revistaFuentes
ISSN: 1575-7072 | e-ISSN: 2172-7775

# Validation of a socioemotional battery for online higher education applicants

## Validación de una batería socioemocional para aspirantes de educación superior en línea

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## Abstract
**Introduction**: This study aimed to validate an institutional socioemotional battery for online bachelor's degree applicants in Mexico, given the importance of these variables for academic success. **Method**: Two samples participated: Sample 1 (N=5272) for exploratory analysis and Sample 2 (N=2227) for confirmatory analysis. A 73-item self-report battery was initially administered. Data analysis involved item screening, exploratory graph analysis, and exploratory factor analysis on Sample 1, followed by confirmatory factor analysis on Sample 2 to validate the structure and assess reliability. **Results**: The final 30-item battery yielded seven stable dimensions: academic self-efficacy, family support, growth expectations, emotional expression, expressive suppression, emotional dysregulation, and adaptive emotional regulation. The model fit was excellent in both samples, with strong factor loadings, distinct inter-factor correlations, and high reliability. Most scales exhibited skewed distributions. **Discussion**: The identified dimensions align with literature on online academic success. The reduced, validated instrument enhances measurement efficiency and provides crucial early information on socioemotional factors. The combined use of network psychometric and traditional factor analytical methods strengthens the findings. **Conclusions**: This battery is a valid tool for assessing socioemotional characteristics in online learning, enabling early identification of risks and informing pedagogical strategies.

## Resumen
**Introducción**: Este estudio tuvo como objetivo validar una batería socioemocional institucional para aspirantes a licenciatura en línea en México, dada la importancia de estas variables para el éxito académico. **Método**: Participaron dos muestras: Muestra 1 (N=5272) para el análisis exploratorio y Muestra 2 (N=2227) para el análisis confirmatorio. Inicialmente se administró una batería de autoinformes de 73 ítems. El análisis de datos incluyó la selección de ítems, el análisis gráfico exploratorio y el análisis factorial exploratorio en la Muestra 1, seguidos del análisis factorial confirmatorio en la Muestra 2 para validar la estructura y evaluar la fiabilidad. **Resultados**: La batería final (30 ítems) arrojó siete dimensiones estables: autoeficacia académica, apoyo familiar, expectativas de crecimiento, expresión emocional,

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*Revista Fuentes*
**2026, *28*(1), 14-27**
**https://doi.org/10.12795/revistafuentes.2026.28828**

**Received:** 2025-08-22
**Reviewed**: 2025-09-03
**Accepted:** 2025-12-10
**First Online:** 2025-12-15
**Final Publication:** 2026-01-15

supresión expresiva, desregulación emocional y regulación emocional adaptativa. El ajuste del modelo fue excelente en ambas muestras, con fuertes cargas factoriales, claras correlaciones entre factores y alta confiabilidad. La mayoría de las escalas mostraron distribuciones sesgadas. **Discusión**: Las dimensiones identificadas coinciden con la literatura sobre el éxito académico en línea. El instrumento reducido y validado mejora la eficacia de la medición y proporciona información temprana sobre los factores socioemocionales. El uso combinado de métodos psicométricos en red y de análisis factorial tradicional refuerza los resultados. **Conclusiones**: Esta batería es una herramienta válida para evaluar las características socioemocionales en el aprendizaje en línea, permitiendo la identificación temprana de riesgos e informando las estrategias pedagógicas.

## Palabras clave / Keywords
Keywords: academic success, emotional regulation, factor analysis, higher education, higher education, online education, psychometric validation, socioemotional variables.
Palabras clave: éxito académico, análisis factorial, educación en línea, educación superior, preparación para el aprendizaje, regulación emocional, validación psicométrica, variables socioemocionales.

## 1. Introduction
Recent literature has identified several indicators associated with academic success in online courses. Among these, academic self-efficacy stands out as a significant predictor of student performance and as a mediator of motivation, learning, and overall achievement (Gao et al., 2021; Lim et al., 2021; Neroni et al., 2022; Panigrahi et al., 2021; Yokoyama, 2024; Yunusa & Umar, 2021). For students in online and virtual environments, higher self-efficacy promotes better learning practices and retention (Kundu, 2020; Lehikko, 2021). It is also linked to the successful completion of educational programs, particularly at higher and graduate levels (Mejri & Borawski, 2023).

Social support is another crucial factor for student engagement and positive academic outcomes (Matteucci & Soncini, 2021; Ozer, 2024). Online students often juggle work, family, and studies, which can affect their ability to stay engaged and complete courses. Recent studies highlight that family involvement in education positively influences student engagement (Ferraces Otero et al., 2020; Yang et al., 2023). Conversely, a lack of this support can lead to students dropping out due to family responsibilities (Hernández González & Blackford, 2022; Hernández Ortiz et al., 2023). In contrast, students who receive support from both their family (partners and parents) and educational environments (teachers and peers) are more likely to engage and achieve academic success in online, hybrid, or face-to-face programs (Borup et al., 2020; Gao et al., 2021; Mensah et al., 2024).

Regarding the personal and work expectations of online students, research shows they are more likely to feel satisfied and continue their studies if their expectations align with their experiences. These expectations include course flexibility, social interaction, teacher support, and the alignment of the course with their personal and educational goals. Students seek to enjoy course content, face challenges that promote learning new things, and achieve rewards such as degrees, personal growth, and professional development (Henry, 2020; Landrum et al., 2021). Those who understand the time and effort required for a program are more likely to persist and complete more courses (James, 2022).

Emotional regulation may play a significant role in students' academic achievement. Studies indicate that academic achievement emotions are influenced by a student's level of emotional regulation (Harley et al., 2019; Nadeem et al., 2023; Pekrun et al., 2023). For instance, emotional dysregulation is associated with lower academic engagement (De Neve et al., 2023). Positive emotions (e.g., pride, confidence, joy) resulting from good grades can improve future grades, whereas negative emotions (e.g., frustration, anxiety, sadness) stemming from poor grades tend to reduce performance, potentially creating a negative cycle. While inadequate emotional regulation can affect both well-being and academic performance, effective emotional regulation fosters them (Harley et al., 2019). Strategies like cognitive reappraisal can boost well-being and help students manage their emotions better, whereas emotional suppression might be detrimental in the long run (Beaumont et al., 2023).

The literature on dropout in Distance Education indicates that it is influenced by a combination of factors related to the instructional modality and the learner's contextual conditions. These include challenges in tracking students' academic trajectories and insufficient instructional and organizational support (Escanés et al., 2014), as well as socioeconomic constraints such as associated costs and difficulties in maintaining enrollment. Academic, personal, and sociocultural factors also play a role, particularly among engineering and social science students (Bardales et al., 2025). Additionally, work schedules, family responsibilities, and gaps between expectations and the actual university experience hinder academic integration (Heredia Ramos, 2024). At the individual level, low motivation, difficulties adapting to online learning, limited self-regulation, and lack of time for autonomous learning significantly increase dropout risk (Delgado & Miranda, 2021; Heredia Ramos, 2024). In this regard, it is important to emphasize that many socioemotional variables associated with success in digital learning environments—such as intrinsic motivation, self-efficacy, self-regulated learning, sense of belonging, and perceived social and instructional support— can also operate as risk factors when they are absent or weakened.

Considering the importance of socioemotional variables for understanding students' experiences in digital learning environments, it is important to consider how these dimensions have been assessed in empirical research. These variables and indicators have primarily been measured using questionnaires designed by participating institutions or by adapting instruments such as the MSLQ (Motivated Strategies for Learning Questionnaire), TOOLS (Test of Online Learning Success), ERQ (Emotion Regulation Questionnaire), Social and Emotional Competencies Questionnaire (SEC Q) and Socioemotional Competencies Scale (ECSE), bot in particular, having been applied in Latin American contexts comparable to of this study. Some studies relied on self-reporting through online surveys, while a smaller number conducted interviews and focus groups with students. In this context, the propaedeutic program offered by National Autonomous University of Mexico (Universidad Nacional Autónoma de México, UNAM) to its applicants and incoming students for distance learning degrees has incorporated several key indicators, including academic self-efficacy, social support, professional development expectations, and emotional regulation. Previous studies have utilized data from this program to examine the online learning skills of these applicants (Hernández Gutiérrez & Enríquez Vázquez, 2022). However, despite the administration of a battery of questions on the socioemotional characteristics of this population at the program's outset, the authors are unaware of any examination of the psychometric properties of this battery to date.

In summary, understanding applicants' readiness for online learning (Hassan Abuhassna et al., 2022) and assessing their intellectual and socioemotional capabilities are essential for designing effective learning experiences. Analyzing these dimensions not only facilitates adaptation to this modality but also helps anticipate and mitigate emotional barriers (Engin, 2017; Li, 2024; Yu et al., 2022). By integrating the assessment of these socioemotional variables into admission and follow-up processes, we contribute to successfully addressing the challenges of digital education, fostering retention and academic performance, and strengthening equity by providing timely support to those with greater needs. Therefore, the present instrumental study aimed to: (1) analyze the internal structure (dimensionality) of this battery of socioemotional variables, as provided in the supplementary materials (Supplementary Table 1, available via the OSF link), within the context of a propaedeutic course for applicants to a distance learning degree program; (2) estimate the reliability of the resulting scales; and (3) examine how these variables are distributed within the target population.

## 2. Method

### 2.1. Participants

The study involved two distinct samples. Sample 1, utilized for exploratory analyses, consisted of 5272 individuals who were in the process of applying to an online bachelor's degree program, with a mean age of 31.33 years (SD = 9.98). The majority were women (67.1%), with men comprising 32.9%. In terms of marital status, most were single (65.7%), followed by those married or cohabiting (31.2%), and a smaller proportion divorced, separated, or widowed (2.9%). A substantial majority (57.6%) reported having no children. Regarding educational attainment, 58.0% had completed high school, 21.1% had incomplete undergraduate studies, 15.7% held an undergraduate degree, and 5.2% had some level of graduate studies. Employment was reported by 76.3% of this sample.

Sample 2, designated for confirmatory purposes, comprised 2227 individuals who had successfully navigated the university application process and had already been selected, with a mean age of 29.80 years (SD=9.44). This sample was composed of 53.0% women, 45.9% men, and 1.1% who preferred not to disclose their sex. Similar to Sample 1, the largest group was single (67.9%), with 26.5% married or cohabiting, and 5.7% divorced, separated, or widowed. A higher percentage (73.3%) in Sample 2 did not have children. Educational backgrounds in Sample 2 showed 40.7% with high school as their highest level, 29.6% with incomplete undergraduate studies, 20.8% with an undergraduate degree, and 8.9% with some graduate studies. Employment rates were comparable, with 74.6% of Sample 2 participants being employed.

## 2.2. Measure

Battery of Academic and Socioemotional Skills. The initial pool of items consisted of 73 self-report items, all responded to on a 7-point Likert-type scale. Its content included items related to academic self-efficacy, social support, emotional regulation, among other constructs. The first 18 items, designed to assess self-efficacy, ranged from 1 ("not at all effective") to 7 ("very effective"). The remaining 55 items were measured on a scale from 1 ("Strongly disagree") to 7 ("Strongly agree"). It is important to note that, while this comprehensive battery of items has been widely used, its psychometric properties had not been previously studied. The original pool of items can be found in Supplementary Table 1.

## 2.3. Procedure

Data for Sample 1 were collected between May and June 2024. Data for Sample 2 were collected from the program conducted between December 2024 and January 2025. Both data collection periods occurred within the context of the propaedeutic program that National Autonomous University of Mexico (Universidad Nacional Autónoma de México, UNAM) offers free of charge to applicants for its online degree programs.

A key distinction between the two cohorts considered for this study is their target populations: the first cohort included all applicants, while the second cohort comprised only those applicants who were selected in the admission process. At the time of this study, participation in the propaedeutic program was not mandatory, meaning all participants in this study did so voluntarily. The battery of questions that is the focus of this research was administered at the beginning of the program, before the official commencement of its three modules.

## 2.4. Data Analysis

Data analyses were conducted separately for the two independent subsamples. The first sample was used for item-level screening and exploratory procedures, while the second sample served as a holdout for confirmatory testing of the final measurement model.

In the first step, item-level descriptive statistics were examined to identify items with problematic distributional properties. Specifically, items with absolute zero-centered kurtosis values equal to or greater than 7 were considered excessively non-normal and were excluded from further analyses (Bandalos & Finney, 2019). Next, an exploratory graph analysis (EGA; Golino & Epskamp, 2017) was conducted on the remaining items to identify the underlying dimensional structure. A bootstrap procedure was applied to assess the stability of the item assignments to dimensions. Items were considered unstable and subsequently removed if they were assigned to the same dimension in less than 65% of the bootstrap replications (Christensen & Golino, 2021).

Within each dimension identified by the EGA, a two-step exploratory factor analytic approach was implemented to refine the item pool. The first step involved applying the Gulliksen's Pool (G-pool) procedure, a diagnostic strategy designed to flag items with potential psychometric weaknesses based on two criteria: item extremeness and suboptimal discrimination indices (Ferrando et al., 2023). Items flagged by the G-pool were not automatically removed; rather, each flagged item was evaluated in context, and decisions regarding item retention or deletion were made based on both statistical output and theoretical relevance. The second step consisted of fitting unidimensional exploratory factor analysis (EFA) models within each community of items, using unweighted least squares estimation with Pearson correlations. In each model, items with loadings below .50 were iteratively removed—one at a time—until all remaining items had loadings greater than or equal to .50 and Horn's parallel analysis supported the extraction of a single factor.

After this initial refinement, the retained items from all dimensions were pooled and subjected to a second EGA (with bootstrapping) and a new EFA (with parallel analysis) to verify the convergence of the factor structures across both methods. These analyses served to ensure that the dimensional configuration observed initially was consistent and replicable. A further round of item refinement was carried out based on the results of the multidimensional EFA. Items with loadings below .50 (or with loadings ≥.32 in more than one factor) were again removed, given that each factor retained at least three items. Subsequently, the expected residual correlation direct change (EREC) procedure was used to identify pairs of items (i.e., doublets) with residual dependencies that could compromise model fit (Ferrando et al., 2022). Starting with the pair showing the highest residual correlation, each doublet was evaluated for potential redundancy. If one of the items in the pair had substantially higher kurtosis or a noticeably lower factor loading than the other, it was considered for deletion. When neither criterion clearly favored one item over the other, the decision was made based on theoretical considerations. This EREC procedure was combined with the factor loading threshold of .50 to ensure that only psychometrically robust items were retained. Next, to enhance the practical utility of the resulting scale and mitigate participant fatigue while maintaining robust psychometric properties, items were also deleted in some dimensions (based on the .50 loading threshold) to ensure that all dimensions comprised a maximum of five items.

To make sure that the refined set of items continued to support the same structural configuration, a final EGA with bootstrapping was conducted. The structure identified was then subjected to a restricted factor analysis, sometimes referred to as a "confirmatory" factor analysis (CFA), but in this context used as an extension of the exploratory phase. This restricted model imposed zero loadings on all cross-loadings, allowing each item to load on only one factor, but did not assume that the structure was final or definitive (Ferrando & Lorenzo-Seva, 2000). The model was estimated using robust maximum likelihood (MLR), and model fit was assessed using conventional indices: the comparative fit index (CFI), Tucker-Lewis index (TLI), root-mean-square error of approximation (RMSEA), and standardized root-mean-square residual (SRMR). Robust versions of CFI, TLI, and RMSEA were also computed to account for potential non-normality (Brosseau-Liard et al., 2012; Brosseau-Liard & Savalei, 2014). Following standard benchmarks, values of CFI and TLI above .95, RMSEA below .06, and SRMR below .08 were interpreted as indicative of good model fit (Hu & Bentler, 1999). When necessary, model refinement was guided by modification indices and theoretical considerations. At the end of this exploratory phase, a final EGA was modeled to make sure that the item-dimension structure remained consistent.

Once the structure was finalized in Sample 1, it was evaluated in Sample 2 through a CFA using the MLR estimator. This step served to assess the replicability of the model in an independent sample. Additionally, internal consistency reliability for each factor was estimated using the omega coefficient. Measurement invariance was assessed using multi-group CFA. We examined invariance across sex (male vs. female) and age. For the latter, participants were grouped into late adolescence (17–24), early adulthood (25–34), and established adulthood (35–72) to balance sample sizes across developmental stages. We tested configural, metric, scalar, and strict invariance hierarchically. Model fit was evaluated using the Satorra-Bentler scaled $\chi^2$ difference test and changes in fit indices. Given the sensitivity of $\chi^2$ to large sample sizes, invariance was primarily determined by the change in CFI (ΔCFI), such that a decrease in CFI exceeding .010 was considered evidence of non-invariance (Cheung & Rensvold, 2002; Chen, 2007).

Finally, the distributional properties of each scale were visually examined with violin plots of their standardized scores. All analyses were conducted using specialized software and R packages. Specifically, for the EGA, the EGAnet package (version 2.3.0), implemented in R, was utilized. EFA was performed using the FACTOR software (version 12.06.07). Finally, for both CFA and the estimation of internal consistency reliability, the lavaan (version 0.6-19) and semTools (version 0.5-7) R packages were employed.

## 3. Results

### 3.1. Initial Screening

Initial inspection of the items revealed that the absolute kurtosis values for items 31 ("I generally have a cordial relationship with my professors"), 41 ("I will succeed in my chosen university career"), and 46 ("Achieving a university degree will motivate me to continue my preparation") were very high (Supplementary Table 2). Consequently, these items were excluded from further analyses.

### 3.2. Exploratory Phase

The initial EGA identified eight item communities, which demonstrated high stability (Supplementary Figure 1). Preliminary item refinement was conducted using the G-pool procedure and a series of unidimensional EFAs. After obtaining robust unidimensional solutions ($\lambda \geq .50$), a new EGA and EFA were simultaneously performed with all refined items, and both techniques converged on the same structure. However, in the EFA, one dimension (containing items related to social relationships) exhibited $\lambda \geq .50$ for only two of its items. Consequently, this dimension was discarded, and the analysis was re-run. Following a new series of analyses, items were progressively eliminated due to low factor loadings, high residual correlations with other items, or to reduce scale length. This process yielded a new, nearly final solution with seven clearly defined dimensions (Supplementary Table 3). Upon examining the item content, the dimensions were named as follows: (1) academic self-efficacy, (2) family support, (3) growth expectations, (4) emotional expression, (5) expressive suppression, (6) emotional dysregulation, and (7) adaptive emotional regulation.

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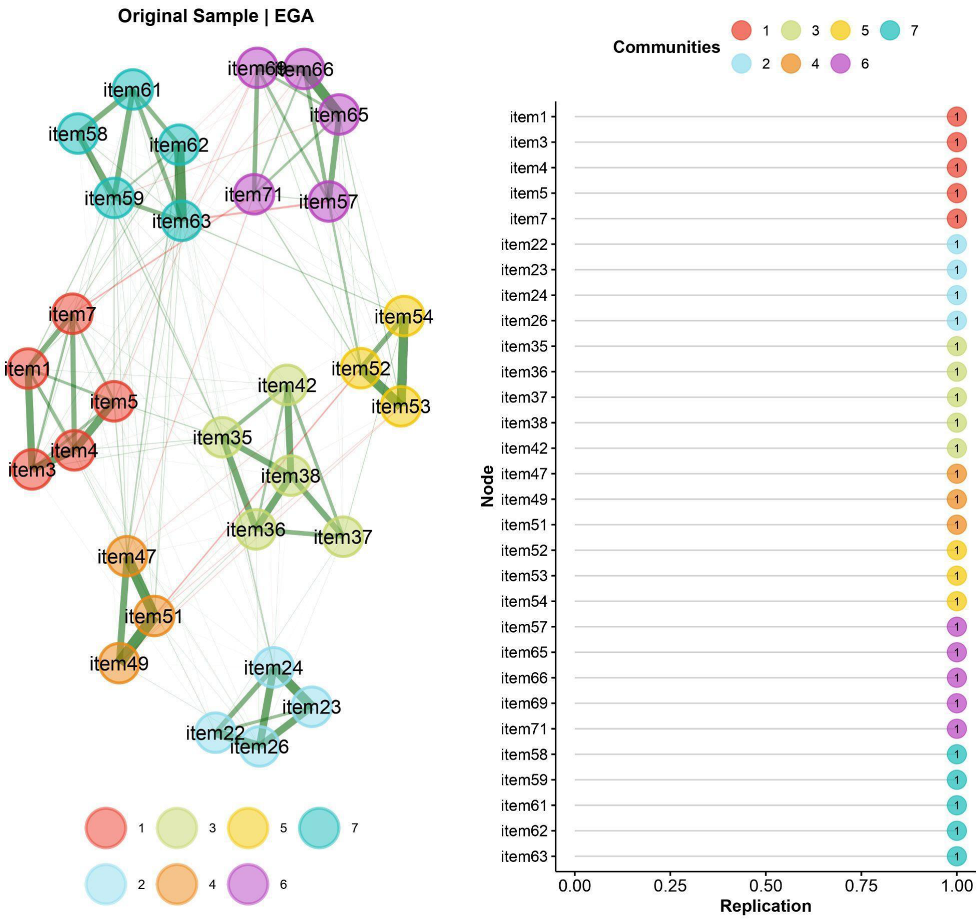
In the final phase of item refinement, a restricted/confirmatory factor analysis (CFA) was performed to test the derived structure. The resulting model demonstrated an acceptable fit (CFI = .95, Robust CFI = .95, TLI = .94, Robust TLI = .94, RMSEA = .04, Robust RMSEA = .04, SRMR = .03). Despite this acceptable fit, modification indices suggested potential model improvement through the inclusion of a residual correlation between items 21 ("My parents or guardians are committed to my education") and 22 ("My parents or guardians are interested in knowing how I am doing in school"). Given that this correlation could be explained by the similar phrasing of the items, item 21 was eliminated due to its lower factor loading. No additional modifications were made, and this final model exhibited a very good fit (CFI = .96, Robust CFI = .96, TLI = .96, Robust TLI = .96, RMSEA = .03, Robust RMSEA = .04, SRMR = .03). This final selection of items was also subjected to a final EGA, yielding a highly stable solution identical to that found with factorial methods (Figure 1).




Note. 1: Self-efficacy; 2: Family support; 3: Growth expectations; 4: Emotional expression; 5: Expressive suppression; 6: Emotional dysregulation; 7: Adaptive emotion regulation (authors' elaboration).

**Figure 1. Exploratory Graph Analysis with the Refined Set of Items**

### 3.3. Confirmatory Factor Analysis & Internal Consistency Reliability

Finally, the CFA performed on Sample 2 showed that the model fit the data very well: CFI = .96, Robust CFI = .96, TLI = .95, Robust TLI = .96, RMSEA = .03, Robust RMSEA = .04, SRMR = .03. As shown in Table 1, all factor loadings (except for item 71 "I feel nervous when taking an exam".) were greater than .50, and no items with complex loadings were identified.

 DOI: 10.12795/revistafuentes.2026.28828

**Table 1.**
*Factor Loadings of the Final Factorial Solution*

| Item | Self-efficacy | Family support | Growth expectations | Emotional expression | Expressive suppression | Emotional dysregulation | Adaptive emotion regulation |
|---|---|---|---|---|---|---|---|
| 1 | .75 | | | | | | |
| 3 | .79 | | | | | | |
| 4 | .84 | | | | | | |
| 5 | .73 | | | | | | |
| 7 | .65 | | | | | | |
| 22 | | .78 | | | | | |
| 23 | | .80 | | | | | |
| 24 | | .82 | | | | | |
| 26 | | .85 | | | | | |
| 35 | | | .73 | | | | |
| 36 | | | .81 | | | | |
| 37 | | | .62 | | | | |
| 38 | | | .85 | | | | |
| 42 | | | .72 | | | | |
| 47 | | | | .85 | | | |
| 49 | | | | .82 | | | |
| 51 | | | | .89 | | | |
| 52 | | | | | .73 | | |
| 53 | | | | | .84 | | |
| 54 | | | | | .73 | | |
| 57 | | | | | | .56 | |
| 65 | | | | | | .76 | |
| 66 | | | | | | .81 | |

| | | |
|---|---|---|
| 69 | .69 | |
| 71 | .43 | |
| 58 | | .53 |
| 59 | | .70 |
| 61 | | .66 |
| 62 | | .76 |
| 63 | | .81 |

Regarding the inter-factor correlations, no instances suggesting redundancy between any two dimensions were observed (Table 2). The highest correlation was found between adaptive emotional regulation and academic self-efficacy. Furthermore, expressive suppression consistently showed low correlations with the other factors, except for an inverse correlation with emotional expression and a direct correlation with emotional dysregulation.

**Table 2**
*Correlations Between Latent Variables of the Final Factorial Solution*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. Self-efficacy | — | | | | | | |
| 2. Family support | .20 | — | | | | | |
| 3. Growth expectations | .37 | .25 | — | | | | |
| 4. Emotional expression | .37 | .17 | .25 | — | | | |
| 5. Expressive suppression | -.07 | -.02 | .04 | -.43 | — | | |
| 6. Emotional dysregulation | -.34 | -.05 | -.06 | -.22 | .31 | — | |
| 7. Adaptive emotion regulation | .59 | .20 | .36 | .44 | -.04 | -.40 | — |

### 3.4. Measurement Invariance

Fit indices for the invariance models are presented in Table 3. Regarding age, the model demonstrated scalar (strong) invariance, as the decrease in fit from the metric to the scalar model was within acceptable limits (ΔCFI = -.005). However, strict invariance was not supported (ΔCFI = -.033). Regarding sex, the model demonstrated strict invariance. Despite significant $\chi^2$ differences attributable to sample size, the changes in CFI never exceeded the -.010 threshold across all nested models. This indicates that factor structure, loadings, intercepts, and residual variances are equivalent between males and females.


DOI: 10.12795/revistafuentes.2026.28828

**Table 3**

*Fit Indices for Measurement Invariance Models by Age and Sex*

| Model | χ² | df | CFI | RMSEA | Δχ² | Δdf | ΔCFI |
|---|---|---|---|---|---|---|---|
| Invariance by Age | | | | | | | |
| Configural | 2144.9 | 1152 | .962 | .037 | — | — | — |
| Metric | 2208.45 | 1198 | .961 | .037 | 65.59* | 46 | -.001 |
| Scalar | 2380.92 | 1244 | .956 | .038 | 188.41*** | 46 | -.005 |
| Strict | 3235.54 | 1304 | .924 | .050 | 570.46*** | 60 | -.033 |
| Invariance by Sex | | | | | | | |
| Configural | 1723.48 | 768 | .962 | .037 | — | — | — |
| Metric | 1748.61 | 791 | .962 | .037 | 27.52 | 23 | 0 |
| Scalar | 2008.5 | 814 | .953 | .040 | 306.32*** | 23 | -.009 |
| Strict | 2039.94 | 844 | .952 | .040 | 48.33* | 30 | -.001 |

*Note.* ΔCFI values ≥ -0.010 indicate invariance is maintained.
*$p$ < .05, ***$p$ < .001.

### 3.5. Distributional Properties

As displayed in Figure 2, most scales had skewed distributions. Adaptive emotion regulation, emotional expression, family support, growth expectations, and self-efficacy were negatively skewed, indicating that most responses were concentrated at the upper tail of the distribution. On the other hand, emotional dysregulation was positively skewed, thus showing the opposite pattern. Finally, only expressive suppression was distributed in an approximately symmetric manner.

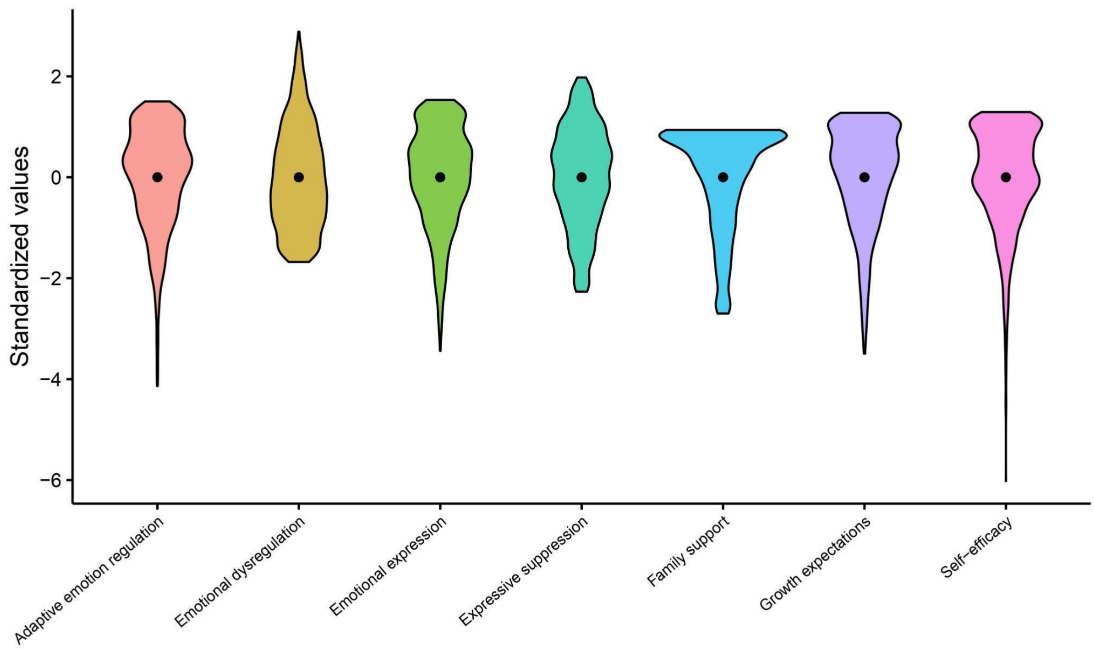



**Figure 2. Violin Plots of the Final Scales**

## 4. Discussion

In the present study, a 30-item battery was empirically derived to measure seven relevant socioemotional characteristics in applicants to online bachelor's degree programs. The analyses were conducted using large applicant samples, which provided robustness and reliability to the findings. Through both exploratory and confirmatory analyses, a clear and coherent structure was identified among the evaluated dimensions. Analysis of the score distributions for the battery's scales revealed a marked asymmetry in most scales, suggesting skewed response patterns at both extremes. This phenomenon may reflect common characteristics of the applicant population concerning their socioemotional skills. The only scale with an approximately symmetrical distribution was expressive suppression, indicating a higher proportion of responses clustered around the average scale value.

The findings from this study are consistent with recent literature on academic success in online education, which has highlighted variables such as academic self-efficacy, family support, growth expectations, and emotional regulation as key factors for student success at higher education levels (Gao et al., 2021; Mejri & Borawski, 2023; Neroni et al., 2022; Panigrahi et al., 2021). These same dimensions were identified in the battery, thereby reinforcing its conceptual soundness. The scales measure self-efficacy and family support, reflecting the importance of these constructs for understanding student responses and, consequently, for implementing retention and academic performance strategies that can support student engagement in online education (Borup et al., 2020; Kundu, 2020; Lehikko, 2021).

Furthermore, the instrument's inclusion of growth expectations aligns with studies linking satisfaction and persistence in online programs to the perception of personal and professional development (Henry, 2020; Landrum et al., 2021). Examining other proposals such as the Social and Emotional Competencies Questionnaire (SEC-Q) analyzed by Figueroa-Varela et al. (2023) and the Socioemotional Competencies Scale (ECSE) reviewed by Vizcaíno-Escobar et al. (2025) further highlights the distinct contribution of this battery. Unlike these instruments, the present measure incorporates dimensions directly tied to the academic context—such as academic self-efficacy and growth expectations—and explicitly considers family support, enabling the assessment of social and personal resources relevant to student performance. Likewise, the differentiation between emotional expression and suppression offers a more nuanced understanding of emotional regulation in learning environments, a feature not addressed in the SEC-Q or ECSE.Similarly, the inclusion of scales on emotional suppression, regulation, and dysregulation strengthens the instrument's capacity to capture the influence of emotions on learning, an aspect that is really important given the role of emotional management in sustaining well-being, performance, and academic engagement (Beaumont et al., 2023; Harley et al., 2019). Taken together, these elements position the battery not only as a validated psychometric tool but also as an instrument aligned with contemporary theoretical trends in distance education, providing context-specific insights into the socioemotional dynamics of university students.

A significant contribution of this research was the reduction of the number of items from 73 to 30, which preserved the instrument's quality without compromising its psychometric properties. This shorter version facilitates its application in other contexts and enhances measurement efficiency. Another important contribution is its responsiveness to the literature and theorists in distance education (Hassan Abuhassna et al., 2022; Li, 2024; Yu et al., 2022), who emphasize the importance of gathering early information on socioemotional and contextual variables that can influence students' adaptation and academic performance in this modality. Another significant methodological strength of this research lies in the integration of both network psychometric (i.e., EGA) and traditional factor analytical methods. This combined approach provides a more robust and comprehensive understanding of the dimensionality of the measure under study, combining the strengths of two prominent paradigms in modern measurement theory (Borsboom et al., 2022). The convergence of findings from these distinct analytical frameworks enhances our confidence in the identified dimensionality and reliability of the scales.

In relation to the social relationships dimension, its removal was based on psychometric considerations related to the heterogeneity of the items originally included. Although all items referred to relevant social agents in students' lives—such as family members, peers, and teachers—they encompassed a mix of distinct constructs (e.g., self-efficacy, support, perception, expectations), which prevented the formation of a theoretically coherent and statistically stable dimension. Theoretically, this decision acknowledges that social relationships in educational contexts constitute a complex domain that cannot be adequately captured through a set of conceptually mixed indicators. Therefore, for future versions of the instrument, we propose re-specifying the social dimension by incorporating more homogeneous items anchored in clearly defined sub-constructs, such as social support, perceived availability of support, expectations from significant others, or interpersonal climate. This approach will enable a more precise assessment of the social environment's

 DOI: 10.12795/revistafuentes.2026.28828

contribution to the phenomenon under study, thereby strengthening the theoretical and psychometric validity of the instrument.

Regarding the limitations of this study, the cross-sectional design does not allow for the observation of temporal changes in constructs such as academic self-efficacy, social support, or emotional regulation evolve in online education. Additionally, information collected through self-report instruments may introduce biases related to social desirability or self-reflection errors, as well as potential effects inherent to this response format, which could affect the accuracy and consistency of student responses. Furthermore, given that the sample is specifically focused on a propaedeutic program at a particular institution, caution should be exercised when attempting to generalize the findings to other institutions with different characteristics and contexts.

Based on these considerations, future research should examine the predictive validity of the constructs analyzed in relation to outcomes such as academic performance or dropout. It would also be valuable to conduct multigroup invariance analyses to determine whether the measurements remain stable across different student profiles. Additionally, future studies could extend the social dimension that was excluded in this research in order to explore more deeply the role of social support in digital learning environments, as well as incorporate test–retest designs to evaluate the temporal stability of the measurements.

These findings provide evidence supporting the battery as a valid and effective tool for assessing key socioemotional variables in online learning modalities. Having a validated version of this battery for students about to commence an online course enables an accurate and adequate assessment of the emotional characteristics that influence academic performance in online and distance learning, while considering the cultural, educational, and social particularities of the country. This facilitates the early identification of risks such as academic lag and dropout. It also strengthens pedagogical decision-making and contributes to the design of institutional strategies for student support. Moreover, the validation of this tool opens the door for educational research that will allow for a deeper understanding of the conditions, strengths, and needs of students in virtual learning environments. Future studies could examine whether the evaluated dimensions act as significant predictors of academic success in distance modalities, which would facilitate the development of longitudinal and cross-sectional studies aimed at designing strategies for prevention and early intervention against risks such as academic lag and dropout.

## 5. Conclusions

The results of this study support the psychometric validity of a 30-item battery designed to assess seven key socioemotional dimensions in applicants to online bachelor’s degree programs. The use of robust analytical methods, including exploratory and confirmatory factor analyses combined with network psychometrics, allowed for the identification of a clear, coherent, and reliable structure. The reduction from 73 to 30 items without compromising measurement quality represents a significant contribution, enhancing the instrument's practical application in real educational settings. The identified dimensions—such as academic self-efficacy, family support, growth expectations, and emotional regulation—are consistent with recent literature on academic success in virtual learning environments, reinforcing the conceptual soundness and relevance of the battery.

Notably, the battery should be understood as an initial diagnostic screening tool, rather than a high-stakes or exclusionary decision mechanism. Its responsible use requires complementing the socioemotional results with academic and psychoeducational indicators to ensure a more comprehensive interpretation of students’ readiness for online learning and to prevent potential biases associated with single-source assessments. Likewise, the socioemotional dimensions included in the instrument provide a valuable lens for understanding students’ initial profiles and for identifying early risk factors such as academic lag or dropout. Their relevance to the processes of adaptation and persistence in online education strengthens the broader contribution of this study to the field. Furthermore, the validation of this battery opens opportunities for future research aimed at exploring the predictive role of these dimensions in academic performance, as well as for developing longitudinal and cross-institutional studies that deepen the understanding of socioemotional readiness in digital learning environments.

Altogether, this study contributes to strengthening more inclusive, evidence-informed, and context-sensitive approaches to online education, highlighting the importance of socioemotional indicators as part of a broader institutional strategy for supporting student success.

## CRedIT

**ADLRG**, **ACRR**: Conceptualization and Methodology; Writing – Original Draft; **PDV**: Data Curation; Formal Analysis; Writing – Original Draft; **ADLRG**, **IOC**: Conceptualization; Writing – Review & Editing; Project Administration; Resources.

## AI Usage Statement

During the preparation of this work, the authors used Gemini in order to proofread the manuscript and improve its readability and language. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

## Data availability statement

Supplementary materials can be accessed at https://osf.io/dtepy/?view_only=00b36d83cc784db19ae6d74e97aeb24a

## Funding and Acknowledgements

The authors would like to express their gratitude to Coordination for Open University and Digital Education (Coordinación de Universidad Abierta y Educación Digital, CUAED) for their valuable support.
No external funding was received for this work.

## Knowledge Transfer

The validated battery from this study can be used by higher education institutions offering online programs to assess applicants' socioemotional skills early on. Its reduced 30-item version facilitates application in admission or diagnostic processes, enabling the identification of academic risks and supporting pedagogical decisions aimed at improving student retention.

## Ethical Considerations

The data used in this study were collected from institutional records and program activities. All participants provided informed consent for the use of their responses for research purposes. The study was conducted in accordance with institutional guidelines, ensuring confidentiality and the ethical handling of all data.

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