frontiers | Frontiers in Education

TYPE Original Research
PUBLISHED 22 October 2025
DOI 10.3389/feduc.2025.1661179

OPEN ACCESS

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RECEIVED 07 July 2025
ACCEPTED 15 September 2025
PUBLISHED 22 October 2025

CITATION
Ventura-León J, Lino-Cruz C, Tocto-Muñoz S, Gamboa-Melgar G and Ruiz-Castro J (2025) Cultural adaptation and psychometric validation of the academic progress goals scale for Peruvian university students. *Front. Educ.* 10:1661179. doi: 10.3389/feduc.2025.1661179

Cultural adaptation and psychometric validation of the academic progress goals scale for Peruvian university students

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Introduction: Academic goal progress is a key motivational construct linked to students' planning, self-regulation, and academic success, yet there is a dearth of culturally adapted, validated instruments for assessing this construct in Peruvian higher-education contexts. Grounded in Social Cognitive Career Theory, this study addresses this gap by adapting and validating the Academic Progress Goals Scale (AGPS) for Peruvian university students.

Methods: A total of 1,157 undergraduate students (Mean Age = 21.55, *SD* = 4.13; 64.4% female) completed the adapted seven-item AGPS. Exploratory Factor Analysis (EFA) with WLSMV estimation and AI-based iterative optimization reduced the scale to five items. Confirmatory Factor Analysis (CFA) tested the resulting unidimensional structure. Internal consistency was estimated via McDonald's omega (ω), bootstrap resampling (1,000 draws) evaluated stability, and structural equation modeling examined convergent validity with an academic satisfaction measure.

Results: EFA supported a single factor comprising five items, with excellent fit ($\chi^2_{[5]}$ = 9.93, CFI = 0.999; RMSEA = 0.041) and reliability (ω = 0.85). The CFA confirmed this structure with near-perfect fit ($\chi^2_{[5]}$ = 3.82, CFI = 1.000; RMSEA = 0.000) and composite reliability ω = 0.85. Bootstrap analyses indicated consistently high reliability (mean ω = 0.85, *SD* = 0.01) and fit (CFI/TLI ≈ 1.00; RMSEA mean = 0.04). SEM revealed a moderate correlation (ϕ = 0.66) between AGPS scores and academic satisfaction, supporting convergent validity.

Conclusion: The five-item AGPS is a brief, reliable, and valid tool for measuring academic goal progress among Peruvian university students. Its strong psychometric properties and cultural adaptation make it suitable for research, educational policy design, and interventions aimed at enhancing academic engagement and reducing dropout rates.

KEYWORDS

academic goals, psychometric validation, university students, goal setting theory, structural equation modeling

1 Introduction

In recent decades, academic goals have been consolidated as fundamental orientators of students' efforts to improve their performance (Mendo-Lázaro et al., 2022). This motivational construct is articulated with the metacognitive skills essential for planning, monitoring and evaluating one's own learning process (Rahman et al., 2024). However, there is still a lack of sufficiently reliable instruments to measure these competencies in current educational environments (Nájera et al., 2020). This lack hinders alignment with SDG 4, which promotes inclusive, equitable and quality education, as curricular rigidity, institutional resistance and lack of funding and teacher training limit its effective implementation (Ferguson and Roofe, 2020; Zickafoose et al., 2024).

Although the Ministry of Education has incorporated participatory methodologies to define and monitor academic goals in higher education, there is still an urgent need to design and validate a specific instrument for university students in Lima (Jara et al., 2022). Closing this gap is essential to strengthen academic engagement, coping with academic stressors, improving academic skills, and achieving academic achievement and success in various academic contexts (Aladini et al., 2024). Likewise, having a validated instrument will facilitate the improvement of the university experience and the incorporation of values such as competitiveness and performance, favoring an excellent education in marginalized contexts (Oliveira et al., 2025; Sloan-Lynch and Morse, 2024).

Bandura (1986) conceptualized academic goals as concrete intentions that channel behavior toward formative achievements, integrating them into his Social Cognitive Theory as key tools of self-regulation. Subsequently, Lent et al. (1994) adapted this framework to the university setting through the Social Cognitive Career Theory (SCCT), highlighting three interrelated components: academic goals, self-efficacy beliefs and outcome expectations, whose interaction determines student planning, perseverance and performance.

Based on the SCCT of Lent et al. (1994), it is postulated that college motivational dynamics are influenced by self-efficacy beliefs, outcome expectations and personal goals. From this foundation, Lent et al. (2007) developed several scales, among them, the Academic Progress Goals Scale, a seven-item unidimensional scale that assesses students' perceived progress in achieving their academic goals, i.e., the degree to which they feel they are making progress toward goals such as "learning and understanding the material in each of their courses" (p. 432). This instrument reported good internal consistency (Cronbach's $\alpha = 0.86$).

To ensure an accurate assessment of the construct, it is essential to operationally define each type of goal, since the motivational process depends on the recognition of aspirations, obstacles and self-perception of one's own performance (Sheu et al., 2010). Therefore, it is proposed to adapt the original scale to correct conceptual ambiguities and improve its applicability in different contexts. This adaptation is based on the theoretical model of Lent et al. (2007), whose robustness allows for a valid assessment of academic goals and the development of interventions aimed at academic and vocational strengthening.

Within the conceptual framework, academic goals symbolize the future objectives that students seek to achieve, conditioning their involvement in specific activities (Bandura, 1986; Zalazar-Jaime and Cupani, 2018b). Two main types are distinguished: (a) Choice goals: linked to the domain or area that the student aspires to master; (b) Performance goals: related to the level of performance that the student wishes to achieve.

Both goals play differentiated roles: one motivates the exploration of educational options; the other drives the achievement of performance standards in specific tasks (Zalazar-Jaime and Cupani, 2018a). Taken together, they support behavioral self-regulation and are associated not only with satisfaction in the academic context, but also with general subjective wellbeing (Lent et al., 2007). Numerous studies have demonstrated their relevance in interaction with variables such as self-efficacy and outcome expectancies (Işik et al., 2018; Sheu et al., 2022; Sheu and Bordon, 2016).

The Lent et al. (2007) scale has been widely used in several countries such as: Spain (Lent et al., 2017), Portugal (Lent et al., 2009), Angola and Mozambique (Lent et al., 2014), Italy (Lent et al., 2011), Argentina (Medrano et al., 2017), Turkey (Işik et al., 2018) and USA (Duffy and Lent, 2009; Hui et al., 2013; Lent et al., 2007) with acceptable internal consistency (α and ω >0.80). However, so far there is only one research that explored its internal structure (Zalazar-Jaime and Cupani, 2018a), finding satisfactory results (CFI.993, TLI.990, RMSEA = 0.072). Therefore, the need emerges to examine in depth the psychometric properties of the Academic Progress Goals Scale, providing solid empirical evidence for its application in various contexts.

The availability of an accurate instrument to measure academic goals in higher education responds to the interest of promoting learning and optimizing the development of student capabilities (Valle et al., 2006). Having an adapted tool contributes to: (a) strengthening research actions and curriculum improvement (Compagnucci and Spigarelli, 2020; Fernández-Bringas et al., 2024; Pérez et al., 2017); (b) identifying areas for improvement in competencies such as critical thinking, creativity, cognitive flexibility and comprehension(Gaviria and Corredor, 2024; Gökçe and Güner, 2024; Rebecchi et al., 2024; Rodríguez Pulido et al., 2021; Weng et al., 2025).

In addition, some studies have linked goal achievement with the behavioral regulation and organization necessary for academic success (Valle et al., 2009), as well as with the explanation of academic satisfaction through outcome expectations (Lent, 2004; Lent et al., 2007). Moreover, motivation, influenced by goals, impacts cognitive, affective and behavioral domains (Closas et al., 2011; Gaeta et al., 2015). In work contexts, the pursuit of career goals does not always lead to satisfaction, which highlights the differences between academic and professional environments (Abraham et al., 2024; Brown and Lent, 2020).

This study is justified by the urgent need to validate an instrument to measure academic goals in university students. The relevance of this measurement is evidenced by the high dropout rates: in Latin America, almost half of the population aged 25–29 did not complete their studies (Seminara, 2021), and in Peru the dropout rate was 12.6% in 2023 (Ministerio de Educación del Perú, 2021). Although the socioeconomic factor stands out as the main cause (Superintendencia Nacional de Educación Superior Universitaria, 2021), there are also elements related to performance, individual characteristics, family environment, academic adaptation and vocational orientation (Bardales et al., 2025; Quincho et al., 2024; Seminara, 2021).

In this framework, academic goals, understood here as a set of intrinsic and extrinsic factors linked to the educational environment, could facilitate the understanding of the causes of dropout, whose consequences include social and economic problems and underemployment (Aisa et al., 2019; Jia and Ericson, 2017; Silva-Laya et al., 2020), increasing inequality gaps. Having a validated and reliable instrument would contribute to mitigating these rates, foster subjective wellbeing, raise academic satisfaction and reinforce learning objectives.

Consequently, the main objective of this work is to validate an instrument to measure academic goals in higher education students, providing empirical evidence on its factorial structure and reliability, and offering a useful resource for researchers, teachers and educational policy makers.

2 Method

2.1 Participants

An a priori power analysis using semPower (Moshagen and Bader, 2023) with $df = 14$, RMSEA = 0.05, power = 0.95 and $\alpha = 0.05$ indicated a minimum of 778 observations. Our sample of 1,157 undergraduates exceeds this requirement. Table 1 summarizes their sociodemographic characteristics for the Total, EFA and CFA subsamples, see the table for full details.

2.2 Instrument

Participant Demographic Information. Participants completed a comprehensive demographic questionnaire that captured their sex, age, faculty affiliation, academic cycle, place of residence, and study modality, as detailed in Table 1.

Academic Goal Progress Scale (AGPS; Lent et al., 2007). This seven-item measure evaluates students' self-perceived progress toward their academic goals (see Appendix A). Items such as "learning and understanding the material in each of your courses" are rated on a 5-point Likert scale (1 = *no progress at all*; 5 = *excellent progress*), with higher scores reflecting greater goal attainment. The AGPS demonstrated good internal consistency, with Cronbach's $\alpha = 0.84$ in the pilot sample and $\alpha = 0.86$ in the main sample.

Academic Satisfaction Scale (ASS; Lent et al., 2007). This seven-item measure was developed to assess how satisfied students feel with their academic experience (e.g., "I enjoy the level of intellectual stimulation in my courses"). Respondents rate each statement on a 5-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*), with higher scores indicating greater academic satisfaction. The ASS showed excellent reliability, with Cronbach's $\alpha = 0.86$ in the pilot sample and $\alpha = 0.87$ in the main sample.

2.3 Procedure

Data was collected through a mass application to a group of students, who then forwarded the online form to other students, inviting them to participate. The protocol received approval from the Ethics Committee of the Universidad Privada del Norte, and all participants signed an informed consent form before beginning. This remote, emergent approach was selected to reach the target population efficiently, without face-to-face contact, ensuring a broad and inclusive sample. The survey covered academic self-efficacy, age, and gender, and could be completed at the participant's convenience in approximately ten minutes (see Appendix A). Data collection took place between April and May 2025, and the anonymized dataset is publicly available in the OSF repository: https://osf.io/p9f37/?view_only=3b1f6989129d4ed893aacaa0a7e58fde.

2.4. Data analysis

Analyses were conducted in RStudio (RStudio Team, 2022) using the psych (Revelle, 2021), lavaan (Rosseel, 2012), semPlot (Epskamp, 2015), and PsyMetricTools (Ventura-León, 2025) packages to manage data and estimate models. Because our variables were ordinal, we confirmed that each Likert category occurred at least 10 percent of the time to avoid estimation biases (Linacre, 2002).

An EFA was first run to identify the number of factors. We began with an initial factor count and added factors until fit indices fell within acceptable ranges: RMSEA and SRMR below 0.08 and CFI and TLI above 0.95 (Hu and Bentler, 1999). Factor loadings of 0.30 or higher and inter-factor correlations above 0.32 were considered meaningful (Tabachnick and Fidell, 2019). We applied oblimin rotation and the WLSMV estimator in lavaan because of its suitability for ordinal data (Li, 2016). We also tested a one-factor model in a separate validation sample to mirror the original proposal (Silvera et al., 2001). Items exhibiting cross-loadings of 0.30 or greater on multiple factors were removed, which improved overall fit (Lloret-Segura et al., 2014).

Additionally, we use the optimal_efa_with_ai function from the OptimalFactor package (Ventura-León, 2024). This routine first fits an EFA with WLSMV and oblimin rotation. If the model shows RMSEA > 0.08 or items with $|\lambda| < 0.30$ or cross-loadings, it removes the single item whose deletion most reduces RMSEA, then refits the model. The loop continues until RMSEA ≤ 0.08 and each factor retains at least two items with $|\lambda| \geq 0.30$, with a maximum of $n - 1$ iteration. Every decision is logged. Once convergence is achieved, the function calls the OpenAI API (model = gpt-4.1, temperature = 0.5, max_tokens = 250, up to three retries) solely to generate a one-sentence conceptual rationale for each removed or retained item; the algorithm—not ChatGPT—makes all deletion decisions. Two independent psychometric experts review these rationales and may reinstate items if theoretical coherence is threatened (no reversals were required). This hybrid procedure guarantees a transparent and theoretically grounded refinement of the factor structure.

This allows for an iterative procedure to improve an EFA model with AI. The function selects an initial set of items, fits an EFA with the WLSMV estimator and oblimin rotation. In this way, it evaluates both the global fit (RMSEA $\leq$ 0.08) and the local structure (loadings $\geq$ 0.30, minimum number of items per factor). In each iteration, it eliminates the item whose exclusion most improves the fit or resolves the cross-loadings, recording each decision. Once the items are eliminated, chatGPT is invoked through an API to

TABLE 1 Descriptive information on study participants.

Sociodemographic variables	Total		EFA		CFA	
	n	%	*n*	%	*n*	%
Sex						
Woman	745	64.39	372	64.36	373	64.42
Man	412	35.61	206	35.64	206	35.58
Age (mean, SD)	21.55 (4.13)		21.25 (4.02)		21.85 (4.22)	
Faculty						
Architecture and Design	16	1.38	4	0.69	12	2.07
Communications	69	5.96	35	6.06	34	5.87
Law	76	6.57	33	5.71	43	7.43
Engineering	124	10.72	68	11.76	56	9.67
Business	232	20.05	98	16.96	134	23.14
Health	640	55.32	340	58.82	300	51.81
Cycle						
1–3 cycle	219	18.93	122	21.11	97	16.75
4–7 cycle	755	65.25	386	66.78	369	63.73
8–10 cycle	155	13.4	60	10.38	95	16.41
More than 10 cycles	28	2.42	10	1.73	18	3.11
Residence						
Cajamarca	291	25.15	179	30.97	112	19.34
Callao	76	6.57	31	5.36	45	7.77
Lima	696	60.16	314	54.33	382	65.98
Trujillo	94	8.12	54	9.34	40	6.91
Modality						
Presential	593	51.25	290	50.17	303	52.33
Semi-presential	529	45.72	271	46.89	258	44.56
Virtual	35	3.03	17	2.94	18	3.11

generate concise justifications for excluding or retaining the items. This approach guarantees a rigorously refined factor solution, maintaining theoretical consistency and empirical robustness.

We then evaluated previously published factor structures using WLSMV. When these models failed to meet fit criteria (CFI $\leq$0.95 or RMSEA $\geq$0.08), we revised them based on modification indices greater than 10, expected parameter changes above 0.20, and large standardized residual covariances above 0.20, always guided by theory and ensuring at least three items per factor. The same 0.30 loading and 0.32 inter-factor correlation thresholds were applied (Tabachnick and Fidell, 2019).

Scale reliability was assessed with omega (ω), which is recommended for congeneric models with unequal factor loadings (McDonald, 2013; Savalei and Reise, 2019; Ventura-León and Caycho-Rodríguez, 2017).

Finally, we used structural equation modeling to examine relationships among latent constructs (Raykov and Marcoulides, 2006). A CFA incorporating Academic Self-Efficacy as a convergence criterion allowed us to account for item weights, measurement error, and indirect effects for a more accurate representation of the latent variables.

3 Results

3.1 Preliminary analysis

Figure 1A displays the frequency distribution of responses for items MPA1 to MPA7. A pronounced preference for the "*Good progress*" category is seen in items such as MPA1 (62 %) and MPA7 (59 %). In contrast, the "*Fair progress*" category peaks at 29 % for MPA3 and 22 % for MPA6. The "*Excellent progress*" category reaches its highest frequency in MPA4 (32 %) and its lowest in MPA1 (14 %). This pattern shows that, although most students report positive academic advancement, each item captures a nuanced self-assessment gradient; notably, MPA3 and MPA4 differentiate modest from exceptional achievements. Overall, responses cluster around "*Good progress*" highlighting a

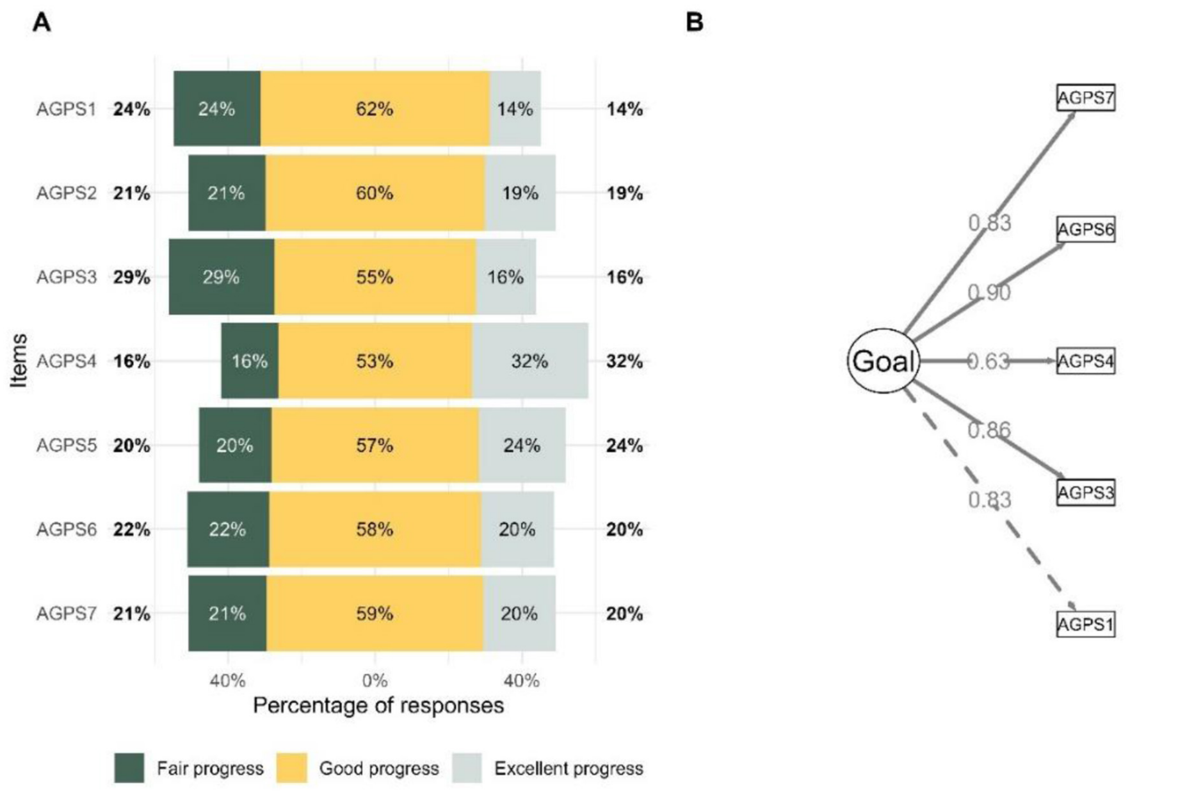

FIGURE 1
Descriptive analysis of the items and structure factorial of AGPS. **(A)** Item response rates. **(B)** Test factor structure.

generally positive perception of academic goal attainment across all items.

3.2 Exploratory factor analysis

Factor analysis was conducted using an optimization procedure that evaluated both global fit (RMSEA) and local structure (loadings $\geq$ 0.30, with a minimum number of items per factor). The procedure iteratively removed the item whose exclusion resulted in the greatest improvement in RMSEA. After two iterations—first excluding AGPS5, which reduced the RMSEA to 0.094, and then AGPS2, bringing the final RMSEA to 0.041—the model retained five items (λ_{AGPS1} = 0.796; λ_{AGPS3} = 0.823; λ_{AGPS4} = 0.645; λ_{AGPS6} = 0.880; λ_{AGPS7} = 0.904). The sharp RMSEA drop, coupled with consistently high loadings, indicates that the remaining items capture the construct's core without redundancy or cross-factor contamination. The model demonstrated excellent fit (χ^2 [5] = 9.932, SRMR = 0.013, WRMR = 0.442, CFI = 0.999, TLI = 0.998), confirming a coherent and robust unidimensional structure. The reliability for this model was also good (ω = 0.85).

3.3 Confirmatory factor analysis

Figure 1B shows the final one-factor CFA for the Academic Goal Progress Scale (AGPS). All five retained items load strongly on the single latent factor, with standardized loadings ranging from 0.626 (AGPS4) to.897 (AGPS6). The model demonstrates exemplary fit under WLSMV estimation: $\chi^2(5)$ = 3.82, SRMR = 0.011, WRMR = 0.279, CFI = 1.000, TLI = 1.001, and RMSEA = 0.000. Composite reliability was also satisfactory (ω = 0.85), confirming that the shortened version preserves the intended one-dimensionality and the internal consistency observed in the EFA.

3.4 Stability of the factorial structure

Figure 2 illustrates the stability of reliability and fit indices across bootstrap resamples. In panel A, the omega coefficient remains tightly clustered around 0.85 (mean = 0.85, SD = 0.01, range 0.81–0.88), indicating consistently high internal reliability. Panel B shows CFI and TLI both hovering at or near 1.00 (CFI mean = 1.00, SD = 0.00; TLI mean = 1.00, SD = 0.00; minimum 0.98, maximum 1.00), reflecting near-perfect factorial fit in every replicate. Panel C presents CRMR, RMSEA, and SRMR: CRMR stays around.02 (mean = 0.02, SD = 0.00), SRMR around.02 (mean = 0.02, SD = 0.01), while RMSEA exhibits greater variability (mean = 0.04, SD = 0.03, range 0–0.13). Moreover, when applying the pre-specified thresholds (CFI <0.95, TLI <0.95, SRMR >0.08, RMSEA >0.08) to each bootstrap replicate, none of the samples fell below acceptable limits for CFI or TLI, nor exceeded acceptable limits for SRMR; only RMSEA marginally violated its cutoff in 6 % of the resamples. This further underscores the robustness of the CFA solution under sampling variability. Taking together, these findings confirm that the factor solution is resilient to sampling variability and that extreme misfit indices are rare events.

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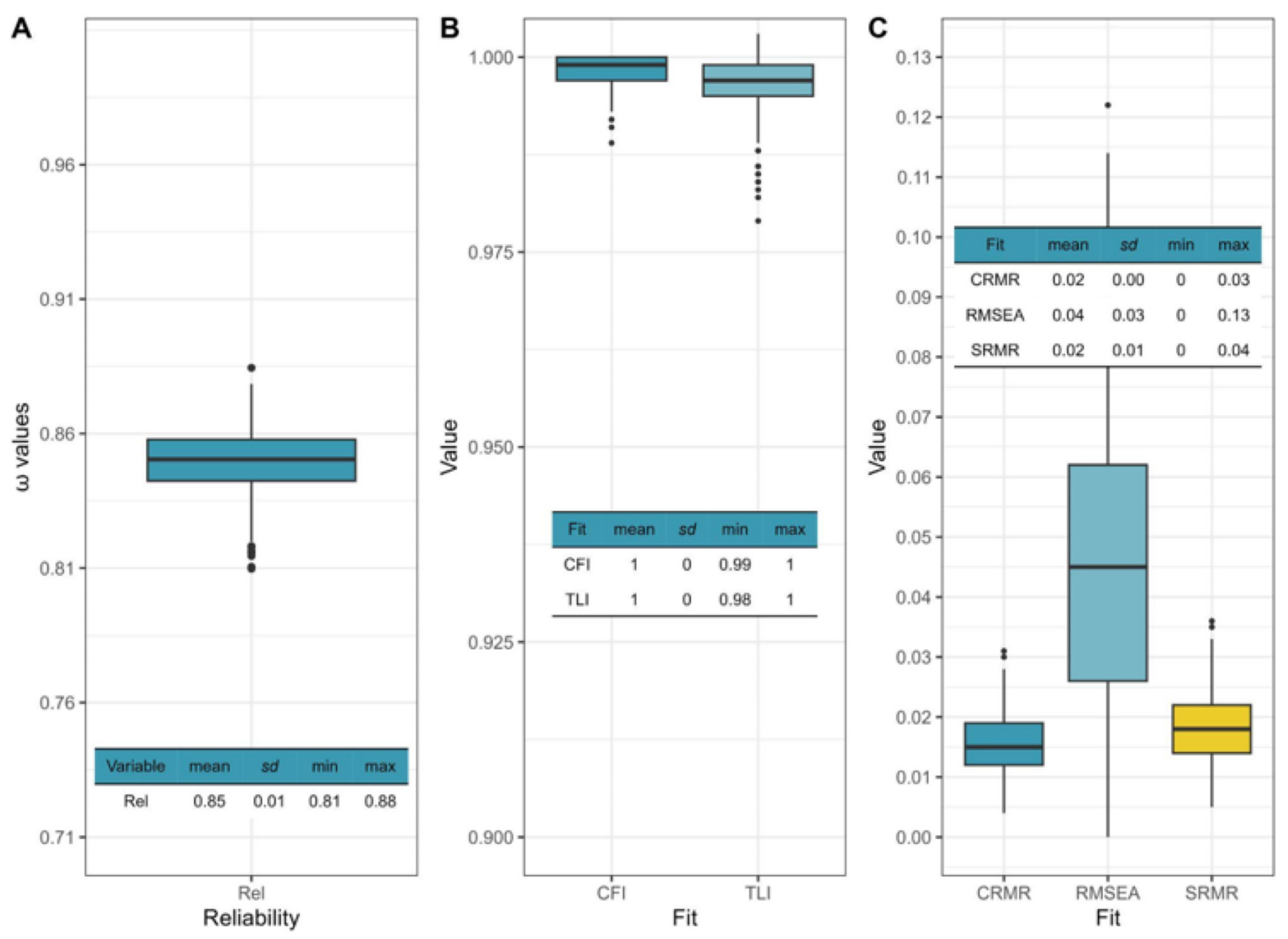

FIGURE 2
Stability of the factorial model. **(A)** Replication of the reliability. **(B)** Replication of comparative goodness-of-fit indices. **(C)** Replication of absolute goodness-of-fit indices.

3.5 Evidence of validity in relation to another variable

Figure 3 presents the relational model between the Academic Goals Progress Scale and academic satisfaction, revealing a moderate interrelation between the factors ($\phi = 0.66$). The model achieved acceptable fit under WLSMV estimation: $\chi^2(63) = 267.50$, SRMR = 0.038, WRMR = 1.174, CFI = 0.984, TLI = 0.981, and RMSEA = 0.075. Both CFI and TLI exceed the 0.95 threshold, while the RMSEA of 0.075 falls below the 0.08 cutoff, indicating a good overall fit. The latent correlation of 0.66 supports the hypothesis that perceived academic progress is substantially (yet not completely) linked to academic satisfaction, implying that each construct adds unique insight into the student experience.

4 Discussion

Consistent with the findings presented, the main objective of this paper is to validate an instrument to measure academic goals in higher education students, providing empirical evidence on its factorial structure and reliability, and offering a useful resource for researchers, teachers and educational policy makers. Based on the theoretical foundation previously exposed, in recent decades academic goals have been consolidated as fundamental orientators of students' efforts to improve their performance (Mendo-Lázaro et al., 2022). Thus, this motivational construct is articulated with the essential metacognitive skills to plan, monitor and evaluate one's own learning process (Rahman et al., 2024). However, there is still a lack of sufficiently reliable instruments to measure these competencies in current educational settings, which hinders alignment with SDG 4 and limits the implementation of inclusive, equitable and quality education (Ferguson and Roofe, 2020; Nájera et al., 2020; Zickafoose et al., 2024). Similarly, this lack prevents the systematic comparison of pedagogical interventions at the international level, making it difficult to identify effective practices that could be replicated in the Peruvian context.

Consequently, in Latin America and, in particular, in the Peruvian context, the need for solid and contextualized psychometric tools persists (Aliaga, 2021; Nájera et al., 2020). In fact, the absence of a validated instrument makes it difficult to detect and mitigate inequalities in the achievement of academic goals, which has repercussions on high university dropout rates (12.6% in 2023) and regional inequity (Aladini et al., 2024; Ministerio de Educación del Perú, 2021; Oliveira et al., 2025; Sloan-Lynch and Morse, 2024). Therefore, the Ministry of Education has

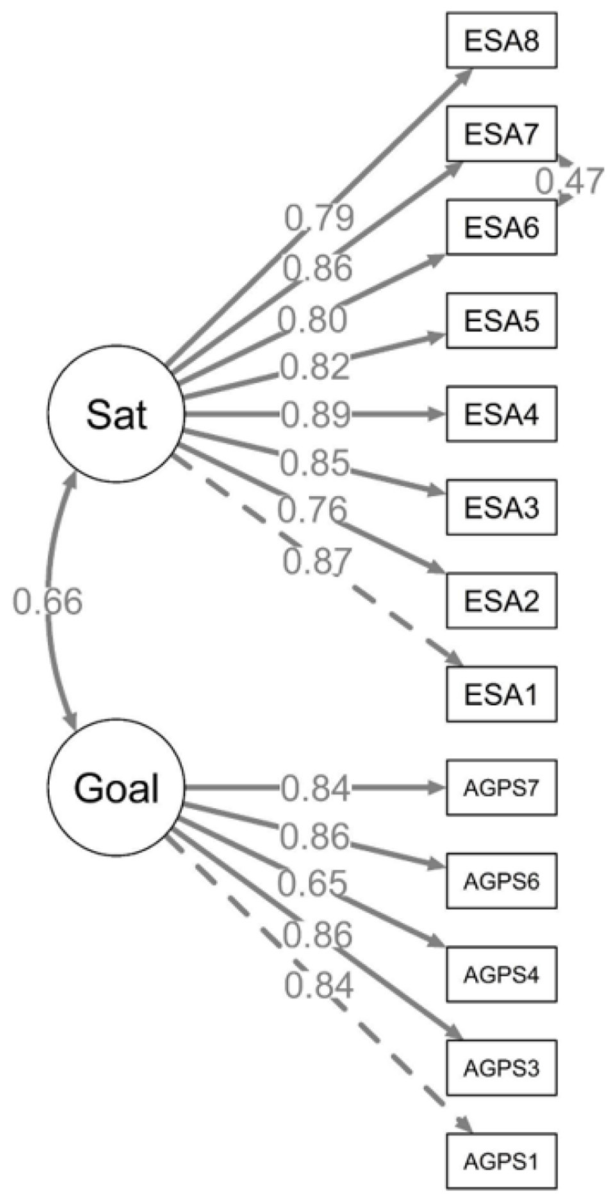

FIGURE 3
Structural model between the relationship between academic progress goals and academic satisfaction.

promoted participatory methodologies (Jara et al., 2022), but a specific instrument for university students in Lima that responds to local cultural and linguistic characteristics is still required. In addition, this instrument will allow evaluating the effectiveness of tutoring and mentoring programs, as well as student retention policies, providing baseline data for the continuous improvement of such strategies.

From a practical standpoint, the five-item AGPS can be administered in less than one minute and therefore lends itself to multiple points of contact within the university support ecosystem. It can be embedded in initial advising forms or orientation interviews to flag students who perceive limited progress, incorporated into learning-management systems and mid-semester surveys as part of early-alert dashboards, or used during one-to-one counseling to inform personalized action plans and referrals to tutoring or wellbeing services. Because of its brevity, the scale can also be re-administered later in the term, allowing advisors to track change over time and adjust interventions in real time.

Based on the Social Cognitive Career Theory (SCCT) of Lent et al. (1994), which integrates academic goals, self-efficacy beliefs and outcome expectations, it is postulated that college motivational dynamics depend on the interaction of these components. In this sense, Bandura (1986) conceptualized academic goals as concrete intentions that channel behavior toward formative achievement, and Lent et al. (2007) developed the Academic Progress Goals Scale, a seven-item unidimensional instrument with good internal consistency ($\alpha = 0.86$). However, its applicability in Peruvian contexts had not been explored, which justifies the present adaptation. To ensure semantic, conceptual and experiential equivalence, each item was reviewed by two bilingual experts and tested with students from the coastal and Andean regions. This process acknowledged the regional variants of Spanish and the collectivist framing of academic success, often experienced as a familial responsibility among first-generation students, thus ensuring that the scale truly resonates with local motivational meanings.

To address this shortcoming, our study implemented an empirical and theoretically grounded adaptation of the original scale, correcting conceptual ambiguities and improving its applicability in diverse academic contexts. Likewise, the introduction of Exploratory and Confirmatory Factor Analysis procedures optimized by means of artificial intelligence represented a relevant methodological innovation (Goretzko and Bühner, 2022; Rodriguez-Rodriguez et al., 2025). In this way, we sought not only to confirm the unidimensional structure, but also to ensure the cultural and linguistic relevance of the instrument. This hybrid approach of traditional psychometrics and artificial intelligence opens new possibilities for the validation of scales in environments with limited technical and human resources.

In descriptive terms, students showed a predominant tendency toward "Good progress" in items MPA1 (62%) and MPA7 (59%), while item MPA4 stood out in "Excellent progress" (32%). In contrast, intermediate categories such as "Fair progress" were concentrated in MPA3 (29%) and MPA6 (22%), which could reflect individual differences in metacognitive skills or specific academic demands. These findings underscore the need for differentiated interventions that enhance learning regulation skills, particularly in those students who perceive moderate progress.

Regarding the internal structure, the AFE indicated that a one-factor configuration with five items (AGPS1, AGPS3, AGPS4, AGPS6 and AGPS7) offers an optimal fit. Specifically, iterative AI eliminated items with insufficient loadings and evaluated comparative and absolute indices, optimizing the model. Next, the CFA confirmed this structure with excellent fit indices, which is consistent with previous evidence in other contexts (Zalazar-Jaime and Cupani, 2018). Thus, it is demonstrated that the scale can be simplified from seven to five items without losing validity, facilitating its administration in environments of high academic demand.

In relation to reliability, the omega coefficient was used, which is more appropriate for congeneric models (Savalei and Reise, 2019; Ventura-León and Caycho-Rodríguez, 2017). The results yielded an average value of $\omega = 0.85$, exceeding the threshold of 0.70 and aligning with international studies reporting α and $\omega > 0.80$ (Lent et al., 2007; Medrano et al., 2017). Therefore, the scale consistently measures different aspects of academic progress goals. This level of reliability allows its use in both longitudinal research and one-off assessments, providing methodological flexibility to users.

Additionally, using a bootstrap procedure of 1,000 replicates in R, the stability of the factor structure was evaluated. This analysis revealed that the CFI and TLI indices maintained mean values of 1.00 (SD = 0.00), while the SRMR and CRMR remained below 0.03. Although the RMSEA showed greater variability (mean = 0.04; SD = 0.03), only 6 % of the replicates exceeded the cutoff point of 0.08. Thus, conclusive evidence was provided on the replicability and structural validity of the model (Awang et al., 2015). These results support the robustness of the instrument, showing that it is resistant to sampling fluctuations and suitable for different cohorts of students.

On the other hand, concurrent validity, evaluated by means of structural equation modeling, confirmed a strong association between academic progress goals and academic satisfaction. This finding supports the proposal of (Lent et al., 2007) and agrees with previous studies in students and teachers (Hui et al., 2013; Lent et al., 2011), evidencing that goal attainment promotes the satisfaction of psychological needs and general subjective wellbeing (Diener, 1984; Klug and Maier, 2015).

However, this study has some limitations. First, non-probability sampling restricts the generalizability of the results and may introduce sampling bias, given the over-representation of female students (64%) and health-science majors (55%). Future work should replicate the study using stratified probability designs or apply post-stratification weights to verify the stability of the findings. Furthermore, although the validated scale retains five items for the factor, future work could explore the incorporation of additional items to enrich the measurement (Brown, 2015). Second, the AI component was limited to producing brief conceptual rationales after a purely statistical, iterative algorithm had determined item retention or deletion; therefore, ChatGPT played no role in the pruning decisions themselves. While two psychometric reviewers screened every rationale, the possibility of incomplete or hallucinated explanations remains, and these narratives should not be regarded as definitive theoretical evidence. Third, because the optimal-deletion algorithm was calibrated on a convenience sample of Peruvian university students, it may capitalize on sample-specific variance; replications with probability samples and in other cultural-linguistic contexts are needed before generalizing the factorial solution. Finally, it would be valuable to extend the sampling to different regions and the social strata of the country to strengthen external validity. It is also suggested to investigate the sensitivity of the scale to specific teacher training interventions and tutoring programs, in order to evaluate changes at the level of academic goals over time.

5 Conclusion

In summary, the validation of the Academic Progress Goals Scale provides a valid, reliable and culturally adapted tool to the Peruvian university context. The results confirm a solid unidimensional structure, high internal consistency ($\omega = 0.85$) and significant relationships with academic satisfaction, supporting its usefulness for identifying motivational profiles and designing pedagogical interventions. Despite sampling and virtual collection limitations, this study lays the groundwork for future research with more representative designs and strengthens the application of SCCT theory in improving student performance and wellbeing. Ultimately, having this adapted instrument contributes to the fulfillment of SDG 4 and the advancement of quality, equity and inclusion in Peruvian higher education, thus fulfilling a central purpose for this work.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://osf.io/p9f37/.

Ethics statement

The studies involving humans were approved by Universidad Privada del Norte Ethics Committee. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation in this study was provided by the participants' legal guardians/next of kin.

Author contributions

JV-L: Investigation, Conceptualization, Writing – review & editing, Writing – original draft. CL-C: Methodology, Writing – review & editing, Writing – original draft. ST-M: Writing – review & editing, Writing – original draft, Data curation. GG-M: Writing – review & editing, Writing – original draft, Methodology. JR-C: Investigation, Writing – review & editing, Writing – original draft.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. The Universidad Privada del Norte will cover the Article Processing Charge (APC) for the publication of this manuscript.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix A

Academic Progress Goals Scale (AGPS)

Instructions: Read each statement and select the option that best describes your academic progress in recent months. There are no right or wrong answers; mark the option that best reflects your personal perception.

Fair progress	Good progress	Excellent progress		
1	2	3		
Ítem	Ítems			
AGPS1	Desempeñarte con excelencia en tu carrera o en los cursos que estás tomando. [Excelling in your academic major or current courses.]	1	2	3
AGPS2*	**Completar eficazmente todas las tareas de los cursos. [Completing all course assignments effectively.]**	1	2	3
AGPS3	Estudiar eficazmente para todos los exámenes. [*Studying effectively for all your exams.*]	1	2	3
AGPS4	Mantenerte matriculado en tu carrera o en los cursos que estás tomando. [Remaining enrolled in your academic major or in current classes.]	1	2	3
*AGPS5**	***Completar satisfactoriamente los requisitos de tu plan de estudios.[Completing academic requirements or other program requirements of your course of study satisfactorily.]***	1	2	3
AGPS6	Alcanzar y mantener notas altas en todos tus cursos. [Achieving/maintaining high grades in all of your courses.]	1	2	3
AGPS7	Aprender y comprender el contenido de cada curso. [Learning and understanding the material in each of your courses.]	1	2	3

In asterisk, bold and italics the items that were eliminated.