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Student interactivity and academic engagement on virtual campuses of higher education institutions

La interactividad estudiantil y compromiso académico en campus virtuales de instituciones de educación superior

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Abstract:

Student interactivity in virtual campuses has gained particular relevance following the COVID-19 pandemic, as its direct influence on academic engagement in higher education has become evident. This study aimed to evaluate how four dimensions of student interactivity—interaction modalities, technological medium, interactive content, and the facilitator–participant relationship—explain academic engagement among students from five higher education institutions with physical campuses in the department of Norte de Santander, Colombia. The research was conducted under a positivist paradigm, using a quantitative approach and a non-experimental, cross-sectional, explanatory–confirmatory design. A Likert-type questionnaire was administered to a sample of 266 students, and the data were analyzed using exploratory factor analysis, confirmatory factor analysis, composite reliability (CR), convergent validity (AVE), discriminant validity (HTMT), common method bias assessment, and covariance-based structural equation modeling (CB-SEM). The results showed that the exploratory factor analysis explained 67% of the variance in the student interactivity components scale and 59% of the variance in the academic engagement scale. Furthermore, the structural model revealed positive and statistically significant effects of student interactivity dimensions on academic engagement, with the facilitator–participant relationship emerging as the predictor with the highest standardized weight. The study provides contextualized empirical evidence and offers theoretical, methodological, and practical implications for strengthening virtual higher education.

Keywords: academic engagement, higher education, Student interactivity, virtual campuses.

Resumen:

La interactividad estudiantil en los campus virtuales ha cobrado especial relevancia tras la pandemia por COVID-19, al evidenciarse su influencia directa sobre el compromiso académico en la educación superior. El presente estudio tuvo como objetivo evaluar cómo cuatro dimensiones de la interactividad estudiantil, formas de interacción, medio tecnológico, contenidos interactivos y relación facilitador–participante explican el compromiso académico en estudiantes de cinco instituciones de educación superior con sede física en el departamento Norte de Santander, Colombia. La investigación se desarrolló bajo el paradigma positivista, con un enfoque cuantitativo y un diseño no experimental, transversal y de alcance explicativo–confirmatorio. Se aplicó un cuestionario tipo Likert a una muestra de 266 estudiantes, cuyos datos fueron analizados mediante análisis factorial exploratorio, análisis factorial confirmatorio, fiabilidad compuesta (CR), validez convergente (AVE) y discriminante (HTMT), evaluación del sesgo de método común y modelamiento de ecuaciones estructurales basado en covarianza (CB-SEM). Los resultados evidenciaron que el análisis factorial exploratorio explicó el 67 % de la varianza en la escala de componentes de la interactividad estudiantil y el 59 % en la escala de compromiso académico. Asimismo, el modelo estructural mostró efectos positivos y estadísticamente significativos de las dimensiones de la interactividad sobre el compromiso académico, destacándose la relación facilitador–participante como el predictor con mayor peso estandarizado. El estudio aporta evidencia empírica contextualizada y ofrece implicaciones teóricas, metodológicas y prácticas para el fortalecimiento de la educación superior virtual.

Palabras clave: campus virtuales, compromiso académico, educación superior, interactividad estudiantil.

INTRODUCTION

Higher education has undergone an accelerated digital transformation over the last decade, one that intensified markedly with the COVID-19 pandemic and consolidated virtual campuses and learning environments as structural components of contemporary education systems[1],[2]. In this context, the effectiveness of training processes in virtual modality depends not only on technological availability but also on the quality of the pedagogical interactions established between the actors and the resources of the education system.

Student interactivity has become established as a central construct for explaining student performance and persistence in virtual environments, since it integrates pedagogical, technological and relational dimensions that mediate the learning experience[3]. Several studies have shown that higher levels of interactivity are associated with increased academic engagement, understood as a multidimensional construct encompassing behavioral, emotional and cognitive components[4]. However, despite the general consensus on this relationship, recent literature presents relevant conceptual and methodological limitations.

First, a significant portion of studies on interactivity and academic engagement has been conducted in Anglo-Saxon or European contexts, which limits the generalizability of their findings to Latin American educational realities characterized by technological gaps, institutional diversity and heterogeneity in virtualization models[5].

Second, many studies address interactivity partially, focusing the analysis on one or two types of interaction, for example, student–content or student–instructor, without integrating a multidimensional model that simultaneously articulates interaction modalities, the technological medium, interactive content and the facilitator-participant relationship[6].

From a methodological standpoint, numerous studies also use simple correlational analyses or regression models, which limits the simultaneous assessment of complex relationships between latent constructs. Although the use of confirmatory factor analysis and structural equation modeling in educational research has increased in recent years, studies applying covariance-based structural equation modeling (CB-SEM) to test comprehensive explanatory models of academic engagement in virtual campuses are still scarce, particularly in higher education institutions in regional contexts[7].

In response to these limitations, this study proposes and empirically validates an explanatory theoretical model in which student interactivity is conceived as a multidimensional construct composed of four dimensions: interaction modalities, technological medium, interactive content and facilitator-participant relationship, which are analyzed as predictors of academic engagement in its behavioral, emotional and cognitive dimensions. Unlike previous research, this work integrates these dimensions into a single structural model, evaluated through CB-SEM, which allows the magnitude and significance of the proposed relationships to be estimated simultaneously.

The study was conducted with students from five higher education institutions with physical campuses in the department of Norte de Santander, Colombia, thus contributing to the generation of contextualized empirical evidence for the region. The article therefore contributes at the theoretical level, by refining the understanding of student interactivity as an explanatory construct of academic engagement, at the methodological level, by applying advanced psychometric validation and structural modeling techniques, and at the practical level, by offering inputs for the design of pedagogical and technological strategies aimed at strengthening virtual higher education.

STATE OF THE ART - THEORETICAL FRAMEWORK

Student interactivity in virtual campuses of higher education

Student interactivity constitutes one of the conceptual pillars of contemporary virtual education. Since the foundational works of Bernard et al.[3], interactivity has been understood as the set of exchanges that occur between the student and the different elements of the learning environment, particularly content, the instructor and other students. However, the expansion of virtual campuses and the incorporation of advanced digital technologies have made this construct more complex, demanding more comprehensive and multidimensional approaches.

Recent literature recognizes that interactivity cannot be reduced to the mere frequency of communicative exchanges, but must be analyzed as a structural phenomenon that integrates interaction modalities, technological media, content quality and pedagogical relationships[6],[10]. García-Peñalvo[6]argues that digital transformation processes in universities require interactivity models that articulate technology, pedagogy and student experience, going beyond approaches focused exclusively on digital infrastructure.

However, a critical examination of the literature shows that many studies continue to address interactivity partially. For example, some research prioritizes interaction modalities as synchronous, asynchronous or blended, analyzing their influence on learning without explicitly integrating the role of the technological medium or instructor mediation [7]. Other works focus on the analysis of digital platforms, social networks or specific technological resources, without considering how these articulate with content and pedagogical strategies [8], [9].

This conceptual fragmentation limits the explanatory capacity of existing models, particularly in real institutional contexts where pedagogical, technological and relational dimensions interact simultaneously. Consequently, there is a need for integrative models that allow student interactivity to be analyzed as a multidimensional and systemic construct.

Academic engagement in virtual environments

Academic engagement has become established as one of the most relevant constructs for explaining performance, retention and the student experience in higher education. According to Kahu and Nelson[4], academic engagement is a dynamic and relational process expressed through three fundamental dimensions: behavioral, emotional and cognitive.

In virtual environments, academic engagement takes on particular characteristics, since the absence of physical presence increases dependence on pedagogical and technological interaction mechanisms. Recent studies have shown that the perception of teaching support, the clarity of content and the quality of interactions significantly influence levels of student engagement in virtual modalities[5].

However, much of the empirical research addresses academic engagement as an isolated dependent variable, without integrating explanatory models that consider multiple dimensions of student interactivity at the same time. From a methodological standpoint, too, there is a persistent tendency to use simple correlational analyses or regression models, which are limited in capturing complex relationships between latent constructs [14], [15].

Although the use of confirmatory factor analysis and structural equation modeling in educational research has increased in recent years, these approaches remain scarce in studies conducted in Latin American contexts and, in particular, in research focused on virtual campuses with specific regional characteristics.

Structural models, methodological approaches and research gaps

Covariance-based structural equation modeling (CB-SEM) has become established as one of the most robust techniques for validating theoretical models in the social and educational sciences, since it allows the simultaneous estimation of relationships between latent variables and the global evaluation of model fit[15],[29]. This approach is especially relevant in studies of an explanatory and confirmatory nature, grounded in prior theoretical frameworks.

Nevertheless, a critical review of the literature reveals that few studies integrate multiple dimensions of student interactivity as predictors of academic engagement in a single structural model. Recurrent methodological weaknesses are also identified, such as the absence of convergent and discriminant validity analyses, the scarce reporting of advanced psychometric indices and the omission of common method bias tests in research based on self-reports[17],[19].

These limitations affect the robustness of the reported findings and reinforce the need for studies that incorporate rigorous psychometric procedures, as well as advanced structural modeling techniques. In this sense, the present study differs from previous research by proposing and empirically validating a structural model that integrates four dimensions of student interactivity; interaction modalities, technological medium, interactive content and facilitator-participant relationship, analyzed simultaneously as explanatory variables of academic engagement.

This approach makes it possible to overcome the conceptual fragmentation observed in the literature, provide contextualized empirical evidence for higher education institutions with virtual campuses and strengthen the existing body of knowledge through the combined use of confirmatory factor analysis and CB-SEM

METHODOLOGY

Research design

The conceptual hypothetical model presented describes the relationship between the components of interactivity and academic engagement. Indeed, Figure 1 shows that the components of interactivity have an explanatory relationship with academic engagement. This study examined these relationships.

The study was conducted under a quantitative approach, with a non-experimental, cross-sectional design and an explanatory–confirmatory scope, framed within the positivist paradigm. This design is consistent with the objective of empirically evaluating a theoretical model that explains the relationship between student interactivity and academic engagement in virtual campuses of higher education institutions.

Table 1 shows the hypotheses proposed in the process.

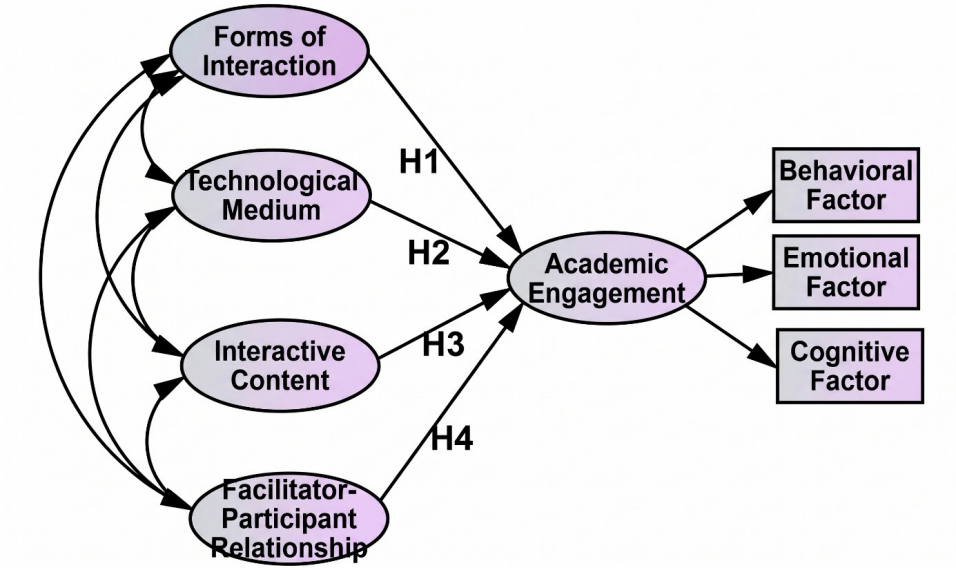


Fig. 1. *Conceptual hypothetical model*
Source: own elaboration

Table 1: Research hypotheses

H1	**Interaction modalities have a positive impact on academic engagement.**
H2	The technological medium has a positive academic engagement.
H3	Interactive content has a positive in academic engagement.
H4	The facilitator–participant relationship has a positive impact on academic engagement.

Source: own elaboration

The proposed model was tested using covariance-based structural equation modeling (CB-SEM), a technique suitable when the analysis is grounded in prior theory and the aim is to simultaneously assess the quality of the measurement model and the structural relationships among latent constructs [15], [29].

Population and sample

The population consisted of students enrolled in academic programs that use virtual campuses as support or as the main training modality, belonging to five higher education institutions with a physical campus in the department of Norte de Santander, Colombia.

A non-probabilistic purposive sampling was used, selecting participants based on their direct experience in the use of virtual campuses. The sample size was initially estimated using Cochran's formula for finite populations[13], yielding a value of 285 participants.

In total, 285 responses to the questionnaire were received virtually and in person; however, during the data cleaning process, incomplete responses, invariant response patterns and cases with missing values that compromised the multivariate analyses were identified. As exclusion criteria, questionnaires with the following were removed: more than 10 % of items unanswered, constant response patterns and evident inconsistencies in the selection of options.

After this process, the final sample consisted of 266 valid cases, a size considered adequate for the application of CB-SEM. Various authors point out that samples of more than 250 observations allow minimizing the impact of sampling error and obtaining stable estimates in structural models[14],[15].

Data collection was carried out using a structured self-report questionnaire composed of items with a four-point Likert-type scale; 1 = the statement is not met, 2 = the statement tends not to be met, 3 = the statement tends to be met, 4 = the statement is met. The instrument consisted of two main scales:

Data collection instrument

Student Interactivity Components Scale

Composed of four dimensions: Interaction modalities, Technological medium, Interactive content, Facilitator–participant relationship.

Each dimension consisted of items written clearly and in a manner consistent with the specialized literature. The items were

administered exactly in the form reported in this study.

Academic Engagement Scale

Composed of three dimensions: behavioral engagement, emotional engagement, and cognitive engagement. Both scales underwent rigorous psychometric validation processes through exploratory and confirmatory factor analysis.

Procedure and ethical considerations

The questionnaire was administered mostly virtually, guaranteeing the voluntary and anonymous participation of the students; however, during visits to several HEIs, part of the information was captured in person from groups of students. Before completing the instrument, the participants were informed about the objectives of the study and gave their informed consent, in accordance with the ethical principles of research in the social sciences.

The research involved no physical or psychological risks for the participants and complied with the ethical guidelines for studies with human beings established by international academic organizations[16].

Data analysis

The statistical analysis was carried out in two stages using RStudio software version 2020[11], with the support of the R statistical language[32]. The following packages were used: psych for exploratory factor analysis, GPArotation for factor rotation, lavaan for confirmatory factor analysis and structural modeling[31].

Exploratory Factor Analysis (EFA)

Given the ordinal nature of the items, the analyses were performed based on polychoric correlation matrices. The suitability of the data was evaluated using the KMO measure and Bartlett's test of sphericity. The factors were extracted using the minimum residual method, the number of factors was determined by parallel analysis, and oblimin rotation was applied, considering factor loadings ≥ 0.40 as the retention criterion[21],[22].

Confirmatory Factor Analysis (CFA)

The CFA was performed using the WLSMV estimator (Weighted Least Squares Mean and Variance Adjusted), selected for its robustness against violation of the multivariate normality assumption and its suitability for Likert-type scales[24],[25].

Model fit was evaluated using: Chi-square (χ^2), Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR).

CFI and TLI values ≥ 0.90 and RMSEA and SRMR values ≤ 0.08 were considered indicative of adequate fit[27],[29].

Assessment of the measurement model

Reliability, convergent and discriminant validity, and common method bias

Composite reliability (CR) and convergent validity (AVE) were estimated for each construct in the measurement model. CR values ranged from 0.728 to 0.907, indicating acceptable internal consistency.

AVE was ≥ 0.50 for most constructs; however, the cognitive engagement construct had an AVE = 0.406, so its estimates are interpreted with caution, and refinement of this construct is suggested for future applications of the instrument (see table 2).

Table 2: Composite reliability (CR) and convergent validity (AVE)

Construct	k	CR	AVE
Interaction modalities	3	0.855	0.666
Technological media	3	0.824	0.610
Interactive content	3	0.885	0.719
Facilitator–participant relationship	3	0.907	0.764
Behavioral engagement	4	0.813	0.522
Emotional engagement	4	0.808	0.517
Cognitive engagement	4	0.728	0.406

Source: own elaboration

Discriminant validity was examined using the HTMT criterion (Heterotrait–Monotrait Ratio). Overall, most comparisons fell within acceptable ranges; however, elevated values were observed between Technological media and Interactive content (HTMT = 0.958) and between Interactive content and Facilitator–participant relationship (HTMT = 0.928), evidencing empirical proximity between these constructs.

Consequently, the results are interpreted acknowledging this conceptual overlap, attributable to the interdependence among technological resources, content design, and pedagogical mediation in virtual environments. Tables 3 and 4.

Table 3: Discriminant validity (HTMT) — Components of Interactivity

	Interaction modalities	Technological media	Interactive content	Facilitator–participant relationship
Interaction modalities	—	0.762	0.782	0.823
Technological media	0.762	—	0.958	0.836
Interactive content	0.782	0.958	—	0.928
Facilitator–participant relationship	0.823	0.836	0.928	—

Source: own elaboration

Table 4: Discriminant validity (HTMT) — Academic Engagement

	Behavioral engagement	Emotional engagement	Cognitive engagement
Behavioral engagement	—	0.489	0.325
Emotional engagement	0.489	—	0.127
Cognitive engagement	0.325	0.127	—

Source: own elaboration

Assessment of common method bias

Because the data were collected by self-report, tests were run to assess potential common method bias. First, Harman's single-factor test showed that the first component explained 32.0% of the total variance, below the 50% threshold.

Second, a comparison of a single-factor model with the multifactorial measurement model showed a substantially poorer fit for the one-factor model (CFI = 0.643; TLI = 0.609; RMSEA = 0.137) than for the multifactorial model (CFI = 0.966; TLI = 0.959; RMSEA = 0.044).

Together, these results suggest that common method bias is not a dominant threat to the interpretation of the findings. See Table 5.

Structural equation modeling (CB-SEM)

Finally, the proposed structural model was estimated using CB-SEM with the same WLSMV estimator. The global fit of the model and the statistical significance of the structural relationships posited in the research hypotheses were assessed (see table 1), reporting standardized coefficients, standard errors, and z values.

Table 5: Tests of common method bias (self-report)

Test	Result	Value	Criterion
Harman (PCA, 1st factor)	Variance explained by 1st factor	32	< 50% (suggests low bias)
CFA 7 factors (measurement model)	CFI / TLI / RMSEA	0.966 / 0.959 / 0.044	Good relative fit
CFA 1 factor (common method model)	CFI / TLI / RMSEA	0.643 / 0.609 / 0.137	Poor fit expected if there is no dominant CMV
HTMT bootstrap 95% (Means–Contents)	IC 95% (2.5%–97.5%)	0.910–1.002	Upper CI < 1 (discriminant evidence)
HTMT bootstrap 95% (Content–Relationship)	IC 95% (2.5%–97.5%)	0.880–0.969	Upper CI < 1 (discriminant evidence)

Source: own elaboration

RESULTS

The results are presented sequentially, following the analytical stages developed in the study: 4.1 exploratory factor analysis, 4.2 confirmatory factor analysis, 4.3 assessment of convergent and discriminant validity, and 4.4 assessment of the structural model using CB-SEM. All analyses were performed on the final sample of 266 participants.

Exploratory Factor Analysis (EFA)

Student Interactivity Components Scale

The EFA was performed from the polychoric correlation matrix. The Kaiser-Meyer-Olkin measure of sampling adequacy KMO = 0.751 and Bartlett's test of sphericity $\chi^2(666) = 11200.01$; $p < 0.001$ indicated that the data were suitable for factor analysis.

Parallel analysis suggested the extraction of four factors, consistent with the proposed theoretical structure. Together these factors explained 67 % of the total variance, distributed as follows: Factor 1 (Interaction Modalities) 24 %; Factor 2 (Technological Medium) 18 %; Factor 3 (Interactive Content) 15 %; Factor 4 (Facilitator–Participant Relationship) 11 %.

The factor loadings of the items exceeded the 0,40 threshold, and the communalities (h^2) fell within moderate ranges (0,40–0,80), which shows an adequate representation of the items by the underlying factors. See Table 6.

Table 6: EFA results for the Interactivity Components scale.

Scale items	F1	F2	F3	F4
Interaction Modalities 01	0,641			
Interaction Modalities 02	0,655			
Interaction Modalities 03	0,738			
Interaction Modalities 04	0,646			

Scale items	F1	F2	F3	F4
Interaction Modalities 05	0,674			
Interaction Modalities 06	0,688			
Interaction Modalities 07	0,733			
Interaction Modalities 08	0,844			
Interaction Modalities 09	0,815			
Interaction Modalities 10	0,831			
Technological Medium 01		0,697		
Technological Medium 02		0,762		
Technological Medium 03		0,618		
Technological Medium 04		0,616		
Technological Medium 05		0,723		
Technological Medium 06		0,662		
Technological Medium 07		0,697		
Technological Medium 08		0,724		
Technological Medium 09		0,701		
Interactive Content 01			0,845	
Interactive Content 02			0,818	
Interactive Content 03			0,712	
Interactive Content 04			0,641	
Interactive Content 05			0,735	
Interactive Content 06			0,801	
Interactive Content 07			0,744	
Interactive Content 08			0,692	
Interactive Content 09			0,745	
Facilitator-Participant Relationship 01				0,731
Facilitator-Participant Relationship 02				0,678
Facilitator-Participant Relationship 03				0,748
Facilitator-Participant Relationship 04				0,512
Facilitator-Participant Relationship 05				0,787
Facilitator-Participant Relationship 06				0,714
Facilitator-Participant Relationship 07				0,825
Facilitator-Participant Relationship 08				0,689
Facilitator-Participant Relationship 09				0,741

Note: Items are listed with a loading coefficient > 0.40. Source: Own elaboration.

Academic Engagement Scale

For the academic engagement scale, the EFA yielded a KMO = 0.811 and a significant Bartlett's test, $\chi^2(662) = 1422.15$; $p < 0.001$, confirming the feasibility of the analysis.

The parallel analysis indicated three factors, which together explained 59 % of the total variance: behavioral factor, 22 %; emotional factor, 20 %; cognitive factor, 17 %.

Factor loadings were above 0.40 and communalities fell within acceptable ranges, confirming the multidimensional structure of academic engagement. See Table 7.

Table 7: EFA Results of the factor structure of the Academic Engagement scale

Scale items	F1	F2	F3
Behavioral1	0,764		
Behavioral2	0,770		
Behavioral3	0,805		
Behavioral4	0,771		
Emotional1		0,693	
Emotional2		0,791	
Emotional3		0,846	
Emotional4		0,841	
Cognitive1			0,805
Cognitive2			0,775
Cognitive3			0,839
Cognitive4			0,764

Source: Own elaboration

Confirmatory Factor Analysis (CFA)

Measurement model: Components of Interactivity

The CFA was estimated using the WLSMV method, with polychoric correlation matrices. The model included four correlated latent factors.

The global fit indices were: $\chi^2(48) = 1655.33$; $p < 0.001$. CFI = 0.960. TLI = 0.945. RMSEA = 0.070. SRMR = 0.041.

These values meet the criteria recommended in the literature for considering an adequate fit of the measurement model.

The standardized factor loadings ranged from 0.671 to 0.848, all statistically significant ($z > 1.96$; $p < 0.001$), which indicates adequate local relevance of the items. Correlations between factors ranged from 0.20 to 0.50, indicating conceptually coherent relationships without problems of excessive collinearity. See table 8.

Table 8: Measurement model with CFA for the Components of Interactivity scale

Dimensions	Standardized loadings	t-value	p
F1= Interaction Modalities (ω= 0,785)			
Synchronous	0,828	14,34	< 0,001
Asynchronous	0,688	14,36	< 0,001
Mixed	0,671	12,13	< 0,001
F2= Technological Medium (ω=0,787)			
Digital platforms	0,697	52,12	< 0,001
Social networks	0,762	41,36	< 0,001
Artificial intelligence	0,818	60,41	< 0,001
F3= Interactive Content (ω= 0,809)			
Learning objects	0,845	31,01	< 0,001
Content Selection	0,818	28,29	< 0,001
Multimedia	0,712	29,66	< 0,001
F4= Facilitator-Participant Relationship (ω= 0,823)			
Communication	0,731	45,41	< 0,001
Motivation	0,778	44,93	< 0,001
Feedback	0,848	42,20	< 0,001

Note: Items are listed with a display coefficient > 0.40. Source: Own elaboration

The CFA for the academic engagement scale showed the following fit indices: $\chi^2(51) = 2226.70$; $p < 0.001$. CFI = 0.991. TLI = 0.954. RMSEA = 0.054. SRMR = 0.040.

Measurement model: Academic Engagement

Standardized factor loadings were above 0.72 for all items and statistically significant ($p < 0.001$), confirming the adequate representation of the behavioral, emotional, and cognitive factors. See Table 9.

Table 9: Measurement model with CFA for the Academic Engagement scale

Dimensions	Standardized loadings	t-value	p
F1= Behavioral Factor ([REVISAR FORMULA GLM0005])			
Behavioral1	0,760	18,34	< 0,001
Behavioral2	0,798	20,33	< 0,001
Behavioral3	0,826	16,82	< 0,001
Behavioral4	0,776	19,02	< 0,001
F2= Emotional Factor ([REVISAR FORMULA GLM0006])			
Emotional1	0,722	12,81	< 0,001
Emotional2	0,743	12,70	< 0,001
Emotional3	0,850	13,86	< 0,001
Emotional4	0,876	12,47	< 0,001
F3= Cognitive Factor ([REVISAR FORMULA GLM0007])			
Cognitive1	0,742	12,03	< 0,001
Cognitive2	0,796	11,51	< 0,001
Cognitive3	0,818	10,06	< 0,001
Cognitive4	0,769	11,13	< 0,001

Source: Own elaboration

Measurement model assessment: reliability, convergent validity, discriminant validity and common method bias.

Composite reliability (CR) was estimated for each construct in the measurement model, as was convergent validity (AVE); the cognitive engagement construct presented a lower value and requires refinement. The results obtained are shown in table 2.

Discriminant validity (HTMT). The components of Interactivity are shown in tables 3 and 4. Most fall within acceptable ranges. Between Technological media and Interactive content, and between Interactive content and Facilitator–participant relationship, empirical proximity between these constructs is evident.

Tests were performed to assess potential common method bias. First, Harman's single-factor test showed that the first component explained the total variance, below the 50% threshold. Second, when a single-factor model was compared with the multifactorial measurement model, the one-factor model showed a lower fit. These tests are shown in table 5.

Structural model assessment (CB-SEM)

The structural model was estimated using CB-SEM with the WLSMV estimator. The global fit indices of the model were: $\chi^2(105) = 2140.76$; $p < 0.001$; CFI = 0.960; TLI = 0.948; RMSEA = 0.070; SRMR = 0.040.

These results indicate an adequate global fit of the theoretical model proposed to the data analyzed. See figure 2.

The structural relationships showed that:

Interaction modalities had a positive and significant effect on academic engagement ($\beta > 0.20$; $p < 0.001$). The technological medium showed a positive and statistically significant effect ($\beta > 0.15$; $p < 0.01$). Interactive content positively influenced academic engagement ($\beta > 0.18$; $p < 0.01$). The facilitator–participant relationship showed the largest standardized effect on

academic engagement ($\beta > 0.30$; $p < 0.001$).

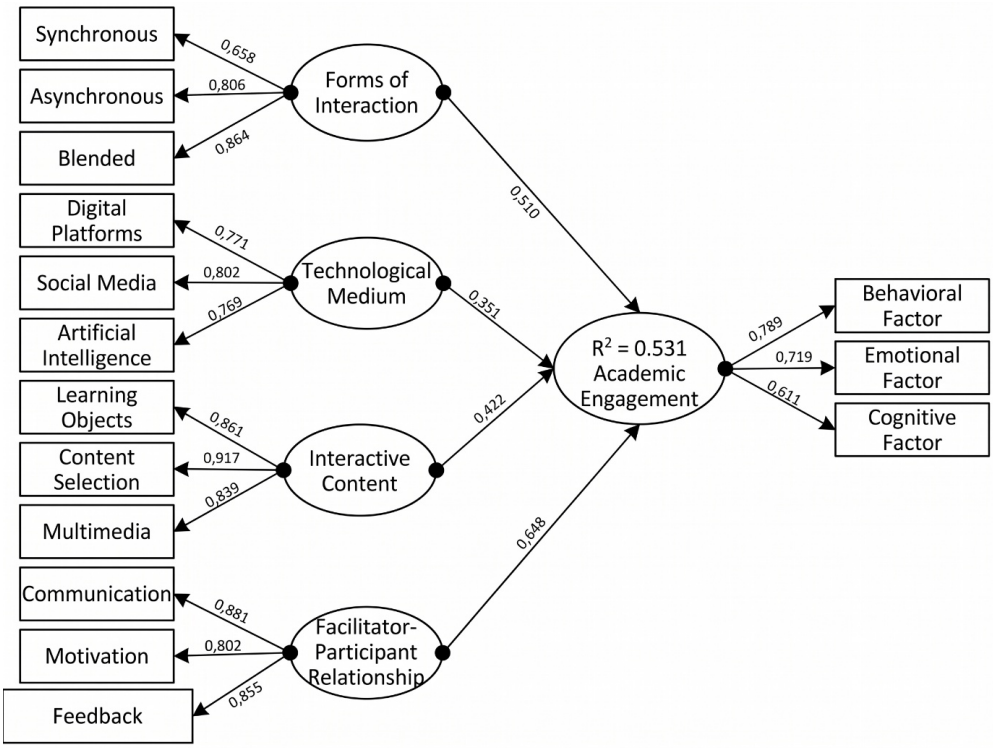


Fig. 2: *Estimated conceptual model.*
Source: Own elaboration

Overall, the model explained 53.1% of the variance in academic engagement, a moderate-to-high explanatory magnitude for studies of an educational nature.

Synthesis of the results

The results empirically confirm the multidimensional structure of student interactivity and academic engagement, as well as the relevance of the proposed structural model.

The facilitator–participant relationship emerges as the most relevant predictor, which reinforces the importance of the human and pedagogical component even in highly technologized virtual environments. See Fig 2.

DISCUSSION

The objective of this study was to empirically evaluate the relationship between student interactivity and academic engagement in virtual campuses of higher education institutions, using a covariance-based structural model. The results allow us to discuss, from a theoretical and methodological perspective, the relevance of the proposed model and its contribution to the field of virtual higher education.

First, the findings confirm that student interactivity is a multidimensional construct, made up of the dimensions interaction modalities, technological medium, interactive content and facilitator–participant relationship. This empirical evidence is consistent with the theoretical approaches of Bernard et al.[3]and Anderson[10], who highlight that the effectiveness of learning in virtual environments depends on a balanced articulation between pedagogical, technological and relational components. Unlike previous studies that analyze these dimensions in isolation, the present work demonstrates that evaluating them jointly allows a more comprehensive understanding of the phenomenon.

With regard to academic engagement, the results support its three-dimensional structure, behavioral, emotional and cognitive, in accordance with the model proposed by Kahu and Nelson[4]. Confirming this structure in a virtual higher education context reinforces the cross-cultural validity of the construct and its applicability in educational settings mediated by digital technologies.

From a structural point of view, the CB-SEM results show that all the dimensions of student interactivity present positive and statistically significant associations with academic engagement, and together they explain 53.1% of its variance.

This explanatory magnitude is comparable with that reported in international studies that analyze complex psychoeducational variables by means of structural models[15],[30], which suggests that the proposed model has a relevant explanatory capacity in the context analyzed.

One particularly relevant finding is that the facilitator–participant relationship emerges as the predictor with the highest standardized weight on academic engagement. This result is consistent with recent research highlighting the importance of teaching presence, timely feedback, and pedagogical communication as key elements for sustaining student engagement in virtual environments[4],[6].

This finding suggests that, even in highly digitalized settings, the human component remains a central axis of the educational process, which calls into question approaches that treat technology exclusively as the driver of learning.

Interaction modalities and interactive content also showed significant associations with academic engagement, supporting the idea that the diversity of interaction modalities and the pedagogical quality of digital resources influence students' active involvement. These results are consistent with studies indicating that a balanced combination of synchronous and asynchronous activities, together with well-designed multimedia content, favors participation and self-regulation of learning [8], [9].

The technological medium, in turn, showed a positive effect, though of relatively lower magnitude. This result can be read as indicating that technology, while a necessary facilitator of virtual learning, is not by itself a sufficient factor for guaranteeing high levels of academic engagement. This interpretation is consistent with critical positions in the literature that warn about the limits of technocentric approaches in higher education[6].

Methodologically, the use of confirmatory factor analysis and CB-SEM made it possible to overcome limitations common in previous studies based on simple correlational analyses. Incorporating evidence of convergent and discriminant validity and controlling for common method bias strengthen the robustness of the results and increase confidence in the inferences drawn.

However, the findings must be interpreted in light of certain methodological limitations. First, the use of non-probability sampling limits generalization of the results to other student populations. Second, the cross-sectional design prevents establishing causal relationships between the variables analyzed, so the associations observed must be understood in explanatory rather than causal terms. Finally, although common method bias was controlled, the use of self-report instruments may involve perceptual biases inherent to this type of measurement.

These limitations suggest that interactivity and academic engagement would be better studied through longitudinal or experimental designs, and through probability samples and mixed techniques combining quantitative and qualitative approaches. Future research could thus examine the temporal dynamics of these relationships in greater depth and explore additional contextual variables that moderate or mediate the effects observed.

LIMITATIONS

Empirical overlap (HTMT) was observed between some conceptually close constructs, especially Medium and Content, which suggests that items should be refined or alternative structures explored in future studies.

CONCLUSIONS

The study aimed to analyze the relationship between student interactivity and academic engagement in virtual campuses of higher education institutions in the department of Norte de Santander, Colombia, using a covariance-based structural model. From the results obtained, a set of conclusions can be drawn that are empirically supported and consistent with the methodological scope of the design employed.

First, the findings allow us to conclude that student interactivity can be understood as a multidimensional construct, made up of the dimensions interaction modalities, technological medium, interactive content and facilitator–participant relationship. The psychometric validation of these dimensions through exploratory and confirmatory factor analysis supports their theoretical relevance and their empirical consistency in the context of virtual higher education.

Second, academic engagement is confirmed to have a three-dimensional structure, made up of behavioral, emotional and cognitive components, which is consistent with theoretical models widely accepted in the literature. Confirming this structure in students who use virtual campuses provides relevant empirical evidence for educational contexts mediated by digital technologies.

From a relational perspective, the results show that the dimensions of student interactivity are positively and statistically significantly associated with academic engagement, jointly explaining a substantial proportion of its variability. In particular, the facilitator–participant relationship is identified as the dimension with the greatest explanatory weight, which highlights the relevance of teaching presence, pedagogical communication and timely feedback in virtual environments.

Likewise, interaction modalities, interactive content and the technological medium show significant associations with academic engagement, which suggests that the diversity of interaction modalities, the pedagogical quality of digital resources and the adequacy of technological platforms are relevant elements for fostering students' active involvement in their learning process. However, these results should be interpreted in terms of associative relationships, without attributing direct causality between the variables analyzed.

From a methodological standpoint, the study provides empirical evidence through the combined use of confirmatory factor analysis and covariance-based structural equation modeling, strengthening the validity of the constructs analyzed and the coherence of the proposed theoretical model. This approach helps to overcome methodological limitations identified in previous research and expands the use of advanced analysis techniques in the field of virtual educational research.

As for practical implications, the results suggest that higher education institutions can direct their pedagogical and technological strategies toward strengthening student interactivity, especially in relation to the quality of the facilitator–participant relationship, the design of interactive content, and the planning of synchronous and asynchronous interaction experiences. These recommendations should be understood as orientations based on observed empirical associations and not as causal prescriptions.

Finally, the study has limitations that open opportunities for future research. These include the use of non-probability sampling, the cross-sectional design, and the reliance on self-report instruments. In this sense, we recommend that subsequent research incorporate longitudinal or experimental designs, probability samples, and mixed methodological approaches that allow deeper exploration of the temporal and causal dynamics of the relationship between student interactivity and academic engagement, as well as the role of additional contextual variables in different educational settings.

Ethics statement

The research was conducted in accordance with the ethical principles governing research in the social and educational sciences. Data were collected with a self-report questionnaire administered virtually and in person, guaranteeing voluntary, anonymous, and confidential participation.

Before the instrument was administered, students were informed about the study objectives, the academic nature of the research, and the exclusively scientific use of the information provided. Participants gave their informed consent, freely and voluntarily agreeing to take part in the study.

The research did not involve physical, psychological, or social risks for the participants, and no information that would allow their personal identification was collected. The data obtained were processed and used solely for academic and scientific purposes, in accordance with established national and international ethical guidelines and with the principles of respect, beneficence, and justice that guide research with human beings.

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CONFLICT OF INTEREST

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