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Scalar consistency of collaborative learning: bifactor structural equation modeling

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ABSTRACT

The way of learning in higher education needs a revaluation, which should consider cooperation as one of the principles to improve the cognitive, procedural, and attitudinal learning of students whose training will allow them to integrate effectively into the work environment. The objective of the study was to validate the consistency of the collaborative learning scale (CLS) using the bifactor structural equation model (SEM) in university students from Junín. It presented a quantitative approach, through a deductive method, of demonstrative and inferential scope and a non-experimental design. The sample was of the probabilistic type, composed of 361 students of the Faculty of Health Sciences from cycles I to VIII at Huancayo University-2023. The results verified that the use of an original bifactor SEM allows the identification of multidimensional sources present in complex psychological measures, such as the evaluation instrument under study. In conclusion, thanks to the analysis of the Chi-square differences between the second-order model and the bifactor model, it can be verified that the bifactor model has a better fit than the second-order model because it has a lower X^2, a lower root mean square error of approximation (RMSEA), a lower weighted root mean residual (WRMR), and a higher ω.

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1. INTRODUCTION

Due to the COVID-19 pandemic, several problems have been revealed that show the complexity of the interconnection of states, as well as the possibility and need for joint action to solve problems that are shared in different scientific disciplines. Global cooperation is the basis on which international institutions direct sustainable development; this cooperation is based on the premise of inclusion and sustainability. However, the framework of global cooperation is characterized by being permeated by power struggles and is defined as a fragmented and incoherent space [1], [2].

In a context as complex as the contemporary scenario, which has faced the precariousness of health and national economies, it is necessary to design the conciliation between international demands, which are restricted to the challenges of globalization. These challenges are reflected in international conflicts, international migration, the number of refugees, and global climate change, all of which are related to national social, economic, and political issues. In light of this, it is essential to discuss the fundamentals of cooperation, including reflection on collaborative work and learning, which would significantly influence national development policies and agendas.

In this area of ideas, international institutions led by countries with strong economies present statistics on the employment of skilled workers compared to qualified workers and exalt the relevance of education at a global level for the social and technological development of nations. However, as a consequence of this, the disengagement of the unskilled population is recorded, as well as increasing rates of underemployment [3], [4]. It is worth discussing what is the fundamental aspect that impedes the direction of higher education concerning current demands, the challenges faced by professionals, and their ways of learning throughout their education.

It is important to note that the 2030 agenda proposes some educational models that allow for achieving sustainable development, namely education for sustainable development, education for global citizenship, and relevant concepts as teaching axes for cooperation. However, this objective is far from the local reality, since in the same the state spending on regular basic education is deficient compared to that proposed by the Organization for Economic Cooperation and Development (OECD) [5]. In addition, the number of vacancies offered by higher education centers is insufficient for applicants, so approximately half of them have to opt for other alternatives.

In this order of ideas, the reality that Peruvian higher education has been facing has exposed it to various challenges that have affected its development and results; this has occurred as a consequence of the different reforms and counter-reforms generated in the social and technological development of the country. It is essential to rethink the epistemological and methodological foundations of the way students learn in higher education, thus emphasizing the relevance of cooperation as one of the principles that allow for improving cognitive, procedural, and attitudinal learning [6]–[8]. In retrospect, since 2016, the Junín region has had several international technical cooperation agreements in which students from the region are provided with the possibility of learning from other regions of the world and other Latin American countries, through study grants.

Addressing one of the fundamental aspects of this study, the most precise definition of cooperative learning is that which emphasizes the purpose of teamwork concerning maximizing one’s learning through common objectives [9], [10]. Regarding the measurement of collaborative learning performance, it is pertinent to note that the application of the collaborative learning scale (CLS) can be subjected to rigorous content validation procedures, employing Aiken’s V coefficients or simply V-Aiken. This coefficient leads to a single summary number (i.e. point estimate), which is used to interpret the relationship between the content of the item and the context domain that contains it.

In this sense, as its value approaches 1, it is assumed that the instrument and its rating scale describe a high content validity [11]; thus, it becomes clear that the scientific question of the present study is focused on the importance of the validation of the CLS to establish the teamwork of university students in Junín. From the perspective of Yuste [12], two aspects of collaborative learning methodology are highlighted: the Jigsaw method and the cooperative teams and performance divisions (STAD), which summarize the divisions of student achievement. The Jigsaw method consists of individual work by each member of the group, who will then discuss what they have learned and help those who did not understand some topics well [12], [13]. In this sense, the discussion and dissemination of knowledge with peers as a way to consolidate what has been learned at the group level is a priority.

On the other hand, cooperative teams and STAD performance divisions consist of individual study of class material after the teacher's session, the group's practice and study continue with an evaluation in which the sum of the individual scores will allow obtaining a final result as a group grade [14], [15]. This strategy motivates the young person to study individually to achieve, together, a good final result together; in the process, they can share study techniques or explain topics that were not processed in class. This technique is more accurate for all learning that is not theoretical, as it takes more time to internalize [15].

Considering the approach of Cuadra-Martínez *et al.* [16], structural equation models (SEM) allow predicting, using statistical inference, the level of relationship and the duration between fully defined variables; the behavior of the school climate and its influence on the educational quality of a given organization can be appreciated with great attention. For this, it is important to start from the use of a previously standardized data collection instrument, whose validity and reliability are significantly acceptable and which facilitates the development of the confirmatory factor analysis. In this sense, the study conducted by Gegenfurtner [17] sought to establish how the fit of the bifactor exploratory SEM (B-ESEM) model differs from other sub-models derived from it; among the dimensions analyzed were instruction, depression, learning, motivation, emotion, identity, and interpersonal relationships. The results of the review show that the fit of the B-ESEM model is above the fit presented by the referential models. Also, the model fit is affected by the sample size, number of items, and the number of general aspects of a model.

Concerning the two-factor analysis, it is a mathematical process that is carried out with the application of a type of second-order confirmatory model, in which it is assumed that there is a general factor (GF), that exposes the covariance of the totality of the observed measures, and synchronously shows different first-order factors that intervene and explain the representation of the same items. From this approach, it is possible to detail the direct responses of the first-order factors and the general, second-order factor, with no proven correlation between them [9], [18]. In keeping with this context, Zakariya *et al.* [19] published an article to present a Norwegian study in which they validated a widely used instrument in the measurement of learning approaches in students, namely the revised two-factor study process questionnaire (R-SPQ-2F). Its assessments of cultural sensitivity and psychometrics have sparked rigorous debate among educators in different languages. These researches employed confirmatory factor analysis to test six models, hypothesized to reflect the factor structures of the R-SPQ-2F and the unidimensionality of its subscales. It could be observed in the results that there are appropriate adjustments of a first-order model, and that, in addition, there are two factors with 10 items referring to the deep approach and 9 items to the superficial approach.

Concerning the above, the need has been detected for a quantitative procedure that allows having an evaluation instrument for the progressive development of cooperative learning, according to the characteristics of university students in the city of Huancayo, Peru. Therefore, the object of the study is the cooperative learning scale; this is the instrument tested and validated by Fernandez-Rio *et al.* [20]. This scale is responsible for measuring the level of group processing, social skills, quality of positive interdependence, promoting interaction, and individual responsibility.

Based on the explanation, the objective of this study is to validate the consistency of the CLS using the bifactor SEM in university students in Junín. The protocol to be used for validation is the bifactor SEM, which is a multivariate statistical analysis technique that supports the analysis of complex patterns of relationships between variables, comparisons between and within groups, and tests of theoretical and empirical models [21]. Hence, it has a significant relevance for assessing collaborative learning, due to the number of variables involved in its assessment. Under this argument, it is possible to use statistical tools in a complementary way to the most recent findings on the strengthening of competencies through cooperative learning of future professionals, making use of the bifactor model of structural equations.

2. METHOD

This research work presented a quantitative approach, using the scientific method, which denotes a deductive process because it is based on general principles, a product of the background review as a basis for the development of a hypothesis that was subsequently corroborated by the collection, systematization, and inferential statistical analysis [22]. This study falls within the applied type range since technological tools are provided to measure the validity and reliability of an instrumented procedure to assess collaborative learning [23]. This is done by applying the bifactor SEM to university students by determining its reliability and validity.

The level of the research covers both demonstrative and inferential aspects since the study addresses the characteristics of the instrument, as well as the mathematical process that requires its validation and determination of reliability and the corroboration of the hypothesis formulated in the study [24]. According to the nature and object of the study, the study is framed in a non-experimental cross-sectional design, since there is no controlled handling or alteration of any variable within the study or the intervention of the researcher since the data with which the acceptance of the instrument will be carried out are obtained at a single moment [25], [26]. Figure 1 shows the graphic representation of the applied design.

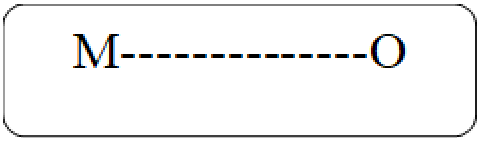

Figure 1. Non-experimental design scheme

The study population was determined by statistical calculation. The population consisted of students from different careers at a university in Huancayo. The type of sample selected was probabilistic [27], which was estimated using the (1):

$$Sample\ size = \frac{\frac{z^2 x p(1-p)}{e^2}}{1 + (\frac{z^2 x p(1-p)}{e^2 N})} \qquad (1)$$

Where:
N=Population size
e=Error margin (percentage expressed with decimals)
z=Punctuation z

The population is 5,936 individuals, including students of Psychology, Nursing, Obstetrics, Dentistry, Nutrition, Medical Technology (Physical Therapy, Laboratory, Optometry, Radiology), Veterinary Medicine, Pharmacy, and Biochemistry from cycle I to VIII, from a university in Huancayo. The confidence level is 95% and the margin of error is 5%. The result indicates that the sample size is 361 students of the Faculty of Health Sciences from cycle I to VIII, of both genders and between 18 and 30 years of age. The following is a schematic presentation of the distribution of the population and the sample of students, according to the eight specialties previously mentioned.

Regarding the techniques and instruments for the collection of information, a survey was used using the questionnaire for measuring cooperative learning in educational contexts (CAC), designed, validated, and applied by Fernandez-Rio *et al.* [20]. Similarly, for its application, authorization was requested from the Faculty of Health Sciences to have access to the directors of the professional schools, to facilitate the application of the instrument, both for the pilot test and the sample. Likewise, with previous coordination with the teachers, the selected classrooms were entered and informed about the objective of the research, making known the benefits, of obtaining the consent of the participants in compliance with the ethics and social responsibility of the researchers. The analysis was carried out by transcribing the responses in the Excel program, where the answers to each item were organized and recorded. Then, these responses were systematized and analyzed in the SPSS V26 statistical program, in which, employing the statistical test, the reliability of the instrument was validated and evaluated.

3. RESULTS AND DISCUSSION

3.1. Analysis of survey data: collaborative learning

The first dimension addressed was interpersonal skills with the indicators of dialogue, group argumentation, active listening, and reaching agreements. Among the most outstanding results that stands out is the willingness to listen to the ideas, opinions, and points of view of others. There were 75.07% of the total respondents agree and strongly agree with this option, as can be seen in Figure 2.

The next dimension is group processing, which includes the indicators of dissemination of information, consensus, discussion, and reflection. On this occasion, most of the participants (74.24%) agree or strongly agree with the statement that they are willing to reach agreements within the group to make decisions. These data can be seen in Figure 3.

The third dimension (positive interdependence) was configured with the indicators mutual support, complementarity, exchanges, and personal demands. A total of 79.78% agreed and strongly agreed with the statement that when each member performs his or her task better, it will be better for the group. On the contrary, 1.66% of the respondents strongly disagreed, as shown in Figure 4.

The fourth dimension, which is related to promoting interaction, is made up of the indicators of communication, focused interaction, team relationships, and direct relationships. In this opportunity, the great majority of the participants (82.55%) agree and strongly agree with the statement that they work together with the rest of their colleagues. On the contrary, 0.55% totally disagreed, as shown in Figure 5.

The fifth dimension involves individual responsibility. Here, participation of all, equitable effort, equitable participation, and responsibility are exposed as indicators. In this section, it could be highlighted that most of the participants (82.27%) agree and strongly agree with the statement that each member of the group must try to participate, even if he/she does not like the task. This is shown graphically in Figure 6.

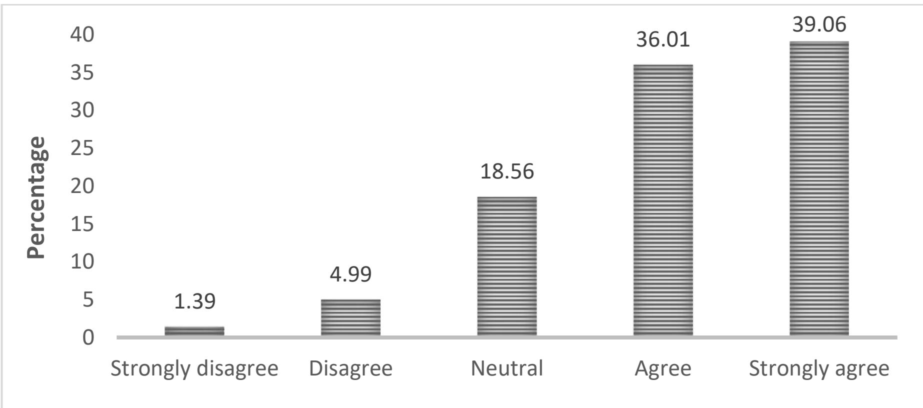

Figure 2. Willingness to listen to the ideas, opinions, and points of view of others

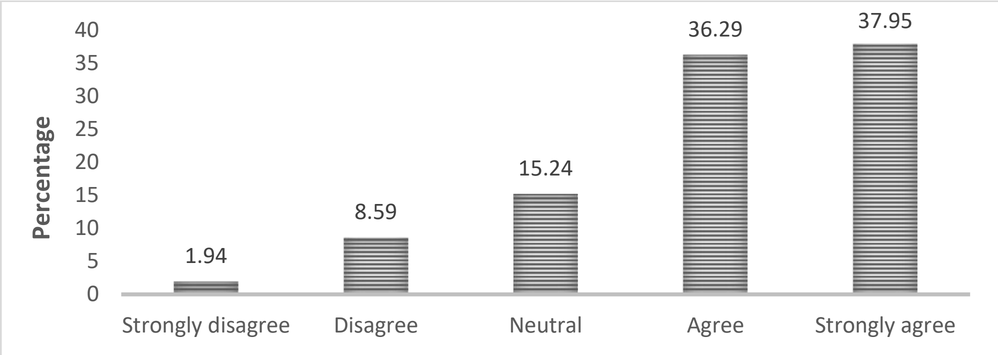

Figure 3. Willingness to reach agreements within the group to make decisions

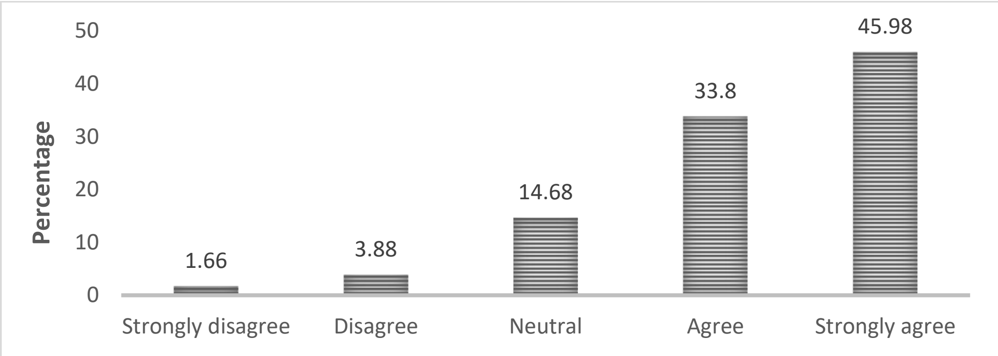

Figure 4. When each member performs his or her task better, it will be better for the group.

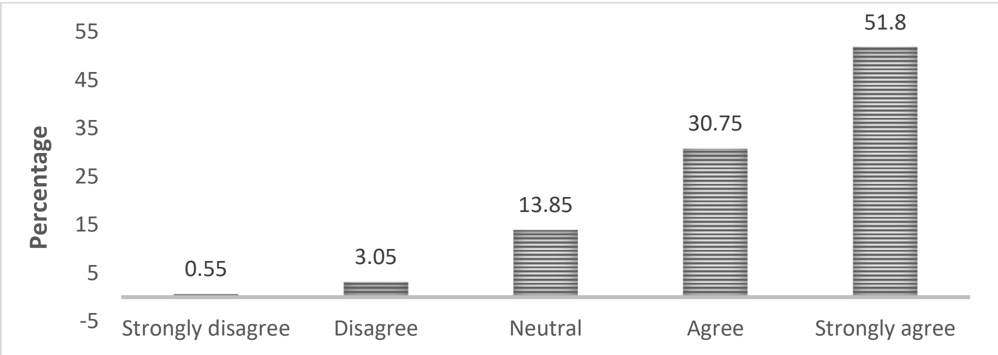

Figure 5. Working together with the rest of colleagues

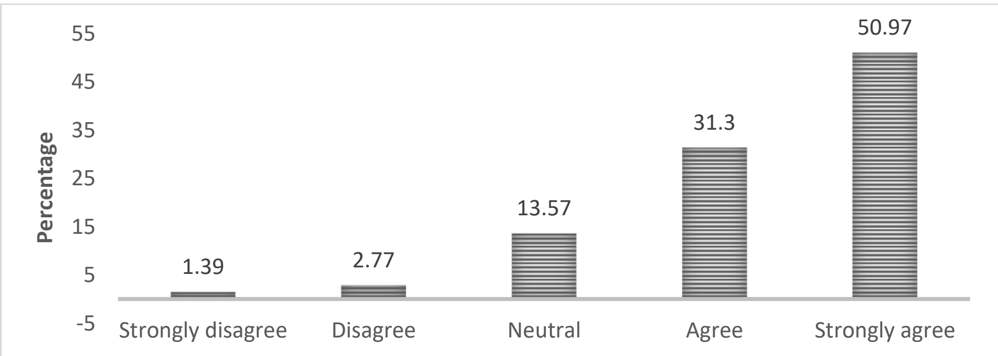

Figure 6. Each member of the group must try to participate, even if he/she does not like the task

The V-Aiken coefficient is a measure of agreement between the judges that varies between -1 and 1, with 1 being the maximum agreement and -1 being the minimum agreement. One of the advantages of using this method is that it provides a measure of the proportion of judges who rate the object under analysis positively, which can be used as a criterion for deciding whether to revise or eliminate items. The following criterion is used to interpret the coefficient:

i) If V-Aiken<0.5, the item has low content validity and should be revised or deleted.
ii) If 0.5≤V-Aiken<0.7, the item has acceptable content validity but can be improved.
iii) If V-Aiken≥0.7 the item has high content validity and should be retained.

In this case, most of the items have a V-Aiken coefficient of 1.00, except for 5, 6, and 8, which have a coefficient of 0.95, but which is also higher than 0.7, meaning that all judges assigned the same rating of 4 (high level). Consequently, all of the items have high content validity and should be retained. In addition, the asymmetric confidence interval for the V-Aiken coefficient can be calculated, using Penfield and Giacobbi's method, to estimate the range of possible values of the coefficient in the group of judges. A narrower confidence interval indicates a higher precision of the coefficient. In this case, the confidence interval for item 1 is [0.99, 1.00], indicating that the V-Aiken coefficient is very precise and close to 1.

3.2. Two-factor analysis

This section presents the descriptive statistics by dimensions of the CLS for the sample of Peruvian students of the Faculty of Health Sciences, from cycle I to VIII, as shown in Table 1. Regarding the scores, these have a minimum value of 3.00 up to a maximum of 15.00. The tabulated values are expressed in fractions of three digits (in some cases).

It is highlighted in Table 1 that the positive interdependence dimension (PID) achieved the highest mean value according to the total score (Mean=12.39), with a standard deviation of 2.31 and the Omega value equal to 0.698; however, the highest Omega value was reflected by the interpersonal skills dimension (HI) with 0.725, which indicates that the three items (1, 6 and 11) that compose it measure the same construct. Next, the normalized scale is presented according to the percentile distribution for the CLS in the Huancayo University students in this study, considering the mean and standard deviation for each dimension of the instrument, as shown in Table 2.

Table 1. Descriptive statistics by dimensions of the CLS for the sample of Peruvian students

Dimensions	Minimum score	Maximum score	Media (total score)	Standard deviation	Omega	Number of items
Interpersonal skills (HI)	4.00	15.00	11.64	2.47	0.725	3(1,6,11)
Group processing (GP)	3.00	15.00	11.62	2.40	0.684	3(2,7,12)
Positive interdependence (PII)	3.00	15.00	12.39	2.31	0.698	3(3,8,13)
Promoting interaction (PI)	4.00	15.00	12.21	2.22	0.649	3(4,9,14)
Individual responsibility (IR)	3.00	15.00	11.42	2.22	0.663	3(5,10,15)

Table 2. Distribution of percentiles for the CLS in Huancayo university students

Dimensions	Minimum score	Maximum score	Media	Standard deviation	Percentiles			
					25	50	75	90
Interpersonal skills (HI)	4	15	11.64	2.47	9	11	13	14
Group processing (GP)	3	15	11.62	2.4	9	11	13	14
Positive interdependence (PII)	3	15	12.39	2.31	10	12	14	14.4
Promoting interaction (PI)	4	15	12.21	2.22	10	12	14	14.4
Individual responsibility (IR)	3	15	11.42	2.22	9	11	13	14

Table 2 shows that the dimensions of positive interdependence (PID) and promoter interaction (PI) achieved the highest value of 14.4 at the 90th percentile with minimum scores of 3 and 4, respectively. We continue with the first-order factor analysis, and Table 3 shows the important aspects of this analysis. The table shows the results obtained with the KMO and Bartlett's test [28].

According to Table 3, the KMO measure is 0.947, which indicates that the data have an excellent fit for factor analysis. The p-value of Bartlett's test is less than 0.001, which means that the correlation matrix is significantly different from the identity matrix. Therefore, it is possible to conclude that the data are appropriate for factor analysis. As a complement, the commonalities matrix is presented in Table 4.

Table 3. KMO and Bartlett's test

KMO measurement and Bartlett sphericity		
Sampling adequacy (KMO measurement)	Sphericity	
0.947	Aprox. Chi-cuadrado	2460.435
	GL	105
	Sig.	<0.001

Table 4. Communalities matrix

	Initial	Extraction
P1	1	0.595
P2	1	0.503
P3	1	0.570
P4	1	0.508
P5	1	0.498
P6	1	0.639
P7	1	0.476
P8	1	0.529
P9	1	0.487
P10	1	0.557
P11	1	0.507
P12	1	0.535
P13	1	0.578
P14	1	0.670
P15	1	0.600

Extraction method: principal component analysis

The communalities matrix shows that the data vary between 0 and 1, with 1 being the optimal value. The communalities are expected to be high considering that the observed variables are strongly related to the factors. For the case study, the communalities are all greater than 0.8, indicating that the observed variables have a high variance explained by the factors. This suggests that the extracted factors are relevant and representative of the observed variables. In the same vein, the results of the total variance explained matrix are shown in Table 5.

Table 5 presents the total explained variance and the percentage of variance explained by each component extracted. The analysis extracted two components, explaining 55.00% and 31.70% of the total variance, respectively, for a cumulative total of 86.70%. Table 6 presents the correlation of the correction between each item and the dimension of the CLS.

Table 6 shows the corrected item-test correlation of the CLS for the five dimensions considered for a group of 361 students. Each dimension includes 3 items, and the correlation coefficients indicate the strength of the relationship between each item and the total scale score. In general, the correlation coefficients are relatively high, with most items in the range of 0.6 to 0.7. This suggests that the items are indeed measuring the ability they are supposed to measure and that the scale as a whole appears to be a reliable measure of ability on each dimension.

Table 5. Matrix of total variance explained

	Initial eigenvalues			Sums of squared extraction charges			Sums of loads squared by rotation		
Items	Total	% of variance	% cum.	Total	% of variance	% cum.	Total	% of variance	% acum.
1	7.048	46.98	46.98	7.04	46.98	46.98	4.75	31.70	31.70
2	1.203	8.01	55.00	1.20	8.01	55.00	3.49	23.30	55.00
3	0.878	5.85	60.86						
4	0.777	5.17	66.03						
5	0.657	4.37	70.41						
6	0.583	3.88	74.30						
7	0.556	3.70	78.00						
8	0.496	3.31	81.31						
9	0.475	3.16	84.4						
10	0.438	2.92	87.40						
11	0.430	2.86	90.26						
12	0.392	2.61	92.88						
13	0.377	2.51	95.39						
14	0.355	2.36	97.76						
15	0.335	2.23	100.00						

Extraction method: principal component analysis

Table 6. Corrected item-test correlation of the CLS

Items	HI	PG	IDP	IP	RI
1	0.667				
6	0.714				
11	0.636				
2		0.606			
7		0.632			
12		0.661			
3			0.660		
8			0.599		
13			0.663		
4				0.617	
9				0.540	
14				0.638	
5					0.628
10					0.632
15					0.514

3.3. Confirmatory factor analysis: model with first- and second-order factors

As a first step, the estimation of the model with four first-order factors and one second-order factor for the CLS is presented, as shown in Table 7. This presents the first-order factor model with an X^2 value of 274.516, with 78 degrees of freedom, implying an X^2/df ratio of 3.52. This value is higher than the suggested cutoff of 3, indicating a poor model fit. The root mean square error of approximation (RMSEA) value is 0.084, which is above the threshold of 0.08, and the 90% confidence interval for RMSEA includes the value of 0.10, which also suggests a poor fit. The weighted root mean residual (WRMR) value is 2.912, which is above the threshold of 1, reflecting a poor fit. The comparative fit index (CFI) and Tucker-Lewis's index (TLI) values are 0.918 and 0.891, respectively, which are below the criterion of 0.90, indicating an insufficient fit. Therefore, it can be concluded that the first-order factor model is not correctly fitted to the EAC data.

The second-order factor model has an X^2 value of 284.612, with 80 degrees of freedom, implying an X^2/df ratio of 3.56. This value is similar to that of the first-order model and also indicates a poor fit. The RMSEA value is 0.086, which is above the threshold of 0.08, and the 90% confidence interval for the RMSEA includes the value of 0.10, which also suggests a poor fit. The WRMR value is 2.978, which is above the threshold of 1, reflecting a poor fit. The CFI and TLI values are 0.915 and 0.887, respectively, which are below the criterion of 0.90, indicating an insufficient fit. Therefore, it can be concluded that the second-order factor model also does not fit the CAD data well.

Table 7. Estimates of the model with four first-order and one second-order factor for the CLS

X2	df	RMSEA	(90% CI)	WRMR	IFC	TLI
274.516	78	0.084	0.073 - 0.095	2.912	0.918	0.890

When comparing the two models, it can be observed that the second-order factor model does not improve the fit of the first-order factor model, but rather worsens it slightly. This may be because the introduction of the second-order factors reduces the variance explained by the model, and increases the complexity of the model. In addition, the second-order factors may not have a clear theoretical interpretation and may be redundant with the first-order factors. Therefore, it can be suggested that the first-order factor model is more parsimonious and adequate than the second-order factor model for CAD. The factor loadings for the CLS are presented in Table 8.

Table 8 of factor loadings of an item represents the magnitude of the relationship between that item and the dimension to which it belongs, according to the results of the factor analysis performed. Therefore, the higher the factor loadings, the greater the degree of relationship between the item and the dimension. Relatively high factor loadings can be observed for most of the items in each dimension. For example, the factor loading of item 1 in the interpersonal skills dimension is 0.773 with a standard error of 0.025. Similarly, the factor loading of item 12 in the promotive interaction dimension is 0.785 with a standard error of 0.016. This suggests that the items are indeed measuring the ability they are supposed to measure and that the scale as a whole appears to be a reliable measure of ability on each dimension.

Table 8. Factor loadings for the CLS

Items	HI	PG	IDP	IP	RI
1	0.773 (0.025)				
6	0.756 (0.020)				
11	0.754 (0.019)				
2		0.701 (0.01)			
7		0.732 (0.013)			
12		0.785 (0.016)			
3			0.760 (0.015)		
8			0.701 (0.012)		
13			0.724 (0.010)		
4				0.702 (0.012)	
9				0.621 (0.014)	
14				0.705 (0.016)	
5					0.721 (0.014)
10					0.703 (0.015)
15					0.685 (0.016)

3.4. Two-factor model

For the presentation of the model, Table 9 shows the estimates of the bifactor model of the CLS. This table shows the estimates of the bifactor model of the CLS, where the same first-order factors were considered as in the CFA, as well as a second-order factor (bifactor), in which each item was also subsumed (GF) [29]. The results indicate that this model fits the observed data better than the model in Table 1. The chi-square value is significantly reduced to 201.124 ($p<0.01$) and the RMSEA is less than 0.05 (RMSEA=0.051), suggesting a better fit of the model to the observed data. In addition, the WRMR indicates a very acceptable fit (WRMR=1.201), while the comparative fit indices CFI and TLI suggest an acceptable fit (CFI=0.925, TLI=0.847).

In summary, the bifactor model appears to be a better representation of the underlying structure of the CLS, as it provides a better fit than the first- and second-order factor model. This model suggests that the items are measuring both specific skills (first-order factors) and a general skill related to collaborative learning (second-order factor). In turn, the items of each dimension of the CLS present high and significant factor loadings in both the first-order factors and the GF as shown in Figure 7.

Table 9. Estimates of the bifactor model of the CLS

X^2	df	RMSEA	(90% CI)	WRMR	IFC	TLI
201.124	85	0.051	0.053 - 0.065	1.201	0.925	0.908

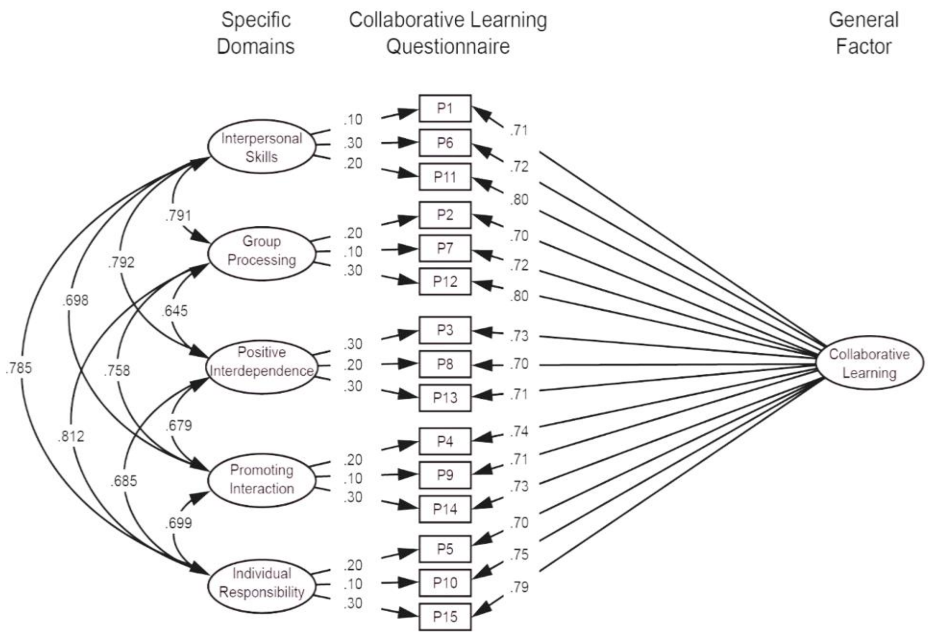

Figure 7. Bifactor structure diagram of the school participation scale

To analyze the degree or level at which the data can be considered to have an overall unidimensional structure, three additional calculations were made using Dueber's bifactor index calculator [30]. Specifically, three bifactor indices were used to measure internal consistency and validity that allow the psychometric quality of the scale and the contribution of each factor to the total score to be evaluated. These indices are the internal consistency coefficient (ECV), the omega hierarchical coefficient (OmegaH), the percentage of common variance explained by the factor (PUC), the factor loading of the GF, and the factor loading of the specific factor 1.

To interpret the bifactor indices, they should be compared with the criteria established by the literature [31]. For example, a scale is considered to have an adequate bifactor structure if the life cycle assessment (LCA) is greater than or equal to 0.80, the OmegaH is greater than or equal to 0.70, the PUC is greater than or equal to 0.50 and the factor loadings of the GF are greater than or equal to 0.3012. Table 10 shows the matrix of Dueber’s bifactor indexes.

Table 10 shows the results of a two-factor analysis of a scale measuring five dimensions of collaborative learning: interpersonal skills, group processing, positive interdependence, promoting interaction, and individual responsibility. In addition, a GF representing the global construct of collaborative learning is included [31]. According to the aforementioned criteria, it is observed that the bifactor model is adequate for the scale since the LCA of the GF is 64.8%, the Omega H is 0.81, and the PUC is 83.3%. The specific factor "Interpersonal skills" is relevant, since the LCA of the specific factor is 23.5%, and the factor loading of the specific factor is greater than or equal to 0.3 for all the items that comprise it. Thus, this finding responds to the scientific question, which refers to the importance of the validation of the CLS to establish teamwork among university students in Junín.

Items 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, and 12 are suitable for the bifactor model, since the factor loading of the GF is greater than or equal to 0.4, and the factor loading of the specific factor is less than or equal to 0.2 for all of them. Items 13, 14, and 15 are not suitable for the bifactor model, since the factor loading of the GF is less than 0.4, and the factor loading of the specific factor is greater than 0.2 for all of them. Finally, the estimation of the global cooperation factor considers the factor loading of each factor, according to Table 10, as interpersonal skills=0.74 (90% CI [0.71, 0.80]), group processing =0.74 (90% CI [0.70, 0.80]), positive interdependence =0.71 (90% CI [0.70, 0. 73]), promotive interaction =0.73 (90% CI [0.71, 0.74), and individual responsibility =0.75 (90% CI [0.70, 0.79]), and overall cooperation factor =0.85 (90% CI [0.82, 0.88]).

Table 10. Matrix of Dueber’s bifactor indexes

Factor	ECV	OmegaH	PUC	Factor loading of the GF	Factorial loading of the specific factor
Specific factor 1 - Interpersonal skills	0.12	0.27	0.39	0.74	0.20
Item 1	0.04	0.09	0.12	0.71	0.10
Item 6	0.05	0.08	0.15	0.72	0.30
Item 11	0.03	0.1	0.12	0.80	0.20
Specific factor 2 - Group processing	0.18	0.33	0.36	0.74	0.20
Item 2	0.05	0.11	0.11	0.70	0.20
Item 7	0.04	0.12	0.1	0.72	0.10
Item 12	0.09	0.1	0.15	0.80	0.30
Specific factor 3 - Positive interdependence	0.11	0.24	0.4	0.71	0.27
Item 3	0.03	0.09	0.15	0.73	0.30
Item 8	0.02	0.09	0.12	0.70	0.20
Item 13	0.06	0.06	0.13	0.71	0.30
Specific factor 4 - Promoting interaction	0.13	0.34	0.39	0.73	0.20
Item 4	0.06	0.09	0.12	0.74	0.20
Item 9	0.04	0.13	0.13	0.71	0.10
Item 14	0.03	0.12	0.14	0.73	0.30
Specific factor 5 - Individual responsibility	0.09	0.31	0.34	0.75	0.20
Item 5	0.02	0.08	0.11	0.70	0.20
Item 10	0.01	0.11	0.1	0.75	0.10
Item 15	0.06	0.12	0.13	0.79	0.30
GF	0.81	0.79	0.82	0.85	0.20
Total	1.44	2.28	2.70	4.52	1.27

3.5. Hypothesis testing between the second-order models and the bifactor model

The analysis was carried out by setting out the working hypotheses. We then proceeded to perform the Chi-square test with the data collected in the study. Thus, the results were obtained as shown in Table 11. The alternative hypothesis (H1) and the null hypothesis (Ho) are: i) There is no significant difference between the second-order model and the two-factor model (nested comparison) for the CLS (Ho); ii) There is a significant difference between the second-order model and the two-factor model (nested comparison) for the CLS (H1). The Chi-square test was performed with the data collected in the study, obtaining the results as shown in Table 11.

According to Table 11, it can be seen that the two-factor model fits better compared to the second-order model, as it has a lower X², a lower RMSEA, a lower WRMR, and a higher ω. Furthermore, the Chi-square difference between the models is significant, indicating that the two-factor model is preferable to the second-order model. Therefore, it can be concluded that the CLS has an appropriate bifactor structure, reflecting the existence of one GF and four specific factors. This implies that the scale measures both the global construct of collaborative learning and the particular dimensions that compose it.

Table 11. Chi-square differences between the second-order model and the two-factor model (nested comparison) for the CLS

	X^2		df	RMSEA	(90% CI)	WRMR	IFC	Second order Vs bifactorial		
								Δx^2	Δdf	ω
Second order model	274.51	78	0.084	0.073 - 0.095	2.91	0.918	274.516	152.	78	0.26
Two-factor model	201.12	85	0.051	0.053 - 0.065	1.20	0.925	201.124	215		

The main objective of the study was to validate the consistency of the CLS using the bifactor SEM in university students from Junín. It is worth noting that there are a variety of studies in which other scales have been developed to measure cooperative learning in different student populations [20], [29]–[31]; however, this bifactor model has never been validated. For this reason, we propose the validation of the learning scale in students from Junín.

The results achieved have shown that the objective was satisfactorily achieved since it is evident that the CLS is an instrument with a high level of validity since the V-Aiken coefficient is very precise and close to 1 [11]. The B-ESEM, whose purpose is the identification of multidimensional sources in complex psychological measures, showed correctly defined factors according to Cuadra-Martínez *et al.* [16]. It should be noted that the totality of the specific factors presents a significant factor loading and is related to the idea that each student in a group should be responsible for his or her progress in learning, which is explained by the incidence of the GF, based on an instrument already solidly validated for educational contexts.

The totality of the adjustment indexes and informative aspects considered showed that the cooperative learning scale is a valid instrument for measuring the performance of students at the University of Junín, according to Vázquez-Toledo *et al.* [15]. In addition, it represents the first evaluation guide in which the five basic elements of cooperative learning are found. Finally, the newly validated instrument, when compared with its predecessor, has only three items in each factor, while the others had 4. This is very important because researchers and academics are looking for easy-to-use assessment instruments, as pointed out by Gegenfurtner [17]. In other words, these three ideas represent the implications resulting from the validation conducted, and which are practical and innovative at the educational level.

Thus, according to the study carried out, the cooperative learning scale represents a novel advance at the scientific level, especially because it allows the evaluation of cooperative learning. Likewise, it was shown that this scale and the bifactor SEM present a well-defined and significant G factor, which supports the fact that there is a global factor of cooperation [9], [18]. This result demonstrates the significant advance it represents for the scientific literature on the evaluation of cooperative learning because it is the first time that a global factor of cooperation is introduced, very similar to other measures; for example, the index of self-determination reported by Zakariya *et al.* [19]. Consequently, as far as the methodological aspect is concerned, the analysis carried out exposed the use of an original bifactor SEM that allows the identification of important multidimensional sources existing in complex psychological measures [11], [16], [17]. Thus, the use of the cooperative learning scale succeeded in demonstrating that it is a valid instrument for conducting an assessment of cooperative learning at the university level.

4. CONCLUSION

It was possible to construct the evidence of content validity according to the expert criteria of the EAC in the university students of Huancayo, 2023, considering aspects such as clarity, coherence, and relevance of an item, using the V-Aiken coefficient, which showed an increasing tendency towards the value of 1. This value ensures that the instrument presents high validity. Regarding the consolidation of the evidence of construct validity employing the confirmatory bifactor analysis method of the EAC in university students in Huancayo, it was possible to specify that, by analyzing the behavior of each of the five dimensions, important information is provided on the different aspects of collaborative learning among the sample of Peruvian students. Based on this, the scale used is very useful for guiding educational interventions aimed at improving collaborative learning skills. Concerning the determination of construct validity through the bifactor structural equation analysis model of the CLS among university students in Huancayo, the internal consistency coefficient (ICC) was used, determining the value of each of the specific factors, according to the respective dimension. This was located in a percentage value above 60%, which qualifies it with a high construct validity. This percentage assigns a level of validity to the CLS and constitutes the nature of the evidence to support the LCA.

As for the reliability of the CLS through the omega coefficient, it was determined at a value above 0.80, very close to the maximum value of 1, which favors its use with high reliability. In addition, the estimation of the global cooperation factor in the CLS was achieved by combining the factor loadings of the specific factors and their verification with the GF loading, according to the construction of Dueber's bifactor index matrix. Finally, it was evidenced that the validity and reliability of the cooperative learning scale applied is achieved through the bifactorial model of structural equations. This is thanks to the analysis of the Chi-square differences between the second-order model and the bifactor model (nested comparison) for the CLS, given by the observation carried out which allowed verifying that the bifactor model has a better fit than the second-order model since it has a lower X^2, a lower RMSEA, a lower WRMR and a higher ω. The validation of this scale using the bifactor model of structural equations is of great importance since it is possible to use instruments to measure the level of collaborative work at the educational level; and, with this tool, to apply strategies in favor of teamwork to strengthen one's learning through common objectives.

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