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Acceptance-related perceptions of ChatGPT among first-year engineering students with prior academic use

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Abstract

This study examined acceptance-related perceptions of ChatGPT among first-year engineering students at a Chilean university. Psychometric analyses included 206 respondents completing all 32 items; inferential analyses included 178 reporting study-related use. Drawing on an extended technology acceptance model as a descriptive framework, we analyzed perceived usefulness, perceived ease of use, perceived intelligence, perceived trust, awareness, and adoption intention in relation to gender, school sector, prior academic performance, and usage frequency. Internal consistency estimates were high, but exploratory factor analysis showed incomplete separation of the dimensions, limiting claims of construct validity. After Holm correction, no comparisons by gender, school sector, or prior academic performance remained statistically significant. More frequent use was associated with higher scores across all six dimensions. The findings provide preliminary psychometric evidence and identify usage frequency as the most consistent correlate of acceptance-related perceptions. However, the cross-sectional design does not permit conclusions about directionality, causality, or educational benefits.

Keywords: technology acceptance model, ChatGPT, engineering education, generative AI, equity in higher education

INTRODUCTION

Artificial intelligence (AI) has emerged as one of the most transformative technologies of the 21st century, generating profound changes across a wide range of sectors, including higher education (García-Martínez et al., 2023). Among these advancements, large language models (LLMs), such as ChatGPT—developed by OpenAI—have demonstrated considerable potential to enhance teaching and learning processes. These tools enable students to interact dynamically with knowledge, facilitating improved access to information, resolution of complex problems, and the development of critical thinking and analytical skills (Kasneci et al., 2023).

Academic debate about AI in education frequently emphasizes academic integrity and learning quality, but students' rapid uptake of generative tools also warrants empirical examination. ChatGPT differs from conventional institutional platforms because it offers immediate, conversational, and adaptive responses. These characteristics may help explain its appeal in demanding academic contexts, but their educational value and risks must be assessed rather than assumed (Vieriu & Petrea, 2025).

In engineering education, the integration of AI holds particular significance. First-year students are transitioning to more abstract forms of reasoning, greater autonomy, and demanding quantitative coursework. Recent work suggests that AI-based mathematics platforms may support personalized learning pathways, immediate feedback, and students' self-reported learning experiences, although evidence of performance improvement remains limited (Vintere et al., 2025). AI competence and attitudes have also been examined as predictors of first-year students' intended and reported use of AI tools, highlighting the need to

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Contribution to the literature

- This study contributes empirical evidence from a Latin American context—substantially underrepresented in TAM-based research on generative AI in education—and examines how sociodemographic variables relate to acceptance-related perceptions among prior academic users.
- After Holm correction, gender, high school sector, and prior academic performance were not associated with statistically detectable differences across the six dimensions; usage frequency was the only consistently associated variable.
- The study uses an extended TAM-based descriptive framework that distinguishes core TAM constructs from complementary dimensions particularly relevant to generative AI, including perceived intelligence (PI), perceived trust (PT), awareness (AW), and adoption intention (AIN).

integrate AI competence into instructional design (Delcker et al., 2024). More broadly, the integration of AI into higher education assessment has been discussed as an opportunity to redesign learning activities while maintaining critical attention to validity and academic integrity (Williams, 2025).

Despite growing interest, empirical research on the adoption and use of ChatGPT in the educational domain remains in its early stages (Opesemowo & Adewuyi, 2024). This situation is particularly critical in Latin American contexts, where there is a notable lack of studies examining how sociocultural factors and structural inequalities shape the acceptance and pedagogical use of these technologies, particularly within STEM disciplines. While some institutions promote the responsible integration of AI into education, others raise ethical concerns, including plagiarism and algorithmic bias, as well as the potential threats these tools may pose to educational equity. In this polarized landscape, it is imperative to examine how individual variables—such as gender, high school sector, and academic performance—influence students' perceptions and acceptance of ChatGPT.

Studies based on the technology acceptance model (TAM) provide a useful framework for examining acceptance-related perceptions of new technologies (Davis, 1989; Venkatesh & Davis, 2000). Core TAM constructs include perceived usefulness (PU) and perceived ease of use (PE), while later applications have incorporated complementary dimensions relevant to generative AI. Three gaps motivate the present study:

(a) geographic concentration of research in Europe, Asia, and North America, leaving Latin American contexts underrepresented (Crompton & Burke, 2023),

(b) limited examination of gender, prior schooling, and educational background (Hussein et al., 2025; Nyaaba et al., 2024; Ramírez-Correa et al., 2015; Russo et al., 2025), and

(c) insufficient evidence about whether students from different educational backgrounds assign different academic value to ChatGPT in demanding STEM subjects (Shahzad et al., 2024).

This study addresses these gaps by examining acceptance-related perceptions among first-year engineering students with prior academic use of ChatGPT at a Chilean university. Because the design is cross-sectional and descriptive, the study evaluates associations among measured dimensions and background variables rather than causal relationships or actual reductions in educational inequality. Two research questions (RQs) guide the analysis:

RQ1. How are gender, high school sector (private paid vs. public/subsidized), and academic performance related to key TAM dimensions in the academic use of ChatGPT?

RQ2. How is self-reported frequency of academic ChatGPT use associated with students' scores across the six acceptance-related dimensions in the extended TAM-based framework?

Our objective is to characterize acceptance-related perceptions among prior academic users, examine whether these perceptions vary by gender, educational background, and prior academic performance, and assess their association with self-reported usage frequency in Latin American engineering education.

BACKGROUND

TAM

The TAM, developed by Davis (1989), has been widely validated as a robust theoretical framework for studying the adoption of technologies in educational contexts. The model posits that PU and PE are the primary predictors of users' attitudes toward adopting a technology, which in turn directly influence their behavioral intention and actual usage (Venkatesh & Davis, 2000). Over the past decades, TAM has been applied and extended across various educational domains, showcasing its versatility in analyzing the acceptance of digital tools at various levels of education, from primary to higher education. Its ability to incorporate external variables—such as technological trust or perceived risk—has enabled the model to be adapted to emerging technologies, including generative AI (Alshurideh et al., 2024; Barakat et al., 2025).

Although the present study is grounded in the original TAM proposed by Davis (1989), it does not test the original TAM or estimate a structural causal model. Instead, it adopts an extended TAM-based descriptive framework informed by Shahzad et al. (2024). PU and PE are treated as core TAM constructs, whereas PT, PI, AW, and AIN are complementary dimensions used to characterize acceptance of generative AI.

Previous Studies on the Adoption of ChatGPT and Technology in Education

The integration of ChatGPT into educational settings has prompted a growing body of empirical research employing the TAM as an analytical framework. Studies conducted in China, Jordan, and the United Kingdom have demonstrated that both PU and PE significantly predict the willingness to use ChatGPT among university students and faculty members (Alshurideh et al., 2024; Kumar & Lohan, 2024; Ma et al., 2025).

Related research has also shown that perceived value and AI literacy contribute to students' intentions to use ChatGPT, supporting the inclusion of complementary variables beyond the original TAM constructs (Al-Abdullatif & Alsubaie, 2024).

In STEM contexts, students' evaluations of ChatGPT also depend on the perceived scientific accuracy and linguistic quality of its responses, highlighting the importance of examining perceptions related to system capability and reliability (Dahlkemper et al., 2023).

Moreover, several studies have proposed extensions of TAM that incorporate factors such as trust in AI, enjoyment, social influence, and personality traits. For instance, Dahri et al. (2024) identify PT, AI, and personal competence as key elements influencing the acceptance of ChatGPT among pre-service teachers. Similarly, Du et al. (2025) found that personality characteristics were associated with ChatGPT acceptance in language-learning contexts. In mathematics education, TAM has been applied to analyze acceptance of technologies such as educational games and other digital learning tools (Lin & Wang, 2022; Sun et al., 2025). In engineering education, recent research shows that students use generative AI for ideation, feedback, and conceptual support, while adoption remains shaped by task demands, perceived value, and concerns about output limitations (Dai, 2025; El Fathi et al., 2025). Bernabei et al. (2023) likewise report that engineering students perceive LLMs as useful for academic writing and problem-solving, with evaluations shaped by PE, perceived effectiveness, and prior experience.

Individual Variables in Technology Adoption

The integration of AI tools into university students' academic routines is expanding rapidly. Peer-reviewed studies report substantial but heterogeneous use of generative AI in higher education; a sector survey is cited here only as descriptive context, because prevalence estimates vary by country, sample, measurement, and reference period (Freeman, 2025; Morell-Mengual et al., 2025; Sergeeva et al., 2025).

Technological adoption in education is far from homogeneous. Individual characteristics such as gender, educational background, prior technological experience, and self-perceived digital competence may shape how students interact with ChatGPT. Russo et al. (2025) found that women reported higher AI anxiety and less positive attitudes, while gender differences in positive attitudes were less evident at high anxiety levels. In a large peer-reviewed student survey, usage patterns also differed by gender (Morell-Mengual et al., 2025). Other studies have found no gender differences in perceived effectiveness even when frequency of use differs (Iddrisu et al., 2025), while earlier research in Chile and Spain documented context-dependent gender patterns in e-learning acceptance (Ramírez-Correa et al., 2015). The evidence therefore does not support a single universal gender pattern.

In the Chilean educational system, school sector is often associated with socioeconomic differences, but it is not an individual-level measure of socioeconomic status. Research from a different higher-education context has documented variation in early ChatGPT AW and academic use across student-background characteristics, but those findings do not map directly onto Chilean school-sector categories (Arum et al., 2025). Prior experience with educational technologies has also been associated with PU, PE, and behavioral intention in extended TAM research, although this evidence comes from teachers' use of e-learning rather than students' early exposure to generative AI (Mailizar et al., 2021). These findings provide contextual background but do not establish equivalence between school sector and socioeconomic status in the present sample.

Rationale for the Study

Despite the growing literature on AI in education, few studies examine how demographic and educational-background variables relate to ChatGPT perceptions in Latin American engineering programs. The first year is a distinctive STEM transition: students encounter abstract quantitative content, unfamiliar problem-solving practices, and increased expectations for autonomous learning. Examining ChatGPT at this stage can therefore inform support strategies while avoiding assumptions that perceptions necessarily translate into learning gains.

METHOD

Context

The study was conducted during the first semester of the 2025 academic year at a private university in Chile. All 289 first-year students enrolled in a common

engineering program were invited during orientation activities, and 216 participated voluntarily. Of these, 206 completed the 32 questionnaire items and were included in the psychometric analyses. A total of 203 reported having used ChatGPT, and 178 reported study-related use during 2024; these 178 prior academic users comprised the inferential analytic sample (127 male, 51 female). Students without prior academic use were excluded from group comparisons because several dimensions required evaluation of direct experience with the tool.

Instrument

The instrument was adapted from TAM (Davis, 1989) and informed by the extended framework of Shahzad et al. (2024). It comprised six dimensions. PE concerns how easy ChatGPT is to access, understand, and use for academic purposes. PU concerns its perceived value for academic tasks and learning activities. PI captures the apparent cognitive capability of the system, including coherent, adaptive, and context-sensitive responses. PT concerns confidence in the reliability and credibility of responses. AW concerns familiarity with the tool, its functions, and its limitations. AIN concerns willingness to continue academic use. PI is conceptually distinct from PU and PT: it concerns apparent intelligent response behavior rather than academic value or reliability.

Each dimension was assessed with five-point Likert-type items (1 = strongly disagree; 5 = strongly agree). The Spanish adaptation was reviewed within the four-member research team and subsequently by five external experts with backgrounds in technology, psychology, and sociology. The review addressed translation adequacy, semantic clarity, item relevance, and suitability for the Chilean context. Item wording was refined in response to the feedback, and final wording decisions were reached by consensus within the research team. This expert review supported the linguistic and contextual adaptation but was not treated as definitive evidence of content validity. Reliability and internal structure were subsequently examined using participant responses, as described below. The adapted questionnaire is publicly available (Tapia-Sobarzo et al., 2025). The complete Spanish wording administered through the institutional platform, together with English translations prepared for reporting, is provided in **Appendix A**.

Procedure

The questionnaire was administered in person during one orientation session. Students accessed it on mobile phones through an internal digital platform. The activity was implemented as part of the regular educational module on intellectual honesty and the use of generative AI. The educational protocol was reviewed and approved by the Faculty Council, and participation in the research component was voluntary. All participants provided informed consent for their data to be used for research purposes. The survey was not anonymous because personal information was collected. The average completion time was 6 minutes and 12 seconds. Non-anonymous administration may have increased social-desirability or response bias and is considered when interpreting the findings.

Data Analysis

Analyses were conducted in R/RStudio. Psychometric analyses used the 206 respondents who completed all 32 ordinal items. Internal consistency was examined with ordinal alpha based on polychoric correlations and McDonald's omega (Gadermann et al., 2012); sampling adequacy was assessed with KMO and Bartlett's test. Internal structure was explored with a six-factor exploratory factor analysis (EFA) of the polychoric matrix using maximum-likelihood extraction and oblimin rotation, following recommendations for exploratory item factor analysis and transparent reporting of factorial solutions (Boateng et al., 2018; Ferrando & Lorenzo-Seva, 2017; Lloret-Segura et al., 2014).

Inferential analyses were restricted to the 178 participants with prior study-related use. Valid cases were used separately for each background variable: gender n = 178 (127 male, 51 female), high school sector n = 156 (129 private paid, 27 public or subsidized), and Ranking n = 140 (84 high, 56 low). This variable-specific approach excluded missing admission records rather than coding them as a substantive category. Because the study is exploratory and cross-sectional, the analyses estimate associations and group differences rather than causal effects.

Academic performance was represented by the Puntaje Ranking de Notas, an official Chilean university-admission score reported on a 100-1,000 scale that considers students' secondary-school performance in relation to their educational context. Based on the observed distribution, an operational threshold of 850 was selected pragmatically to avoid a highly uneven split and retain adequate sample sizes for subgroup comparisons. Scores were classified as low (< 850; n = 56) and high (≥ 850; n = 84). This study-specific threshold does not represent an official national cutoff for classifying academic performance. Zero, nonnumeric, and unavailable values were treated as missing and excluded, leaving n = 140 for Ranking comparisons.

Self-reported ChatGPT use among prior academic users was grouped as low (n = 87: 1-10 times during the year or once/twice per month) and high (n = 91: weekly or more frequently). The previously reported counts of 101 and 77 corresponded to a different subset selected for availability of school-sector data and included 22

participants without prior academic use; those counts are not used in the revised analysis.

Group comparisons across the six dimensions used Welch's independent-samples t-test. Distributional diagnostics showed no severe skewness or kurtosis. Chi-square tests examined associations between categorical variables; Yates' continuity correction was used for 2 × 2 tables. Effect magnitude was summarized with Cohen's d and 95% confidence intervals (CIs) for mean differences and Cramér's V for categorical associations (Lakens, 2013).

Within each family of six dimensional comparisons, Holm-adjusted p-values controlled multiplicity (Holm, 1979). All four families—usage frequency, gender, high school sector, and Ranking—were recalculated from the merged participant-level data using the coherent prior-user sample and variable-specific valid cases.

RESULTS

Preliminary Psychometric Evidence

The following analyses provide preliminary evidence of internal consistency and internal structure for this Spanish-language adaptation. They do not establish definitive validation for other populations or settings. Scale-development guidance recommends transparent item-level reporting, examination of cross-loadings, and confirmation in independent samples (Boateng et al., 2018).

The psychometric sample comprised 206 complete cases. The full EFA pattern matrix, including all primary and cross-loadings, communalities, uniqueness, and complexity, is reported in **Appendix B**.

Overall ordinal internal consistency was high (αordinal = .946; Guttman's λ6 = .976; mean inter-item correlation = .356). Ordinal alpha by proposed dimension was .861 for AW, .928 for AIN, .910 for PU, .837 for PI, .853 for PE, and .861 for PT. McDonald's ωtotal was .91, .95, .94, .84, .90, and .91, respectively; ωhierarchical was .63, .87, .78, .05, .72, and .80. The very low ωhierarchical for PI cautions against a hierarchical interpretation of that dimension.

Sampling adequacy based on the polychoric correlation matrix was satisfactory (overall KMO = .89; item-level KMOs ≥ .66), and Bartlett's test was significant ($p < .001$). EFA of the polychoric matrix using maximum-likelihood extraction and oblimin rotation yielded a six-factor solution explaining 66% of the variance (RMSR = .03; df-corrected RMSR = .04; off-diagonal fit = .99). However, the empirical pattern did not cleanly reproduce six separate theoretical subscales: AIN and PU largely shared ML1, AW divided mainly across ML3 and ML4, and several items cross-loaded. Therefore, the solution is evidence of a related multidimensional structure, not confirmation of a simple six-factor measurement model.

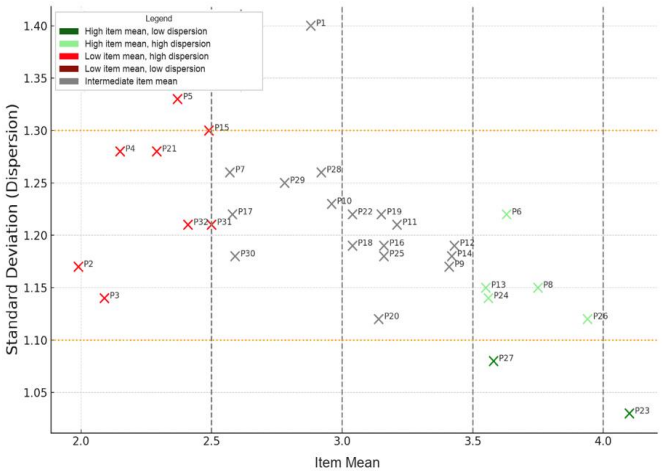


Figure 1. Descriptive mean-dispersion plot for the 32 items of the adapted TAM instrument (Point colors combine item-mean bands of low (< 2.50), intermediate (2.50-3.49), or high (≥ 3.50) with relatively lower (< 1.10) versus higher (≥ 1.10) dispersion. The intermediate mean band is centered on the scale midpoint (3.0); the additional guides at 3.0 and 4.0 mark descriptive mean subdivisions, while 1.30 marks very high dispersion within the higher-dispersion group. These author-defined categories summarize the present sample; they are not theoretically established TAM thresholds or diagnostic cutoffs.) (the authors' own elaboration based on the study data)

The incomplete separation of AIN and PU may partly reflect overlap in item wording: P13 and P14 explicitly refer to usefulness or potential benefits, while P28 combines PE with task completion and finding answers. This post hoc interpretation is descriptive and motivates item refinement; it is not presented as evidence of a definitive measurement structure.

Taken together, the results indicate generally high ordinal internal consistency for the proposed composite scores and suggest a related multidimensional structure in this sample. However, the cross-loadings and incomplete separation of the proposed dimensions limit claims of construct validity. Independent replication, item refinement, and confirmatory comparison of correlated-factor, bifactor, and alternative models are required before the instrument is described as fully validated.

General Results

Figure 1 displays the 32 questionnaire items by mean (M) and standard deviation (SD) using author-defined descriptive bands. These bands summarize positions on the five-point response scale and the observed item dispersion; they are not theoretically established TAM thresholds and should not be interpreted diagnostically. Exact cutoffs are reported in **Figure 1** note.

Figure 2 summarizes the six dimensions. PE had the highest mean, whereas AIN had the highest median but a lower mean and broad interquartile range.

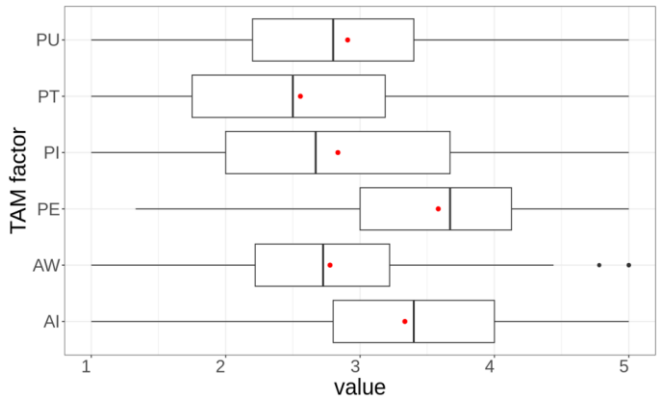


Figure 2. Boxplots of the six TAM dimensions, showing distributions, medians, and means (red markers) (the authors' own elaboration based on the study data)

PT and AW showed varied responses. PT scores clustered around the scale midpoint, whereas AW had wider dispersion with outliers.

Scores were higher in the high usage-frequency group across all six dimensions (**Table 1** and **Figure 3**). After Holm correction, the differences remained statistically detectable for AW (adjusted p = .025) and for the other five dimensions (all adjusted p < .001). Standardized effects ranged from d = 0.34 for AW to d = 0.78 for AIN. These cross-sectional associations do not show that repeated use caused more favorable evaluations.

The largest usage-frequency difference was observed for AIN, d = 0.78, 95% CI [0.48, 1.09], followed by PT, d = 0.75 [0.44, 1.05], and PU, d = 0.73 [0.43, 1.04]. Differences were moderate for PI and PE (both d = 0.57) and smaller for AW (d = 0.34).

Demographic Differences and Educational Backgrounds

Gender comparisons used all 178 prior academic users (127 male, 51 female). **Figure 4** shows the six dimension scores by gender, with red markers for group means.

Men reported higher AW than women (M = 2.89 vs. 2.57), Welch's t(91.26) = 2.35, unadjusted p = .021, d = 0.39, 95% CI [0.06, 0.72]. However, this difference did not remain statistically detectable after Holm correction across the six gender comparisons (adjusted p = .126). The other adjusted p-values were 1.00. High-frequency use was reported by 52.8% of men and 47.1% of women; the association was not statistically detectable, Yates' $\chi^2(1) = 0.27$, p = .602, Cramér's V = .04.

Table 1. Usage-frequency comparisons with multiplicity-adjusted inference

Dimension	Low (n = 87)	High (n = 91)	Δ [95% CI]	Welch t (df)	p	Holm p	d [95% CI]
AW	2.66 (0.73)	2.93 (0.88)	0.27 [0.03, 0.51]	2.25 (172.69)	.025	.025	0.34 [0.04, 0.63]
AI	3.08 (0.91)	3.77 (0.88)	0.70 [0.43, 0.96]	5.21 (174.98)	< .001	< .001	0.78 [0.48, 1.09]
PU	2.62 (0.85)	3.31 (1.03)	0.69 [0.41, 0.97]	4.90 (172.32)	< .001	< .001	0.73 [0.43, 1.04]
PI	2.62 (0.89)	3.17 (1.06)	0.56 [0.27, 0.84]	3.80 (173.08)	< .001	< .001	0.57 [0.27, 0.87]
PE	3.38 (0.73)	3.82 (0.83)	0.45 [0.21, 0.68]	3.80 (174.85)	< .001	< .001	0.57 [0.27, 0.87]
PT	2.28 (0.77)	2.95 (1.00)	0.67 [0.41, 0.93]	5.01 (168.83)	< .001	< .001	0.75 [0.44, 1.05]

Note. Positive differences are high minus low; Holm-adjusted p-values control the six tests in this family; Cohen's d uses the pooled SD; CIs are approximate large-sample intervals

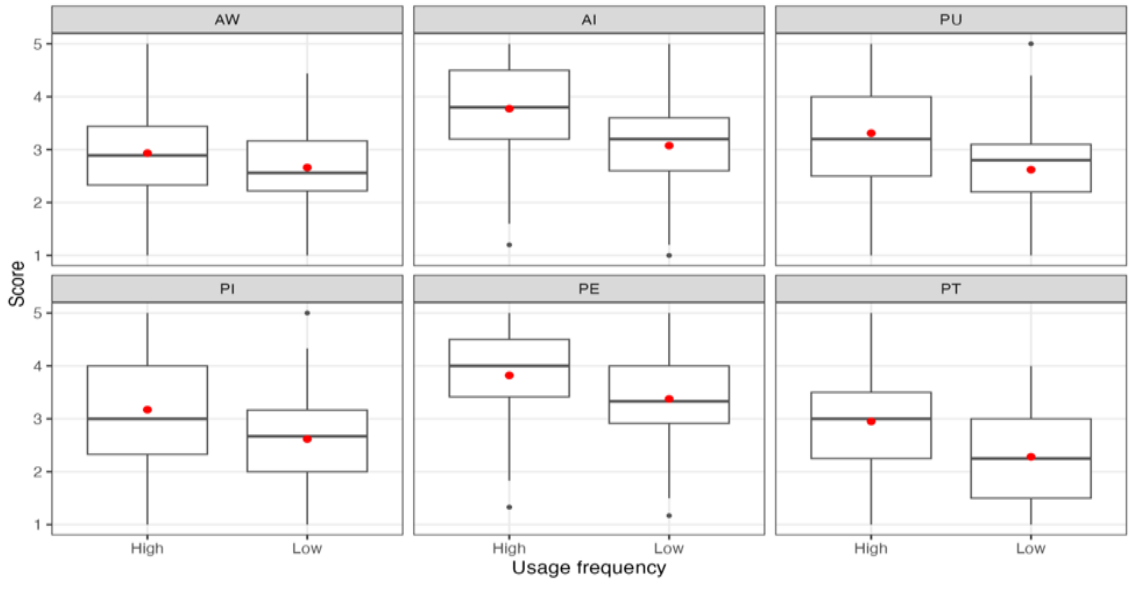


Figure 3. Boxplots of TAM dimension scores by self-reported ChatGPT usage frequency (high vs. low) (red markers indicate group means) (the authors' own elaboration based on the study data)

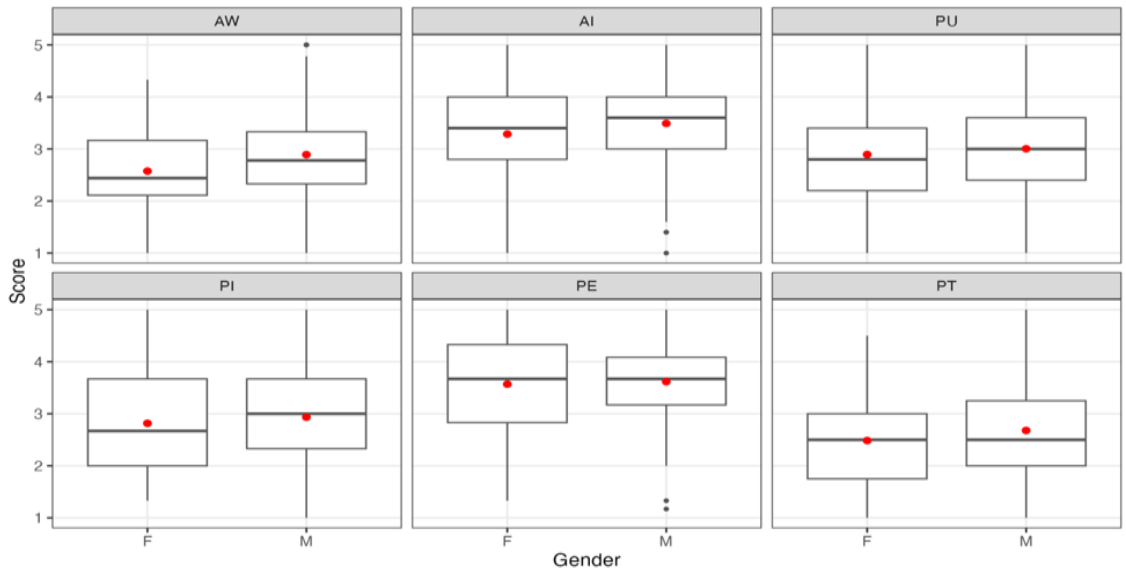


Figure 4. Boxplots of TAM dimension scores by gender (red markers indicate group means) (the authors' own elaboration based on the study data)

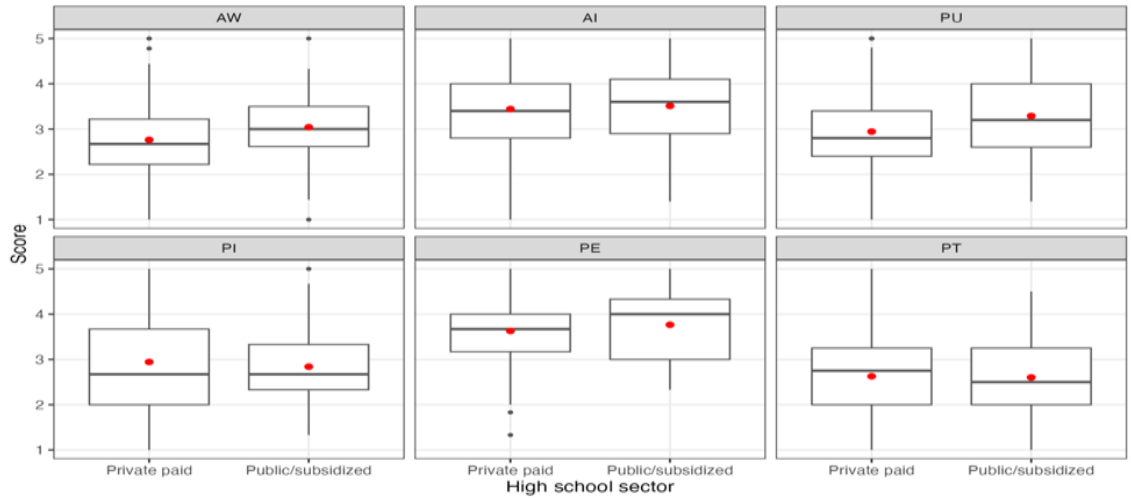


Figure 5. Boxplots of TAM dimension scores by high school sector (private paid vs. public/subsidized) (red markers indicate group means) (the authors' own elaboration based on the study data)

High school sector comparisons included the 156 prior academic users with valid sector information (129 private paid; 27 public or subsidized) (**Figure 5**). PU was somewhat higher in the public/subsidized group (M = 3.29, SD = 1.06) than in the private paid group (M = 2.94, SD = 0.96), but the difference was not statistically detectable, Welch's t(35.43) = 1.56, unadjusted p = .128, Holm-adjusted p = .770, d = 0.35, 95% CI [-0.06, 0.77]. No sector comparison was statistically detectable after correction. Usage-frequency group was also not associated with sector, Yates' $\chi^2(1) = 1.43$, p = .231, Cramér's V = .10.

Ranking comparisons included 140 prior academic users with valid positive scores (84 high; 56 low). None of the six dimension differences remained statistically detectable after Holm correction. The smallest unadjusted p-value concerned PT: the low group reported M = 2.84 (SD = 0.94) and the high group M = 2.51 (SD = 0.90), Welch's t(114.69) = 2.04, unadjusted p = .044, Holm-adjusted p = .261, d = 0.36, 95% CI [0.01, 0.70]. This nominal result is not interpreted as confirmatory. **Figure 6** presents the distributions of the six dimension scores by Ranking class.

Ranking class was not associated with usage-frequency group, Yates' $\chi^2(1) = 0.01$, p = .918, Cramér's V = .01. The data therefore provide little evidence of an association between valid prior academic performance scores and declared frequency of academic ChatGPT use.

DISCUSSION

This study is situated at a particularly meaningful juncture in participants' academic trajectories: their entry into higher education. At this transitional stage—marked by new cognitive, organizational, and cultural

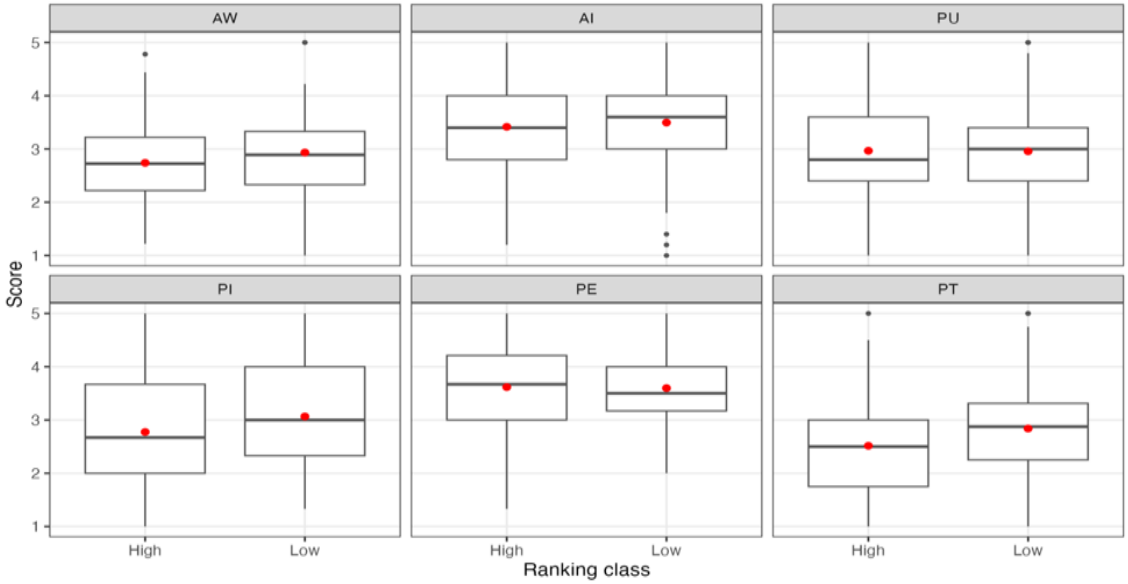


Figure 6. Boxplots of TAM dimension scores by Ranking class (high vs. low) (red markers indicate group means) (the authors' own elaboration based on the study data)

Table 2. Demographic and educational-background comparisons with the lowest unadjusted p-values

Grouping variable	Dimension	Groups	Mean (SD)	p/Holm p	Cohen's d [95% CI]
Gender	AW	Female (n = 51) Male (n = 127)	2.57 (0.82) 2.89 (0.81)	.021/.126	0.39 [0.06, 0.72]
School sector	PU	Private paid (n = 129) Public/subsidized (n = 27)	2.94 (0.96) 3.29 (1.06)	.128/.770	0.35 [-0.06, 0.77]
Ranking	PT	High (n = 84) Low (n = 56)	2.51 (0.90) 2.84 (0.94)	.044/.261	0.36 [0.01, 0.70]

Note. Positive d values indicate the second listed group scored higher; Holm-adjusted p-values control the six dimension tests within each comparison family; None of these comparisons remained statistically detectable after adjustment

demands—tools such as ChatGPT may serve as strategic academic resources. Assessing students' acceptance of this technology in such a context not only provides a snapshot of their initial perceptions but also offers insights into the appropriation processes that are likely to unfold throughout their university journey.

In relation to **RQ1**, the coherent prior-user reanalysis found no demographic or educational-background difference that remained statistically detectable after Holm correction. The unadjusted AW difference by gender ($p = .021$), the PU difference by school sector ($p = .128$), and the PT difference by Ranking ($p = .044$) yielded small standardized effects but adjusted p-values of .126, .770, and .261, respectively. These adjusted nonsignificant comparisons indicate only that no subgroup differences were detected under the present analytical conditions; they do not establish group equivalence or the absence of differences, particularly given the unequal subgroup sizes and uncertainty in the estimates.

The school-sector results do not provide statistically detectable evidence that prior users from public or subsidized schools assign greater academic value to ChatGPT after restricting the analysis to prior users and correcting for multiple comparisons. The direction and uncertainty of the PU estimate may motivate replication with larger and more balanced groups, but it does not support an equity or compensatory conclusion.

For usage-frequency comparisons, standardized differences ranged from $d = 0.34$ to 0.78 and all six remained statistically detectable after Holm correction. By contrast, none of the gender, school-sector, or Ranking comparisons survived family-wise correction. Effect sizes and CIs for the lowest unadjusted p-value in each demographic family are summarized in **Table 2**.

Regarding **RQ2**, participants reporting more frequent academic use scored higher across all six acceptance-related dimensions. This is an association between self-reported use and self-reported perceptions. The cross-sectional design cannot establish whether use leads to more favorable perceptions, whether favorable prior attitudes encourage more use, or whether both processes occur. The findings therefore support further study of ChatGPT as an accessible academic resource among existing users but do not establish an equalizing effect.

Prior academic performance was not associated with statistically detectable differences in the six dimensions or in usage frequency. This absence of evidence should not be interpreted as proof that achievement is irrelevant

in other populations. It indicates only that no association was detected under the present measures and sample conditions.

These findings also invite a broader theoretical reflection on TAM in the context of generative AI. Traditional TAM applications often emphasize technologies as instrumental systems evaluated through usefulness and PE. ChatGPT is also interactive, generative, and conversational, so users may evaluate the apparent intelligence, reliability, adaptability, and pedagogical relevance of its responses. PI and PT may therefore be especially salient complementary dimensions, although the present descriptive design does not test their causal role. Variation in PU and PI may depend on the academic tasks for which students use ChatGPT and their user profiles, and mid-scale PT may reflect concerns about source transparency and generated responses; these possibilities were not measured directly. In contexts marked by educational inequality, PU may also be shaped by prior educational opportunities and access to academic support. An extended TAM-based analysis of generative AI should consequently interpret acceptance within its sociocultural context without assuming compensatory or equity effects.

Taken together, the results characterize acceptance-related perceptions among prior academic users at one institution. Declared use frequency was consistently associated with more favorable perceptions, whereas no association with prior academic performance was statistically detected under the present analytical conditions. Institutional responses should therefore support critical AI literacy and equitable opportunities to evaluate these tools, while avoiding the assumption that encouraging frequency of use will itself improve acceptance or educational outcomes.

CONCLUSIONS

After family-wise correction, the study did not detect differences in acceptance-related perceptions across gender, high school sector, or prior academic-performance groups. By contrast, more frequent self-reported use was associated with higher scores across all six dimensions. The small unadjusted AW difference by gender did not remain statistically detectable after Holm correction. These nonsignificant findings do not establish equivalence or the absence of differences. Unequal subgroup sizes—especially by school sector—and uncertainty in the estimates may have limited sensitivity to smaller group differences.

Methodologically, the study provides preliminary evidence of internal consistency and a related multidimensional structure for a Spanish-language instrument adapted to generative AI. However, incomplete separation of the proposed dimensions limits claims of construct validity. Broader validation requires independent samples, further item refinement, and confirmatory analyses before cross-institutional comparison can be recommended.

Theoretically, the study suggests that an extended TAM-based analysis of generative AI should complement instrumental constructs with perceptions of apparent intelligence, trust, and the sociocultural conditions shaping the academic value attributed to the tool.

Technology alone does not transform education. Any educational value depends on the pedagogical, ethical, and institutional conditions of implementation. Higher education should therefore integrate AI critically and inclusively while evaluating, rather than presuming, its contribution to educational equity.

Several limitations constrain interpretation. The cross-sectional design precludes causal conclusions. Both perceptions and usage frequency were self-reported and may reflect social-desirability or novelty effects, particularly because administration was not anonymous. Voluntary participation may have overrepresented students with greater technological affinity, and complete-case subgroup sizes were unequal by gender and especially by school sector. Admission data were missing for some prior users, so school-sector analyses used n = 156 and Ranking analyses used n = 140. These imbalances reduced precision and may have limited the study's ability to detect small or moderate subgroup differences. The Ranking score was dichotomized at a study-specific threshold of 850 for subgroup comparisons. This reduced the information retained from the continuous measure and may have obscured performance gradients or attenuated differences, particularly among students close to the cutoff. Ranking-group findings should therefore be interpreted cautiously. Most importantly, the analytic population included only students with prior study-related ChatGPT use; the results characterize existing users rather than the entire first-year cohort and do not address initial adoption or non-user perceptions. Future research should use longitudinal and performance-based measures, anonymous administration where feasible, full item-level psychometric reporting, and multi-institutional samples with more balanced subgroups.

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Ethical statement: This study was conducted as part of a regular educational activity on intellectual honesty and the use of generative AI. The educational protocol was reviewed and approved by the Faculty Council. Participation in the research component was voluntary, and informed consent was obtained from all participants for the use of their data for research purposes.

AI statement: The authors stated that OpenAI's ChatGPT and Codex, using GPT-5, were used during manuscript revision and proof preparation to assist with English-language editing, consistency checks, and bibliographic verification. The authors reviewed and verified all AI-assisted output and take full responsibility for the final content. These tools were not used to collect or generate research data, perform the statistical analyses, or determine the study findings or conclusions.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: The deidentified data supporting the findings of this study are available from the corresponding authors upon reasonable request and subject to applicable institutional and ethical requirements.

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APPENDIX A

Table A1. Complete wording of the 32 questionnaire items by proposed dimension

Item	Proposed dimension	Spanish wording administered	English translation
P1	Awareness (AW)	Estoy al tanto de las versiones de ChatGPT.	I am aware of the versions of ChatGPT.
P2		Sigo las noticias sobre ChatGPT.	I follow news about ChatGPT.
P3		Me informo sobre ChatGPT para alcanzar mis objetivos educativos.	I seek information about ChatGPT to achieve my educational goals.
P4		Hablo de las características de ChatGPT con la gente que me rodea.	I discuss the features of ChatGPT with people around me.
P5		Me informo sobre los problemas de ChatGPT.	I seek information about issues related to ChatGPT.
P6		Entiendo el impacto general que tiene el uso de ChatGPT en la educación.	I understand the general impact of using ChatGPT in education.
P7		Conozco sobre IA generativa, como por ejemplo las normas y reglamentos de ChatGPT.	I am knowledgeable about generative AI, including rules and regulations concerning ChatGPT.
P8		Conozco las implicancias de usar ChatGPT en mi educación.	I know the implications of using ChatGPT in my education.
P9		Soy consciente de todo el contenido proporcionado por ChatGPT.	I am aware of all the content provided by ChatGPT.
P10	Adoption intention (AI)	Después de obtener autorización de mi universidad, tengo la intención de usar ChatGPT para mis estudios y evaluaciones.	After obtaining authorization from my university, I intend to use ChatGPT for my studies and assessments.
P11		Tengo la intención de usar ChatGPT para obtener respuestas a mis preguntas relacionadas con mi studio.	I intend to use ChatGPT to obtain answers to questions related to my studies.
P12		Siento que usaría ChatGPT con fines académicos.	I feel that I would use ChatGPT for academic purposes.
P13		Creo que ChatGPT sería beneficioso y más útil para mi trabajo académico.	I believe ChatGPT would be beneficial and more useful for my academic work.
P14		Estoy dispuesto a usar ChatGPT, ya que sus beneficios potenciales son lo suficientemente buenos.	I am willing to use ChatGPT because its potential benefits are sufficiently good.
P15	Perceived usefulness (PU)	ChatGPT me ayuda con todo mi trabajo académico	ChatGPT helps me with all my academic work.
P16		Creo que ChatGPT mejoraría mi aprendizaje.	I believe ChatGPT would improve my learning.
P17		ChatGPT me daría respuestas a todas mis preguntas y expectativas.	ChatGPT would give me answers to all my questions and expectations.
P18		ChatGPT me permitiría aumentar la calidad y la eficacia del aprendizaje.	ChatGPT would allow me to increase the quality and effectiveness of learning.
P19		ChatGPT me daría acceso inmediato a problemas relacionados con el estudio, independientemente de la ubicación.	ChatGPT would give me immediate access to study-related problems, regardless of location.
P20	Perceived intelligence (PI)	ChatGPT puede enseñar y dar respuestas sensatas.	ChatGPT can teach and provide sensible answers.
P21		Creo que ChatGPT es inteligente, como un profesor en la sala de clases.	I believe ChatGPT is intelligent, like a teacher in the classroom.
P22		ChatGPT está lo suficientemente bien informado como para responder a mis preguntas.	ChatGPT is sufficiently well informed to answer my questions.
P23	Perceived ease of use (PE)	ChatGPT es intuitivo y de fácil manejo.	ChatGPT is intuitive and easy to use.
P24		Para mis estudios, sería fácil acceder a ChatGPT.	It would be easy to access ChatGPT for my studies.
P25		Las respuestas de ChatGPT son claras y concisas.	ChatGPT's responses are clear and concise.
P26		Siento que las habilidades necesarias para usar ChatGPT son básicas.	I feel that the skills needed to use ChatGPT are basic.
P27		Sería sencillo adquirir información relacionada con mi estudio a través de ChatGPT.	It would be easy to obtain information related to my studies through ChatGPT.
P28		Utilizo ChatGPT, ya que me hace más fácil completar tareas y encontrar respuestas a preguntas.	I use ChatGPT because it makes it easier for me to complete assignments and find answers to questions.
P29	Perceived trust (PT)	Creo que usar ChatGPT para interactuar sería suficientemente Seguro.	I believe using ChatGPT for interaction would be sufficiently safe.
P30		Confío en que todas las actividades que haga en ChatGPT sean confidenciales y seguras.	I trust that all activities I perform in ChatGPT are confidential and secure.
P31		Siento que ChatGPT mantendría la privacidad de mis datos.	I feel that ChatGPT would maintain the privacy of my data.
P32		Creo que ChatGPT no permitirá que nadie acceda a mi información personal.	I believe ChatGPT would not allow anyone to access my personal information.

Note. Spanish wording is reproduced from the institutional-platform version administered to participants; English translations were prepared for reporting and were not administered; Responses used a five-point Likert-type scale (1 = strongly disagree; 5 = strongly agree); Dimension labels correspond to the proposed scales evaluated in the exploratory psychometric analysis

APPENDIX B

Table B1. EFA pattern matrix for the 32 ordinal items (N = 206)

Item	Scale	ML1	ML3	ML5	ML2	ML6	ML4	h^2	u^2	IC
P1		0.05	0.64	-0.14	0.10	0.16	-0.03	0.45	0.55	1.3
P2		-0.06	0.97	0.03	0.03	-0.02	-0.06	0.88	0.12	1.0
P3		0.16	0.71	0.15	-0.02	-0.14	0.04	0.72	0.28	1.3
P4		0.22	0.47	0.11	-0.07	-0.02	0.15	0.47	0.53	1.9
P5	AW	0.11	0.64	-0.17	-0.10	0.00	0.23	0.60	0.40	1.5
P6		0.06	0.10	-0.10	-0.03	0.32	0.61	0.57	0.43	1.6
P7		-0.09	0.49	0.14	-0.03	0.08	0.39	0.51	0.49	2.3
P8		-0.04	-0.02	0.04	0.01	0.01	0.87	0.75	0.25	1.0
P9		0.15	0.06	0.02	0.15	-0.18	0.65	0.54	0.46	1.4
P10		0.70	0.04	0.12	0.03	-0.10	0.04	0.59	0.41	1.1
P11		0.86	-0.12	0.02	0.01	0.01	0.12	0.72	0.28	1.1
P12	AI	0.80	0.03	-0.09	0.11	0.05	0.10	0.72	0.28	1.1
P13		0.91	0.03	-0.08	0.04	0.02	-0.01	0.81	0.19	1.0
P14		0.86	0.01	0.06	-0.01	-0.03	0.03	0.78	0.22	1.0
P15		0.56	0.17	0.29	0.02	-0.10	-0.18	0.66	0.34	2.1
P16		0.76	0.14	-0.05	0.00	0.16	-0.12	0.76	0.24	1.2
P17	PU	0.51	0.00	0.47	-0.02	-0.12	0.03	0.63	0.37	2.1
P18		0.73	0.10	0.06	-0.01	0.16	0.02	0.80	0.20	1.2
P19		0.42	0.12	0.26	0.03	0.26	0.03	0.66	0.34	2.7
P20		0.21	-0.04	0.47	0.12	0.27	-0.01	0.63	0.37	2.2
P21	PI	0.08	0.13	0.73	0.11	-0.07	0.03	0.73	0.27	1.2
P22		0.03	0.06	0.61	0.12	0.23	-0.02	0.64	0.36	1.4
P23		0.13	-0.03	0.07	-0.03	0.63	0.02	0.51	0.49	1.1
P24		0.32	0.10	0.13	0.05	0.45	0.02	0.60	0.40	2.1
P25	PE	-0.05	0.00	0.56	0.13	0.39	0.00	0.64	0.36	1.9
P26		0.06	-0.03	0.01	-0.04	0.74	0.07	0.60	0.40	1.0
P27		0.28	-0.04	0.18	-0.04	0.47	-0.07	0.51	0.49	2.1
P28		0.61	0.02	0.12	0.12	0.14	-0.15	0.65	0.35	1.4
P29		0.35	0.04	0.19	0.27	0.17	-0.12	0.54	0.46	3.4
P30	PT	0.06	0.03	0.21	0.64	0.09	-0.05	0.64	0.36	1.3
P31		0.07	-0.04	-0.10	0.98	-0.02	0.02	0.93	0.07	1.0
P32		-0.09	0.04	0.06	0.91	-0.06	0.04	0.82	0.18	1.0

Note. Polychoric correlation matrix; maximum-likelihood extraction; oblimin rotation; six factors fixed a priori; h^2: Communality; u^2: Uniqueness; IC: Item complexity; Loadings are shown in full to make cross-loadings visible; Factor order follows the analysis output; ML1 combined most AI and PU items; AW split mainly across ML3 and ML4; ML5 contained most PI items; ML6 contained most PE items; and ML2 contained P30–P32 from PT; This imperfect alignment warrants cautious, preliminary interpretation rather than a claim of definitive six-scale validation