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Research Article

Psychometric network of the online learning strategies questionnaire in Peruvian university students

Manuel Alejandro Concha-Huarcaya [1]
0000-0002-8564-7537

Antonio Serpa-Barrientos [2]
0000-0002-7997-2464

Luis Alberto Sosa-Aparicio [1]
0000-0002-5903-4577

Enrique Giovanni Pérez-Flores [1]
0000-0002-4640-2502

Jacksaint Saintila [3*]
0000-0002-7340-7974

[1] Departamento de Psicología, Universidad César Vallejo, Lima, PERU
[2] Departamento de Psicología, Universidad Nacional Mayor de San Marcos, Lima, PERU
[3] Escuela de Posgrado, Universidad Peruana Unión, Lima, PERU
[*] Corresponding author: jacksaintsaintila@gmail.com

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ABSTRACT

Online learning strategies refer to the methods and approaches students use to organize study activities, manage course content, and regulate participation in virtual learning environments. These strategies are relevant to educational technology because they provide measurable indicators that can inform instructional design, learning analytics, adaptive learning systems, and student support in online and blended courses. This study examined the psychometric properties of the online learning strategies scale (OLSS) using a psychometric network analysis approach in Peruvian university students. The sample included 520 university students (389 women = 74.8%; 131 men = 25.2%) aged 18 to 40 years. Descriptive analyses were conducted to evaluate item distributions. The psychometric network structure of the OLSS was then estimated using exploratory graph analysis with bootstrap procedures, followed by assessment of community stability and structural consistency. The results identified a four-community structure corresponding to motivation, self-control, Internet literacy, and Internet anxiety. The network showed high structural stability, with bootstrap replication values close to 1.00 for most items and high structural consistency across communities. These findings support the internal structure and reliability of the OLSS in the studied population. From an educational technology perspective, the OLSS may help instructors and instructional designers identify students requiring motivational, self-regulatory, digital literacy, or affective support in technology-enhanced learning environments.

Keywords: online learning, online learning strategies, educational technology, network analysis, psychometrics, university students

INTRODUCTION

Educational institutions have adopted face-to-face, online, and blended modalities to respond to diverse educational needs (Islam et al., 2023). Although online learning is not a recent phenomenon (Moore, 2023), the COVID-19 pandemic accelerated the implementation of virtual classrooms and consolidated this modality as a stable alternative in higher education (Islam et al., 2023; Mheidly et al., 2020).

This shift expanded opportunities for access and academic continuity, but it also increased the demands placed on students, who must assume greater levels of autonomy, digital competencies, and sustained engagement in their studies with less immediate instructional support (Broadbent, 2017; Hodges et al., 2020). Consequently, online learning is currently understood as a challenging educational strategy that requires both technological and psychological preparedness from institutions as well as from students themselves (Zekaj, 2023).

In this context, online learning strategies are defined as methods and approaches that enable students to organize their study, manage course content, and regulate their participation in virtual platforms (Zekaj, 2023). These strategies include promoting interactivity through communication, facilitating the application of concepts using multimedia resources (e.g., video demonstrations), and strengthening the sense of belonging to a learning community (Palaming, 2022). Additionally, they are associated with competencies such as self-regulation, time management, and the maintenance of motivation, which are particularly relevant in environments where students must sustain academic routines with greater personal responsibility (Broadbent, 2017; Luo & Zhou, 2024). From a broader perspective, students may employ cognitive, metacognitive, resource management, and affective strategies to cope with the demands of online learning (Halim & Sunarti, 2021), aiming to improve learning and participation in the virtual classroom, even though their relationship with academic performance may vary depending on contextual conditions (Broadbent, 2017). Beyond individual academic behavior, online learning strategies have direct implications for educational technology design. When students report difficulties in motivation, self-control, Internet literacy, or Internet anxiety, these indicators can inform the design of course interfaces, feedback mechanisms, onboarding tutorials, and instructor interventions. For example, low self-control may indicate the need for structured pacing, calendar-based reminders, and progress dashboards; difficulties in Internet literacy may justify digital search and platform training; and high Internet anxiety may guide the inclusion of low-stakes orientation activities and human support channels. Thus, the assessment of online learning strategies is not only a psychometric task but also an applied component of technology-enhanced learning design.

From a theoretical perspective, the online strategic learning model is relevant for understanding this phenomenon, as it describes how individuals acquire knowledge, skills, and attitudes through the use of digital tools in environments characterized by flexibility in time and space. Such environments may enhance indirect social interactions and facilitate access to richer informational resources through dynamic interfaces (Tsai, 2009). Within this perspective, the student is positioned at the center of the learning process, and their strategies are linked to domains such as self-regulation, affect, and perceived competence (Tsai, 2009).

Based on this model, Tsai (2009) developed the online learning strategies scale (OLSS) to assess learning strategies specific to virtual environments. The OLSS was initially proposed in a preliminary version consisting of 22 items and seven factors and was later refined to 20 items and five dimensions (Meza-López et al., 2016). Previous studies have reported favorable psychometric evidence, including acceptable indicators of validity and internal consistency (Tsai, 2009). In summary, the OLSS represents an instrument specifically designed for virtual contexts, as it incorporates components related to Internet use and self-regulatory processes characteristic of digital learning (Tsai, 2009).

In Latin America, instruments originally designed for face-to-face contexts are frequently used, such as the CEMA (Beltrán et al., 2006), the CEVEAPEU (Gargallo et al., 2009), and the ACRA scale (Román & Gallego, 2008). These instruments do not sufficiently incorporate features specific to virtual learning, such as digital self-regulation, online communication, and the affective demands associated with platform-mediated learning (de Oliveira et al., 2022). Compared with these general learning strategy scales, the OLSS is more closely aligned with virtual learning because it includes Internet use, online self-regulation, and affective reactions to digital environments. Some Spanish-language work has addressed online learning strategies and anxiety in university students (Castillo et al., 2021; Meza-López et al., 2016), but evidence on the network organization of OLSS items in Latin American samples remains limited. Consequently, the present study extends prior work by examining not only whether the instrument is internally consistent but also how its items organize into communities that are potentially actionable for educational technology practice.

Furthermore, the study of these strategies can be enriched through psychometric network analysis, an approach that allows the examination of association patterns among variables in multivariate data and the description of the relational structure of an instrument (Briganti et al., 2022; Freeborn et al., 2023). This methodology provides additional value by enabling the identification of central items that may sustain the structure of the system, as well as those that contribute less to its connectivity, which is useful for understanding the internal functioning of the instrument and guiding psychometric decisions (Epskamp et al., 2018). However, studies that examine online learning strategies from this perspective remain scarce, creating a methodological and applied gap within the psychometric literature. Within contemporary educational technology, validated measures of online learning strategies can support learning analytics and adaptive learning systems. Instruments such as the OLSS can provide interpretable self-report indicators that complement platform traces, such as logins, task completion, and interaction data. When integrated responsibly, these indicators may help institutions identify students who require differentiated instructional support, design adaptive prompts, and evaluate whether digital learning environments promote autonomy, persistence, and effective use of online resources. This applied function is particularly relevant in Latin American higher education, where online and blended learning have expanded but context-sensitive measurement tools remain limited.

Based on the above, the objective of this study was to examine the psychometric evidence of the OLSS in a sample of Peruvian university students using a psychometric network analysis approach. Specifically, the internal structure was analyzed by evaluating item communities, item centrality, and system connectivity. The stability and precision of the model were estimated using bootstrapping and iterative procedures, and the internal consistency of the scores was assessed as evidence of reliability. In addition, the study discusses how the resulting communities may inform online course design, learning analytics, and adaptive support in higher education.

MATERIALS AND METHODS

Type and Design

The study is instrumental in nature, as it aims to examine the psychometric evidence of a measurement instrument (Ato et al., 2013). In addition, the research adopted a psychometric network approach, which allows the observation of how items are interconnected within a system and enables the identification of elements that play a more central role in the relational structure of the instrument (Borsboom & Cramer, 2013; Epskamp et al., 2018; Fonseca-Pedrero, 2018).

The study followed a non-experimental, cross-sectional design, as variables were not manipulated and data were collected at a single point in time (Hernández-Sampieri & Mendoza, 2018).

Participants

The study population consisted of Peruvian university students. Inclusion criteria were being between 18 and 40 years of age, having Peruvian nationality, being enrolled in university studies, and providing informed consent. No exclusion criterion was applied based on sex. Individuals who did not wish to participate or did not provide informed consent were excluded. To determine the sample size, an a priori sample size calculator was used (Soper, 2023). The calculation indicated a minimum sample of 478 participants based on the following parameters: predicted effect size (f^2) = 0.02, desired statistical power = 0.80, number of predictors = 2, and probability level = 0.05. A total of 520 university students were recruited through an online survey (389 women = 74.8%; 131 men = 25.2%), with an age range of 18-40 years.

Instrument

The OLSS was used, a self-report measure composed of 20 items grouped into five dimensions: motivation, self-control, web/digital literacy, Internet anxiety, and concentration. The scale uses a five-point Likert response format ranging from 1 (“not at all like me”) to 5 (“very much like me”), with a total score ranging from 20 to 100. Previous studies have reported an explained variance of 60.80% and acceptable levels of internal consistency both for the total scale (α = .86) and for its dimensions (α ranging from .67 to .86) (Tsai, 2009). For the present study, a translated version of the scale was used, developed through forward translation and equivalence review procedures (Hambleton & Patsula, 1999).

Procedure

Data collection was conducted through an online survey. An electronic questionnaire was developed that included the study objectives, informed consent form, and the research instrument. The survey was distributed through online communication channels such as WhatsApp, Facebook, and Instagram. Participation was voluntary and anonymous, and the confidentiality of participants' responses was ensured. Ethical principles were strictly respected, including the participants' right to withdraw from the study at any time without any consequences.

This study was derived from a faculty research project that received ethical approval from the Research Ethics Committee of Universidad Cesar Vallejo (Peru). All procedures involving human participants were conducted in accordance with the ethical principles for research involving human subjects and followed the relevant institutional guidelines. Prior to participation, all individuals were provided with information about the purpose of the study, the voluntary nature of their participation, the confidentiality of their responses, and their right to withdraw at any time without any negative consequences. Only participants who provided informed consent were allowed to proceed with the questionnaire. Data were collected anonymously and used exclusively for academic and scientific purposes.

Data Analysis

The data were initially organized using SPSS version 25 and subsequently analyzed in R. First, descriptive statistics of the items were calculated and the quality of the dataset was examined, including the assessment of missing values and response patterns. Given that the items are ordinal in nature, an appropriate association matrix for ordinal variables was used.

The internal structure of the instrument was examined using exploratory graph analysis (EGA) in order to identify item communities (dimensions) and compare them with the theoretical organization of the OLSS (Golino & Epskamp, 2017). Subsequently, a psychometric network based on regularized partial correlations was estimated using a Gaussian graphical model, specifically the EBICglasso approach. This method allows for a more parsimonious network structure and reduces the likelihood of spurious associations (Epskamp & Fried, 2018).

From the estimated network, centrality indices were calculated, primarily strength and, when appropriate, expected influence, in order to identify items with greater structural relevance. The accuracy of edge weights and the stability of centrality metrics were evaluated using bootstrap procedures (Epskamp et al., 2018). Finally, internal consistency was estimated using the omega coefficient (ω), considering values ≥ .70 as acceptable. Network comparisons by gender were not conducted because the sample showed a substantial sex imbalance; therefore, group invariance and network comparison analyses were considered beyond the scope of the present study and are proposed for future research.

RESULTS

The results are presented as follows. First, the extreme scores of the items are evaluated. Subsequently, the psychometric network is analyzed, including graph analysis using bootstrap procedures, the identification of item communities, and the assessment of both item stability and structural consistency of the network.

Overall, the items of the OLSS showed moderate to high mean values, ranging from 3.06 to 4.41. The highest mean scores were observed for OS11 (mean [M] = 4.41, standard deviation [SD] = 0.72), OS13 (M = 4.38, SD = 0.73), and OS10 (M = 4.32, SD = 0.73), which also showed relatively lower dispersion. In contrast, the lowest mean values corresponded to OS15 (M = 3.06, SD = 1.07) and OS14 (M = 3.14, SD = 1.09), suggesting greater variability in these responses. Regarding distributional properties, items with higher mean scores showed negative skewness, particularly OS11 (Skew = -1.59) and OS10 (Skew = -1.40), along with higher kurtosis values, especially OS11 (Kurtosis = 4.10). This pattern suggests a concentration of responses toward the upper response categories of the scale. Conversely, items with lower mean values showed more

Table 1. Descriptive analysis of the items of the OLSS

Items	Mean	Standard deviation	Skewness	Kurtosis	Standard error
OS1	3.37	1.05	-0.32	-0.41	0.05
OS2	3.37	1.02	-0.28	-0.43	0.05
OS3	3.31	1.05	-0.28	-0.49	0.05
OS4	3.28	1.04	-0.25	-0.49	0.05
OS5	3.29	1.02	-0.29	-0.53	0.05
OS6	3.36	1.03	-0.30	-0.58	0.05
OS7	3.96	0.85	-1.04	1.58	0.04
OS8	3.79	0.84	-0.92	1.27	0.04
OS9	3.73	0.96	-0.62	0.00	0.04
OS10	4.32	0.73	-1.40	3.43	0.03
OS11	4.41	0.72	-1.59	4.10	0.03
OS12	4.20	0.78	-1.04	1.58	0.04
OS13	4.38	0.73	-1.28	2.20	0.03
OS14	3.14	1.09	0.01	-0.74	0.05
OS15	3.06	1.07	0.04	-0.73	0.05
OS16	3.55	1.04	-0.53	-0.33	0.05
OS17	3.45	1.12	-0.38	-0.70	0.05
OS18	3.42	1.08	-0.36	-0.62	0.05
OS19	3.16	1.06	0.02	-0.77	0.05
OS20	3.33	1.06	-0.29	-0.58	0.05

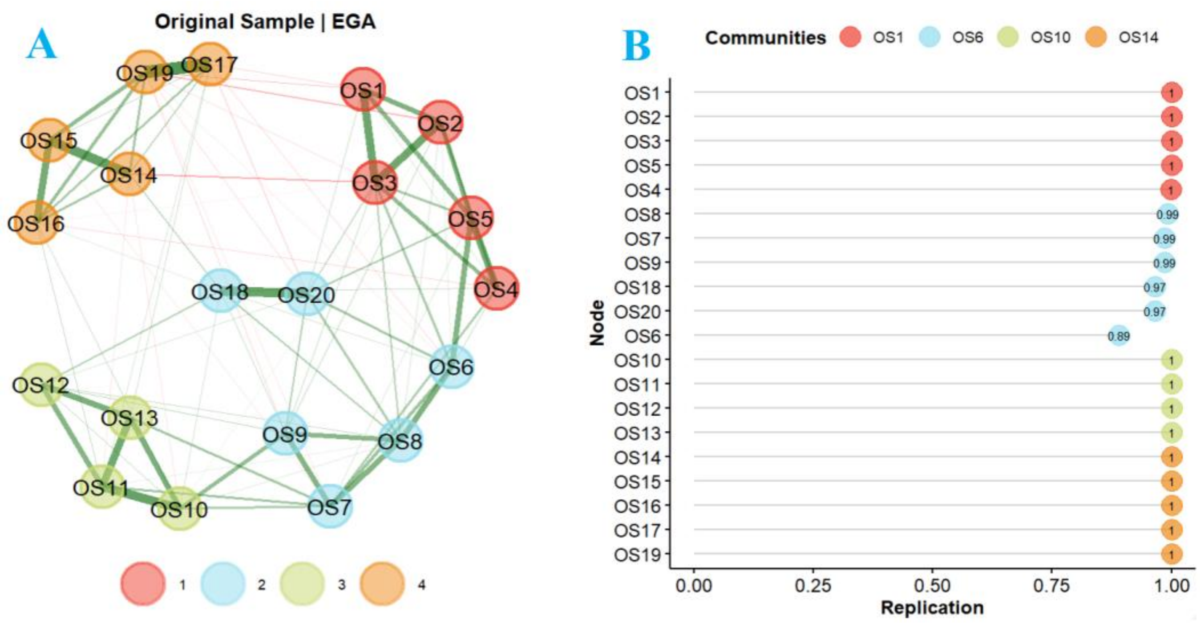

Figure 1. Psychometric network graph analysis (orange nodes represent Internet anxiety, green nodes represent Internet literacy, light blue nodes correspond to self-control, and red nodes represent motivation) (the authors' own work)

symmetric distributions and negative kurtosis, indicating greater dispersion of responses across response options (**Table 1**).

Psychometric Network Evaluation: Bootstrap

Part A in **Figure 1** presents the psychometric network obtained from the bootEGA applied to the OLSS. In the network, nodes represent the items of the instrument, while edges indicate the partial relationships between them, where the thickness of the connections reflects the magnitude of the association. Positive connections are represented by green lines, whereas negative connections are shown in red.

Regarding the network structure, four clearly differentiated communities can be observed, represented by different colors. Orange nodes correspond to the Internet anxiety dimension, green nodes represent

Table 2. bootEGA

n.Boots	median.dim	SE.dim	CI.dim	Lower.CI	Upper.CI	Lower.Quantile	Upper.Quantile
500	4	0.18	0.35	3.65	4.35	4.00	4.53

Note. n.Boots: Number of bootstrap resamples; median.dim: Median number of dimensions identified across bootstrap samples; SE.dim: SE of the estimated number of dimensions; CI.dim: Width of the confidence interval for the number of dimensions; Lower.CI and Upper.CI: Lower and upper bounds of the CI; & Lower.Quantile and Upper.Quantile: Lower and upper quantiles of the distribution of estimated dimensions across bootstrap samples

Internet literacy, light blue nodes are grouped within the self-control dimension, and red nodes correspond to the motivation dimension.

A higher density of connections within each community is observed, suggesting adequate internal cohesion among the items that compose each dimension. In addition, connections between communities are less frequent and weaker, supporting the conceptual differentiation of the constructs assessed. In particular, the Internet literacy and self-control dimensions show moderate positive associations with each other, while Internet anxiety displays more specific links with certain dimensions, maintaining its distinct structural identity within the network.

Part B in **Figure 1** shows the results of the community stability analysis obtained through the bootstrap procedure. The graph displays the replication proportion of each item within its original community across the bootstrap samples, allowing the evaluation of the consistency of item assignment to their respective dimensions.

The results indicate high structural stability, as most items reached replication values close to or equal to 1.00. Items associated with the motivation (red), Internet literacy (green), and Internet anxiety (orange) dimensions showed perfect replication, suggesting a consistent and robust assignment within their respective communities.

In contrast, items belonging to the self-control dimension (light blue) presented slightly lower but still high values (between .89 and .99), indicating adequate stability and a well-defined structure. Overall, these findings support the robustness of the four-dimension solution, demonstrating that both the items and the overall network structure remain stable across sampling variations.

Consistent with the psychometric network and the community stability analysis, the results of the EGA with bootstrap (bootEGA; see **Table 2**) are presented. Based on 500 bootstrap resamples, the median number of identified dimensions was four, with a low standard error (SE) (= 0.18), suggesting a stable estimation of the community structure. The confidence interval showed a narrow width (confidence interval [CI] = 0.35), with lower and upper bounds between 3.65 and 4.35, respectively, indicating a clear concentration of solutions around a four-community structure. Likewise, the lower and upper quantiles (4.00 and 4.53) further support the stability of this solution, showing that most bootstrap samples consistently replicated a four-community structure.

Regarding the item stability and structural consistency analysis, the values represent the probability that each item is assigned to a specific community across the bootstrap resamples.

Items belonging to community 1 (motivation) showed near-perfect stability, with values equal to 1.00 in most cases and minimal probabilities of assignment to other communities, indicating a clear and consistent delimitation of this dimension. Similarly, items from community 3 (Internet literacy) and community 4 (Internet anxiety) exhibited perfect stability (values of 1.00), demonstrating a robust and unambiguous assignment within their respective communities.

For community 2 (self-control), although most items showed a high probability of belonging to their corresponding community, some presented a slight probability of cross-assignment to adjacent communities. Nevertheless, the predominant values remained high (≥ .89), suggesting adequate stability consistent with the overall structure of the instrument.

Regarding structural consistency, the results indicated very high values across all communities, with community 3 and community 4 showing perfect consistency (1.00), followed by community 1 (0.998). community 2 showed a slightly lower value (0.874), although still within acceptable ranges, supporting the overall stability of the identified four-community solution (see **Table 3**).

Table 3. Item stability and structural consistency

Items	Community 1	Community 2	Community 3	Community 4
OS1	**1.000**	0.000	0.000	0.000
OS2	**1.000**	0.000	0.000	0.000
OS3	**1.000**	0.000	0.000	0.000
OS4	**0.998**	0.002	0.000	0.000
OS5	**1.000**	0.000	0.000	0.000
OS6	0.110	**0.890**	0.000	0.000
OS7	0.000	**0.986**	0.012	0.000
OS8	0.000	**0.992**	0.006	0.000
OS9	0.000	**0.986**	0.012	0.000
OS10	0.000	0.000	**1.000**	0.000
OS11	0.000	0.000	**1.000**	0.000
OS12	0.000	0.000	**1.000**	0.000
OS13	0.000	0.000	**1.000**	0.000
OS14	0.000	0.000	0.000	**1.000**
OS15	0.000	0.000	0.000	**1.000**
OS16	0.000	0.000	0.000	**1.000**
OS17	0.000	0.000	0.000	**1.000**
OS18	0.010	**0.966**	0.000	0.000
OS19	0.000	0.000	0.000	**1.000**
OS20	0.010	**0.966**	0.000	0.000
Structural consistency	0.998	0.874	1.000	1.000

Note. Community 4: Internet anxiety; Community 3: Internet literacy; Community 2: Self-control; Community 1: Motivation

DISCUSSION

The present study examined the psychometric evidence of the OLSS in a sample of Peruvian university students using a psychometric network analysis approach, addressing the need to evaluate instruments specifically designed for online learning contexts and relevant to educational technology practice (Meza-López et al., 2016; Tsai, 2009). Overall, the findings support the structural validity, stability, and internal consistency of the OLSS, while also showing how its item communities can inform technology-enhanced learning design, learning analytics, and adaptive student support in a Latin American higher education context.

First, the descriptive analyses showed that the items of the scale presented moderate to high mean values, with a tendency for responses to cluster at the higher levels of the scale, particularly for items associated with the motivation and Internet literacy dimensions. This pattern is consistent with the literature highlighting the central role of motivation, digital self-efficacy, and information-search skills in online learning (Broadbent, 2017; Luo & Zhou, 2024; Tsai & Tsai, 2003).

Likewise, the negative skewness and high kurtosis values observed in these items suggest that participants more frequently reported favorable behaviors and attitudes toward the strategic use of the Internet for learning. This tendency may be explained by the progressive normalization of virtual learning in higher education following the COVID-19 pandemic (Hodges et al., 2020; Islam et al., 2023).

From a structural perspective, the bootEGA consistently identified a four-community solution corresponding to motivation, self-control, Internet literacy, and Internet anxiety. This organization is conceptually consistent with the online strategic learning model proposed by Tsai (2009), which suggests that digital learning strategies are structured around motivational, self-regulatory, cognitive-technological, and affective components. Although the original version of the OLSS reported five dimensions, including concentration (Meza-López et al., 2016), the present network did not reproduce concentration as an independent community. Instead, items theoretically related to concentration, particularly OS18 and OS20, were assigned with high probabilities to the self-control community in the bootstrap solution, suggesting that concentration may operate in this sample as part of a broader self-regulatory control process rather than as a fully separate dimension. Conceptually, concentration in online learning requires sustained attention, planning, control of distractions, and monitoring of behavior, which overlap with self-control processes in virtual environments. Therefore, the four-community model should not be interpreted as a rejection of the original OLSS model, but as a context-specific empirical organization in which concentration is integrated into the self-regulatory component.

From a methodological perspective, the psychometric network approach made it possible to examine the internal structure of the instrument beyond the assumptions of traditional factor analysis, by modeling the direct relationships between items through regularized partial correlations (Epskamp & Fried, 2018). The high density of connections within each community and the low connectivity between communities support the internal cohesion and conceptual differentiation of the identified dimensions. This finding is consistent with the perspective proposed by Borsboom and Cramer (2013) and Fonseca-Pedrero (2018), who conceptualize psychological constructs as systems of interrelated components. At the same time, network analysis should be interpreted as complementary to, rather than superior to, confirmatory factor analysis (CFA). EGA identifies communities based on patterns of item connectivity and is useful for examining the relational organization of an instrument, whereas CFA tests prespecified latent structures and model fit. Accordingly, future studies should compare the four-community network solution with alternative confirmatory models, including the original five-dimensional structure of the OLSS.

A particularly relevant finding is the high stability of the communities, evidenced both by the median number of dimensions identified through bootEGA and by the item stability and structural consistency indicators. The high replication values (≥ .89) and structural consistency values close to or equal to 1.00 indicate that the network structure is robust to sampling variations, meeting the precision and stability criteria recommended in the specialized literature (Epskamp et al., 2018). This result is particularly important in instrumental studies, as it suggests that the identified dimensions are not the product of chance or specific characteristics of a particular sample.

However, the self-control dimension showed slightly lower structural consistency values compared with the other communities, as well as a minimal probability of cross-assignment of some items. This finding may be interpreted in light of previous research suggesting that self-regulation strategies in virtual environments tend to be more dynamic and sensitive to contextual factors, such as academic workload, instructional design, or prior experience with digital platforms (Broadbent, 2017; Halim & Sunarti, 2021). In this sense, the psychometric network not only confirms the existence of this dimension, but also reveals its more complex relational nature, which represents an advantage of the network approach over traditional latent variable models.

The theoretical contribution of this study lies in refining the empirical organization of Tsai's (2007) model within a Latin American online-learning context through a network psychometric framework. Rather than merely replicating the original factor structure, the results show that motivational, digital literacy, affective-anxiety, and self-regulatory/concentration strategies function as interconnected communities that may be linked to educational technology interventions. In this sense, the OLSS can be used not only as a measurement instrument, but also as a diagnostic tool for identifying areas in which online students may require instructional support.

Practical Implications for Educational Technology

For online instructors, the four communities identified in the network provide a practical framework for designing targeted support. Motivation-related indicators can guide the use of relevance-based tasks, timely feedback, and opportunities for student autonomy. Self-control and concentration indicators can inform structured pacing, weekly checklists, automated reminders, and progress-monitoring tools. Internet literacy indicators can support the inclusion of digital search tutorials, platform orientation, and guidance on evaluating online academic resources. Internet anxiety indicators can alert instructors to the need for low-stakes practice activities, clear technical instructions, and accessible help channels.

For instructional designers and educational technology teams, the OLSS communities may inform learning analytics dashboards and adaptive learning systems. For instance, self-report OLSS indicators could be combined with platform data to identify students who show low engagement, difficulty managing tasks, or anxiety toward online learning. Adaptive systems could then provide differentiated prompts, study-planning resources, digital literacy micro-lessons, or instructor alerts. These applications align the psychometric contribution of the OLSS with practical decisions about course design, student support, and quality improvement online and blended higher education.

Limitations

This study has several limitations that should be considered when interpreting the findings. First, the cross-sectional design limits the possibility of establishing causal relationships between the variables examined in the psychometric network and does not allow conclusions about longitudinal stability. Second, the use of a non-probabilistic sampling strategy and online recruitment may restrict the generalizability of the findings to the broader population of Peruvian university students. Third, the sample was predominantly female (74.8%), which limits the robustness of gender-based comparisons; therefore, network comparison or invariance analyses by gender were not conducted and should be examined in future studies with more balanced samples. Fourth, although the sample size of 520 participants is adequate for a 20-item EGA, larger samples would allow additional sensitivity analyses and stronger evaluation of the replicability of the network structure. Fifth, although the psychometric network approach provides valuable information about the relational structure among items, it should be considered complementary to CFA rather than a replacement for it. Additional studies should compare the present four-community solution with alternative CFA models, including the original five-dimensional OLSS structure. Finally, the study relied exclusively on self-report data, which may be subject to response bias such as social desirability or recall bias.

CONCLUSIONS

The present study examined the psychometric properties of the OLSS using a psychometric network analysis approach in a sample of Peruvian university students. The findings support the structural validity, stability, and internal consistency of the instrument, identifying a four-community structure composed of motivation, self-control, Internet literacy, and Internet anxiety. The integration of concentration-related items within the self-control community suggests that, in this sample, concentration may function as part of a broader self-regulatory process in online learning. Beyond its psychometric contribution, the OLSS provides actionable information for technology-enhanced learning design, learning analytics dashboards, adaptive support systems, and instructor-led interventions aimed at strengthening students' online learning strategies. Overall, the OLSS appears to be a reliable and valid instrument for assessing online learning strategies in university contexts, particularly in Latin American populations where research in this area remains limited.

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Data availability: Data generated or analyzed during this study are available from the authors on request.

REFERENCES

Ato, M., López, J. J., & Benavente, A. (2013). A classification system for research designs in psychology. *Anales de Psicología / Annals of Psychology, 29*(3), 1038-1059. https://doi.org/10.6018/analesps.29.3.178511

Beltrán, J., Pérez, L., & Ortega, M. (2006). *Cuestionario de estrategias de aprendizaje* [Learning strategies questionnaire]. TEA Ediciones.

Borsboom, D., & Cramer, A. O. J. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology, 9*, 91-121. https://doi.org/10.1146/annurev-clinpsy-050212-185608

Briganti, G., Decety, J., Scutari, M., McNally, R. J., & Linkowski, P. (2022). Using Bayesian networks to investigate psychological constructs: The case of empathy. *Psychological Reports, 127*(5), 2334-2346. https://doi.org/10.1177/00332941221146711

Broadbent, J. (2017). Comparing online and blended learner's self-regulated learning strategies and academic performance. *The Internet and Higher Education, 33*, 24-32. https://doi.org/10.1016/j.iheduc.2017.01.004

Castillo, V., Cabezas, N., Vera, C., & Toledo, C. (2021). Ansiedad al aprendizaje en línea: Relación con actitud, género, entorno y salud mental en universitarios [Online learning anxiety: Relationship with attitude, gender, environment and mental health in university students]. *Revista Digital de Investigación en Docencia Universitaria, 15*(1), 2223-2516. https://doi.org/10.19083/10.19083/ridu.2021.1284

de Oliveira, P. D., da Veiga-Simão, A. M. V., Ferreira, P. C., & Ferreira, A. I. (2022). Perceiving learning regulation with Moodle: Implications for guidance. *Revista Española de Orientación y Psicopedagogía, 33*(1), 87-107. https://doi.org/10.5944/reop.vol.33.num.1.2022.33759

Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods, 23*(4), 617-634. https://doi.org/10.1037/met0000167

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods, 50*(1), 195-212. https://doi.org/10.3758/s13428-017-0862-1

Fonseca-Pedrero, E. (2018). Análisis de redes en psicología [Network analysis in psychology]. *Papeles del psicólogo, 39*(1), 1-12. https://doi.org/10.23923/pap.psicol2018.2852

Freeborn, L., Andringa, S., Lunansky, G., & Rispens, J. (2023). Network analysis for modeling complex systems in SLA research. *Studies in Second Language Acquisition, 45*(2), 526-557. https://doi.org/10.1017/S0272263122000407

Gargallo, B., Almerich, G., Suárez-Rodríguez, J., & García-Félix, E. (2009). Estilos y estrategias de aprendizaje en estudiantes universitarios y su relación con el rendimiento académico [Learning styles and strategies in university students and their relationship with academic performance]. *Revista de Psicodidáctica, 14*(1), 25-46. https://doi.org/10.7203/relieve.18.2.2000

Golino, H. F., & Epskamp, S. (2017). Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research. *PLoS ONE, 12*(6), Article e0174035. https://doi.org/10.1371/journal.pone.0174035

Halim, A., & Sunarti, S. (2021). Online instructional strategies for English language learning during COVID-19 pandemic: A case from a creative teacher. *Journal of Applied Linguistics and Literature, 6*(1), 87-96. https://doi.org/10.33369/joall.v6i1.12452

Hambleton, R. K., & Patsula, L. (1999). Increasing the validity of adapted tests: Myths to be avoided and guidelines for improving test adaptation practices. *Journal of Applied Testing Technology, 1*, 1-13.

Hernández-Sampieri, R., & Mendoza, C. (2018). *Metodología de la investigación. Las rutas cuantitativa, cualitativa y mixta* [Research methodology. The quantitative, qualitative, and mixed approaches]. McGraw Hill.

Hodges, C., Moore, S., Lockee, B., Trust, T., & Bond, A. (2020). *The difference between emergency remote teaching and online learning*. Educause Review. https://er.educause.edu/articles/2020/3/the-difference-between-emergency-remote-teaching-and-online-learning

Islam, M., Mazlan, N. H., Al, M. G., Hoque, M. S., Karthiga, S. V., & Reza, M. (2023). UAE university students' experiences of virtual classroom learning during COVID-19. *Smart Learning Environments, 10*(1), Article 5. https://doi.org/10.1186/s40561-023-00225-1

Luo, R.-Z., & Zhou, Y.-L. (2024). The effectiveness of self-regulated learning strategies in higher education blended learning: A five years systematic review. *Journal of Computer Assisted Learning, 40*(6), 3005-3029 . https://doi.org/10.1111/jcal.13052

Meza-Lopez, L., Torres Velandia, S., & Lara-Ruiz, J. (2016). Estrategias de aprendizaje emergentes en la modalidad e-learning [Emerging learning strategies in e-learning]. *RED-Revista de Educación a Distancia, 48*(5), 2-21. https://doi.org/10.6018/red/48/5

Mheidly, N., Fares, M., &., & Fares, J. (2020). Coping with stress and burnout associated with telecommunication and online learning. *Frontiers in Public Health, 8*. https://doi.org/10.3389/fpubh.2020.574969

Moore, M. G. (2023). From correspondence education to online distance education. In O. Zawacki-Richter, & I. Jung (Eds.), *Handbook of open, distance and digital education* (pp. 27-42). Springer. https://doi.org/10.1007/978-981-19-2080-6_2

Palaming, A. G. (2022). Online instructional strategies. *EPRA International Journal of Multidisciplinary Research, 8*(5), 176-179. https://doi.org/10.36713/epra10171

Román, J. M., & Gallego, S. (2001). *ACRA, escalas de estrategias de aprendizaje* [ACRA, learning strategies scales]. TEA Ediciones.

Soper, D. S. (2023). A-priori sample size calculator for structural equation models. *Dr. Daniel Soper*. https://www.danielsoper.com/statcalc/calculator.aspx?id=89

Tsai, M.-J. (2007). A pilot study of the development of online learning strategies scale (OLSS). In *Proceedings of the 7th IEEE International Conference on Advanced Learning Technologies* (pp. 108-110). IEEE. https://doi.org/10.1109/ICALT.2007.30

Tsai, M.-J. (2009). The model of strategic e-learning: Understanding and evaluating student e-learning from metacognitive perspectives. *Educational Technology & Society, 12*(1), 34-48.

Tsai, M.-J., & Tsai, C.-C. (2003). Information searching strategies in web-based science learning: The role of Internet self-efficacy. *Innovations in Education and Teaching International, 40*(1), 43-50. https://doi.org/10.1080/1355800032000038822

Zekaj, R. (2023). The impact of online learning strategies on students' academic performance: A systematic literature review. *International Journal of Learning, Teaching and Educational Research, 22*(2), 148-164. https://doi.org/10.26803/ijlter.22.2.9