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Research Article

Factorial validation of the university students' attitudes toward blended learning scale: An exploratory and confirmatory analysis

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The importance of understanding student attitudes has become paramount in the successful deployment of blended learning. This study aimed to examine the factorial structure of a scale designed to assess university students' attitudes towards blended learning. Using a descriptive quantitative research approach, the study included a sample of 889 male and female students from the University of Tabuk, located in the Kingdom of Saudi Arabia. The participants were selected randomly from different academic majors and levels of study. The instrument employed in this study was the *Blended Learning Attitudes Scale*, a tool designed by the researcher and subjected to rigorous validation procedures. The researcher utilised exploratory and confirmatory factor analyses to understand the latent variables the scale represented comprehensively. The study's findings indicated the presence of a three-factor model, encompassing participants' perceptions of the nature of blended learning, its perceived importance, and their willingness to utilise it. The combined influence of these three factors accounted for 64% of the observed variance. The scale had noteworthy psychometric features, as evidenced by its high-reliability coefficients and robust validity indicators. This study presents a reliable instrument that educators and researchers may utilise to assess university students' attitudes towards blended learning.

Keywords: Attitudes scale; Blended learning; Confirmatory factor analysis; Exploratory factor analysis; Higher education; Learning preferences; Online education

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1. Introduction

The global outbreak of coronavirus disease (COVID-19) has had a substantial effect on the landscape of higher education, accelerating the implementation and enhancement of blended learning approaches (Al-khresheh, 2022 & 2023; Mali & Lim, 2021; Megahed & Hassan, 2022; Mudjijanti & Srimulyani, 2023). This pedagogical technique, which combines traditional in-person instruction with online methods, has proven to be an essential strategy for confronting the challenges posed by the pandemic (Kumar et al., 2021). In response to health restrictions and the need for social segregation, educational institutions have adopted the blended learning model as a viable alternative. Digital courses provide students with a secure and adaptable learning environment while preserving the essential element of interactive classroom discussions. This

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strategy effectively addresses the changing educational needs in pre-pandemic and current contexts (Bruggeman et al., 2021; Halverson & Graham, 2019).

However, a significant barrier is a lack of explicitly defined tools for interpreting students' attitudes towards blended learning. These attitudes affect their academic engagement, trajectory of achievement, and general satisfaction with the educational framework. Educators, curriculum developers, and academic policymakers must recognise and comprehend these perspectives. Understanding students' perspectives on blended learning can stimulate increased motivation and enhanced academic performance. On the other hand, ignoring negative emotions may result in the development of opposition, a decrease in engagement, and a reduction in the overall effectiveness of instruction.

This study's primary objective is to close this knowledge deficit, which is reflected in the study's design. Through developing and validating a comprehensive scale that effectively captures the multifaceted attitudes of university students towards blended learning, this research endeavour seeks to provide an invaluable instrument to the academic community worldwide. This device can modify educational strategies, improve pedagogical decisions, and facilitate a seamless and effective transition to blended learning environments. In light of this context, the investigation aims to address the following research questions:

RQ 1) What model explains the factorial structure of the scale of university students' attitudes towards blended learning?

RQ 2) What are the quality fit indices for the model that explains the factorial structure of the scale of university students' attitudes towards blended learning?

RQ 3) Does the scale of university students' attitudes towards blended learning and the explanatory model possess good psychometric properties?

Through these questions, the research intends to clarify and validate the proposed scale, thereby improving blended learning experiences in higher education institutions.

2. Literature Review

2.1. Blended Learning in Higher Education

Blended learning, as characterised by Alshahrani (2023) and other scholars, is the deliberate combination of traditional in-person instruction with online educational methods. This strategy has acquired ground in higher education over time. As a pedagogical approach, blended learning combines the synchronous interactions in traditional classroom contexts with the asynchronous flexibility provided by online modules. This integration produces a novel educational model designed to meet the requirements of the digital age (Luo et al., 2022; Marinagi & Skourlas, 2013).

Historically, traditional face-to-face instructional methods have comprised the majority of higher education. Due to their emphasis on providing a comprehensive campus environment, historically successful educational institutions such as Oxford and Harvard have flourished (Rivera, 2019). In this environment, lecture halls serve as vibrant forums for intellectual exchange, whereas libraries serve as havens for those desiring knowledge (Hrastinski, 2019; Lim & Graham, 2021). Nonetheless, the beginning of the 21st century, marked by significant technological advancements and the pervasive internet adoption, ushered in a period of transformation in academia. Massive Open Online Courses [MOOCs] have been introduced by innovative online learning platforms such as Coursera and edX, facilitating the democratisation of education and increasing its accessibility to a global audience. Blended learning has emerged as a prominent educational approach that combines the physical aspects of traditional classrooms with the extensive capabilities of digital platforms (Cheung & Wang, 2019; Masitoh & Sufirmansyah, 2022).

In the context of higher education, integrated learning offers a multitude of benefits. According to a study by Means et al. (2013), blended learning environments produce more successful students than face-to-face or online-only classes. The inherent flexibility of the model accommodates various learning preferences, allowing students to navigate learning resources independently. This element has been shown to improve both student engagement and comprehension. The 'BlendKit' initiative at the University of Central Florida is a successful example of blended learning implementation. This initiative has increased retention rates and student satisfaction in integrated course offerings.

However, the process of implementing integrated learning is not devoid of obstacles. The presence of technological disparities, particularly in areas characterised by low internet connectivity, can hinder the attainment of equitable access (AL-Qadri et al., 2021; Şentürk, 2021). In addition, Poon (2013) conducted a study highlighting instructors' concerns about the labour-intensive nature of developing blended courses. The efficacy of blended learning is closely tied to the perspectives of students. Some factors, including technological preparedness, the perceived utility of online components, and the efficacy of in-person interactions, influence individual attitudes. These factors were investigated by López-Pérez et al. (2011), who discovered that they significantly impact the formation of these attitudes. In order to enhance and maximise blended learning models in higher education institutions, it is essential to comprehend students' perspectives in depth.

2.2. Assessing Students' Attitudes towards Blended Learning

In education, attitudes are frequently both the protagonist and the narrator. The characters have a substantial impact on the plot, the narrative, and the outcomes. With the increasing prevalence of blended learning in higher education, it becomes crucial to decipher the intricate narrative surrounding student perspectives. Numerous studies have cast light on diverse facets of the complex environment surrounding student attitudes and readiness for blended learning.

It has been suggested by Dziuban et al. (2018) that students' attitudes are reliable predictors of their intent to enrol in blended courses. According to their argument, these viewpoints are affected by various factors. For instance, a student's technological background, perception of the efficacy of online classes, and level of comfort with face-to-face interactions may all contribute to a complex array of attitudes. Despite the significance of these attitudes, however, the available instruments for measuring them have occasionally lacked sophistication and profundity. As exemplified by Walker and Fraser's (2005) Online Learning Environment Survey [OLES], initial efforts demonstrated significant progress in evaluating students' perspectives. However, these tools were frequently restricted to the initial phases of online education and did not cover the entire spectrum of blended learning. The difficulty was multifaceted. Blended learning is characterised by its inherent dynamic nature. The characteristics of blended learning have evolved and been refined in tandem with technological and pedagogical advances (Bouilheres et al., 2020; Şentürk, 2021). Instruments such as the Blended Learning Student Satisfaction (BLSS) scale, developed by Padilla Rodriguez and Armellini (2017), capture the dynamics of blended learning. The scope of their study extended beyond technological convenience to include topics such as the perceived importance of course material and the effectiveness of instructor feedback in a blended learning environment.

Despite the development of these technologies, new obstacles have emerged. The heterogeneous student population in higher education, characterised by varying levels of technological proficiency, distinct learning preferences, and diverse cultural contexts, necessitated the acknowledgement that a uniform approach was frequently insufficient. Henrie et al. (2015) conducted a study that highlighted the effect of students' cultural backgrounds on their perceptions and preferences regarding blended learning.

Researchers and educators have also utilised qualitative methods to pursue a comprehensive instrument. As McGee and Reis (2012) examined, using focus groups, interviews, and open-ended surveys has provided a valuable and comprehensive understanding of student perspectives. The combination of qualitative insights and quantitative metrics has the potential to produce a more comprehensive understanding.

As we investigate the complex landscape of integrated learning, developing an effective instrument for assessing student attitudes represents both a significant challenge and a promising opportunity. The process entails the pursuit of continuous development and has the potential to redefine the fundamental structure of blended learning in higher education.

2.3. Studies on Blended Learning

In the dynamic domain of blended learning, it is crucial to prioritise the students' attitudes and readiness. This necessitates using trustworthy and exhaustive measurement instruments to evaluate these subjective judgements accurately. As a result, researchers have been tasked with developing and validating various metrics specifically tailored to different contexts. Contemporary scholarly research reveals a complex network of endeavours, each contributing uniquely to this academic endeavour while highlighting neglected areas.

In their study, Lazar et al. (2020) expanded the Technology Acceptance Model [TAM] scope to better understand the factors influencing students' intentions to use digital tools in the context of blended learning in higher education. The distinctive aspect of their strategy was incorporating an external bidimensional element, focusing on digital tool proficiency. The researchers used a rigorous four-step methodology to construct a comprehensive scale, resulting in a questionnaire with seven dimensions and 25 items. By administering this instrument to multiple student samples, the researchers validated the scale and highlighted its reliability across various academic achievement levels.

Shakeel et al. (2023) narrowed the scope of their study by focusing on the context of Technical and Vocational Education and Training in Bangladesh. The study aimed to develop and validate a scale for assessing suitability for blended learning in collaboration with educators and librarians. The researchers' findings revealed complex interrelationships, as evidenced by the positive correlation between students' preparedness for blended learning and their attitudes towards online learning. This study emphasises the significance of contextual factors, such as cultural and educational frameworks, in influencing the perspectives of individuals on blended learning. In their study, Bedebayeva et al. (2022) focused on computer education in Kazakhstan's secondary schools, particularly evaluating teachers' skills. Their study revealed many disparities, including gender differences, in educators' abilities in blended learning environments. These findings shed light on the multitude of variables that influence the efficacy of educators in these settings. Bhagat et al. (2023) created a measurement instrument to evaluate students' experiences in mixed-learning environments. This study's instrument underwent comprehensive validation procedures, including exploratory and confirmatory factor analyses. These analyses ensured that the instrument accurately captured the nuances of blended learning experiences, such as course design and individual variables. This emphasis on the multifaceted nature of integrated learning experiences exemplifies the holistic approach adopted in this study.

Liu (2022) and Zheng et al. (2022) studied the educational landscape in China in order to obtain a more comprehensive understanding of several situations. Liu examined the adoption of blended learning in elementary science curricula. Zheng et al. (2022) compared integrated learning enabled by social media interactions to conventional face-to-face methods. The distinct perspectives of notable contributors, such as Yusuf et al. (2023), Sergi et al. (2023), and Xiang and Duangekanong (2022), have enriched the literature. These researchers have made significant contributions by examining various facets, such as the construct validity of integrated learning instruments and the measurement of student satisfaction in particular courses.

Several notable studies in integrated and e-learning evaluation in higher education have advanced our understanding of assessment methodologies. Akkoyunlu and Ylmaz-Soylu (2008) created a dependable 50-item scale to capture the perspectives of learners on blended learning. Their analysis revealed two significant components related to the learning process's complexities, highlighting the scale's potential to optimise integrated learning experiences. Matosas-López et al. (2019) simultaneously addressed the urgent need for refined assessment tools in integrated learning environments. Utilising the BARS methodology, they developed a test based on the insights of many students and a faculty council of experts. This instrument focuses on crucial elements of integrated learning, such as teacher-student communication and course design, and is believed to provide educators with actionable feedback. In addition, Ginns and Ellis (2009) developed a scale to evaluate the efficacy of e-learning in campus-centric contexts. In light of the accelerated ICT advancements in higher education, their study compared this e-learning scale to the established Student Course Experience Questionnaire, validating its reliability and validity for evaluating the quality of ICT-enhanced learning. These studies emphasise the evolving landscape of assessment tools tailored to blended and e-learning environments.

While considerable advancement has been made in these studies, a significant gap remains. Even though several individuals have created tools tailored to specific circumstances, no universally adaptable and comprehensive instrument has yet been developed. The necessity is evident: a tool that transcends limitations, encapsulating the fundamental nature of students' perspectives on blended learning across various cultural, institutional, and demographic contexts. As the concept of integrated learning continues to evolve, it is essential that our analytical tools also evolve to comprehend and accommodate not only the current state but also the anticipated future changes.

3. Method

3.1. Research Design

The study utilized a descriptive quantitative research design to analyze university students' attitudes towards blended learning. Through this method, the student attained a comprehensive and structured understanding of the perceptions, preferences, and obstacles associated with blended learning. The quantitative framework facilitated objective data collection and analysis, thereby facilitating the generalization of the results to a larger student population. Without experimental interventions, this design was crucial for capturing the holistic perspective of students' experiences and attitudes at a particular time (Creswell, 2014).

3.2. Participants

Participants were recruited from the University of Tabuk in the Kingdom of Saudi Arabia for the study. Specifically, these participants were Bachelor's students representing a variety of majors and spanning various academic levels, from freshmen to seniors. A representative sample of 889 male and female students was randomly selected for the study. This selection assured a comprehensive representation, allowing for a nuanced understanding of attitudes towards blended learning across various academic contexts and phases of the university journey. In relation to the research sample, the overarching population consists of 8,000 students, both male and female. A stratified random sample, constituting 11% of the main population, was meticulously selected to ensure representativeness. According to Steven Thompson's formula for determining optimal sample size, the baseline requisite for this study stands at 370 participants. Given the study's objective—to formulate a scale and elucidate its psychometric attributes via factor analysis—a relatively expansive sample is imperative. Hence, the decision to adopt this specific sample size. The precision and suitability of the sample for the employed statistical methodologies were rigorously verified through the Kaiser-Mayer-Olkin [KMO] index and Bartlett's Test of Sphericity. These tests affirmed the sample's appropriateness for undertaking exploratory factor analysis, as delineated in the study.

3.3. Instrument

This study employed the *Blended Learning Attitudes Scale* developed by the researcher. This instrument was created after a comprehensive review of the pertinent literature. Using a five-point Likert scale, the thirty-item questionnaire measures the students' perspectives on blended learning. A rating of '1' indicates strong disagreement, while a rating of '5' indicates strong concurrence. A panel of education and psychology experts evaluated the instrument. Their input was indispensable in evaluating the relevance and clarity of each item. After analyzing the consensus, items supported by at least 90% of the panel were kept. Certain items were modified or eliminated based on additional feedback, culminating in a refined 27-item scale. This rigorous procedure strengthened the instrument's apparent credibility. As the study's primary purpose was to decipher the scale's factorial structure through exploratory and confirmatory factor analysis and to delineate its psychometric properties, a thorough validation of the instrument's properties was delegated to the results section.

3.4. Data Collection Procedure

A methodical and stringent data collection procedure was employed to ensure the reliability and consistency of the data gathered for the study. The initial step was obtaining permission from the University of Tabuk to distribute the *Blended Learning Attitudes Scale* to a specified student cohort. Once approved, the electronic format of the survey was sent to participants via the university's sanctioned email platform.

Upon receiving the survey, participants were acquainted with the study's purpose and were reassured about the utter privacy of their inputs. The voluntary nature of their participation was emphasized, as was the option to withdraw without repercussions. To ensure data consistency, step-by-step instructions for survey completion were incorporated. In addition, a dedicated support line was established to resolve participant questions and provide clarifications during the survey administration. After completing the survey, participants were prompted to transmit their responses electronically. A follow-up email was sent to non-responders after one week to increase the response rate. After the designated period for data collection, the received responses were meticulously compiled in preparation for subsequent analysis.

3.5. Data Analysis

An exploratory factor analysis was initiated to unveil the inherent factorial structure of a scale tailored to assess university students' attitudes towards blended learning. The objective was to decipher these perceptions' multifaceted nature and fine-tune the scale for heightened precision. *The Principal Components* method was selected for its prominence and precision as one of the preeminent techniques in factor analysis. This methodology boasts multiple merits: it yields meticulous factor loadings, capitalizes on variance extraction for each individual factor, minimizes residual values, and efficiently distils the correlation matrix to a minimized set of orthogonal, non-interrelated factors (Jollife, 2016; Tabachnick & Fidell, 2013). The method was also leveraged to extract pivotal factors based on their eigenvalues and the variance they encapsulated within the data. The orthogonal rotation technique, Varimax, was employed to refine the factor loadings further. The choice of Varimax rotation stems from its capability to simplify the factor structure by clarifying the item-factor relationships, ensuring that each factor has a distinct cluster of items. There exists a myriad of mathematical techniques, among which Kaiser's Varimax method stands out as particularly eminent. This method is lauded for its capacity to uphold a simple structural framework, all while ensuring factor orthogonality. It is noteworthy that a predominant segment of educational researchers gravitates towards employing Kaiser's Varimax primarily because it consistently delivers solutions that epitomize the essence of a streamlined structural design (Acal et al., 2020). Through this comprehensive process, the primary factors shaping the initial form of the scale were derived, offering a solid foundation for analyzing university students' perspectives on blended learning. This was done in accordance with the Kaiser Criterion, which requires keeping the factor with an eigenvalue greater than 1 (Warne & Larsen, 2014). Byrne (2010) used the Guilford criterion to evaluate the saturation of the item with the factor, determining that an item is saturated with the factor if the magnitude of saturation exceeds .30. In addition, confirmatory factor analysis was employed by using AMOS Software to validate the proposed model structure and derive model fit quality indicators. Furthermore, rigorous validation of the scale's psychometric properties was undertaken. This encompassed the assessment of convergent validity, discriminant validity, composite reliability, and reliability as determined by Cronbach's Alpha methodology. Tables 4 and 5 illustrate the validation process in the next section.

4. Findings

The results of this section are presented based on the study's research questions. The first question states, "What model explains the factorial structure of the scale of university students' attitudes towards blended learning?" Specific steps were followed to answer this question. The first step was using Exploratory Factor Analysis [EFA] to identify the latent factors on which the scale's phrases saturate. The Principal Components Method was employed, identifying factors with Eigenvalues greater than one. An orthogonal rotation using the "varimax rotation method" was performed, showcasing phrases with a saturation rate on the factor exceeding .35 (Byrne, 2010; Suhr, 2006). The factor analysis results were presented as follows: To ensure the suitability of the data for factor analysis, sample accuracy measures were extracted using the Kaiser-Mayer-Olkin (KMO) index, which assesses the sampling adequacy, and Bartlett's Test of Sphericity, which tests the assumption that variables are correlated in the population. The outcomes of these tests are detailed in Table 1.

Table 1
Kaiser–Meyer–Olkin and Bartlett's Sphericity tests

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.956
Bartlett's Test of Sphericity	Approx. Chi-Square	11649.606
	df	351
	Sig.	.000

As delineated in Table (1), the Kaiser-Meyer-Olkin (KMO) measure yielded a value of 0.956, surpassing the established threshold of 0.5, thus affirming the sampling adequacy. Furthermore, the statistical significance of Bartlett's Test of Sphericity, evidenced at a 0.05 significance level, underscores the suitability of the study's sample for an Exploratory Factor Analysis (EFA) execution as referenced by (Byrne, 2010; Suhr, 2006).

4.1. Exploratory Factor Analysis

Having validated the prerequisites for factor analysis, an exploratory factor analysis was executed. The outcomes identified three distinct factors, representing 64.039% of the cumulative variance in the correlation matrix. This affirmation is visually corroborated by Figure 1. A comprehensive breakdown of this data can be perused in Table 2.

Figure 1
Graphical Representation of the Values of the Eigenvalues of the Scale

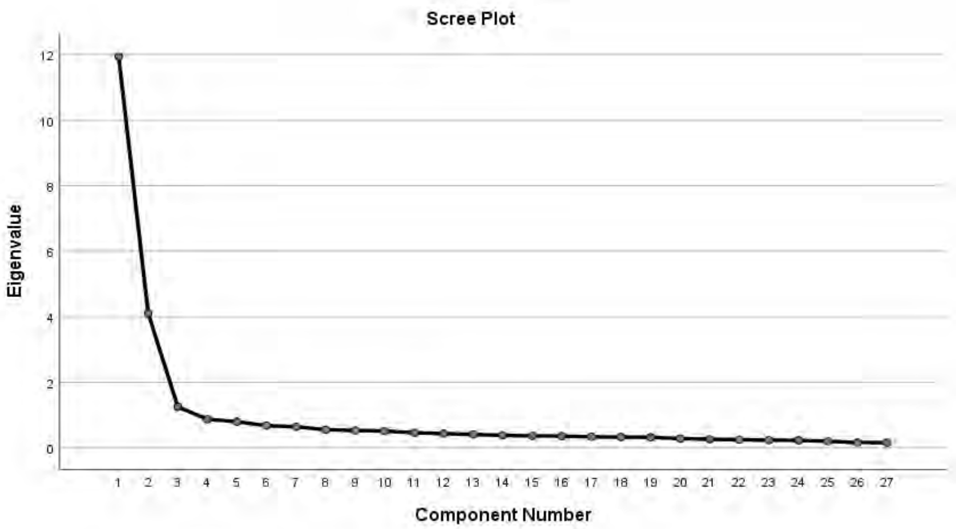


Table 2
Eigen values, explained variance, cumulative explained variance for the factors explaining

Component	*Extraction Sums of Squared Loadings*			*Rotation Sums of Squared Loadings*		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.940	44.222	44.222	7.421	27.486	27.486
2	4.100	15.184	59.406	5.810	21.519	49.005
3	1.251	4.633	64.039	4.059	15.034	64.039

As delineated in Table (2):

- The principal factor boasts an eigenvalue of 7.421, elucidating 27.486% of the cumulative variance observed within the scale. The prominence of items (27, 21, 22, 23, 26, 19, 24, 18, 20, 17) on this factor is aptly designated as "Perception of the Nature of Blended Learning." Factor loadings for these items span from a robust 0.831 to a still significant 0.638.
- The secondary factor, with an eigenvalue of 5.810, contributes an interpretation of 21.519% to the overall scale variance. Items (6, 4, 5, 8, 3, 9, 7, 1, 2, 16) that predominantly load onto this factor led to its nomenclature, "Significance of Blended Learning," with factor loadings oscillating between 0.819 and 0.501.
- The tertiary factor, christened "Desire to Use Blended Learning," is characterized by seven items (14, 15, 10, 11, 13, 12, 25). These items have factor loadings ranging from 0.721 to 0.622.

Of particular note is that four distinct items (17, 18, 11, 12) exhibit loadings on multiple factors. In such instances, items were allocated based on their highest factor loading. The intricate details, including factor loadings for each item, are meticulously catalogued in Table 3.

Table 3
Factor loadings for items based on exploratory factor analysis

N	*Item*	*PoN-BL*	*IoBL*	*DU-BL*
27	I believe the blended learning environment ensures effective communication with the teaching staff.	0.831		
21	The blended learning style is more inclusive, flexible, and effective than traditional education.	0.825		
22	My lack of computer and internet skills poses a challenge in blended learning.	0.822		
23	Blended learning allows me to access information easily and quickly.	0.817		
26	Blended learning facilitates the exchange of experiences among students.	0.799		
19	Blended learning offers various teaching methods and techniques.	0.721		
24	I believe that the assessment methods in blended learning are appropriate and diverse.	0.706		
18	I feel that the faculty members have adequate skills for teaching via blended learning.	0.692		0.413
20	I believe blended learning hinders social interaction and the exchange of experiences with peers.	0.667		
17	I think the blended learning strategy has transformed education for the better.	0.638		0.408
6	I believe that blended learning assists me in developing my electronic media usage skills.		0.819	
4	I believe that one can learn a lot in a short time through blended learning.		0.808	
5	I believe blended learning has helped me understand the presented course concepts better.		0.802	
8	I find that using blended learning in teaching makes the subject more tedious.		0.798	
3	Blended learning enhances the educational activities related to the courses.		0.790	

Table 3 continued

N	*Item*	*PoN-BL*	*IoBL*	*DU-BL*
9	I believe blended learning contributes to successful active participation in the lecture.		0.784	
7	I believe blended learning helps access the latest information related to scientific material.		0.775	
1	Blended education contributes to interaction between students, faculty members, and the study content.		0.714	
2	I feel that using blended learning helps me overcome some educational challenges.		0.570	
16	I see the need to generalize the blended learning experience due to its numerous advantages in the educational process.		0.504	
14	Using blended learning makes learning more exciting and motivating for me.			0.721
15	I feel comfortable and confident due to studying the scientific material in blended learning.			0.693
10	I feel satisfied when I receive constructive feedback during blended learning lectures.			0.692
11	I enjoy the tasks assigned to me electronically.	0.419		0.678
13	I am active and interactive in studying during blended learning.			0.666
12	I see that dealing with blended learning is worth paying attention to.	0.382		0.634
25	I feel at ease when talking about blended learning and its various uses.			0.622

Note. PoN-BL: Perception of the Nature of Blended Learning; IoBL: Importance of Blended Learning; DU-BL: Desire to Use Blended Learning.

Given that the results of the exploratory factor analysis for the actual sample data of this study indicated the presence of three dominant factors influencing the responses of the sample members to the scale, and with the scale items distributed across these factors, the confirmatory factor analysis was employed to assess the quality of the proposed model.

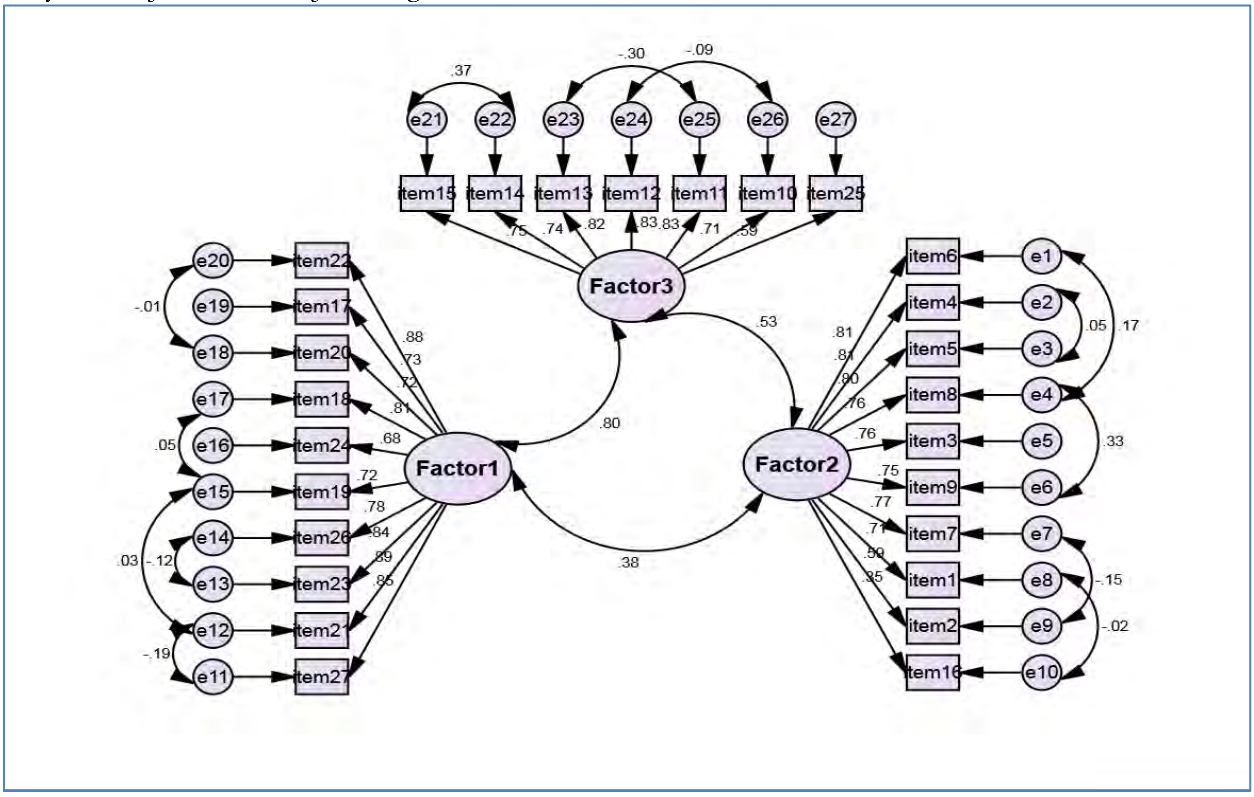
4.2. Confirmatory Factor Analysis

To further validate and corroborate the initial findings from the Exploratory Factor Analysis (EFA), a Confirmatory Factor Analysis (CFA) was conducted. Notably, while the considerable sample size can inherently influence the Chi-square (χ^2) value and its associated significance, it was deemed imperative to retain the entire sample for a holistic representation, in line with the guidance from Rodríguez (2019).

The latent variables in the model were represented by the factors identified during the EFA. In contrast, the manifest variables (or observed indicators) corresponded to the specific items or statements from the questionnaire that loaded onto these factors. Any unidentified variables, primarily representing measurement error, were subsequently labelled for clarity. The culmination of these analytical processes yielded a refined structural model pictorially represented in Figure 2.

Figure 2 illustrates the structural model that elucidates the factors on which the statements are saturated, specifically in terms of the standardized estimates. This model was derived after multiple iterations to reduce the variances emanating from the measurement errors, denoted as "e" or "Error of Measurement." The "Modification Index" was utilized to fine-tune the model, revealing significant correlations between measurement errors. These correlations might arise from a latent fourth factor or due to overlap in measurement methodology. Consequently, the model was refined to account for shared variance among the errors of particular statements, notably those denoted as (e11, e12, e13, e14, e15, e18, e20, e10, e9, e8, e7, e4, e3, e1, e21, e22, e23, e24, e25) as posited by Byrne (2010) and Suhr (2006). This procedural modification led to a reduction in the Chi-square value, degrees of freedom (df), and consequently, the ratio of Chi-square to degrees of freedom (χ^2/df <5). This adjustment significantly enhanced the robustness of the model fit indices, aligning with the guidelines presented by Byrne (2010).

Figure 2
Confirmatory Factor Analysis Diagram



The second research question is framed as, “What are the quality fit indices for the model that explains the factorial structure of the scale of university students' attitudes towards blended learning?” To address this query, the necessary fit indices were computed to ascertain the adequacy of the model fit. The subsequent findings are as follows:

The Confirmatory Factor Analysis (CFA) results indicated that the chi-square value (χ^2) was 1394.75 with degrees of freedom (df) equating to 308, a value significant at a level less than 0.05. Although the chi-square value was found to be significant at the 0.05 level, diminishing its strength in evaluating the model fit—primarily due to the sample size—the standardized chi-square value (χ^2/df) was less than 5 (specifically 4), suggesting a satisfactory model fit (Tartakovsky, 2016).

Furthermore, other indices provided robust evidence for the model's goodness of fit. The Goodness of Fit Index [GFI], which gauges the variance that the model can elucidate, was 0.850. The Adjusted Goodness of Fit Index (AGFI) was at 0.817, with both indices approaching 1, indicating a good model fit (Lecerf & Canivez, 2018). The Root Mean Square Residual [RMR] was 0.08, while the Root Mean Square Error of Approximation [RMSEA] was 0.077, both suggesting a high-quality model fit (Morin et al., 2016). The Normed Fit Index [NFI] stood at 0.882, the Comparative Fit Index [CFI] was 0.905, and the Tucker-Lewis Index [TLI] was at 0.892, all of which underscore a superior model fit (Lecerf & Canivez, 2018). The residual root mean square [RMR] was 0.108, indicating a good model match.

In light of the computed fit indices (GFI, AGFI, RMR, RMSEA, NFI, CFI, TLI, and RMR), it is evident that all index values are high and lie within the accepted range (Lecerf & Canivez, 2018). These values attest to the model's quality fit, implying negligible disparity between the assumed model variance indices and the sample variance indices.

Regarding the third question, “Does the scale of university students' attitudes towards blended learning and the explanatory model possess good psychometric properties?” We calculated the Convergent Validity, Discriminant Validity, and Composite Reliability coefficients to address this. The results are summarized in Table 4.

Table 4
Convergent and discriminant validity, composite reliability

Factor	*CR*	*AVE*	*MSV*	*Factor1*	*Factor2*	*Factor3*
Factor1	0.943	0.627	0.2704	0.79		
Factor2	0.914	0.524	0.2704		0.724	
Factor3	0.903	0.572	0.2704			0.756

As evident from Table 4, the Composite Reliability [CR] indicators are based on the standardized factor loadings (λ) and the shared variances. From the table, it is noticeable that the CR value for the first factor was 0.943. For the second factor, it was 0.914, and for the third factor, it was 0.903. These coefficients indicate high reliability. When comparing these values with the reliability values calculated using Cronbach's alpha for the overall sample, the values are as depicted in Table 5.

Table 5
Indicators of reliability values calculated using Cronbach's alpha

Factors	*Factor1*	*Factor 2*	*Factor3*	*Scale all*
Reliability	0.912	0.926	0924	0.951

Table 5 shows that the reliability values computed using Cronbach's Alpha equation are approximately equal to those computed for the model. These values indicate high reliability, suggesting that the scale possesses a significant degree of consistency (Hair et al., 2010). Furthermore, Table 4 also presents indicators of convergent and discriminant validity. These indicators rely on standardized loadings and variance values. As illustrated in the previously mentioned Table 4, the Average Variance Extracted (AVE) for the first factor was 0.627, for the second factor was 0.524, and for the third factor was 0.572. These coefficients suggest good values for all three factors, where the AVE values should be less than the Composite Reliability (CR) values (Hair et al., 2010). Moreover, Table 4 shows that the Maximum Shared Variance (MSV) for the first, second, and third factors was 0.2704. These coefficients also indicate good values, as the MSV values should be less than the AVE values for a valid discriminant validity (Hair et al., 2010).

5. Discussion

Upon thoroughly examining the study's findings, it becomes evident that the set of 27 statements, of the scale of university students' attitudes towards blended learning predominantly align with three distinct factors. These factors' eigenvalues exceed the threshold of one (1), a criterion rooted in the standards of exploratory factor analysis as outlined by some studies (Byrne, 2010; Ginns & Ellis, 2009). It is generally accepted in factor analysis that factors with eigenvalues surpassing one (1) are considered significant. Specifically, the first factor boasts an eigenvalue of 7.421, while the subsequent factors register values of 5.810 and 4.059, respectively. Collectively, these factors account for a substantial 64% of the total variance.

After a thorough analysis, ten statements that chiefly align with the first factor have been identified. This alignment adheres to a set criterion requiring factor loadings of 0.35 or above, as advocated by esteemed scholars Byrne (2010) and Suhr (2006). The factor loadings for these particular statements concerning this dominant factor range from 0.638 to 0.831. This concentration of statements within this factor could suggest that these items collectively represent a specific aspect or dimension of students' attitudes towards blended learning, potentially focusing on their technological adaptability or belief in the effectiveness of blended approaches. Alternatively, the clarity or universal relevance of these statements might elicit more consistent responses, thereby driving the high factor loadings. Such pronounced loadings underscore the significance and reliability of these statements in delineating this specific facet of blended learning attitudes. Delving deeper into the content and context of these statements could offer more clarity on the common themes they represent, further illuminating the multifaceted nature of student perceptions.

This principal factor has been called "Perception of Blended Learning Characteristics." Intriguingly, all statements that manifest significant loadings on this factor encapsulate the students' nuanced understanding of the blended learning paradigm, their adeptness in navigating blended learning platforms, and the structured support they receive. The pronounced factor loadings of these statements afford their unambiguous classification under this factor, especially since they do not exhibit significant loadings on any alternative factor. This ensures a pristine lack of redundancy in gauging these statements, underscoring their intrinsic association with this factor.

However, an exception is observed in statements 17 and 18. These statements demonstrate cross-loadings between the inaugural and the tertiary factors. Their loadings on the second factor are quantified at 0.413 and 0.408, juxtaposed with their loadings on the first factor, which are 0.692 and 0.638, respectively. Given their focus on the pedagogical competencies of faculty within the blended learning environment, they have been astutely categorized under the first factor, aptly titled "Perception of Blended Learning Characteristics."

Upon a comprehensive review of the dataset, a distinct second factor was identified, represented by ten specific statements. These statements showcased factor loadings that spanned from 0.501 to 0.819. "Significance of Blended Learning" was aptly designated to this factor. Each affiliated statement highlights the diverse advantages, fundamental values, and unique strengths of blended learning. These insights go beyond general benefits, illuminating the pedagogical intricacies, especially the innovative methods of information dissemination and the enriched interactions between students and their instructors. Such emphasis implies that blended learning is perceived not just as a hybrid teaching method but as a strategic approach that harnesses the best of both online and face-to-face instruction. The consistent factor loadings suggest a cohesive understanding among students about the transformative potential of blended learning, accentuating its integral role in elevating the academic journey. This factor underscores the essence of blended learning as a comprehensive educational approach, balancing content mastery with meaningful interpersonal dynamics.

The pronounced factor loadings of these statements reinforce their categorization under this specific domain. Furthermore, it is imperative to note that these statements do not overlap loadings with other factors, ensuring the absence of measurement redundancy. This, in turn, underscores these statements' veracity and exclusive alignment with the delineated factor, a trend consistent across all the encompassed statements.

These items demonstrated factor loadings that varied between 0.622 and 0.721. This factor was aptly named "Inclination Towards Blended Learning Implementation." Each item within this factor delves into the motivational underpinnings of students concerning blended learning. The pronounced factor loadings accentuate the pertinence of these items to this distinct construct. Now, a possible deeper explanation: The focus on motivation suggests that students' willingness to engage with blended learning is not just a passive acceptance but is driven by internal factors that propel them to seek such an educational approach. These could range from perceived benefits like flexibility and personalized learning to a deeper appreciation of the hybrid methodology. The consistent factor loadings further underscore the cohesiveness of these items in capturing this motivational essence. The exclusivity of the factor loadings for these items is crucial. It ensures that each item uniquely contributes to understanding this construct without overlap. This not only strengthens the validity of the construct but also ensures that the assessment captures a broad spectrum of motivational elements without repetition, thereby providing a comprehensive insight into students' inclination towards implementing blended learning (Bhagat et al., 2023).

However, an exception is observed in items 11 and 12. These items displayed concomitant loadings between the first and third factors. Specifically, their loadings on the first factor stood at 0.419 and 0.382, while for the third factor, they registered at 0.678 and 0.634, respectively. Given the thematic essence of these items, which revolves around students' predisposition and enthusiasm for blended learning, they were judiciously incorporated within the third factor, encapsulating “Inclination Towards Blended Learning Implementation.”

Pertaining to the model's fit indices, they predominantly showcased elevated metrics in alignment with established benchmarks (Byrne, 2010; Suhr, 2006)—the χ^2 statistic registered at 1394.75, reflecting a significance threshold below 0.05. Notwithstanding the significance of the χ^2 value, the ratio of χ^2 to its degrees of freedom remained at 4, comfortably beneath the stipulated threshold of 5, which denotes an adequate model fit.

An essential observation to underscore is the inflationary effect of large sample size on the χ2 value, a phenomenon well documented in the literature. As the sample size augments, there is an inherent tendency for the χ^2statistic to escalate, which inversely impacts its significance level. This observation holds even after accommodating the variance attributed to measurement errors by delineating shared variance among items influenced by similar measurement modalities. This persistently elevated $^2\chi^2$ value warrants further scrutiny (Byrne, 2010; Matosas-López et al., 2019).

The derived model exhibits a remarkable degree of conformity, as indicated by its robust quality fit indices. It demonstrates a striking alignment between the explanatory model and the sample variances. Notably, all these fit indices (GFI, AGFI, RMA, RMSEA, NFI, CFI, TLI, RMR) present exceptionally high values, suggesting a pronounced degree of congruence between the model and the empirical data (Suhr, 2006).

Concerning the psychometric properties of the scale, specifically the validity and reliability indices, Cronbach's alpha values suggest a high degree of reliability for the scale. These values ranged between 0.912 and 0.926, indicating the scale's robustness. Moreover, when assessed using the "Validity and Reliability Test" within the AMOS software, reliability values ranged from 0.903 to 0.943. Observing these metrics, it is evident that the model possesses a commendable level of consistency. These values closely align with those derived from Cronbach’s alpha equation, implying that both the scale and the model manifest high reliability (Suhr, 2006).

Regarding the convergent and discriminant validity indices calculated for the model, the convergent validity indices for the dimensions ranged between 0.524 and 0.627. Given that the Average Variance Extracted (AVE) represents the degree of shared or common variance among the items of a factor, these values need to be substantial (> 0.5) to be deemed acceptable (Hu & Bentler, 1999). Upon examining the convergent validity values, it is evident that the scale's dimensions exhibit satisfactory and acceptable levels of convergent validity.

The discriminant validity indices determined for the model uniformly stood at 0.27 for all scale dimensions. This value is considered satisfactory as an indicator of discriminant validity, which denotes the distinctiveness between items of different factors. These values must be lower than the convergent validity values (Hair et al., 2010). Upon thoroughly examining the research outcomes, the metrics consistently indicate that the proposed model exhibits superior congruence. The attributes of this model align closely with the characteristics inherent in the sample, suggesting that the model provides an accurate representation of the sample. Consequently, this study strongly advocates using this instrument to gauge university students' attitudes towards blended learning.

6. Implications

Based on the study’s primary findings, the established model provides an in-depth look at the experiences and preferences of students within the blended learning paradigm. This insight provides curriculum designers and educators with a compass, highlighting the need to create content and instructional strategies that resonate with student preferences. The model's precision facilitates enhanced engagement and comprehension and furnishes educators with a tool for ongoing assessment and iterative refinement of blended learning modules. In addition, the results provide institutional policymakers with a more nuanced understanding of the landscape of blended learning. Institutions can make well-informed decisions regarding investments in cuttingedge blended learning platforms and tools in light of the importance and effectiveness of blended learning. These proactive strategies ensure that the technological infrastructure and pedagogical methods are aligned with the requirements of the students, fostering an all-encompassing and applicable learning environment.

7. Limitations and Recommendations for Further Studies

Based on the study's findings, certain limitations and recommendations arise. The study predominantly focuses on university students' attitudes towards blended learning, potentially missing broader educational perspectives. Thus, future studies should expand the sample to include diverse educational levels. The research's geographical scope might also be limiting, suggesting the need for a more global approach in subsequent investigations. Additionally, the reliance on self-reported questionnaires might introduce biases. It would benefit future research to combine quantitative methods with qualitative tools for a comprehensive view. Given the ever-evolving nature of e-learning, it is also essential to consider the temporal limitations of this study. Longitudinal studies could provide insights into changing attitudes over time. Lastly, with the dynamic nature of blended learning, instruments should be regularly evaluated and updated in future studies to remain relevant.

8. Conclusion

This research presents a meticulous examination of university students' perceptions regarding blended learning. As evidenced by the acquired metrics, the formulated model uniquely aligns with the sampled data, emphasizing its pertinence in the current educational milieu. The model's integrity, supported by consistent empirical outcomes, positions it as an indispensable tool for educators, academic strategists, and institutional decision-makers. This tool is essential in decoding the intricacies of student predilections towards blended learning, thereby formulating more informed and efficacious educational approaches. As the blended learning landscape evolves, this study is a pivotal benchmark, offering invaluable insights for future academic explorations and implementations.

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