ISSN: 1692-7257 – Volume 1 – Number 47 - 2026

RCTA
Revista Colombiana de Tecnologías de Avanzada
UNIPAMPLONA

Digital Object Identifier: 10.24054/rcta.v1i47.4130

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

MSc. Ciro Antonio Carvajal Labastida [1], Dra. Milvia Lissette Peñaloza de Arias [1]

[1] ***Universidad Nacional Experimental del Táchira (UNET)**, Graduate School, PhD Program in Evaluative Management Technological Business and Educational. San Cristóbal, Táchira State, Venezuela.*

***Correspondence:** cirocarvajal@gmail.com*

***Received:** August 06, 2025. **Accepted:** December 20, 2025. **Published:** January 01, 2026.*

***How to cite:** C. A. Carvajal Labastida and M. L. Peñaloza de Arias, "Student interactivity and academic engagement on virtual campuses of higher education institutions", RCTA, vol. 1, n.º. 47, pp. 137-149, Jan. 2026.*
Recovered from https://ojs.unipamplona.edu.co/index.php/rcta/article/view/4130

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.

1. INTRODUCTION

Higher education has undergone an accelerated process of digital transformation over the last decade, which was significantly intensified by the COVID-19 pandemic, consolidating virtual campuses and online learning environments as structural components of contemporary educational systems [1], [2]. In this context, the effectiveness of virtual education does not depend solely on technological availability, but rather on the quality of pedagogical interactions established among educational actors and system resources.

Student interactivity has emerged as a central construct for explaining student performance and retention in virtual learning environments, as it integrates pedagogical, technological, and relational dimensions that mediate the learning experience [3]. Numerous 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 regarding this relationship, recent literature reveals 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 settings characterized by technological gaps, institutional diversity, and heterogeneous virtual education models [5].

Second, many studies address interactivity in a partial manner, focusing the analysis on one or two types of interaction—such as student–content or student–instructor—without integrating a multidimensional model that simultaneously articulates forms of interaction, technological media, interactive content, and the facilitator–participant relationship [6].

From a methodological perspective, it is also observed that numerous studies rely on simple correlational analyses or regression models, which limits the simultaneous evaluation of complex relationships among latent constructs. Although the use of confirmatory factor analysis and structural equation modeling has increased in recent years within educational research, studies applying covariance-based structural equation modeling (CB-SEM) to test comprehensive explanatory models of academic engagement in virtual campuses remain scarce, particularly in higher education institutions located in regional contexts [7].

In response to these limitations, the present study proposes and empirically validates a theoretical explanatory model in which student interactivity is conceptualized as a multidimensional construct composed of four dimensions: forms of interaction, technological media, interactive content, and the facilitator–participant relationship. These dimensions are analyzed as predictors of academic engagement in its behavioral, emotional, and cognitive dimensions. Unlike previous research, this study integrates these dimensions into a single structural model evaluated using CB-SEM, allowing for the simultaneous estimation of the magnitude and significance of the proposed relationships.

The study is conducted with students from five higher education institutions with a physical presence in the department of Norte de Santander, Colombia, thereby contributing contextualized empirical evidence for the region. Accordingly, this article provides theoretical contributions by refining the understanding of student interactivity as an explanatory construct of academic engagement, methodological contributions through the application of advanced psychometric validation techniques and structural modeling, and practical contributions by offering insights for the design of pedagogical and technological strategies aimed at strengthening virtual higher education.

2. STATE OF THE ART - THEORETICAL FRAMEWORK

2.1 Student Interactivity in Virtual Campuses of Higher Education

Student interactivity constitutes one of the conceptual pillars of contemporary virtual education. Since the foundational work 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, instructors, and other students. However, the expansion of virtual campuses and the incorporation of advanced digital technologies have increased the complexity of this construct, calling for more comprehensive and multidimensional approaches.

Recent literature recognizes that interactivity cannot be reduced to the mere frequency of communicative exchanges; rather, it should be analyzed as a structural phenomenon that integrates forms of interaction, 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 the student experience, moving beyond approaches focused exclusively on digital infrastructure.

Nevertheless, a critical review of the literature reveals that many studies continue to address interactivity in a partial manner. For example, some investigations prioritize synchronous, asynchronous, or blended forms of interaction, analyzing their influence on learning outcomes without explicitly integrating the role of technological media or instructional mediation [7].

Other studies focus on the analysis of digital platforms, social networks, or specific technological resources, without considering how these elements are articulated with content design 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 clear need for integrative models that allow student interactivity to be analyzed as a multidimensional and systemic construct.

2.2 Academic Engagement in Virtual Learning Environments

Academic engagement has become one of the most relevant constructs for explaining student performance, retention, and learning experiences 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 learning environments, academic engagement acquires distinctive characteristics, as the absence of physical presence increases reliance on pedagogical and technological interaction mechanisms. Recent studies have shown that perceived instructional support, content clarity, and the quality of interactions significantly influence student engagement levels in virtual modalities [5]. However, a large proportion of empirical research addresses academic engagement as an isolated dependent variable, without integrating explanatory models that simultaneously consider multiple dimensions of student interactivity.

Moreover, from a methodological perspective, there remains a tendency to rely on simple correlational analyses or regression models, which are limited in their ability to capture complex relationships among latent constructs [14], [15].

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

2.3 Structural Models, Methodological Approaches, and Research Gaps

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

Nevertheless, a critical review of the literature reveals that studies integrating multiple dimensions of student interactivity as predictors of academic engagement within a single structural model remain limited. In addition, recurrent methodological weaknesses are identified, such as the absence of convergent and discriminant validity analyses, the limited reporting of advanced psychometric indices, and the omission of common method bias assessments in self-report–based research [17], [19].

These limitations undermine the robustness of reported findings and reinforce the need for studies that incorporate rigorous psychometric procedures as well as advanced structural modeling techniques. In this regard, the present study differs from previous research by proposing and empirically validating a structural model that integrates four dimensions of student interactivity—forms of interaction, technological media, interactive content, and the 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.

3 METHODOLOGY

3.1 Research Design

The proposed hypothetical conceptual model describes the relationship between the components of student interactivity and academic engagement. As shown in Fig. 1, the components of interactivity exhibit an explanatory relationship with academic engagement. This study examined these relationships empirically.

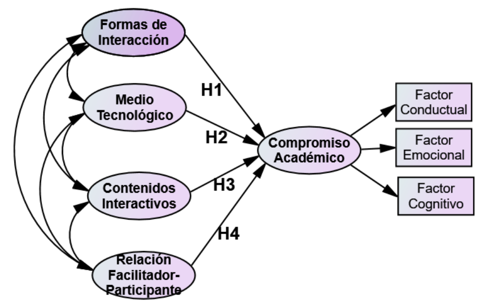

Fig. 1. *Hypothetical conceptual model*
Source: Own elaboration

The study was conducted under a quantitative approach, using a non-experimental, cross-sectional design with 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 presents the research hypotheses formulated in the study.

Table 1: *Research hypotheses*

H1	H1: Forms of interaction have a positive impact on academic engagement
H2	Technological media have a positive impact on academic engagement
H3	Interactive content has a positive impact on 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 that is appropriate when the analysis is grounded in prior theory and seeks to simultaneously evaluate the quality of the measurement model and the structural relationships among latent constructs [15], [29].

3.2 Population and Sample

The study population consisted of students enrolled in academic programs that use virtual campuses either as a support tool or as the primary mode of instruction, belonging to five higher education institutions with a physical presence in the department of Norte de Santander, Colombia.

A non-probabilistic purposive sampling strategy was employed, 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 an initial target of 285 participants.

A total of 285 questionnaire responses were collected through both online and face-to-face administration. However, during the data screening process, incomplete responses, invariant response patterns, and cases with missing values that could compromise multivariate analyses were identified.

As exclusion criteria, questionnaires were removed if they presented more than 10% unanswered items, constant response patterns, or evident inconsistencies in option selection.

After this data cleaning process, the final sample consisted of 266 valid cases, a size considered adequate for the application of CB-SEM. Several authors indicate that sample sizes exceeding 250 observations help minimize sampling error and yield stable parameter estimates in structural equation models [14], [15].

3.3 Data Collection Instrument

Data were collected using a structured self-report questionnaire composed of items measured on 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, and 4 = the statement is met. The instrument consisted of two main scales:

3.3.1 Student Interactivity Components Scale

This scale comprised four dimensions: forms of interaction, technological media, interactive content, and the facilitator–participant relationship.

Each dimension was composed of items clearly formulated and theoretically grounded in the specialized literature. The items were administered exactly as reported in the present study.

3.3.2 Academic Engagement Scale

This scale consisted of three dimensions: behavioral engagement, emotional engagement, and cognitive engagement. Both scales were subjected to rigorous psychometric validation processes through exploratory and confirmatory factor analyses.

3.4 Procedure and Ethical Considerations

The questionnaire was administered primarily online, ensuring voluntary and anonymous participation. However, during visits to several higher education institutions, part of the data was collected through face-to-face administration with groups of students. Prior to completing the instrument, participants were informed about the objectives of the study and provided informed consent, in accordance with ethical principles governing social science research.

The study did not involve physical or psychological risks for participants and adhered to ethical guidelines for research involving human subjects established by international academic bodies [16].

3.5 Data Analysis

Statistical analyses were conducted in two stages using RStudio software version 2020 [11], supported by the R statistical programming language [32]. The following packages were employed: *psych* for exploratory factor analysis, *GPArotation* for factor rotation, and *lavaan* for confirmatory factor analysis and structural equation modeling [31].

3.5.1 Exploratory Factor Analysis (EFA)

Given the ordinal nature of the items, analyses were conducted using polychoric correlation matrices. Data suitability was assessed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity. Factors were extracted using the minimum residuals method, the number of factors was determined through parallel analysis, and oblimin rotation was applied. Factor loadings ≥ 0.40 were considered as the criterion for item retention [21], [22].

3.5.2 Confirmatory Factor Analysis (CFA)

CFA was conducted using the Weighted Least Squares Mean and Variance Adjusted (WLSMV) estimator, selected for its robustness to violations of multivariate normality assumptions and its suitability for Likert-type scales [24], [25].

Model fit was evaluated using the following indices: 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 acceptable model fit [27], [29].

3.6 Evaluation of the Measurement Model:

3.6.1 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 between 0.728 and 0.907, indicating acceptable internal consistency.

AVE values were ≥ 0.50 for most constructs; however, the Cognitive Engagement construct exhibited an AVE value of 0.406. Therefore, its estimates should be interpreted with caution, and further refinement of this construct is recommended in future applications of the instrument (see Table 2).

Table 2: *Composite Reliability (CR) and Convergent Validity (AVE)*

Construct	k	CR	AVE
Forms of interaction	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: *Authors owns elaboration*

Discriminant validity was examined using the Heterotrait–Monotrait Ratio (HTMT) criterion. Overall, most pairwise comparisons fell within acceptable thresholds; however, elevated values were observed between Technological Media and Interactive Content (HTMT = 0.958), as well as between Interactive Content and the Facilitator–Participant Relationship (HTMT = 0.928), indicating empirical proximity between these constructs.

Accordingly, the results are interpreted by acknowledging this conceptual overlap, which can be attributed to the interdependence among technological resources, content design, and pedagogical mediation in virtual learning environments (see Tables 3 and 4).

Table 3: *Discriminant Validity (HTMT) — Student Interactivity Components*

	Forms of interaction	Technological media	Interactive content	Facilitator – participant relationship
Forms of interaction	—	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: *Authors owns 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: *Authors owns elaboration*

3.7 Assessment of Common Method Bias

Given that the data were collected using self-report measures, procedures were implemented to assess potential common method bias. First, Harman's single-factor test indicated that the first factor accounted for 32.0% of the total variance, which is below the 50% threshold.

Second, a comparison between a single-factor model and the multifactor measurement model revealed a substantially poorer fit for the single-factor model (CFI = 0.643; TLI = 0.609; RMSEA = 0.137) compared to the multifactor model (CFI = 0.966; TLI = 0.959; RMSEA = 0.044).

Taken together, these results suggest that common method bias does not represent a dominant threat to the interpretation of the study findings (see Table 5).

Table 5: *Common Method Bias Tests (Self-Report Data)*

Test	Outcome	Value	Criterion
Harman's test (PCA, first factor)	Variance explained by first factor	32	< 50% (suggests low bias)
CFA – seven-factor model (measurement model)	CFI / TLI / RMSEA	0.966 / 0.959 / 0.044	Good relative fit
CFA – one-factor model (common method model)	CFI / TLI / RMSEA	0.643 / 0.609 / 0.137	Poor fit expected if no dominant CMV
HTMT bootstrap 95% (Technological media–Interactive content)	IC 95% (2.5%–97.5%)	0.910–1.002	Upper bound < 1 (discriminant evidence)
HTMT bootstrap 95% (Interactive content–Facilitator–participant relationship)	IC 95% (2.5%–97.5%)	0.880–0.969	Upper bound < 1 (discriminant evidence)

Source: *Authors owns elaboration*

3.8 Structural Equation Modeling (CB-SEM)

Finally, the proposed structural model was estimated using covariance-based structural equation modeling (CB-SEM), employing the same WLSMV estimator. The overall model fit and the statistical significance of the structural relationships specified in the research hypotheses (see Table 1) were evaluated, reporting standardized coefficients, standard errors, and *z*-values.

4 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) evaluation of the structural model using CB-SEM. All analyses were conducted based on the final sample of 266 participants.

4.1 Exploratory Factor Analysis (EFA)

4.1.1 Student Interactivity Components Scale

The EFA was conducted using a polychoric correlation matrix. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.751, and Bartlett's test of sphericity was significant, $\chi^2(666) = 11{,}200.01$; $p < 0.001$, indicating 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 (Forms of Interaction) 24%; Factor 2 (Technological Media) 18%; Factor 3 (Interactive Content) 15%; and Factor 4 (Facilitator–Participant Relationship) 11%.

Item factor loadings exceeded the 0.40 threshold, and communalities (h^2) were within moderate ranges (0.40–0.80), indicating an adequate representation of the items by the underlying factors (see Table 6).

Table 6: *EFA Results for the Student Interactivity Components Scale*

Scale items	F1	F2	F3	F4
Forms of Interaction 01	0,641			
Forms of Interaction 02	0,655			
Forms of Interaction 03	0,738			
Forms of Interaction 04	0,646			
Forms of Interaction 05	0,674			
Forms of Interaction 06	0,688			
Forms of Interaction 07	0,733			
Forms of Interaction 08	0,844			
Forms of Interaction 09	0,815			
Forms of Interaction 10	0,831			
Technological Media 01		0,697		
Technological Media 02		0,762		
Technological Media 03		0,618		
Technological Media 04		0,616		
Technological Media 05		0,723		
Technological Media 06		0,662		
Technological Media 07		0,697		
Technological Media 08		0,724		
Technological Media 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 factor loadings greater than 0.40.*
Source: *Own elaboration.*

4.1.2 Academic Engagement Scale

For the Academic Engagement scale, the EFA yielded a KMO value of 0.811 and a significant Bartlett's test of sphericity, $\chi^2(662) = 1{,}422.15$; $p < 0.001$, confirming the suitability of the data for factor analysis.

Parallel analysis indicated the presence of three factors, which together explained 59% of the total variance: Behavioral Factor (22%), Emotional Factor (20%), and Cognitive Factor (17%).

Factor loadings exceeded the 0.40 threshold, and communalities were 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
Behavioral 1	0,764		
Behavioral 2	0,770		
Behavioral 3	0,805		
Behavioral 4	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*

4.2 Confirmatory Factor Analysis (CFA)

4.2.1 Measurement Model: Student Interactivity Components

The CFA was estimated using the WLSMV method, based on polychoric correlation matrices. The model included four correlated latent factors.
Global model fit indices were as follows: $\chi^2(48) = 1{,}655.33$; $p < 0.001$; CFI = 0.960; TLI = 0.945; RMSEA = 0.070; and SRMR = 0.041.

These values meet the criteria recommended in the literature to indicate an adequate fit of the measurement model.

Standardized factor loadings ranged from 0.671 to 0.848, all of which were statistically significant ($z > 1.96$; $p < 0.001$), demonstrating adequate local item relevance. Inter-factor correlations ranged between 0.20 and 0.50, indicating conceptually coherent relationships without evidence of excessive multicollinearity (see Table 8).

Table 8: *Measurement Model (CFA) for the Student Interactivity Components Scale*

Dimensions	Standardized loadings	t-value	*p*
F1= Forms of Interaction ($\omega = 0{,}785$)			
Synchronous	0,828	14,34	< 0,001
Asynchronous	0,688	14,36	< 0,001
Blended	0,671	12,13	< 0,001
F2= Technological Media ($\omega = 0{,}787$)			
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 ($\omega = 0{,}809$)			
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 ($\omega = 0{,}823$)			
Communication	0,731	45,41	< 0,001
Motivation	0,778	44,93	< 0,001
Feedback	0,848	42,20	< 0,001

Note: ω denotes McDonald's omega. All standardized loadings are significant at $p < 0.001$.
Source: *Own elaboration.*

4.2.2 Measurement Model: Academic Engagement

The CFA for the Academic Engagement scale yielded the following fit indices: $\chi^2(51) = 2{,}226.70$; $p < 0.001$; CFI = 0.991; TLI = 0.954; RMSEA = 0.054; and SRMR = 0.040.

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

Table 9: *Measurement Model (CFA) for the Academic Engagement Scale*

Dimensions	Standardized loadings	t-value	*p*
F1= Behavioral Factor ($\omega = 0{,}812$)			
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 ($\omega = 0{,}802$)			
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 ($\omega = 0{,}793$)			
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*

4.3 Evaluation of the Measurement Model: Reliability, Convergent Validity, Discriminant Validity, and Common Method Bias

Composite reliability (CR) and convergent validity (AVE) were estimated for each construct in the measurement model. With the exception of the Cognitive Engagement construct, which exhibited a lower AVE value and therefore requires further refinement, the results indicated adequate reliability and convergent validity across constructs. Detailed results are presented in Table 2.

Discriminant validity was assessed using the Heterotrait–Monotrait Ratio (HTMT). Results for the Student Interactivity Components are reported in Tables 3 and 4. Most HTMT values were within acceptable ranges; however, empirical proximity was observed between Technological Media and Interactive Content, as well as between Interactive Content and the Facilitator–Participant Relationship.

To assess potential common method bias, multiple tests were conducted. First, Harman's single-factor test showed that the first factor accounted for a proportion of the total variance below the 50% threshold. Second, a comparison between a single-factor model and the multifactor measurement model indicated substantially poorer fit for the single-factor model. These tests are reported in Table 5.

4.4 Evaluation of the Structural Model (CB-SEM)

The structural model was estimated using covariance-based structural equation modeling (CB-SEM) with the WLSMV estimator. Global model fit indices were as follows: $\chi^2(105) = 2{,}140.76$; $p < 0.001$; CFI = 0.960; TLI = 0.948; RMSEA = 0.070; and SRMR = 0.040.

These results indicate an adequate overall fit of the proposed theoretical model to the analyzed data (see Fig. 2).

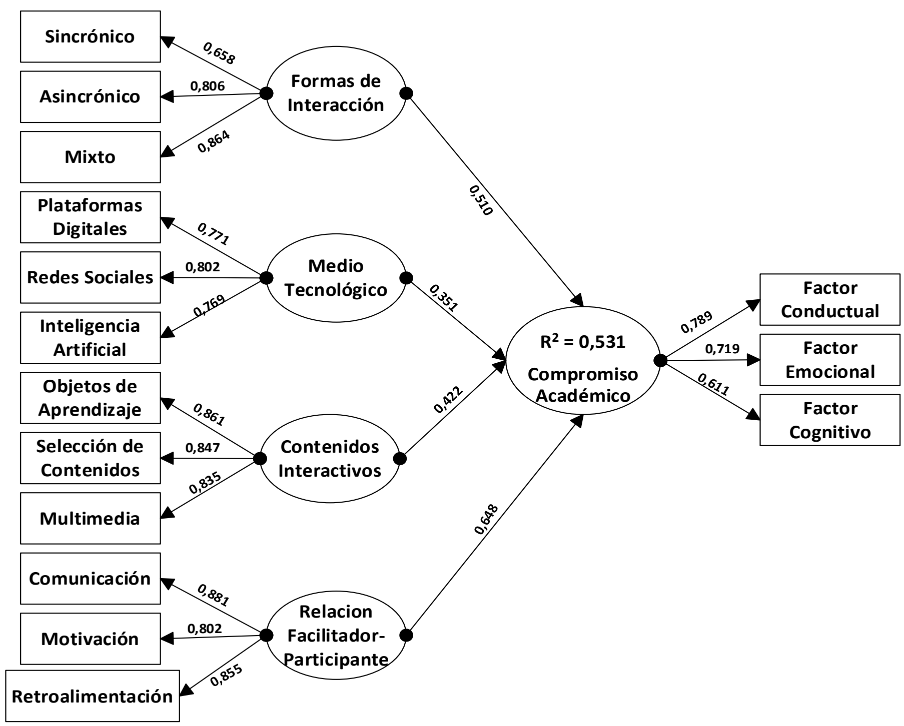

Fig. 2. *Estimated Conceptual Model.* ***Source:*** *Own elaboration*

The structural relationships indicated that:

Forms of interaction had a positive and significant effect on academic engagement ($\beta > 0.20$; $p < 0.001$). Technological media exhibited a positive and statistically significant effect ($\beta > 0.15$; $p < 0.01$). Interactive content exerted a positive influence on academic engagement ($\beta > 0.18$; $p < 0.01$). The facilitator–participant relationship showed the largest standardized effect on academic engagement (β > 0.30; $p < 0.001$).

Overall, the model explained 53.1% of the variance in academic engagement, representing a moderate-to-high explanatory power in educational research contexts.

4.5 Synthesis of Results

The findings empirically confirm the multidimensional structure of both student interactivity and academic engagement, as well as the adequacy of the proposed structural model.
The facilitator–participant relationship emerged as the most relevant predictor, reinforcing the importance of the human and pedagogical component even in highly technologized virtual learning environments (see Fig. 2).

5. 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 through a covariance-based structural equation model. The findings allow for a theoretical and methodological discussion regarding the adequacy of the proposed model and its contribution to the field of virtual higher education.

First, the results confirm that student interactivity constitutes a multidimensional construct composed of forms of interaction, technological media, interactive content, and the facilitator–participant relationship. This empirical evidence is consistent with the theoretical propositions of Bernard et al. [3] and Anderson [10], who emphasize that the effectiveness of learning in virtual environments depends on a balanced articulation of pedagogical, technological, and relational components.

Unlike previous studies that examine these dimensions in isolation, the present research demonstrates that their joint assessment enables a more comprehensive understanding of the phenomenon.

With respect to academic engagement, the results support its three-dimensional structure—behavioral, emotional, and cognitive—consistent with the model proposed by Kahu and Nelson [4]. The confirmation of this structure within 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 perspective, the CB-SEM results indicate that all dimensions of student interactivity exhibit positive and statistically significant associations with academic engagement, jointly explaining 53.1% of its variance. This level of explanatory power is comparable to that reported in international studies examining complex psychoeducational variables through structural models [15], [30], suggesting that the proposed model has substantial explanatory capacity within the analyzed context.

A particularly relevant finding is that the facilitator–participant relationship emerges as the strongest standardized predictor of academic engagement. This result aligns with recent research highlighting the importance of instructional 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 educational settings, the human component remains a central axis of the learning process, challenging approaches that prioritize technology as the sole driver of learning.

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

Technological media, in turn, exhibited a positive but relatively smaller effect. This result may be interpreted as indicating that technology, while a necessary facilitator of virtual learning, is not by itself a sufficient factor to ensure high levels of academic engagement. This interpretation is consistent with critical perspectives in the literature that caution against technocentric approaches in higher education [6].

From a methodological standpoint, the use of confirmatory factor analysis and CB-SEM made it possible to overcome common limitations of prior studies based on simple correlational analyses. The incorporation of evidence of convergent and discriminant validity, as well as the control of common method bias, strengthens the robustness of the findings and increases confidence in the inferences drawn.

Nevertheless, the findings should be interpreted in light of certain methodological limitations. First, the use of non-probabilistic sampling limits the generalizability of the results to other student populations. Second, the cross-sectional design precludes establishing causal relationships among the analyzed variables; therefore, the observed associations should be understood as explanatory rather than causal. Finally, although common method bias was assessed and controlled, the use of self-report instruments may involve perceptual biases inherent to this type of measurement.

These limitations suggest the need to address the study of interactivity and academic engagement through longitudinal or experimental designs, as well as the inclusion of probabilistic samples and mixed-method approaches integrating quantitative and qualitative perspectives. In this way, future research could further examine the temporal dynamics of these relationships and explore additional contextual variables that may moderate or mediate the observed effects.

6. LIMITATIONS

Empirical overlap (HTMT) was observed between some conceptually related constructs, particularly between Technological Media and Interactive Content. This finding suggests the need to refine measurement items or explore alternative factor structures in future studies.

7. CONCLUSIONS

The purpose of this study was to analyze the relationship between student interactivity and academic engagement in virtual campuses of higher education institutions located in the department of Norte de Santander, Colombia, using a covariance-based structural equation model. Based on the results obtained, a set of empirically grounded conclusions can be drawn, consistent with the methodological scope of the research design.

First, the findings indicate that student interactivity can be understood as a multidimensional construct composed of forms of interaction, technological media, interactive content, and the facilitator–participant relationship. The psychometric validation of these dimensions through exploratory and confirmatory factor analyses supports their theoretical relevance and empirical consistency within the context of virtual higher education.

Second, the study confirms that academic engagement exhibits a three-dimensional structure comprising behavioral, emotional, and cognitive components, in line with widely accepted theoretical models in the literature. The confirmation of this structure among students using 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 emerges as the dimension with the greatest explanatory weight, highlighting the importance of instructional presence, pedagogical communication, and timely feedback in virtual learning environments.
Likewise, forms of interaction, interactive content, and technological media demonstrate significant associations with academic engagement, suggesting 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 the learning process. Nevertheless, these findings should be interpreted in terms of associative relationships, without attributing direct causality between the analyzed variables.

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 analyzed constructs and the coherence of the proposed theoretical model. This approach helps to overcome methodological limitations identified in previous research and expands the application of advanced analytical techniques in the field of virtual education research.

Regarding practical implications, the results suggest that higher education institutions may orient their pedagogical and technological strategies toward strengthening student interactivity, particularly with respect 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 guidance based on observed empirical associations rather than as causal prescriptions.

Finally, the study presents limitations that open avenues for future research, including the use of non-probabilistic sampling, the cross-sectional design, and reliance on self-report instruments. Accordingly, future studies are encouraged to incorporate longitudinal or experimental designs, probabilistic samples, and mixed-method approaches to further examine the temporal and causal dynamics of the relationship between student interactivity and academic engagement, as well as to explore the role of additional contextual variables across diverse educational settings.

ETHICS STATEMENT

This research was conducted in accordance with the ethical principles governing research in the social and educational sciences. Data were collected through a self-report questionnaire administered both online and in person, ensuring voluntary, anonymous, and confidential participation.

Prior to completing the instrument, participants were informed about the objectives of the study, its academic nature, and the exclusive scientific use of the information provided. All participants gave their informed consent, freely and voluntarily agreeing to participate in the study.

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

REFERENCES

[1] A. Bozkurt *et al.*, “A global outlook to the interruption of education due to COVID-19 pandemic: Navigating in a time of uncertainty and crisis,” *Asian Journal of Distance Education*, vol. 15, no. 1, pp. 1–126, 2020.

[2] M. Area-Moreira, A. San Nicolás-Santos y F. J. García-Peñalvo, “Modelos de blended learning en educación superior,” *Pixel-Bit. Revista de Medios y Educación*, no. 64, pp. 7–46, 2022.

[3] R. M. Bernard, P. C. Abrami, E. Borokhovski, C. A. Wade, R. M. Tamim, M. A. Surkes y E. C. Bethel, “A meta-analysis of three types of interaction treatments in distance education,” *Review of Educational Research*, vol. 79, no. 3, pp. 1243–1289, 2009.

[4] E. R. Kahu y K. Nelson, “Student engagement in the educational interface: Understanding the mechanisms of student success,” *Higher Education Research & Development*, vol. 37, no. 1, pp. 58–71, 2018.

[5] J. Cabero-Almenara, J. Barroso-Osuna y A. Palacios-Rodríguez, *Literacy and Digital Inclusion in Higher Education*, Cham, Switzerland: Springer, 2024.

[6] F. J. García-Peñalvo, “Transformación digital en las universidades: Implicaciones educativas,” *Education in the Knowledge Society*, vol. 22, pp. 1–10, 2021.

[7] D. R. Garrison, T. Anderson y W. Archer, “The first decade of the Community of Inquiry framework: A retrospective,” *The Internet and Higher Education*, vol. 13, no. 1–2, pp. 5–9, 2010.

[8] G. J. Hwang, C. L. Lai y S. Y. Wang, “Seamless flipped learning: A mobile technology-enhanced flipped classroom with effective learning strategies,” *Journal of Computers in Education*, vol. 2, no. 4, pp. 449–473, 2015.

[9] P. M. Moreno-Marcos, C. Alario-Hoyos, I. Estévez-Ayres y C. Delgado-Kloos, “Comparing different approaches for learning analytics interventions in MOOCs,” *IEEE Transactions on Learning Technologies*, vol. 12, no. 3, pp. 384–401, 2019.

[10] T. Anderson, *The Theory and Practice of Online Learning*, 3rd ed. Edmonton, Canada: AU Press, 2019.

[11] RStudio Team, *RStudio: Integrated Development Environment for R*, Boston, MA, USA, 2020.

[12] R Core Team, *R: A Language and Environment for Statistical Computing*, Vienna, Austria: R Foundation for Statistical Computing, 2023.

[13] W. G. Cochran, *Sampling Techniques*, 3rd ed. New York, NY, USA: Wiley, 1977.

[14] J. C. Anderson y D. W. Gerbing, “Structural equation modeling in practice: A review and recommended two-step approach,” *Psychological Bulletin*, vol. 103, no. 3, pp. 411–423, 1988.

[15] R. B. Kline, *Principles and Practice of Structural Equation Modeling*, 5th ed. New York, NY, USA: Guilford Press, 2023.

[16] American Educational Research Association (AERA), American Psychological Association (APA) y National Council on Measurement in Education (NCME), *Standards for*

Educational and Psychological Testing, Washington, DC, USA, 2018.

[17] P. J. Ferrando y U. Lorenzo-Seva, "Assessing the quality and appropriateness of factor solutions and factor score estimates in exploratory item factor analysis," *Psicothema*, vol. 34, no. 1, pp. 1–10, 2022.

[18] U. Lorenzo-Seva, "Promin: A method for oblique factor rotation," *Behavior Research Methods*, vol. 54, no. 6, pp. 2999–3011, 2022.

[19] S. Lloret-Segura, A. Ferreres-Traver, A. Hernández-Baeza y I. Tomás-Marco, "El análisis factorial exploratorio de los ítems: Una guía práctica," *Anales de Psicología*, vol. 33, no. 2, pp. 417–432, 2017.

[20] I. Izquierdo, E. Olea y A. Abad, "Exploratory factor analysis in validation studies: Uses and recommendations," *Psicothema*, vol. 26, no. 3, pp. 395–400, 2014.

[21] R. E. Schumacker y R. G. Lomax, *A Beginner's Guide to Structural Equation Modeling*, 4th ed. New York, NY, USA: Routledge, 2016.

[22] P. Lei y Q. Wu, "Introduction to structural equation modeling: Issues and practical considerations," en *Handbook of Structural Equation Modeling*, R. H. Hoyle, Ed. New York, NY, USA: Guilford Press, 2012, pp. 92–109.

[23] T. A. Brown, *Confirmatory Factor Analysis for Applied Research*, 2nd ed. New York, NY, USA: Guilford Press, 2015.

[24] P. M. Bentler, "Comparative fit indexes in structural models," *Psychological Bulletin*, vol. 107, no. 2, pp. 238–246, 1990.

[25] L. Hu y P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives," *Structural Equation Modeling*, vol. 6, no. 1, pp. 1–55, 1999.

[26] R. C. MacCallum, M. W. Browne y H. M. Sugawara, "Power analysis and determination of sample size for covariance structure modeling," *Psychological Methods*, vol. 1, no. 2, pp. 130–149, 1996.

[27] R. McDonald, *Test Theory: A Unified Treatment*, Mahwah, NJ, USA: Erlbaum, 1999.

[28] J. F. Hair, G. T. M. Hult, C. M. Ringle y M. Sarstedt, "A primer on partial least squares structural equation modeling (PLS-SEM)," *Journal of Advertising*, vol. 46, no. 1, pp. 184–185, 2017.

[29] Y. Rosseel, "lavaan: An R package for structural equation modeling," *Journal of Statistical Software*, vol. 48, no. 2, pp. 1–36, 2012.

[30] A. A. Beaujean, *Latent Variable Modeling Using R: A Step-by-Step Guide*, New York, NY, USA: Routledge, 2014.

[31] M. Revelle, *psych: Procedures for Psychological, Psychometric, and Personality Research*, Evanston, IL, USA: Northwestern University, 2023.

[32] U. Lorenzo-Seva y P. J. Ferrando, *FACTOR: A Computer Program to Fit the Exploratory Factor Analysis Model*, Tarragona, Spain, 2022.