answering questions from students and stimulating them to develop.

The general goal of our research is to analyze and highlight the mediating effect of Intrinsic Motivation and Academic Engagement. This effect is analyzed in the relationship that exists between Student Support Online Learning and Academic Performance.

To accomplish this research goal, this article will generate answers to the following three research questions:

- RQ1: To what extent does the Support that students receive during Online Learning (SSL) influence their Academic Performance (AP)?
- RQ2: To what extent is the Support that students receive during Online Learning (SSL) influenced by student Intrinsic Motivation (IM)?

- RQ3: To what extent is the Support which students receive during Online Learning (SSL) influenced by student Academic Engagement (AE)?

2 Literature review and hypotheses development

Academic performance in the online educational environment has been analyzed by Britto and Rush (2013) who highlighted the fact that student retention in higher education has become a very important issue for modern universities. The Lone Star College-Online study showed that student retention rates depend directly on students' own online experience, with direct implications for academic performance. A "student helpdesk" in the form of several communication channels (phone, chat, email) is in fact an extension of the "classic" way of face-to-face education, but in the online environment many more tools and resources are needed such as tutorials, customized courses, FAQs, etc. Although the resources are diverse, it is recommended that students interact with a single point of contact with technical staff.

Regarding the way of effectively delivering online learning support, the research conducted by Rotar (2022) highlights the importance of the timing and of the different stages in the learning cycle in which online learning support is offered, and how it impacts on academic performance. The analysis carried out suggests that the moment of time in which support is granted has a very important influence on the effectiveness of that support. It is also noted that technology is playing an increasingly important role in supporting students for online learning and in moving to a more personalized but holistic approach to online learning support.

At the European level, research conducted by Sánchez-Elvira Paniagua and Simpson (2018) shows that at the continental level there is a clear trend to support online learning in order to increase student retention, integration and satisfaction with the educational process and thus affect student academic performance. Lloyd-Jones (2021) highlighted the fact that the support for student online learning has multiple valences, which go beyond the purely technical and informational aspects. Thus, in certain situations, the students need, in addition to technical support, coaching support, care and collaboration. Research conducted by Mollenkopf and Gaskill (2020) in the United States has shown that supporting students engaged in online learning has a very relevant and direct influence on their academic performance. This support consists of a mixture of several aspects such as the degree of autonomy the students enjoy, the way in which they are responsible for their actions, their interactions with instructors, as well as the influence of other various factors from life and society. This approach is compatible with the one proposed by Vinţe et al. (2021) and Coman et al. (2016) in terms of technical support for students in various forms. A study conducted by Voicu and Muntean (2023) shows the importance of the online and mobile technologies to support the students during the educational process. All of these factors influence student academic performance in a variety of ways.

Considering the scientific data from the previously referenced and specialized literature (Britto & Rush, 2013; Coman et al., 2016; Lloyd-Jones, 2021; Mollenkopf & Gaskill, 2020; Rotar, 2022; Sánchez-Elvira Paniagua & Simpson, 2018; Vinţe et al., 2021; Voicu & Muntean, 2023), we formulate the following research hypothesis:

H1: The support which students receive during Online Learning affects their Academic Performance.

Taking into consideration the intrinsic motivation, Martin and Bolliger (2018) show that the involvement of students in the online environment has a direct effect on their satisfaction in learning new things. It also diminishes the feeling of social isolation and significantly improves academic performance. Properly implemented by teachers, student engagement and motivation strategies are a real support for online learning and academic performance.

Abou-Khalil et al. (2021) consider that different engagement strategies are available in the academic environment. Thus, it has been shown that students are particularly attracted to techniques such as screen sharing, recording class hours and summaries of various lessons. At the same time, the motivational benefit of strategies involving inter student activities (group chat, group communications and work on collaborative environments) is not perceived as effective. According to Lamanauskas et al. (2021), there are significant differences in extrinsic and intrinsic motivation because extrinsic motivation is associated with utility, while intrinsic motivation is associated with perceived pleasure. The results obtained show that in the case of online education, there is a moderate to low intrinsic motivation, with significant differences depending on the country of origin of the students (Romania and Lithuania). Pocatilu et al. (2020) took the research further to the recruitment process through various modern methods such as semantic web technologies with augmented reality.

In Turkey, research conducted by Mese and Sevilen (2021) found a reduction in intrinsic motivation in the case of online learning, where this type of educational process can have a negative impact on student motivation if there are problems in the organization of the learning environment. Zhang et al. (2020) consider that one of the most important sources of vitality in organizational environments is intrinsic motivation. Regarding the intrinsic motivation in the online environment, the research highlighted the fact that highly motivated students showed greater fluency and flexibility in the creative accomplishment of work tasks.

In West Java, research by Widiyanti et al. (2021) has shown that students who use online learning have a strong motivation that has multiple causes, from the real need to learn something new to the hope that online courses will be officially recognized by education regulators. Also, the possibilities offered by online learning have a positive impact on a lifelong learner attitude. Duggal et al. (2021) reveal that the transition from classical education to online learning is a difficult process, in which motivation plays an extremely important role. This is due to the fact that the usual teaching techniques are not always suitable for the online environment and are not able to involve the students to the maximum of their possibilities. The mediating role of intrinsic motivation on academic performance and creativity was also analyzed by Malik et al. (2020) and they discovered that intrinsic motivation is a relevant mediator between the use of social media and student academic performance. A recent study published by Ferrer et al. (2022) has also analyzed the issue of student commitment in higher education through the lens of their attitude towards the process of online learning, proving that in the modern educational world, intrinsic

motivation plays a central role in academic performance in the context of online learning.

Based on the considerations in the above research (Abou-Khalil et al., 2021; Duggal et al., 2021; Ferrer et al., 2022; Lamanauskas et al., 2021; Malik et al., 2020; Martin & Bolliger, 2018; Mese & Sevilen, 2021; Pocatilu et al., 2020; Widiyanti et al., 2021; Zhang et al., 2020), we propose the following research hypothesis:

H2: Intrinsic Motivation is a crucial factor in the relationship between the Support that students receive during Online Learning and their Academic Performance.

Regarding academic engagement, this element includes several aspects that refer to the degree of student involvement in the educational process. This is often determined by the teaching style of the lecturers (personal style, expert style, delegator style). According to Kheir-Faddul and Dănăiaţă (2019), the teacher's motivation is influenced by leadership style.

A comparative scientific study developed by Martínez et al. (2019) in two countries (Spain and Portugal) showed that psychological factors have a strong influence on student academic engagement and academic performance. The results highlight the importance of psychological predictors compared to traditional predictors of academic performance.

The results obtained by Robayo-Tamayoa et al. (2020) show that student academic commitment is influenced by self-motivation, which in turn makes academic support more effective. Also, they interestingly discovered that student curiosity and academic engagement are strongly related. Heidari et al. (2021) pointed out that academic engagement is strongly correlated with the level of digital skills of students. Edu (2022) is of the same opinion, considering that academic engagement depends a lot on educational technology.

In Egypt, the results obtained by El-Sayad et al. (2021) reveal that academic engagement is strongly influenced by academic self-sufficiency and research conducted by Netanda et al. (2019) has shown that the support which students receive during online learning results in an increasing competitive advantage, a high degree of student retention, and a high success rate in terms of academic performance. Although online learning usually makes us especially consider tools strictly dedicated to the educational process, Gulzar et al. (2021) found that in China the use of social networks is positively related to academic commitment and the intrinsic motivation to learn.

According to Danaiata et al. (2018) and Bibu et al. (2020), academic performance can also be influenced by academic engagement through the involvement of external and internal stakeholders, which in turn, can generate positive changes in the educational process. In addition, the academic performance can influence the future entrepreneurial intentions of the students and the future working track. Thus, Niţu-Antonie et al. (2023) highlighted the direct impact for the field of sustainable entrepreneurship. During the pandemic COVID-19 period, the performance and the satisfaction of students in Indian universities was analyzed by Gopal et al. (2021), revealing the factors influencing the level of satisfaction

and academic performance. Rajabalee and Santally (2021) conducted a study regarding the relationships between the students' general performance, and their engagement in online courses, covering more than 800 students across different disciplines like Humanities, Agriculture, Engineering, Management and Science. According to Baragash and Al-Samarraie (2018) student academic engagement is a trendy topic for science because it is very important for student performance. Therefore, based on the aforementioned studies (Baragash & Al-Samarraie, 2018; Dănăiaţă et al. 2018; Kheir-Faddul & Dănăiaţă, 2019; Martínez et al., 2019; Netanda et al., 2019; Bibu et al., 2020; Robayo-Tamayoa et al., 2020; El-Sayad et al., 2021; Gopal et al., 2021; Gulzar et al., 2021; Heidari et al., 2021; Rajabalee & Santally, 2021; Edu, 2022; Niţu-Antonie et al., 2023), we propose the following research hypothesis:

H3: Student Academic Engagement plays a crucial role in the relationship between the Support given to students during their Online Learning and their Academic Performance.

Figure 1 shows in a graphic way the proposed model in this research, with H2 and H3 referring to mediations.

The model proposed in this study aims to validate the general hypothesis according to which the academic performance of students is influenced by the support which students receive during Online Learning. This hypothesis is evaluated in the context in which the parallel mediating effects described in hypotheses H2 and H3 regarding intrinsic motivation and student academic engagement are analyzed. Thus, the model evaluates the amplitude of direct and indirect effects. The proposed model as well considers gender as a control variable.

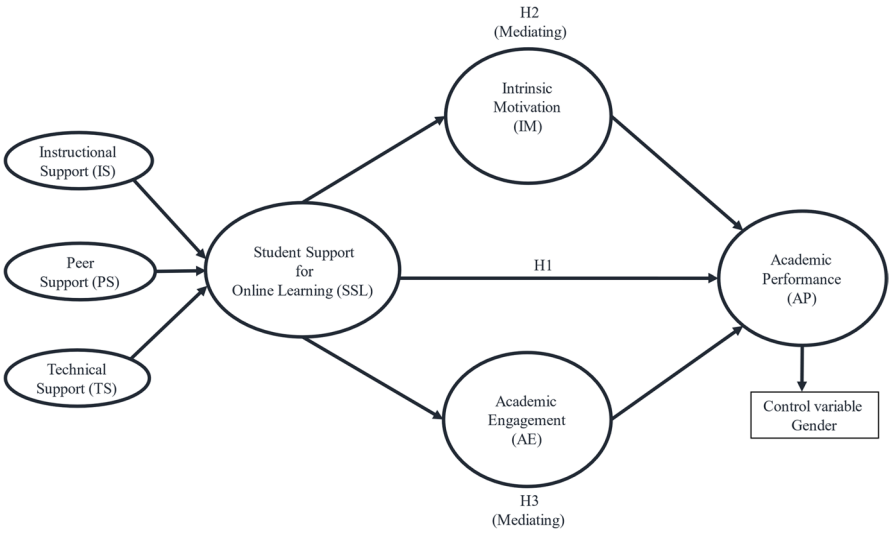

Fig. 1 Research model and hypotheses

3 Research methodology

Social science research frequently highlights a whole world of complex interactive variables with the result that research in this area requires very sophisticated research instruments. The methodology used in this particular research included explanatory research, which tries to identify links between data in order to explain a specific phenomenon, and confirmatory research, which gathers data to test pre-stated hypotheses. So, the methodology employed in this research was a combination of both exploratory and confirmatory types. In addition, a quantitative approach with a cross-sectional design was adopted to identify any causal relationships between the influential variables. Hence, the research here is called an explanatory-confirmatory research technique, sometimes referred to as causal research. As many latent variables were operationalised as composites, we used a composite-based method like PLS-SEM for analysis. In such cases, PLS is a suitable technique for both explanatory and confirmatory purposes if one or more variables in the structural model can be identified as composite in form. In the first case, the main focus fell on the R^2 of the endogenous variables, the statistical significance of path coefficients and effect sizes; whereas in the second one, the focus mainly fell on the model's goodness of fit (Henseler, 2018). As a result, the analysis of the hypothesized model was conducted applying PLS-SEM algorithm and PLS-SEM bootstrapping procedures (Hair et al., 2022).

3.1 Reliability and validity

In order to ensure the reliability and validity of the measurement models, we followed the guidelines of Creswell and Creswell (2018). These ways of validating the measures considered three aspects: (1) content validity, in terms of whether the items measured the content they were intended to measure, (2) predictive validity, in terms of predicting scores, and (3) construct validity, in terms of whether the items measured the constructs or the conceptual variables. In terms of the reliability of the instrument, we checked for internal consistency, that is, that sets of items in an instrument perform in the same way, and one of the measures we checked this was through internal consistency.

3.2 Method bias

One of the concerns in research is the common method variance that is due to the measurement method (Podsakoff et al., 2003). In this sense, in the present research, when designing the measurement instrument, we followed the guidelines established by Podsakoff et al. (2012) to control bias by considering two aspects: (1) procedural and (2) statistical remedies. In the context of PLS, we considered the first by checking the wording of the items to avoid ambiguity and the response scale as part of the instrument design phase, and secondly, we

followed Kock (2015), who considers VIF values below 3.3 as a statistical criterion to avoid bias.

3.3 Data collection and sampling

The research sample for this study was randomly selected using a simple probability sampling method, due to its ability to produce representative samples of the object of study (Sarstedt et al., 2018). A total of 1004 questionnaires were issued through online surveys to a student population from nine university degrees and bachelor-level programs in two universities: (1) the Autonomous University of the State of Mexico (Mexico), and (2) the Alexandru Ioan Cuza University of Iași (Romania). After the survey time had elapsed (from November 2021 to January 2022) and invalid questionnaires had been excluded, 822 valid questionnaires were collected, achieving an effective rate of 81.8%. According to Nitzl (2016), it satisfies the criterion for the sample size in PLS-SEM, since for a statistical power of 80%, three predictors, a medium effect size of 0.15, and a significance level of 0.05, a size of 77 is recommended. In addition, using the statistical power analyses program GPower

Table 1 Demographic characteristics

	Num	%
Gender		
Male	265	32.2%
Female	557	67.8%
Educational Program		
Administration (M)	180	22.0%
Accounting (M)	98	12.0%
Marketing (M)	107	13.0%
Administrative Informatics (M)	30	3.6%
Accounting (R)	57	7.0%
Marketing/Management (R)	122	14.8%
Business Informatics (R)	132	16.0%
Program Educational (R)	1	0.00%
Public Administration (R)	95	11.6%
Age		
16–20 years	352	42.8%
21–25 years	458	55.7%
+25 years	12	1.5%
Semester		
First	222	27.0%
Second to sixth	485	59.0%
Seventh to last	115	14.0%
Country		
México	415	50.5%
Romania	407	49.5%

(Faul et al., 2009), exactly the same number of 77 observations would be needed, with the same levels of significance and statistical power. Table 1 contains the analytical demographic details of the sample.

3.4 Measures

The measurement of the constructs in our current proposed model was based on an analysis of the existing literature. To measure the composite construct "Support provided for students during their Online Learning" (the independent variable), the measurement scale provided by Lee et al. (2011) was adapted. "Instructional Support" dimension was measured by way of eight items, "Peer Support" by way of seven items, and "Technical Support" by way of five items. All the constructs were measured with Likert-type scales. The responses ranged from “totally disagree” to “totally agree”.

The intrinsic motivation construct was based on Jaramillo et al. (2013) and used seven items, on a nine-point Likert scale. Academic performance was measured by means of an adaptation of the scale proposed by Realyvásquez-Vargas et al. (2020), with eight items on a five-point Likert-type scale. The academic engagement construct was measured according to an adaptation of the scale found in Kim et al. (2019), and used a seven-point Likert scale.

A questionnaire formed the basis of construct measurement. The same survey, adapted from English into the mother tongues of both countries (Spanish and Romanian) was used and consisted of two sections. The first section included questions regarding the socio-demographic factors of the students, such as gender, age, academic program, current semester, and country of origin. The second section included the elements of each construct. In addition, a pilot test was carried out to guarantee the validity of the content of the research instrument. Therefore, the questionnaire was made up of six constructs, with a total of 43 items: (1) instructional support with 8, (2) peer support with 7, (3) technical support with 5, (4) intrinsic motivation with 8, (5) academic performance with 8, and (6) academic engagement with 7, which is shown in Appendix A available at: https://doi.org/10.6084/m9.figshare.21727871.

3.5 Data analysis

In order to test the proposed research model, we used Partial Least Squares (PLS) technique. This method is a variance-based structural equation modelling (SEM) approach consisting of a two-step process: The first step tests the measurement theory to confirm the reliability and validity of the measurement models. Once this has been proved, the last step tests the structural relationships or structural theory (Hair et al., 2022). The decision to use PLS-SEM technique in this research is justified for several reasons: (1) Hierarchical component model or higher order component model, (2) the complexity of the model, (3) Direct relationships, and (4) the presence of mediators. In general terms, it is a robust statistical technique. This research was completed using SmartPLS 3.4 software (Ringle et al., 2015). Furthermore, we

took a theoretical approach in order to validate the “reflective or formative” measurement model. Based on the theoretical foundation, we carried out a “Confirmatory Tetrad Analysis (CTA)” statistical test. Based on this theoretical background and the empirical confirmation of the results (CTA), "The Support for Student Online Learning" construct was considered as a Reflective-Formative Higher-Order Construct (HOC) or type II, which procedure followed a Hierarchical Component Model (HCM) analysis. That is, a two-stage HCM analysis where, in addition, Academic Performance, Intrinsic Motivation, and Academic Engagement constructs were evaluated reflectively, as "Lower-Order Constructs" (LOCs).

4 Results

4.1 Evaluation of the global model fit

According to Henseler (2018), confirmatory research requires a test of global goodness of model fit. For the validity of reflective and composite measurement models, a composite confirmatory analysis is necessary (Benitez et al., 2020). Then, the estimated model was evaluated, because now it is suitable to test the overall model fit in the context of PLS to obtain empirical evidence for the proposed theory (Benitez et al., 2020). We ran a bootstrapping process and analyzed the standardized root mean square residual (SRMR) based on heuristic rule, where the SRMR value is less than 0.08 (Hair et al., 2022). Furthermore, two indicators proposed by Dijkstra and Henseler (2015) are computed as an exact fit: unweighted least squares discrepancy (d_{ULS}) and geodesic discrepancy (d_G). The obtained values are less than significant percentiles (HI95) and (HI99). These values are here analytically presented within Table 2, which shows the fit indexes within the appropriate parameters. This implies a correct fit between the empirical and the model implied matrixes.

4.2 Evaluation of measurement models

The reflective measurement model guarantees the reliability and validity of the constructs by aligning itself with the quality criteria: composite reliability, Cronbach’s

Table 2 Global model fit measures

Criterion	Value	HI95	HI99
Saturated model			
SRMR	0.020	0.023	0.025
d_{USL}	0.134	0.175	0.199
d_G	0.066	0.081	0.088
Estimated model			
SRMR	0.023	0.028	0.031
d_{USL}	0.175	0.257	0.319
d_G	0.067	0.081	0.088

Alpha, the average variance extracted (AVE), the Fornell-Larcker criterion, and the Heterotrait-Monotrait Ratio (HTMT) (Hair et al., 2022). In this case, all the indicators show loads greater than 0.7. Regarding composite reliability, the results are also satisfactory, with parameters greater than 0.7. Convergent validity was evaluated with the average variance extracted (AVE), where all AVEs exceed the established parameter equal to or greater than 0.50. Additionally, it reports the total amount of variance in the indicators in the latent construct. Table 3 shows the reliability and convergent validity of the reflective first-order measurement models.

4.2.1 Discriminant validity

Discriminant validity indicates that the constructs only measure what they are supposed to measure and differ from the other constructs. In this context, all constructs show discriminant validity according to the most recent variance-based Heterotrait-Monotrait ratio criterion in SEM, whose recommended threshold is below 0.90 or a more conservative value of 0.85 (Henseler et al., 2015). Table 4 shows the results of the HTMT criterion.

Also, HTMT inference was evaluated by bootstrapping to test whether the HTMT ratio is significantly different from 1 in the Confidence Intervals Bias Corrected (Hair et al., 2022). Table 5 shows the results of the HTMT inference.

In addition, the traditional statistic Fornell-Larcker criterion is reported in Table 6. Therefore, the results show discriminant validity for both methods, which implies that each construct measures its own domain, and makes it distinct from the others (i.e., redundancy is avoided).

4.2.2 Assessment of formative measurement model

Based on the quality criteria in Hair et al. (2022), Table 7 shows that the results of these type of models are satisfactory. In this sense, we observe that the regression weights and VIF values fit correctly. Therefore, we obtain significant *t*-values and *p*-values.

4.3 Evaluation of structural model (hypothesis testing)

Once the reliability and validity of the measurement models had been confirmed, the structural model was evaluated according to the criteria of Hair et al. (2022). This means that the structural relationships between the exogenous and endogenous constructs were tested. This was done by calculating: (1) collinearity, (2) the significance and relevance of the structural relationships of the model, (3) the coefficient of determination with the value of R^2, (4) the size of the effect of f^2, and (5) the predictive relevance with Q^2. To verify these statistical data, the "bootstrapping" procedure was run, and the direct and indirect effects were observed.

In this context, step 1 was the evaluation of collinearity using the Variance Inflation Factor (VIF), which recommended values lower than 3.3. All VIF values of our model are below this established threshold. The second step was the

Table 3 Reliability and convergent validity

	Loading	Cronbach´s alpha	Composite reliability	AVE
Instructional Support (IS)		0.902	0.921	0.594
IS1	0.775			
IS2	0.808			
IS3	0.792			
IS4	0.757			
IS5	0.784			
IS6	0.776			
IS7	0.792			
IS8	0.677			
Peer Support (PS)		0.889	0.913	0.600
PS-1	0.747			
PS-2	0.828			
PS-3	0.815			
PS-4	0.771			
PS-5	0.768			
PS-6	0.711			
PS-7	0.781			
Technical Support (TS)		0.883	0.915	0.682
TS1	0.832			
TS2	0.757			
TS3	0.844			
TS4	0.848			
TS5	0.845			
Intrinsic Motivation (IM)		0.903	0.924	0.635
IM-1	0.836			
IM-2	0.839			
IM-3	0.712			
IM-4	0.817			
IM-5	0.740			
IM-6	0.780			
IM-7	0.841			
Academic Performance (AP)		0.908	0.925	0.607
AP1	0.788			
AP2	0.772			
AP3	0.731			
AP4	0.817			
AP5	0.778			
AP6	0.807			
AP7	0.768			
AP8	0.769			
Academic Engagement (AE)		0.898	0.920	0.623

Table 3 (continued)

	Loading	Cronbach´s alpha	Composite reliability	AVE
AE1	0.790			
AE2	0.855			
AE3	0.812			
AE4	0.809			
AE5	0.803			
AE6	0.671			
AE7	0.773			

Table 4 Discriminant validity assessment (HTMT)—correlations

Constructs	AP	AE	IS	IM	PS	TS
AP						
AE	0.634					
IS	0.510	0.538				
IM	0.853	0.710	0.644			
PS	0.524	0.566	0.637	0.574		
TS	0.481	0.397	0.630	0.582	0.506	

Table 5 Discriminant validity assessment (HTMT) – Confidence interval bias corrected

Constructs	Original sample (O)	Sample Mean (M)	Bias	2.50%	97.5%
AE ⇒ AP	0.634	0.633	-0.001	0.579	0.685
IS ⇒ AP	0.510	0.509	-0.001	0.437	0.576
IS ⇒ AE	0.538	0.539	0.000	0.456	0.607
IM ⇒ AP	0.853	0.853	0.000	0.824	0.883
IM ⇒ AE	0.710	0.709	-0.001	0.653	0.760
IM ⇒ IS	0.644	0.643	-0.001	0.581	0.699
PS ⇒ AP	0.524	0.523	-0.001	0.463	0.586
PS ⇒ AE	0.566	0.567	0.001	0.490	0.634
PS ⇒ IS	0.637	0.636	-0.001	0.570	0.697
TS ⇒ IM	0.574	0.573	-0.001	0.501	0.638
TS ⇒ AP	0.481	0.480	-0.001	0.409	0.549
TS ⇒ AE	0.397	0.398	0.001	0.319	0.477
TS ⇒ IS	0.630	0.631	0.000	0.572	0.689
TS ⇒IM	0.582	0.582	0.000	0.523	0.639
IS ⇒ PS	0.506	0.505	-0.001	0.436	0.576

Table 6 Discriminant validity assessment (Fornell-Larcker criterion)

Constructs	AP	AE	IS	IM	PS	TS
AP	0.879					
AE	0.579	0.789				
IS	0.466	0.491	0.771			
IM	0.778	0.642	0.588	0.797		
PS	0.472	0.511	0.572	0.519	0.775	
TS	0.437	0.357	0.568	0.525	0.453	0.826

Table 7 Evaluation of formative measurement model

Composite formative (second-order construct)	First-order construct	Weight	VIF	*t*-values	*p*-values
Student Support for Online Learning	Instructional Support	0.452	1.810	7.765	0
	Peer Support	0.459	1.542	8.588	0
	Technical Support	0.286	1.531	5.593	0

Table 8 Structural model – hypotheses test results

Direct effects/Constructs	Path Coefficient	95% (CIBC)	*t-value	p-value	f^2	Support
AE ⇒AP	0.123***	[0.056, 0.183]	3.693	0.000	0.022	
IM ⇒AP	0.670***	[0.604, 0.733]	20.317	0.000	0.544	
SSL ⇒AP	0.046	[-0.013, 0.109]	1.420	0.156	0.003	No (H1)
SSL ⇒AE	0.559***	[0.498, 0.612]	19.462	0.000	0.454	
SSL ⇒IM	0.654***	[0.604, 0.696]	27.889	0.000	0.747	
Indirect Effects/Constructs	Path coefficient	95% CIBC	*t-value	p-value	f^2	Support
SSL⇒IM⇒AP	0.069***	[0.032, 0.105]	3.630	0.000	N.A	Yes (H2)
SSL⇒AE⇒AP	0.438***	[0.384, 0.493]	16.497	0.000	N.A	Yes (H3)

CIBC: Confidence Intervals Bias Corrected, * $t(0.10, 4999 = 1.28)$, ** $t(0.05, 4999 = 1.65)$, *** $t(0.01, 4999 = 2.33)$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, two-tailed test

evaluation of the importance and relevance of the relationships of the structural model by means of the path coefficients. Bootstrapping also allows for the verification of the empirical t-values and p-values for all path coefficients. In our case, we obtained $\beta = 0.046$, t-value $= 1.391$, and $p > 0.05$ in the structural relationship of Student Support for Online Learning with Academic Performance. Therefore, it does not support hypothesis H1 (see Table 8).

In the third step, the coefficient of determination R^2 was analyzed. This is considered a measure of predictive power within the sample (Hair et al., 2022). R^2 values of 0.75, 0.50, and 0.25 are considered strong, moderate, and weak respectively across many social science disciplines. In step four, effect size f^2 is linked to R^2. f^2 values, ranging from 0.02, 0.15, and 0.35, represent small, medium and

large effects. The obtained results showed large effects except for SSL⇒AP, and AE ⇒AP.

In step five, Stone-Geisser's Q^2 value was evaluated to measure to what extent the proposed model can predict the observed values, where estimates greater than zero suggest predictive relevance. Thus, our results showed predictive relevance with $Q^2 > 0$. On the other hand, the indirect effects were analyzed to evaluate the mediation hypotheses. According to the findings, full mediation was found. These results support hypotheses H2 and H3. This shows that the effect of online learning support on academic performance is fully achieved via mediating variables as they have significant results.

Finally, Fig. 2 and Table 8 present the values of the structural model assessment with the hypothesis testing. These findings allow us to argue that the hypotheses have been satisfactorily tested. However, it is observed that the hypothesis (H1) was not supported according to the initial approach.

4.4 Control variable

To test the effect of the control variable, a multi-group analysis was conducted. The measurement invariance was assessed first. These contrast the estimates of the group-specific measurement model, with those obtained from an estimate of the model using pooled data. For this process, the permutation algorithm was run and the Measurement Invariance of Composite Models (MICOM) procedure with its quality criteria were verified. Table 9 shows compliance with the invariance of measures attributable to the same measuring instrument across the groups analyzed.

The results of the MICOM procedure support measurement invariance completely. Therefore, we can compare the standardized path coefficients between groups using multigroup analysis with certainty (Hair et al., 2022; Henseler et al., 2016). The results of MGA (Multi-Group Analysis) are shown in Table 10.

The *p*-value indicates whether the path coefficient is significantly larger in the first group than in the second group. In this case, all the *p*-values are > 0.05, which allows us to infer that there are no differences across groups, according to the grouping variable "gender".

5 Discussion, conclusion, and implications

The purpose of this study is to determine the mediating effect of student intrinsic motivation and academic commitment, and analyze the relationship between the support given to students during online learning with their academic performance. Data were collected in two countries: Mexico and Romania. We also investigated whether there is any difference between the students participating in this research regarding gender, since gender is considered a control variable of great importance.

The study's findings may be relevant to the theoretical advancement of online learning and academic performance by introducing a new mediator in a structural relationship, as suggested by Colquitt and Zapata-Phelan (2007). The main

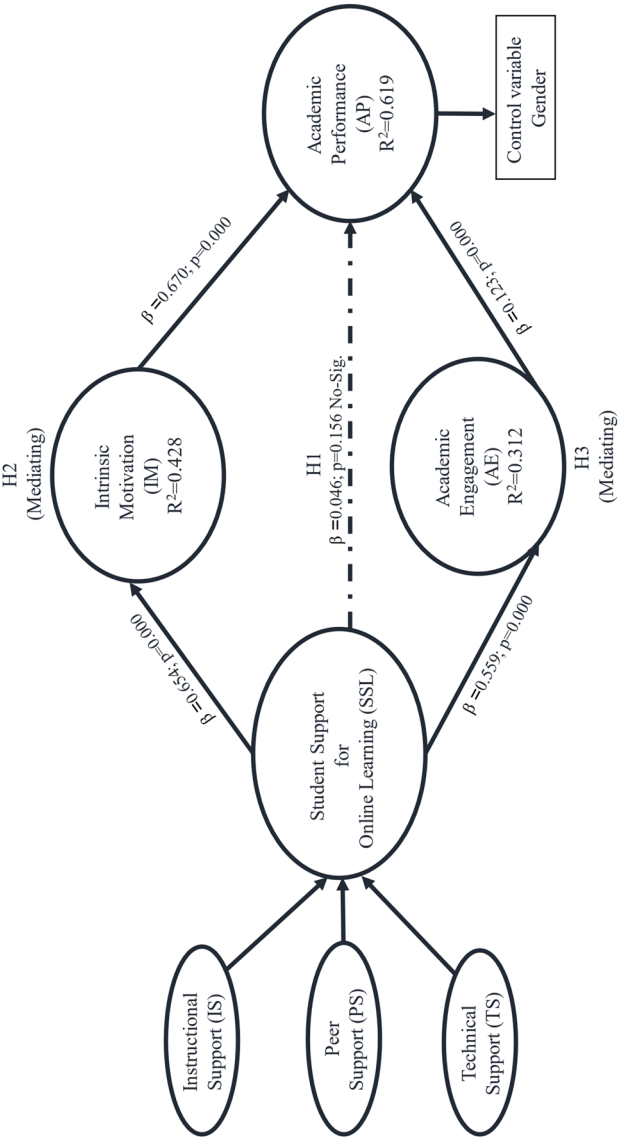

Fig. 2 Theoretical model estimation

Table 9 Results of the measurement invariance (MICOM) procedure

MICOM Step 1. Configural Invariance Configural invariance established across groups? Yes				
MICOM Step 2. Established across groups? Yes				
Construct	Original Correlation C	5% Quartile of the empirical distribution of c_u	*p*-value	Compositional Invariance Established?
AP	1.000	0.999	0.365	Yes
AE	1.000	0.999	0.444	Yes
IM	1.000	0.999	0.700	Yes
SSL	0.997	0.970	0.735	Yes
MICOM Step 3a. Equality of construct´s mean values				
Construct	Difference of the composite´s mean value (=0)	95% Confidence Interval	*p*-value	Equal mean values?
AP	0.000	[-0.151, 0.152]	0.955	Yes
SSL	0.003	[-0.140, 0.156]	0.838	Yes
IM	0.003	[-0.143, 0.157]	0.659	Yes
AE	0.002	[-0.150, 0.140]	0.097	Yes
MICOM Step 3b. Equality of construct´s variance values				
Construct	Logarithm of the composite´s variance value (=0)	95% Confidence Interval	*p*-value	Equal Variance
AP	-0.005	[-0.195, 0.188]	0.393	Yes
SSL	-0.002	[-0.267, 0.143]	0.830	Yes
IM	-0.008	[-0.247, 0.208]	0.321	Yes
AE	-0.003	[-0.247, 0.221]	0.139	Yes

contribution of the study is the parallel mediating effects of intrinsic motivation and students' academic engagement. When instructional support includes efficient instructions, peer support is promoted, and there is adequate technical support, academic performance tends to be maximised.

However, it is likely that when students are engaged and intrinsically motivated in their online learning, they act more out of self-determination, perhaps because they enjoy this type of learning, rather than out of obligation or instruction. This is also related to self-determination theory, which explains people's intrinsic motivation to learn in social interactions with other learners (Deci et al., 2017; Ryan & Deci, 2019). Therefore, our findings are consistent with Alemayehu and Chen (2021) and Afzal and Crawford (2022) who suggest that motivation and engagement are prerequisites for improved learning, and that self-motivation plays a mediating role between engagement and academic performance.

The mediation results show statistical significance. These findings are considered full mediation. This, in turn, implies a mechanism able to explain the relationship between student support during online learning and academic performance through the two indirect effects.

Table 10 Multi-group analysis

Constructs	*PLS-MGA*	
	Path Coefficients-difference (Group (1.0) – Group (2.0))	*p*-value
AE ⇒AP	0.057	0.413
IM ⇒AP	0.068	0.333
SSL ⇒AP	*NS	*NS
SSL ⇒AE	0.032	0.566
SSL ⇒IM	0.047	0.324
Constructs	*Parametric Test*	
	Path Coefficients-difference (Group (1.0) – Group (2.0))	*p*-value
AE ⇒AP	0.057	0.406
IM ⇒AP	0.068	0.323
SSL ⇒AP	*NS	*NS
SSL ⇒AE	0.032	0.596
SSL ⇒IM	0.047	0.362
Constructs	*Welch-Satterthwait Test*	
	Path Coefficients-difference (Group 1.0) – Group (2.0))	*p*-value
AE ⇒AP	0.057	0.418
IM ⇒AP	0.068	0.329
SSL ⇒AP	NS*	*NS
SSL ⇒AE	0.032	0.569
SSL ⇒IM	0.047	0.321

Sometimes, a cause-effect relationship does not show the real effects due to the influence of other variables that can explain the complete nature or give a broader explanation of the endogenous variable or result. In this case, the more support the online learning students receive, the higher the SSL⇒IM intrinsic motivation ($\beta = 0.654$, t-value = 27.889, $p = 0.000$). Similarly, SSL⇒AE academic commitment will also be higher ($\beta = 0.559$, t-value = 19.462, $p = 0.000$), and therefore academic performance will be better. These findings are consistent with previous research. For example, motivation plays an important role in student achievement, and it is a factor that influences academic performance positively (Eccless & Wigfield, 2002). Meanwhile, academic engagement is a variable with a significant role in promoting student learning (Wonglorsaichon et al., 2014). According to Kim et al. (2019), academic engagement is a mediating variable in the assimilation of online learning and academic achievement.

University students today are considered to be digital natives, yet supporting their online learning is still required. This type of learning has become an increasingly prevalent approach in higher education institutions as the result of fast-growing technology (Chopra et al., 2019). In addition, the contingency due to the COVID-19 pandemic with the consequent confinement to homes, has forced educational institutions to use various electronic platforms to teach classes, making it a trend that requires further research to improve students' academic performance.

Many universities are implementing online courses to improve the education offered to the public and to increase enrolment. Online educational platforms are essential tools to support the teaching–learning process. The use of online technology as an e-learning model is an increasingly challenging new paradigm in universities. The current perspective of the teaching–learning process must be aligned to the technological context in order to benefit students' performance and successfully achieve the transition towards technology-supported education. Otherwise, these new learning environments will use technology but will not maximize its potential in aiming to achieve the expected results.

In summary, the authorities in higher education institutions must constantly monitor the support that students receive for online learning, especially with regards to educational support, technological support and peer interaction. What is more, a clear vision of the mediating constructs for academic performance should be shared with students and professors. According to Rotar (2022), support is a very significant influential factor in the success of students engaged in online learning.

5.1 Implications for theory and practice

From a theoretical perspective, the results have revealed two mediator variables, which strengthen academic performance. Academic performance is enhanced by the support students receive during online learning. Thus, the results of our research show in a quantitative manner that the support, which students' receive during their online learning, is not enough to achieve the desired academic performance. From a theoretical perspective, our study establishes a very important vision: the support for student online learning is important for academic performance only in relation to two relevant mediators: student intrinsic motivation and student academic engagement. From a practical perspective, it is well known that universities and students are very interested in obtaining a higher academic performance. According to the results of the present study, all the participants engaged in the educational process should firstly take into consideration the need for effective support for students engaged in online learning and the role of intrinsic motivation and academic engagement, because they are "the keys" for success fin academic performance. Given the stable and consistent relationships between the variables of our proposed model, the hypotheses H2 and H3 are very relevant for the managers of universities and the academic collectives of professors who aim to use the correct triggers to increase the academic performance of their students. From an economical point of view, education is nowadays a very important budgetary component both for governments and for students and their sponsors. As a result, improving academic performance can be cost-optimized if educational decisions take into account the results of our research. The financial implications are both at the level of the government budget and at the individual level of each student.

5.2 Limitations of the study and future research directions

The limitations of the current study are also opportunities for further research directions. Firstly, data was collected from only two higher-education institutions. This research could be expanded to include other universities in order to further validate the results. Secondly, this study was transversal; data was collected at a single point in time. This study has the potential to be expanded into a longitudinal study by taking into consideration a longer period of time, because the research carried out by Englund et al. (2017) demonstrated that teaching with technology in higher education is a process that adapts over time and undergoes significant transformations. This model may open new areas of research, through incorporating other constructs or control variables, which may have significant influence on academic performance. Another important research direction could be an analysis that takes into account the types of study programs (social sciences, applied sciences, theoretical sciences). In this way, it could be analyzed if there are significant differences between these potential clusters, because previous studies conducted by Hossain et al. (2022) and Al-Emran et al. (2016) reveal that the use of information technologies in higher education is influenced by different clusters.

Thirdly, stemming from the recent COVID-19 pandemic and its aftermath, it would also be interesting to do a longitudinal study of student attitudes before they begin online learning, questioning them on why they are doing the course; why choose online learning; what problems do they foresee; what do they hope to achieve; what kind of support they think they will need. Then they could be surveyed at the end of year one to see what problems they encountered; which support they received was most and least useful; would they do anything differently if they had their first year again, etc. Afterwards, they could be asked at the end of the course on their experience to find out whether they would recommend their online learning course to other young students and why/why not; which technological skills they found to be most useful. Moreover, it would be most important to survey those students who drop out. There could be loads of data to collect in order to be able to design future courses more effectively, with better student support, and perhaps run in-depth early courses in certain online technologies which were going to help students in their courses. Young people today spend so much time alone with computers and phones that they are more prepared than ever for doing online courses. However, human beings are social animals and the regular contacts with lecturers and other students will still be necessary to avoid isolation. So, there is so much more material just waiting to be collected in this area.

Regarding the economic profitability of the educational process, our study can constitute a plausible basis for a comparative analysis of economic efficiency: what are the costs and benefits if the educational process takes into account the mediating relationship of intrinsic motivation and academic engagement, and what are the costs and benefits if these relationships highlighted in our study are not taken into account.

In conclusion, the results of our research are important both for students and teachers, as well as for managers of universities and educational programs. In addition, the results can be used for more elaborate analyzes in space and time.

Acknowledgements We express our gratitude to Prof. Kevin Pender for his thorough written review of this article and insightful comments.

Authors' contributions Conception: J.J.G.M, M.M.A., Design of the work: J.J.G.M, M.M.A., N.D., O.D., Literature review: J.J.G.M, M.M.A., N.D., O.D., Software and interpretation of data: J.J.G.M, M.M.A., Writing initial draft: J.J.G.M, M.M.A., N.D., O.D., Writing final version of the article: J.J.G.M, M.M.A., N.D., O.D. All authors read and approved the final manuscript.

Funding This research received no external funding. Funding for open access charge: Universidad de Huelva/CBUA.

Availability of data and materials The datasets used and/or analyzed during the current study are available from the authors on reasonable request.

Declarations

Competing interests The authors declare that they have no competing interests.

References

Abou-Khalil, V., Helou, S., Khalifé, E., Chen, M., Majumdar, R., & Ogata, H. (2021). Emergency online learning in low-resource settings: Effective student engagement strategies. *Education Sciences, 11*(1), 24. https://doi.org/10.3390/educsci11010024

Afzal, F., & Crawford, L. (2022). Student's perception of engagement in online project management education and its impact on performance: The mediating role of self-motivation. *Project Leadership and Society, 3*(20), 100057. https://doi.org/10.1016/j.plas.2022.100057

Alemayehu, L., & Chen, H. (2021). The influence of motivation on learning engagement: The mediating role of learning self-efficacy and self-monitoring in online learning environments. *Interactive Learning Environments, 31*, 4605–4618. https://doi.org/10.1080/10494820.2021.1977962

Al-Emran, M., Elsherif, H. M., & Shaalan, K. (2016). Investigating attitudes towards the use of mobile learning in higher education. *Computers in Human Behavior, 56*, 93–102. https://doi.org/10.1016/j.chb.2015.11.033

Anthony, B., Kamaludin, A., Romli, A., Raffei, A. F. M., Eh Phon, D. N. A. L., Abdullah, A., & Ming, G. L. (2022). Blended learning adoption and implementation in higher education: A theoretical and systematic review. *Technology, Knowledge and Learning, 27*, 531–578. https://doi.org/10.1007/s10758-020-09477-z

Baragash, R. S., & Al-Samarraie, H. (2018). Blended learning: Investigating the influence of engagement in multiple learning delivery modes on students' performance. *Telematics and Informatics, 35*(7), 2082–2098. https://doi.org/10.1016/j.tele.2018.07.010

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management, 57*(2), 1–16. https://doi.org/10.1016/j.im.2019.05.003

Bibu, N., Mihali, L., Munteanu, V., & Sala, D. (2020). Evaluating the performance of university innovative companies: The management of academic spin-offs and start-ups in Romania. In O. Nicolescu,

& C. Oprean (Eds.), *The best romanian management studies 2017–2018* (pp. 84–99). Trivent Publishing. https://www.semanticscholar.org/paper/Evaluating-the-Performance-of-University-Innovative-Bibu-Mihali/c9fb8fdaee1e1a7cd26795d60d42ee345c4d5ecb

Britto, M., & Rush, S. (2013). Developing and implementing comprehensive student support services for online students. *Journal of Asynchronous Learning Networks, 17*(1), 29–42. https://doi.org/10.24059/olj.v17i1.313

Chen, J.J.-L. (2005). Relation of academic support from parents, teachers, and peers to Hong Kong adolescents' academic achievement: The mediating role of academic engagement. *Genetic, Social, and General Psychology Monographs, 131*(2), 77–127. https://doi.org/10.3200/MONO.131.2.77-127

Chopra, G., Madan, P., Jaisingh, P., & Bhaskar, P. (2019). Effectiveness of e-learning portal from students' perspective: A structural equation model (SEM) approach. *Interactive Technology and Smart Education, 16*(2), 94–116. https://doi.org/10.1108/ITSE-05-2018-0027

Colquitt, J. A., & Zapata-Phelan, C. P. (2007). Trends in theory building and theory testing: A five-decade study of the Academy of Management Journal. *Academy of Management Journal, 50*(6), 1281–1303. https://doi.org/10.5465/AMJ.2007.28165855

Coman, A., Cîtea, A., & Buraga, S. C. (2016). Towards open source/data in the context of higher education: Pragmatic case studies deployed in Romania. *IFIP International Conference on Open Source Systems* (pp. 184–191). Springer. https://doi.org/10.1007/978-3-319-39225-7_15

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). Sage.

Danaiata, D., Hurbean, L., & Isbanionly, M. (2018). Managing the implementation process of educational system reform in Israel. *Procedia - Social and Behavioral Sciences, 238*, 259–266. https://doi.org/10.1016/j.sbspro.2018.04.001

Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-determination theory in work organizations: The state of a science. *Annual Review of Organizational Psychology and Organizational Behavior, 4*, 19–43. https://doi.org/10.1146/annurev-orgpsych-032516-113108

Dijkstra, T., & Henseler, J. (2015). Consistent and asymptotically normal PLS estimators for linear structural equations. *Computational Statistics & Data Analysis, 1*, 10–23. https://doi.org/10.1016/j.csda.2014.07.008

Duggal, K., Singh, P., & Gupta, L. (2021). Intrinsic and extrinsic motivation for online teaching in COVID-19: Applications, issues, and solution. In F. Al-Turjman, A. Devi, & A. Nayyar (Eds.), *Emerging technologies for battling Covid-19. Studies in systems, decision and control* (Vol. 324). Springer. https://doi.org/10.1007/978-3-030-60039-6_1

Eccless, J., & Wigfield, A. (2002). Motivational beliefs, values and goals. *Annual Review of Psychology, 53*, 109–132. https://doi.org/10.1146/annurev.psych.53.100901.135153

Edu, A. S. (2022). Toward improving students' academic engagement: The role of educational technology. In R. Beatong (Ed.), *Delivering distinctive value in emerging economies* (p. 23). Productivity Press. https://www.taylorfrancis.com/chapters/edit/10.4324/9781003152217-28/toward-improving-students-academic-engagement-role-educational-technology-abeeku-sam-edu

El-Sayad, G., Saad, N. H., & Thurasamy, R. (2021). How higher education students in Egypt perceived online learning engagement and satisfaction during the COVID-19 pandemic. *Journal of Computers in Education, 8*, 527–550. https://doi.org/10.1007/s40692-021-00191-y

Englund, C., Olofsson, A. D., & Price, L. (2017). Teaching with technology in higher education: Understanding conceptual change and development in practice. *Higher Education Research & Development, 36*, 73–87. https://doi.org/10.1080/07294360.2016.1171300

Falloon, G. (2020). From digital literacy to digital competence: The teacher digital competency (TDC) framework. *Educational Technology Research and Development, 68*, 2449–2472. https://doi.org/10.1007/s11423-020-09767-4

Faul, F., Erdfelder, E., Buchner, A. & Lang, A-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Ferrer, J., Ringer, A., Saville, K., Parris, M., & Kashi, K. (2022). Students' motivation and engagement in higher education: The importance of attitude to online learning. *Higher Education, 83*, 317–338. https://doi.org/10.1007/s10734-020-00657-5

Gasiewski, J., Eagan, M., & Garcia, G. (2012). From Gatekeeping to engagement: A multicontextual, mixed method study of student academic engagement in introductory STEM courses. *Research in Higher Education, 53*, 229–261. https://doi.org/10.1007/s11162-011-9247-y

Gopal, R., Singh, V., & Aggarwal, A. (2021). Impact of online classes on the satisfaction and performance of students during the pandemic period of COVID 19. *Education and Information Technologies, 26*, 6923–6947. https://doi.org/10.1007/s10639-021-10523-1

Greenhow, C., & Galvin, S. (2020). Teaching with social media: Evidence-based strategies for making remote higher education less remote. *Information and Learning Sciences, 121*(7/8), 513–524. https://doi.org/10.1108/ILS-04-2020-0138

Gulzar, M. A., Ahmad, M., Hassan, M., & Rasheed, M. I. (2021). How social media use is related to student engagement and creativity: Investigating through the lens of intrinsic motivation. *Behaviour & Information Technology, Ahead-of-print*, 1–11. https://doi.org/10.1080/0144929X.2021.1917660

Hair, J., Hult, G., Ringle, C., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Thousand Oaks.

Heidari, E., Mehrvarz, M., Marzooghi, R., & Stoyanov, S. (2021). The role of digital informal learning in the relationship between students' digital competence and academic engagement during the COVID-19 pandemic. *Journal of Computer Assisted Learning, 37*(4), 1154–1166. https://doi.org/10.1111/jcal.12553

Henseler, J. (2018). Partial least squares path modeling: Quo vadis? *Quality & Quantity, 52*(1), 1–8. https://doi.org/10.1007/s11135-018-0689-6

Henseler, J., Ringle, C., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of Academy of Market Science, 43*, 115–135. https://doi.org/10.1007/s11747-014-0403-8

Henseler, J., Ringle, C., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International Marketing Review, 33*(3), 405–431. https://doi.org/10.1108/IMR-09-2014-0304

Hossain, S. F. A., Xi, Z., Nurunnabi, M., & Anwar, B. (2022). Sustainable academic performance in higher education: A mixed method approach. *Interactive Learning Environments, 30*(4), 707–720. https://doi.org/10.1080/10494820.2019.1680392

Jaramillo, F., Locander, W., Spector, P., & Harris, E. (2013). Getting the Job Done: The Moderating Role of Initiative on the Relationship Between Intrinsic Motivation and Adaptive Selling. *Journal of Personal Selling & Sales Management, 27*(1), 59–74. https://doi.org/10.2753/PSS0885-3134270104

Kheir-Faddul, N., & Dănăiaţă, D. (2019). The influence of leadership style on teachers' job motivation and satisfaction in the Druze sector of Israel. *Timisoara Journal of Economics and Business, 12*(1), 17–42. https://www.tjeb.ro/index.php/tjeb/article/view/316

Kim, H., Hong, A., & Song, H. (2019). The roles of academic engagement and digital readiness in students' achievements in university e-learning environments. *International Journal of Educational Technology in Higher Education, 16*(21), 1–18. https://doi.org/10.1186/s41239-019-0152-3

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, *11*(4). https://doi.org/10.4018/ijec.2015100101

Lamanauskas, V., Makarskaitė-Petkevičienė, R., Gorghiu, G., Manea, V. I., & Pribeanu, C. (2021). Extrinsic and intrinsic motivation in online education during the pandemic as perceived by Lithuanian and Romanian university students. *Proceedings of the international conference on human-computer interaction - RoCHI 2021* (pp. 147–154). MATRIX ROM. https://doi.org/10.37789/rochi.2021.1.1.23

Lee, S. J., Srinivasan, S., Trail, T., Lewis, D., & Lopez, S. (2011). Examining the relationship among student perception of support, course satisfaction, and learning outcomes in online learning. *The Internet and Higher Education, 14*(3), 158–163. https://doi.org/10.1016/j.iheduc.2011.04.001

Lloyd-Jones, B. (2021). Developing competencies for emotional, instrumental, and informational student support during the COVID-19 pandemic: A human relations/human resource development approach. *Advances in Developing Human Resources, 23*(1), 41–54. https://doi.org/10.1177/1523422320973287

Malik, M., Ahmad, M., Kamran, M., Aliza, K., & Elahi, M. (2020). Student use of social media, academic performance, and creativity: The mediating role of intrinsic motivation. *Interactive Technology and Smart Education, 17*(4), 403–415. https://doi.org/10.1108/ITSE-01-2020-0005

Martin, F., & Bolliger, D. (2018). Engagement matters: Student perceptions on the importance of engagement strategies in the online learning environment. *Online Learning, 22*(1), 205–222. https://doi.org/10.24059/olj.v22i1.1092

Martínez, I., Youssef-Morgan, C., Chambel, M., & Marques-Pinto, A. (2019). Antecedents of academic performance of university students: Academic engagement and psychological capital resources. *Educational Psychology, 39*(8), 1047–1067. https://doi.org/10.1080/01443410.2019.1623382

Mese, E., & Sevilen, Ç. (2021). Factors influencing EFL students' motivation in online learning: A qualitative case study. *Journal of Educational Technology and Online Learning, 4*(1), 11–22. https://dergipark.org.tr/en/pub/jetol/issue/60134/817680. Accessed 1 June 2023.

Mollenkopf, D., & Gaskill, M. (2020). Technological transience in a time of unprecedented change: Student support strategies in college courses for those "Suddenly Online". *The Journal of Literacy and Technology, 21*(2), 130–148. https://bit.ly/3WOufM4.

Netanda, R. S., Mamabolo, J., & Themane, M. (2019). Do or die: Student support interventions for the survival of distance education institutions in a competitive higher education system. *Studies in Higher Education*, 397–414. https://doi.org/10.1080/03075079.2017.1378632

Niţu-Antonie, R. D., Feder, E.-S., Niţu-Antonie, V., & György, R.-K. (2023). Predicting Sustainable Entrepreneurial Intentions among Romanian Students: A Mediated and Moderated Application of the Entrepreneurial Event Model. *Sustainability, 15*(6), 5204. https://doi.org/10.3390/su15065204

Nitzl, C. (2016). The use of partial least squares structural equation modelling (PLS-SEM) in management accounting research: Directions for future theory development. *Journal of Accounting Literature, 37*(1), 19–35. https://doi.org/10.1016/j.acclit.2016.09.003

Pocatilu, P., Enăchescu, M. I., & Diţă, A. (2020). Assessing a candidate's seniority level in computer science field by integrating semantic web technologies with augmented reality. *Economic Computation and Economic Cybernetics Studies and Research*, 3, 231–248. https://doi.org/10.24818/18423264/54.3.20.14

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Podsakoff, P. M., MacKenzie, S. B., & Podsakof, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology, 63*, 539–569. https://doi.org/10.1146/annurev-psych-120710-100452

Rajabalee, Y., & Santally, M. (2021). Learner satisfaction, engagement and performances in an online module: Implications for institutional e-learning policy. *Education and Information Technologies, 26*, 2623–2656. https://doi.org/10.1007/s10639-020-10375-1

Realyvásquez-Vargas, A., Maldonado-Macías, A., Arredondo-Soto, K., Baez-Lopez, Y., Carrillo-Gutiérrez, T., & Hernández-Escobedo, G. (2020). The impact of environmental factors on academic performance of university students taking online classes during the COVID-19 pandemic in Mexico. *Sustainability, 12*(21), 1–22. https://doi.org/10.3390/su12219194

Ringle, C., Wende, S., & Becker, J. (2015). SmartPLS 3. Boenningstedt: SmartPLS GmbH. http://www.smartpls.com

Robayo-Tamayoa, M., Blanco-Donoso, L. M., Román, F. J., Carmona-Cobo, I., Moreno-Jiménez, B., & Garossa, E. (2020). Academic engagement: A diary study on the mediating role of academic support. *Learning and Individual Differences, 80*, 101887. https://doi.org/10.1016/j.lindif.2020.101887

Rotar, O. (2022). Online student support: A framework for embedding support interventions into the online learning cycle. *Research and Practice in Technology Enhanced Learning, 17*(2). https://doi.org/10.1186/s41039-021-00178-4

Ryan, R. M., & Deci, E. L. (2019). Brick by brick: The origins, development, and future of self-determination theory. In A. J. Elliot (Ed.), *Advances in motivation science* (pp. 111–156). Elsevier Academic Press. https://doi.org/10.1016/bs.adms.2019.01.001

Sánchez-Elvira Paniagua, A., & Simpson, O. (2018). Developing student support for open and distance learning: The EMPOWER project. *Journal of Interactive Media in Education, 1*(9), 1–10. https://doi.org/10.5334/jime.470

Sarstedt, M., Bengart, P., Shaltoni, A. M., & Lehmann, S. (2018). The use of sampling methods in advertising research: A gap between theory and practice. *International Journal of Advertising, 37*(4), 650–663. https://doi.org/10.1080/02650487.2017.1348329

Stone, C. (2019). Online learning in Australian higher education: Opportunities, challenges and transformations. *Student Success, 10*(2), 1–11. https://doi.org/10.5204/ssj.v10i2.1299

Vinţe, C., Reveiu, A., Dârdală, M., & Lupu, V. (2021). Perspectives of digital identity–the case of online education during the COVID-19 pandemic. *Proceedings of the International Conference on Business Excellence* (pp. 1162–1170). https://doi.org/10.2478/picbe-2021-0108

Voicu, M. C., & Muntean, M. (2023). Factors that influence mobile learning among university students in Romania. *Electronics, 12*(4), 938. https://doi.org/10.3390/electronics12040938

Widiyanti, I. A., Ardiwinata, J., & Dewi, L. (2021). Online learning motivation. *Proceedings of the First Transnational Webinar on Adult and Continuing Education (TRACED 2020)* (pp. 68–72). Atlantis Press. https://doi.org/10.2991/assehr.k.210508.013

Wonglorsaichon, B., Wongwanich, S., & Wiratchai, N. (2014). The influence of students school engagement on learning achievement: A structural equation modeling analysis. *Procedia - Social and Behavioral Sciences, 116*, 1748–1755. https://doi.org/10.1016/j.sbspro.2014.01.467

Zhang, X., Pi, Z., Li, C., & Hu, W. (2020). Intrinsic motivation enhances online group creativity via promoting members' effort, not interaction. *British Journal of Educational Technology, 52*(2), 606–618. https://doi.org/10.1111/bjet.13045

Authors and Affiliations

Juan José García-Machado[1] · Minerva Martínez Ávila[2] · Nicoleta Dospinescu[3] · Octavian Dospinescu[4]

✉ Juan José García-Machado
machado@uhu.es

Minerva Martínez Ávila
mmartineza@uaemex.mx

Nicoleta Dospinescu
dnicole@uaic.ro

Octavian Dospinescu
doctav@uaic.ro

[1] Department of Financial Economics, Accounting and Operations Management, University of Huelva, Huelva, Spain

[2] Department of Administration, Universidad Autónoma del Estado Mexico, Mexico City, Mexico

[3] Department of Management, Marketing and Business Administration, University Alexandru Ioan Cuza, Iasi, Romania

[4] Department of Accounting, Business Information Systems and Statistics, University Alexandru Ioan Cuza, Iasi, Romania