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iJEP International Journal of Engineering Pedagogy

iJEP | eISSN: 2192-4880 | Vol. 15 No. 2 (2025) | OPEN ACCESS

https://doi.org/10.3991/ijep.v15i2.51561

PAPER

Collaborative Skills Developed in Collaborative Online International Learning as a Multivariate Research Subject

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ABSTRACT

When attending Collaborative Online International Learning (COIL), professors and students engage in synchronous teaching-oriented activities with telecommunication technologies to foster knowledge exchange and cross-cultural professional skills. COIL is crucial in promoting student collaboration, making it a desirable research subject that matches quality education as a sustainable goal. Here, we illustrate some challenges for applied researchers who promote COIL-based innovations. We examined the psychometric structure of a collaboration scale in a COIL experience with a small sample of 65 attendees from Colombia and Ecuador, two Latin American developing countries. The study found that COIL experiences effectively foster collaboration skills, measured through the Transactive Memory System (TMS) framework, emphasizing expertise, credibility, and coordination. In a COIL environment between Colombia and Ecuador, they learned collaboratively in an interdisciplinary formative research educational experience. The results of the collaboration measurement demonstrated the potential to integrate research-based learning with collaborative learning methodologies in global educational contexts. We discuss the implications for educators and policymakers seeking to enhance student collaboration and foster meaningful interactions in online learning environments.

KEYWORDS

collaborative skills, transactive memory system (TMS), structural equation modeling, higher education, educational innovation

1 INTRODUCTION

In today's rapidly evolving knowledge-based economies, higher education institutions are increasingly called to foster technical expertise and the development of essential "soft skills." Among these skills, collaboration is particularly crucial, as it allows students to effectively navigate the complexities of a globalized and

García-Chitiva, M.P., Vázquez-Villegas, P., Correa, J.C. (2025). Collaborative Skills Developed in Collaborative Online International Learning as a Multivariate Research Subject. *International Journal of Engineering Pedagogy (iJEP)*, 15(2), pp. 74–92. https://doi.org/10.3991/ijep.v15i2.51561

Article submitted 2024-08-03. Revision uploaded 2024-11-16. Final acceptance 2024-11-16.

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interconnected society and expand their learning possibilities from interaction with others [1], [2]. These skills empower students to work in diverse teams, solve complex problems, and engage in meaningful exchanges across cultural boundaries—indispensable competencies in the modern data-driven workforce. Consequently, there is a growing emphasis within universities on integrating these skills into academic programs to enhance the holistic development of students and prepare them for professional success [3].

One innovative approach to gaining traction is Collaborative Online International Learning (COIL). COIL represents an educational strategy where students and faculty from different cultural and academic backgrounds collaborate online on shared projects and learning activities. These experiences are intentionally designed to develop and enhance learning and collaboration skills through real-world applications and cross-cultural exchanges [4]. COIL differs significantly from traditional distance education or MOOCs (Massive Open Online Courses) as it emphasizes synchronous, interactive learning that builds intercultural competence and fosters deep collaborative engagement. By participating in COIL activities, students are exposed to diverse perspectives, enhancing their ability to communicate effectively in multicultural environments and work collaboratively on global issues [5].

The COIL approach fosters the development of various soft skills among students by engaging them in cross-cultural and interdisciplinary projects. Key soft skills can be grouped into four categories: (1) intercultural competencies [6]; (2) communication and collaboration skills [7], [8], [9]; (3) critical thinking and problem-solving [8], [10]; and (4) cultural competency [10]. However, it is important to recognize potential challenges, such as barriers to interacting and working as a team when learning online [11], because collaboration depends on aspects within groups and among their members (e.g., match, empathy, trust, etc.). Additionally, the balance between soft skills, such as empathy and ethical thinking, should be considered to ensure comprehensive skill development [4].

The COIL model is particularly impactful for institutions in low-income countries or regions with limited travel opportunities for students and faculty. By facilitating international exposure without the costs associated with physical mobility, COIL provides a cost-effective means to develop global awareness and intercultural skills [12]. This approach aligns with broader educational goals, such as the United Nations Sustainable Development Goals (SDGs), by promoting sustainable educational practices, encouraging knowledge exchange, global citizenship, and active participation in local and international communities [13]. Moreover, COIL can serve as a medium for bridging educational inequalities by providing opportunities for all students to engage in intercultural learning, regardless of their socioeconomic status.

1.1 Addressing research gaps in COIL

Despite the increasing adoption of COIL as a strategy for developing soft skills, there are notable research gaps that this study aims to address. Firstly, much of the existing research on COIL is observational or descriptive, often based on qualitative accounts or anecdotal evidence [14]. While these studies provide valuable insights into participants' experiences, they fail to offer robust, quantitative analyses of how COIL influences the development of specific soft skills such as collaboration. In addition, this type of previous study does not use clear, valid measures that allow us to understand the group collaborative process [15]. This lack of empirical evidence limits our understanding of the mechanisms by which COIL fosters these skills and the extent of their impact.

Secondly, there is a geographical bias in COIL research, with most studies focusing on European and North American contexts [15]. This emphasis neglects the diverse experiences and perspectives from regions like Latin America, Asia, and Africa, where COIL is also being implemented but is less studied. Consequently, the findings from current research may not be fully generalizable to a global context, underscoring the need for more inclusive research that considers a wider range of cultural and regional perspectives [16].

Lastly, a validated framework is needed to measure collaboration within COIL experiences. While the importance of these skills is widely recognized, few studies have employed rigorous measurement tools to assess how they are developed in COIL contexts. A framework that accurately captures the dimensions of collaboration can contribute to more effective evaluation and improvement of COIL initiatives [16].

1.2 Objective of the study

To address these gaps, this study proposes using the Transactive Memory Systems (TMS) framework as an innovative approach to measuring collaboration within COIL experiences. Furthermore, it employs Structural Equations (SEM) to analyze the development and impact of collaborative skills (specialization, credibility, and coordination) cultivated through COIL. The objective is to provide a robust, quantitative analysis to clarify how these skills emerge and evolve in COIL settings and offer empirical evidence supporting these skills' development across diverse academic and cultural contexts.

2 THEORETICAL FRAMEWORK

Below, we present why TMS is relevant as a construct that clarifies the measurement of collaboration within learning groups in an international online educational experience such as COIL.

2.1 Transactive memory systems as a framework for measuring collaboration

The TMS framework, developed by Lewis [17], offers a theoretical lens for understanding how groups collaboratively manage knowledge. TMS is particularly suited to measure the dynamics of collaboration in online environments such as COIL, as it captures how teams distribute knowledge, build trust, and coordinate tasks. The framework identifies three key dimensions essential to team effectiveness:

- Specialization (SP): This dimension relates to recognizing and using distinct expertise within a team. In COIL, SP involves how faculty and students identify, acknowledge, and utilize each other's unique skills and knowledge areas, leading to an efficient division of labor and enhancing the learning process. This SP allows teams to maximize their collaborative potential by leveraging diverse areas of expertise within the group [18], [19].
- Credibility (CR): CR refers to team members' trustworthiness and perceived reliability. For successful COIL experiences, CR is crucial, as participants from different cultural, disciplinary, and linguistic backgrounds need to establish trust to facilitate effective communication and ensure that knowledge is shared

accurately and appropriately [20]. Trust-building is particularly important in virtual environments, where non-verbal cues are absent, and CR must be established through consistent and meaningful interaction.

- Coordination (CD): CD encompasses efficiently organizing and synchronizing tasks and actions within the team. Effective CD is necessary in COIL to ensure that all activities are well-structured, align with the learning objectives, and facilitate smooth collaboration across different time zones and cultural contexts [21]. CD in COIL requires setting clear goals, assigning roles, and effectively using online tools to manage workflows.

The TMS framework is particularly appropriate for COIL as it provides a structured and validated method for assessing the processes of knowledge sharing, trust-building, and task CD that are central to collaboration in these experiences. Unlike other frameworks that may focus broadly on team dynamics without accounting for the unique aspects of online intercultural collaboration, TMS is specifically designed to evaluate how distributed knowledge is managed and leveraged within teams. This makes TMS uniquely suited for understanding the collaborative processes in COIL and their relationship to developing essential soft skills.

By applying the TMS scale, which has been validated in various languages and cultural contexts (e.g., Spanish and Chinese) [22], [23], this study provides a rigorous, quantitative framework for assessing collaboration skills development in COIL experiences. Prior research in virtual team environments has demonstrated the ability of TMS to measure how groups manage shared expertise, build mutual trust, and coordinate effectively, indicating its strong applicability for analyzing COIL settings [24].

2.2 COIL and multivariate research through structural equation modeling

This study employs Structural Equation Modeling (SEM) as a multivariate statistical technique to capture the multifaceted nature of collaboration in COIL. SEM allows for examining relationships between latent variables (such as the TMS dimensions) and their observed indicators (e.g., questionnaire responses). It analyzes how these constructs interact and contribute to developing soft skills [25]. This approach helps validate the theoretical structure of TMS within the COIL context and enables a comprehensive understanding of how these experiences foster collaboration [26], [27].

In SEM, the relationships between latent variables and their corresponding observed measures are represented in a path diagram, where single-headed arrows indicate causal links and double-headed arrows denote covariances between variables [28]. The adequacy of the model is evaluated using several fit indices, including the Standardized Root Mean Square Residual (SRMR), Root Mean Square Error of Approximation (RMSEA), and Comparative Fit Index (CFI), which collectively assess the degree to which the theoretical model aligns with the empirical data [28], [29]. A well-fitting model provides evidence that the theoretical assumptions of the TMS framework are reflected in the observed collaborative behavior patterns within COIL participants.

2.3 Challenges and strategies for applying SEM to COIL data

A key challenge in applying SEM to COIL-related research is the small sample sizes, as COIL sessions typically involve a limited number of participants, making

parameter estimation more complex [30], [31]. Furthermore, the data collected from COIL experiences may not meet the normality assumptions required by traditional SEM techniques, potentially impacting the validity of the results [32]. However, some analytical strategies and solutions to this problem are summarized in Table 1.

Table 1. A non-exhaustive list of recommended analytical strategies to deal with the small sample size problem in structural equation modeling

Analytical Strategy	Scrutiny Quality	Recommenders
Univariate Normal Distribution	Distributional Assumptions	[33]
Multivariate Normal Distribution	Distributional Assumptions	[33]
Top-Down Model Specification	Model Complexity Reduction	[32]
Bottom-Up Model Specification	Model Complexity Increase	[32]
ML* Estimation	Statistical Estimation	[32]
Corrected ML* Estimation	Statistical Estimation	[32]
MIIVs** Estimation	Statistical Estimation	[34]
Penalized Likelihood Estimation	Statistical Estimation	[35]
Parameters Significance	Hypothesis Testing	[36]
Confidence Intervals	Hypothesis Testing	[32]
Cutoff Criteria for Fit indexes	Model Goodness-of-Fit	[37]
Swain Correction	Model Goodness-of-Fit	[38]

This study employs various strategies to address the challenges, including top-down model specification to reduce model complexity and bottom-up model specification to build and test the model's components incrementally [32].

Additionally, alternative estimation methods, such as Corrected Maximum Likelihood (ML) and Model Implied Instrumental Variables (MIIVs), are utilized to handle non-normal distributions and improve model accuracy, especially when working with smaller sample sizes [32], [34]. These approaches enhance the robustness of the SEM analysis and ensure that the findings are reliable and generalizable.

In this paper, we pose three research questions:

RQ1: Is the TMS concept relevant to the study of collaboration among students learning in a COIL educational experience?
RQ2: How reliable is it to analyze collaboration among COIL students using the construct dimensions of coordination, CR, and SP?
RQ3: Which alternative estimation methods are best for measuring the effect of collaboration across the dimensions of coordination, CR, and SP in a small sample of students?

3 MATERIALS AND METHODS

We followed a non-experimental, observational-cross-sectional, single-application [39] method at the end of the COIL educational experience, with students from two private universities in Latin America, who worked collaboratively for six weeks while receiving instruction on research training content. In the measurement,

we examined the perception of the level and process of collaboration regarding CR, coordination, and specialization, with the TMS instrument translated into Spanish and validated by García-Chitiva [40]. Table 2 describes the educational strategy's sequence. The participants were 65 students who attended six COIL sessions. These sessions were held online once a week for two hours each and were geared towards teaching basic interdisciplinary research skills at two private South American universities.

Using Google Classroom, participants from Colombia (n = 32) and Ecuador (n = 33) gathered with her local lecturer and her teaching fellow from abroad. Participants from Colombia (aged between 21 and 43) were formally enrolled in either a bachelor's program in social sciences or a program of education in early childhood, while participants from Ecuador (aged between 20 and 25) were formally enrolled in either a bachelor's program in architecture or an undergraduate program in medicine. While in Ecuador, students attended in-person classes to participate in these COIL sessions; in Colombia, students participated in these sessions as part of their regular online classes. Spanish was the official language for all these sessions.

Before launching the sessions, two female instructors (i.e., assistant professors with early-career research trajectories in their countries) organized and designed the teaching-learning activities for each of the six sessions to teach basic interdisciplinary research skills inspired by the open education movement (refer to Table 2).

Table 2. COIL sessions for teaching interdisciplinary research skills

Unit	Topic and Description	Week
1	The welcoming session, ice-breaker activity, conception of research ideas, and research projects	1
2	Maturation of research ideas and projects Information Search through library services	2
3	Research project consolidation: Writing the introduction	3 and 4
4	Research project consolidations: Writing the literature review closing session	5 and 6

In the first week, the students attended the initial session in which they participated in an icebreaker session where they each reported details of themselves (e.g., learning preferences, skills, and aspects in which they are not very skilled academically), which made it easier for the participants to learn details about their peers from the two countries. With this first information, each participant was involved in a group of a maximum of three people with classmates with whom they felt affinity. It was facilitated through an Excel file in the Google Classroom where the groups registered. Spanish was the official language of all these sessions. To begin the development of the activities within the groups, the students had to communicate to agree on the agreements of times and commitments. The teachers developed three synchronous meetings to explain the activities and resolve doubts. During the six weeks, students learned collaboratively in groups about conceptual and technological resources that they can use to increase their ability to search and retrieve technical information published by various scientific and professional sources of recognized academic reputation and CR (e.g., indexed journals or peer-reviewed books) that can be accessed with and without subscription-based online library databases (e.g., Web of Science, Scopus, Lens, Google Scholar, Redalyc, Latindex). These learnings were from materials in video format, PDF, and practical workshops they had to develop. As the purpose of this study was to explore perceptions about the collaboration they

had with their peers at the end of the six-week course, this paper's analyses focus particularly on examining the results obtained on the scale applied to measure collaboration (i.e., illustrating the challenges of making collaborative international online learning skills a multivariate research topic). We developed a rigorous confirmatory factor analysis to provide evidence on the psychometric properties of the TMS scale as a proxy for collaboration skills [17].

3.1 Data collection procedure and data preprocessing

The instructors informed all participants about the teaching purpose of these COIL sessions and why their voluntary participation in an online questionnaire would be used for academic purposes. Instructors followed Helsinki's declaration of ethical principles to preserve participants' personal information confidentiality under informed consent. The data collection relied on the online application of the TMS scale as a proxy for collaboration skills. The scale was translated and empirically validated for Spanish speakers [40].

This scale examines collaboration among team members through a series of 15 Likert-like items. These items were adapted as statements of an electronic Google form that takes around 20 minutes to complete. The scale has the following three dimensions: SP, CR, and coordination (CD), with five items each (see Figure 1). Participants completed the scale under similar synchronous interaction and attendance conditions at the end of the sixth week's last session, summarized in Table 1. Students' answers were saved as a standard Google spreadsheet, the computational input for further statistical analyses.

3.2 Statistical analyses

Statistical analyses were conducted in R [41], and the Supplementary Material followed principles of open science and reproducible research with an Rmarkdown file [42], [43] as part of an R project [44] available as a public GitHub repository.

The analysis initializes by examining the standard assumption of univariate and multivariate normal distribution of observed variables (i.e., the 15 items of the TMS scale). Scrutiny of these assumptions relied on the Henze-Zirkler test [45], included in the R package MVN [33]. This test allows us to address our study's sample size, which is admittedly small from the SEM viewpoint but reasonably typical of a COIL experience from a higher education perspective. Thus, we agree with Rosseel [32] that "small sample sizes are simply a reality."

As this examination is expected to fail due to the small sample of participant students, the possibility of committing confirmation bias is contrasted through a series of subsequent procedures [46]. Subsequent scrutiny relies on a series of confirmatory factor analyses. They are ordered by their model complexity (i.e., the number of parameters to be estimated), starting from the simplest models to the most complex ones. In doing so, the organization of the results mirrors the list of analytical strategies in Table 1. We used the software Ωnyx [47] to depict model specifications and export their associated syntaxes in the R programming language.

These syntaxes allowed us to compare the statistical estimates with the following methods: ML in lavaan [48], penalized ML in lslx [35], and MIIVs estimations in MIIVsem [34]. Models' goodness-of-fit with and without corrections for

non-normality and small sample size are based on ML estimation, employing cutoff criteria proposed by Hu and Bentler [37] and revisited by Wolf and McNeish [49].

4 RESULTS

We began by evaluating the reliability of the TMS scale. The results showed excellent reliability, with Cronbach's $\alpha = 0.829$ and a McDonald's $\omega = 0.872$. This result allowed us to see the instrument's relevance to examining collaboration within collaborative learning groups in COIL. Subsequently, we analyzed the results of the TMS test in greater depth through distribution analysis and confirmatory factor analysis (FCA).

4.1 Distributional assumptions

Figure 1 shows the statistical distribution of observed variables. The symmetry of these distributions is far from the standard Gaussian distribution (e.g., some of them are left-tail skewed, others are similar to a rectangular distribution, while others show a shark-like bite shape). In analyzing these distributions with the MVN algorithm, we confirmed that they did not comply with the assumption of univariate normal distribution, and the Henzel-Zirkler test revealed a significant deviation from the multivariate normal distribution expected for these variables (HZ = 1.14; p = 0.00). The Supplementary Material provides additional evidence on the skewness and kurtosis of these variables. Despite this statistical behavior, these variables are included in further multivariate analyses with confirmatory factor analyses.

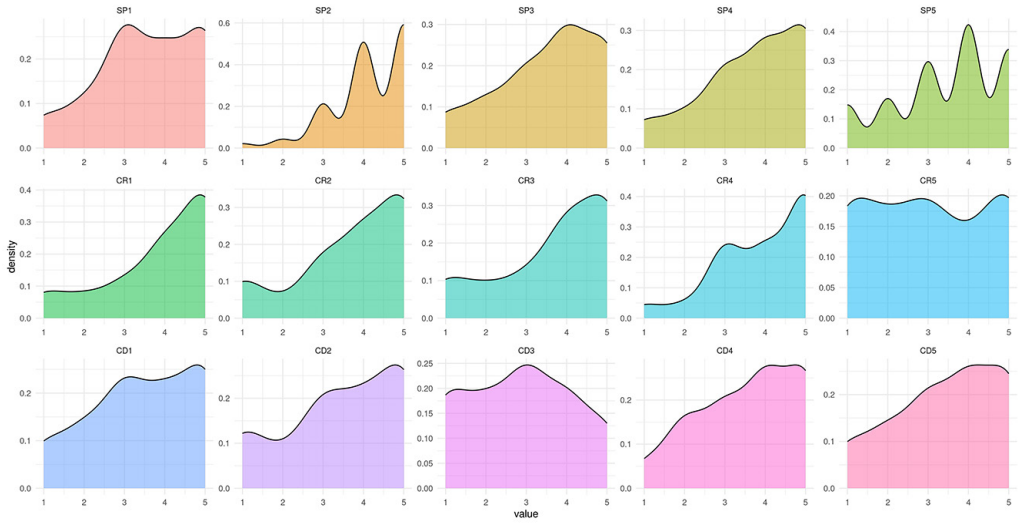

Fig. 1. Univariate distribution of individual items of the TMS scale

4.2 Top-down specification

The top-down specification includes all 15 observed variables with their corresponding theoretical links with the three latent variables representing the theoretical dimensions of collaboration skills in TMS terms, as depicted in Figure 2.

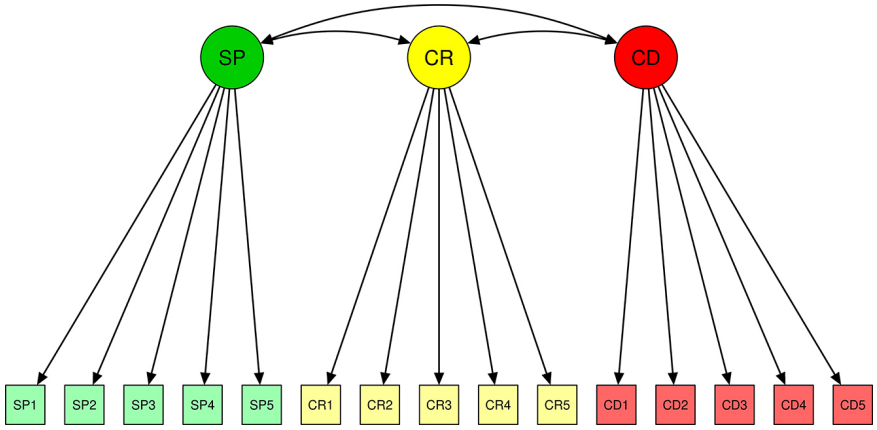

Fig. 2. A visual representation of a confirmatory factor model of collaboration skills in a COIL experience

Table 3 summarizes the statistical estimations of Figure 1 by employing the ML method with and without non-normality corrections.

Table 3. Statistical estimated parameters for collaboration

		Model A			Model B		
		Estimate (SE)	R^2	p	Estimate (SE)	R^2	p
Factor Loadings							
SP	SP1	0.85 (0.10)***	0.73	0.000	0.85 (0.09)***	0.73	0.000
	SP2	0.04 (0.13)	0.00	0.742	0.04 (0.17)	0.00	0.810
	SP3	0.73 (0.11)***	0.54	0.000	0.73 (0.10)***	0.54	0.000
	SP4	0.94 (0.09)***	0.89	0.000	0.94 (0.08)***	0.89	0.000
	SP5	0.68 (0.11)***	0.48	0.000	0.68 (0.11)***	0.48	0.000
CR	CR1	0.64 (0.11)***	0.42	0.000	0.64 (0.12)***	0.42	0.000
	CR2	0.94 (0.09)***	0.89	0.000	0.94 (0.08)***	0.89	0.000
	CR3	0.96 (0.09)***	0.93	0.000	0.96 (0.07)***	0.93	0.000
	CR4	–0.03 (0.13)	0.00	0.781	–0.03 (0.14)	0.00	0.802
	CR5	0.26 (0.12)*	0.07	0.037	–0.26 (0.14)	0.07	0.069
CD	CD1	0.84 (0.10)***	0.72	0.000	0.84 (0.08)***	0.72	0.000
	CD2	0.71 (0.11)***	0.51	0.000	0.71 (0.10)***	0.51	0.000
	CD3	–0.26 (0.13)	0.07	0.041	–0.26 (0.14)	0.07	0.063
	CD4	0.84 (0.10)***	0.72	0.000	0.84 (0.10)***	0.72	0.000
	CD5	–0.29 (0.12)*	0.09	0.019	–0.29 (0.13)*	0.09	0.026
Latent Covariances							
SP	w/CR	0.87 (0.04)***	–	0.000	0.87 (0.04)***	–	0.000
CR	w/CD	0.84 (0.05)***		0.000	0.84 (0.07)***		0.000
SP	w/CD	0.95 (0.03)***		0.000	0.95 (0.02)***		0.000
Fit Indices							
	χ^2(df)	177.64 (87)****		0.000	177.64		
	RMSEA	0.13			0.13		
	SRMR	0.11			0.11		
	CFI	0.86			0.86		
	TLI	0.83			0.83		
				Scaled χ^2(df)	153.85 (87)***		0.000

Notes: +Fixed parameter; *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Model A in Table 3 presents the estimations without using any correction for non-normality. Model B introduces the estimations with the SatorraBentler correction for non-normal distributions (i.e., Scaled χ^2(df)). Most factor loading estimations behaved as expected by the theoretical considerations of the TMS scale. Four items (i.e., CR4, CR5, CD3, and CD5) revealed gross deviations from the theoretical specifications due to their non-significant, negative factor loadings.

In addition, a fifth item (SP2) showed almost null factor loading, an unexpected outcome from the theoretical considerations of the TMS scale. This model's goodness-of-fit indexes that specify a multidimensional structure are far from acceptable following classic rules of thumb for goodness-of-fit indexes (i.e., CFI = 0.856; RMSEA = 0.127; SRMR = 0.109).

Due to the items whose statistical estimation behaved differently than expected, we proceed by reducing the model complexity and estimating a simplified model that preserves the items whose statistical estimations behaved as theoretical expectations. Figure 3 shows the standardized estimates for all item factor loadings and latent correlations. Additional scrutiny is provided in the supplementary Rmarkdown file of our public GitHub repository. This simplified model revealed acceptable goodness-of-fit indexes (i.e., CFI = 0.987; RMSEA = 0.055; SRMR = 0.038).

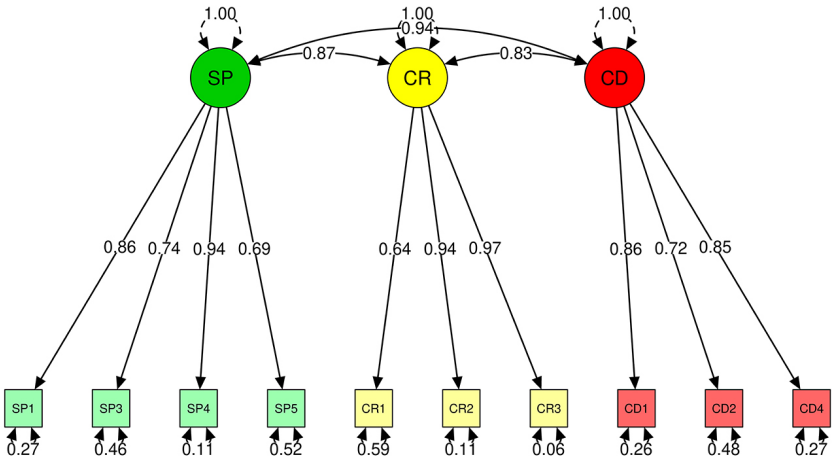

Fig. 3. A simplified model specification for the multidimensional structure of the Transactive Memory Scale as a proxy for students' collaboration in a COIL experience

4.3 Bottom-up specification

In this section, instead of testing the simplified model depicted in Figure 1, we focus on one theoretical dimension at a time to highlight how statistical estimations for factor loadings, residuals, and goodness-of-fit indexes change as a function of the implied variance-covariance matrices for the three model specifications depicted in Figure 4. The results reported here were based on the same ML estimation method employed for the top-down specification shown in Figure 3.

We noted that the statistical estimation for the implied factor loadings did change in all these simple unidimensional model specifications. However, their change is negligible in most cases, as they all preserved statistical significance (see Supplementary Material in our public GitHub repository). Figure 4 also shows that

residuals, represented as curved double arrows below observed variables, revealed tiny changes compared with their counterparts in Figure 3.

In terms of goodness-of-fit indexes, we noted substantial changes that altogether suggest an almost perfect unidimensional structure for the sub-scale of CD (CFI = 1.000; RMSEA = 0.000; SRMR = 3.68e-08), CR (CFI = 1.000; RMSEA = 0.000; SRMR = 8.84e-09), and SP (CFI = 0.997; RMSEA = 0.051; SRMR = 0.021). Another interesting result relates to the sensitivity of goodness-of-fit indexes when the covariance between latent variables is explicitly modeled in a multidimensional specification and when these covariances are not considered in unidimensional specifications.

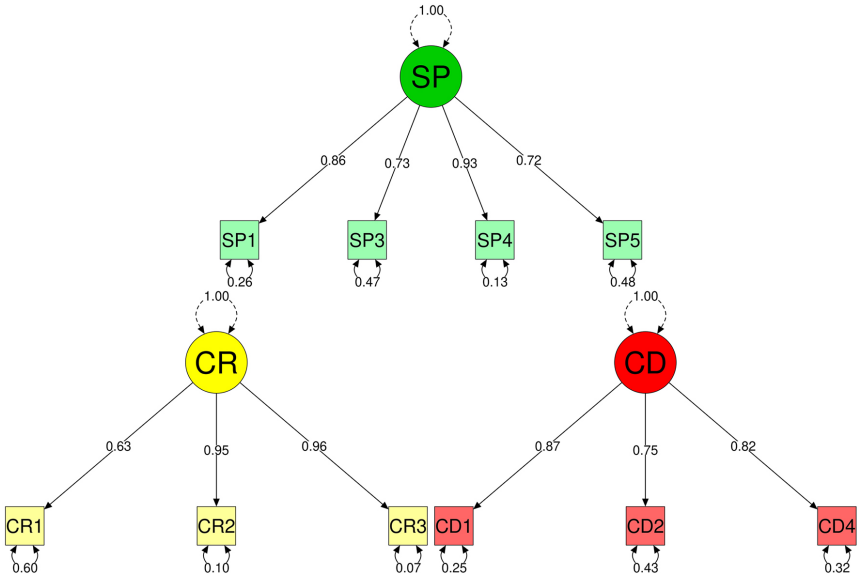

Fig. 4. Simplified unidimensional confirmatory factor models for SP

Notes: Specialization (in green), Credibility (in yellow), and Coordination (in red).

To evaluate to what extent the small sample biases parameter estimations, we conducted further estimations using the strategy of the MIIVs (MIIVs) [36] and the penalized ML [37] for the original theoretical model depicted in Figure 1.

4.4 Estimation methods and estimated parameters

Table 3 showed that one-third of the observed variables in the original model specified in Figure 1 did not behave according to the theoretical expectations due to the values observed for their statistical estimations. To discard any possibility that these estimations were biased by the ML method, in this part of our analysis, we test the same model with two additional statistical estimations: the MIIVs method and the PML method. The emphasis here is not on goodness-of-fit but on each estimated parameter. If the variables and their bivariate relationships are robust enough, their estimated parameters should be similar regardless of the estimation method employed.

The results in Figure 5 show that all estimation methods provide relatively similar results, although those offered by the MIIVs tend to be slightly more precise than those of ML and PL.

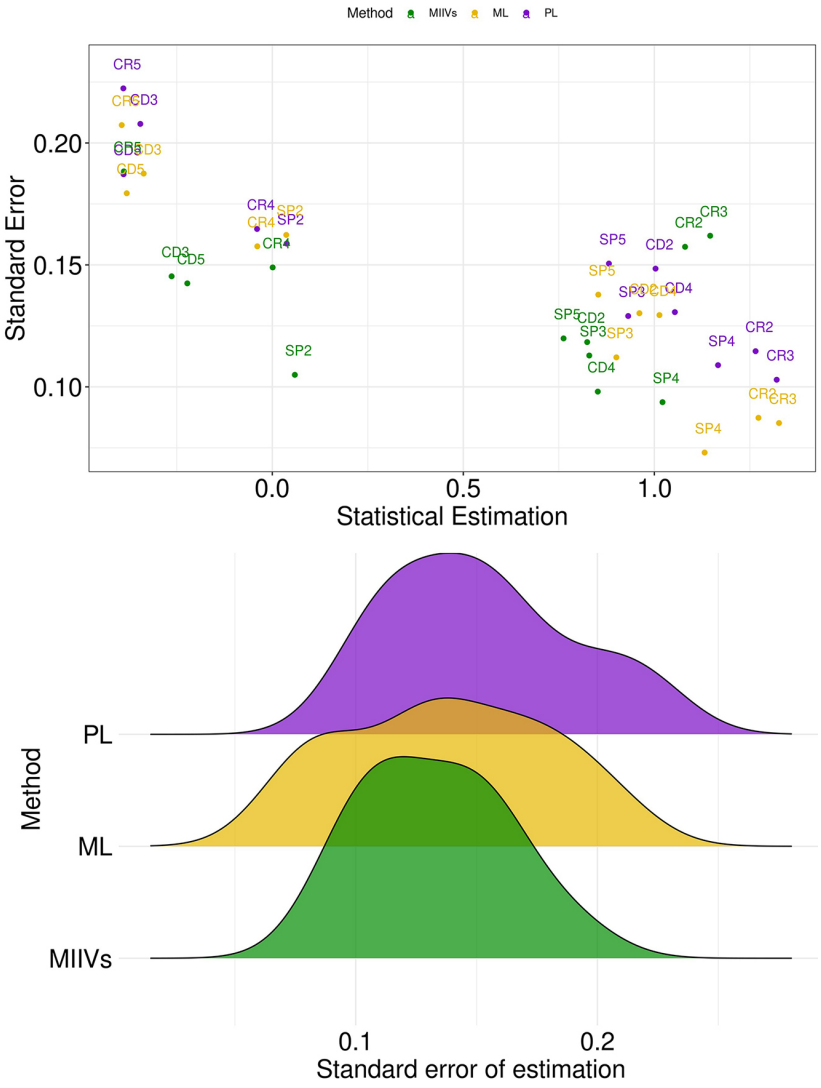

Fig. 5. A scatterplot showing the relationship between statistical estimates and their standard error (on the top) and the resulting observed distributions for each method's standard error of estimations (on the bottom)

Additional information is included in the Supplementary Material of our public GitHub repository. With these results, the educational professional has enough information to claim that the valid measurement of collaboration for the COIL experience is based on a simplified version of the original TMS scale [15] conceived by English speakers and validated for Spanish speakers [23].

5 DISCUSSION AND CONCLUSION

This paper aimed to illustrate why COIL can be framed as a multivariate research subject that matches the goals of a relational approach to knowledge exchange in higher education [50]. We showed why we exploited the measurement of the TMS [17] as a proxy of collaboration to advance our understanding of COIL-related experiences as endeavors oriented to the internationalizing curriculum (RQ1). In pursuing this internationalization, professionals will likely find several challenges summarized in a recent textbook [51].

Our contribution is inspired by methodological challenges related to COIL as a desirable research subject that matches quality education as a sustainable goal. We believe that COIL-based skills training can be a promising and challenging topic. Collaborating is one of the most valued skills in the [52] educational and work environments, which are also among the global goals of the SDGs. It is challenging because it requires a clear understanding on the part of instructors and trainees, where it is understood that the concept of collaboration is deeper than the [53] grouping or meeting people. In addition to the challenges within the classroom (microcurricular), there are also others related to the pedagogical and curricular proposal of the institutions (mesocurricular) to develop collaboration skills and others in a transversal way in teaching. This requirement was promptly addressed in the educational agendas of higher education institutions, considering that today, a large percentage of educational institutions in the world participate in global classroom projects using the COIL educational strategy.

The present work generates relevant empirical evidence that provides a reliable and pertinent measure to examine group collaboration. It is an empirical contribution, from educational implementation to the measurement of collaboration and its analysis, which can be taken as a model to examine collaboration in COIL processes worldwide. The TMS provides information on collaboration within the group, which can be developed intentionally in educational processes to favor the individual's competencies to "know how to collaborate" and, in groups, to effectively manage collaboration in terms of CD, CR, and SP (RQ2). An effective collaborative learning process requires time for its development [2], so it must be cultivated in the educational framework.

Our endeavor illustrated the rigor of a valid collaboration measurement, recognizing the small sample problem as an inherent feature of any COIL-related experience. Our illustration followed some solutions based on state-of-the-art SEM [32] (RQ3). Results confirmed that collaboration among students attending a COIL-related experience is based on getting familiar with others' expertise, CR, and coordination.

Colombia and Ecuador are two Latin American developing countries where interdisciplinary research skills are regarded as transversal across disciplines. Instead of teaching these skills following classic textbooks of research methodology, the COIL sessions showed an updated perspective that recognizes the role of scientific databases with or without subscription-based access (e.g., Google Scholar, Scopus, Web of Science, Lens, Redalyc, Latindex) as fundamental tools for the student's future professional development. These COIL sessions are examples of "inquiry as a way of being," intrinsically connected with meaningful professional learning [54]. We highlight a particular connotation regarding the COIL sessions reported in this work. In these sessions, professors used information search to support the ideas of a thesis proposal. Professors demonstrated the difference in the amount of literature retrieved when using Spanish versus English. Once students were told to apply and compare the quality and quantity of the information retrieved for each topic selected by students, professors explained why professional progress could be difficult in Latin America when English is not their mother tongue [55]. This might prevent them from accessing scientific or technical up-to-date literature [56]. From this viewpoint, several implications can be derived for educators and policymakers.

5.1 Implications of this study

The COIL experience reported in this paper poses several implications considering the countries in which it occurred. One of the first implications of this work is

the empirical contribution that this study makes in approximating TMS as a reliable and pertinent construct to examine the processes of collaboration within groups. This contribution reveals three dimensions (coordination, credibility, and specialization) that make it easier for educators to set educational criteria in teaching so that students develop competencies that facilitate them to interact with others, communicate effectively, and know how to use their knowledge and skills so that their work enriches the work of their team in pursuing common objectives.

The second valuable implication of this work is the understanding of banding competencies, particularly collaboration within the COIL strategy framework as a multivariate research topic. Subsequent studies may develop similar approaches in a teaching-learning framework of another content, with students from another background and examining other types of variables, which can give greater richness in the multivariate understanding of collaboration, e.g., gender, age, the type of program in which the students are enrolled, etc.

A third implication is the role of alphabetizing students on "scholar consumption," using websites that provide subscription-based access to massive databases of scientific research and technical literature [57]. This alphabetization is also pivotal for lecturers focusing on teaching without participating in research projects. From this viewpoint, using a COIL-like format to teach interdisciplinary research skills can boost innovations founded in "research-based teaching" [58]. We argue that if these innovations were aligned with a research-as-a-service mindset aiming to enhance government university-industry interactions, COIL sessions might become a driving mechanism for boosting the economic complexity of these countries [59]. There are many ways to frame COIL experiences as useful and desirable innovations for higher education, but from our perspective, they all converge on collaboration. Collaboration as an isolated concept does not make sense until it is concretely linked to a teaching-learning experience where people must identify the experience, CR, and CD of others to comply with a brief research proposal.

5.2 Contribution of this study

This study contributes significantly to COIL and soft skills development literature by presenting a validated framework, TMS, to measure collaboration in international collaborative online learning environments. It employs robust multivariate analysis SEM to provide empirical evidence of how these skills are fostered in various educational contexts. This approach offers a more nuanced understanding of the impact of COIL on soft skills, providing insights that can inform future research and practical pedagogical strategies to enhance global intercultural learning competence, fostering collaborative competencies by understanding essential components (SP, CR, and CD) for working together in higher education.

5.3 Limitations and future work

We identified at least two constraints that may be an opportunity to develop an alternative approach in future work. In the first, we see that a non-experimental, cross-sectional design showed the perspective from a single group after a single measurement of collaboration, which did not allow us to see the development of collaboration from other groups over a longer time. Future work can take this lesson

learned to make a similar observation in more than one group and for a longer time so that the development of collaboration over time within the groups can be analyzed.

The second limitation is related to the few sessions of synchronous meetings with the teachers and the group in general since the development of collaboration can have a greater scope if there are continuous indications to reinforce collaborative actions within the groups (e.g., clearly inform about their skills and specialty topics, define roles to follow up on collaborative activities, etc.) and whether you can learn from successful actions taken by peers from other groups.

In future works, educators and researchers interested in the subject can undertake studies where they define quasi-experimental designs with a control group and longitudinal designs where they can measure the evolution of TMS in the groups and relate it to achievement, as was done in the work of García-Chitiva [40]. In addition, this work provides a detailed and complete script available in an open-access repository that allows the reproduction of the approximation of the structural equation model we address. Our analysis procedure can be adapted so researchers can perform similar analyses, even with other variables.

6 ACKNOWLEDGMENTS

The authors acknowledge the financial support of Writing Lab, Institute for the Future of Education, Tecnologico de Monterrey, Mexico, in producing this work. In addition, special thanks are given to Professor Ximena Patricia Curay Correa, to the students participating in the Medicine and Architecture programs from the University of Azuay in Ecuador, and to the students of the Bachelor's Degrees in Early Childhood Pedagogy and Social Sciences from the Institución Universitaria Politécnico Grancolombiano de Colombia who participated in the educational experience Collaborative Online International Learning (COIL) with the first author of this paper in the first semester of the year 2022.

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