Identifying Drivers of Academic Commitment: A Hierarchical Regression Approach for Engineering Programs

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Abstract

This research full paper examines how socio-cognitive constructs relate to academic commitment in undergraduate engineering students, addressing the ongoing challenge of student retention and timely graduation. Using social-cognitive self-efficacy, expectancy–value theory, and belonging literature, we provide a reproducible workflow for institutional decision-making. A questionnaire measured self-efficacy, self-regulation, motivation, belonging, employment expectations, perceived value, and academic commitment ($N \approx 950$). After distributional checks (skewness/kurtosis) for approximate normality, we conducted correlations and estimated hierarchical linear regression models, comparing them using ΔR^2, RMSE, and AIC/BIC. We performed diagnostics (tolerance/VIF, residuals, influence statistics) and reported robust BCa bootstrap confidence intervals, with sensitivity analyses excluding high-influence cases. This pipeline clarifies what to check, how to compare models, and how to document robustness when assumptions are only approximately met. The parsimonious model explained approximately 42–44% of the variance in academic commitment. Program-level belonging exhibited the most significant standardized effect (~.30), followed by employability expectations (~.21), self-efficacy (~.18), self-regulation (~.10), and motivation (~.09–.11). STEM-field belonging increased predictive capacity ($\Delta R^2 \approx .02$) yet showed a negative partial coefficient—consistent with a suppression pattern when distal identity is modeled alongside proximal program constructs. These findings suggest that students' daily academic integration and perceived program fit are more influential for academic commitment than broad STEM identification, once motivation and efficacy are accounted for. They point to actionable levers for improving retention in complex engineering programs: strengthening program-level belonging through cohort structures, advising, and faculty–student connections, and enhancing employability signaling via industry projects and mentoring. Results lay a foundation for latent profile and SEM follow-ups to identify subgroups and test pathways.

Keywords: Academic commitment, Engineering education, Belonging, Self-efficacy, Hierarchical linear regression

Introduction

This research full paper uses theory-driven hierarchical regression to model how socio-cognitive constructs relate to academic commitment in undergraduate engineering students, a core concern for programs facing persistent challenges with retention, academic engagement, and timely progression. This makes it critical to understand the motivational and psychological factors driving persistence decisions. A fundamental construct in this regard is academic commitment, defined as a future-oriented intention to remain enrolled in a program despite encountering challenges and alternative options [1], [2].

Theoretical frameworks such as social-cognitive theory and expectancy–value theory provide insight into the antecedents of academic commitment. Constructs like self-efficacy and self-regulation are associated with academic success and persistence [3], [4], while task values (including interest, utility, and importance) predict effort and long-term aspirations in STEM fields [5], [6]. Additionally, students' future expectations, including anticipated academic success and employability, connect present engagement with long-term goals [7], [8], [9]. A growing body of research also highlights the role of belonging, especially program-level belonging, as a predictor of motivation, engagement, and retention, particularly in underrepresented groups in STEM [10], [11], [12]. While each of these constructs has been studied individually, few engineering education studies have examined them jointly. Many rely on single-level regression or structural equation models that overlook how predictors interact, overlap, or lose significance when considered together.

This study addresses that gap by using theory-driven hierarchical regression to model how socio-cognitive constructs relate to academic commitment in undergraduate engineering students. Predictors are entered in blocks, that is, self-system beliefs, motivation and value, future expectations, and belonging, to examine their unique and combined contributions. This approach clarifies the relative importance of each construct and demonstrates how institutional survey data can inform strategies to support commitment and student progression in engineering programs.

Literature Review

Research on student persistence examines socio-cognitive factors influencing engagement and retention in higher education, especially in engineering with high dropout rates. This review highlights antecedents of academic commitment—self-beliefs, expectancy–value appraisals, future success and employability, and sense of belonging. It also identifies gaps in models and outlines the study's approach.

Academic commitment in engineering programs. Academic commitment is a future-oriented stance in which students choose to persist despite challenges or competing options [1]. It reflects a sustained intention to remain in a program, even under pressure. This is particularly relevant in engineering, where rigorous curricula, heavy workloads, and competitive environments often lead to attrition and delays. Research links academic commitment and related constructs, (such as intention to persist, program satisfaction, and academic engagement) to retention, performance, and timely graduation. In STEM contexts, commitment to the degree and institution predicts GPA, academic status, and first-year retention, even after controlling for entry characteristics [2]. Self-efficacy and belonging also influence academic commitment, mediated by expectancy-value beliefs [13]. Course-specific self-efficacy and engagement are associated with performance in technical modules that serve as key progression points [14]. Additionally, studies on hybrid and active learning environments show that course design affects engagement and, indirectly, persistence intentions. Gamification and active methodologies have been linked to higher engagement and improved performance [15], [16]. Overall, these findings position academic commitment and engagement as proximal indicators connecting students' motivational resources and course experiences with long-term outcomes in engineering.

Self-system beliefs: self-efficacy and self-regulation. From a social-cognitive perspective, self-efficacy and self-regulation form a core self-system supporting students' engagement with academic demands [3]. Understanding academic self-efficacy as students' beliefs in their ability to succeed in academic tasks is one of the strongest psychological predictors of achievement and persistence in higher education [4]. In engineering and STEM, higher self-efficacy correlates with stronger persistence intentions, better performance, and lower dropout risk, even when controlling for grades and background [10], [14], [17]. Self-regulation complements self-efficacy by reflecting students' ability to plan, monitor, and sustain study behaviors over time [18]. Research shows that self-regulated learning links self-efficacy with GPA [4], mediates engagement [19], and interacts with expectancy-value beliefs and performance [20], [21]. Self-system variables also respond to the environment: self-efficacy is both personal and influenced by learning context and social support [11]. Studies on process-oriented and collaborative learning extend this by connecting self-regulation to motivation and emotional management in group settings [22]. This evidence shows demanding tasks require learners to regulate cognitive, emotional, and motivational states. Students who see themselves as capable and manage learning tend to stay engaged and achieve better outcomes.

Expectancy–value beliefs: motivation and perceived value of STEM. Expectancy–value theory (EVT) distinguishes between students' expectations for success and the subjective value they assign to academic tasks, such as interest, attainment, utility, and cost; and argues that these beliefs jointly shape motivation and engagement in STEM [5], [23]. In these contexts, competence beliefs more strongly predict academic performance, while task values better explain effort, persistence, and career aspirations. Competence beliefs can also exert lasting direct and indirect effects on later trajectories [6], [7], [24]. Perceived STEM value includes both usefulness and personal or societal significance; motivation increases when careers are seen as meaningful and aligned with students' goals [8]. EVT supports interactive, multidimensional models: outcomes are strongest with high expectations and value, where different value facets, including cost, shape choices and success. [6], [25], [26]. Motivational profiles marked by high expectations, high value, and low cost predict persistence, deep learning, and achievement, and help explain gendered participation in STEM [20], [27]–[29]. These findings suggest interventions should promote expectations and task values, support self-regulation and perseverance, and reduce perceived costs in demanding STEM settings. [21], [30], [31].

Future-oriented expectations: success and employability. Beyond motivation and value, students develop expectations about future outcomes, how well they will perform academically, and the kinds of jobs they can obtain. Within expectancy-value theory, these expectations complement task-specific beliefs by linking present choices to anticipated life paths. Expectations for STEM success refer to beliefs about academic performance, while job expectations reflect anticipated employability in STEM fields [8], [9], [32]. Studies show that expectations of academic success, alongside self-efficacy, predict engagement trajectories over time [19], and that perceived future benefits of STEM are linked to motivation and performance through self-regulated learning and perseverance [21]. Recent research on academic and career expectations highlights constructs like "training for employment" and self-perceived employability as central to how students assess the long-term value of their studies [9], [32]–[34]. Students expecting success and good STEM jobs are more likely to pursue demanding programs and persist despite challenges. Expectations about STEM job availability can also reinforce or undermine motivation, affecting students' willingness to stay when workloads rise or better options emerge.

Belonging in Engineering: Program-Level and STEM-Field Belonging. Belonging, understood as feeling accepted, respected, and valued, is a key factor in student persistence in higher education. In STEM, where underrepresentation and stereotype threat persist, especially for women and marginalized groups, this connection is particularly critical [11], [12], [35]. Students may feel belonging at different levels, either to their specific program or the broader STEM community. Program-level belonging depends on daily interactions, environment, and curriculum, while STEM-field belonging reflects a disciplinary identity. The former is about academic integration; the latter about long-term goals and values [10], [12], [13], [17]. Both forms of belonging have been linked to increased engagement, persistence, and retention. A sense of purpose predicts GPA and retention by shaping academic engagement and identity, highlighting the importance of motivation and commitment [2]. Identity styles also matter, that is, more defined styles support meaning-making and academic investment, while diffuse styles relate to lower engagement [14]. For underrepresented groups, social and cultural self-efficacy reinforces a sense of belonging and supports persistence [10]. In male-dominated fields, gender identity, social support, and stereotype threat affect inclusion by influencing self-efficacy and attitudes [11]. Overall, both immediate academic fit and broader disciplinary identity play meaningful roles in promoting engagement and persistence.

Addressing Methodological Gaps: The Present Study. This study explores gaps in modeling academic commitment in engineering education. While some research uses structural equation modeling to validate instruments and predict outcomes like retention and GPA, many studies rely on single, cross-sectional regressions or limited descriptive comparisons, offering little insight into how coefficients shift with related constructs or under predictor redundancy. In adjacent fields, hierarchical regression has been used to clarify layered contributions and explained variance, with diagnostics and robustness checks (e.g., [36]–[38]), yet such approaches remain rare in engineering education—particularly in models that combine motivation, expectations, and belonging. To address this gap, we analyze data from undergraduate engineering students at a major Chilean university and estimate a blockwise hierarchical regression, entering predictors in theoretically ordered blocks. We present three research questions: (1) What is the relationship between these socio-cognitive constructs and academic commitment? (2) When examined together, do certain constructs show stronger or more consistent correlations with academic commitment? and (3) How do conceptually related constructs interact in terms of redundancy, complementarity, or suppression?

Methodology

The analytic sample comprised 953 engineering undergraduates enrolled in on-campus programs at a large private Chilean university. Students' average age was 19.81 years (SD = 1.79), with ages ranging from 18 to 25 years. The sample was predominantly male: 83.8% identified as men (n = 799) and 16.2% as women (n = 154), mirroring the gender imbalance typically observed in engineering programs at the institution. Overall, the sample reflects a predominantly traditional cohort of young engineering students, concentrated in the early years of their programs but spanning a range of curriculum stages.

Positionality. The authors are researchers at the institution, with some holding faculty positions in its engineering programs. They come from engineering and physics backgrounds and are not Chilean but have worked in Chilean higher education for years. Their interest stems from engaging with students' academic paths and noting that commitment, belonging, and motivation are key to these trajectories. They use a socio-cognitive framework because previous research shows students' beliefs and perceived value of tasks influence persistence in engineering. [3], [4]; alternative framings—structural or critical—could surface mechanisms our model does not capture. As institutional insiders, we have privileged access but also an interest in retention outcomes, which we address through transparent diagnostics, sensitivity analyses, and bootstrap inference, following guidance for engineering education research [39].

A structured survey was administered, where participants responded to 5-point Likert scale items on motivation, expectations, perceived STEM value, belonging, and academic commitment. It also gathered sociodemographic data. Reliability was assessed using Cronbach's alpha and McDonald's omega, most constructs showing good reliability (α, $\omega \geq .75$). Subscales for intrinsic and extrinsic motivation had acceptable values ($\alpha \approx .69$, $\omega \approx .63$–$.73$), supporting composite scores. The questionnaire was handed out during class after obtaining consent, designed and distributed via Qualtrics, with data anonymized and stored securely. Analyses used JASP, averaging items for composite scores.

We estimated blockwise hierarchical linear regression models with *academic commitment (AC)* as the dependent variable. Predictors were entered in theoretically ordered blocks. Figure 1 summarizes the block structure and ordering based on theoretical proximity to *academic commitment*. At each step, we examined changes in explained variance (ΔR^2), RMSE, and information criteria (AIC, BIC), interpreting standardized coefficients (β) at $\alpha = .05$. Model assumptions were checked via multicollinearity diagnostics and influence statistics. We also computed bootstrap confidence intervals with 1,000 resamples to assess estimate robustness.

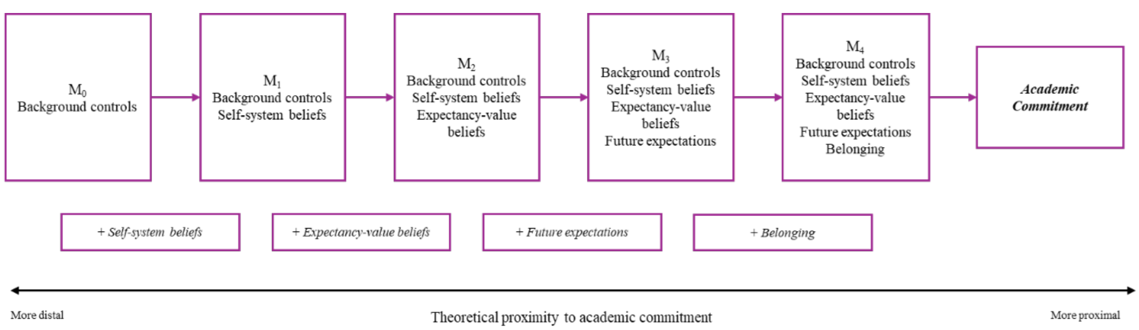

Figure 1. Blockwise hierarchical regression model: ordered predictors of academic commitment.

Results

Table 1 shows descriptive statistics for study variables. On a 1-5 scale, means ranged from 3.45 (STEM membership) to 4.53 (academic commitment), indicating high self-beliefs, motivation, expectations, and belonging (N=953). Standard deviations ranged from 0.56 to 0.89. Distributions were negatively skewed (–1.52 to –0.29), with all indicating agreement on positive items. Kurtosis ranged from 0.37 to 4.25, with academic commitment most peaked (4.25). Departures from normality were moderate, suitable for linear modeling, especially with robustness checks.

Correlations were examined as a preliminary step (see Appendix 1). *Academic commitment* positively correlated with all predictors ($r = .28$–$.53$, all $p < .001$), especially for *belonging to* *major* and *expectancy–value* indicators. Intercorrelations among predictors were mostly moderate, but expectancy–value constructs, such as success expectations with STEM value and STEM job expectancy, were strongly linked, indicating shared variance and overlap in their unique contributions in hierarchical regression models.

Table 1. Reliability, information, and descriptive data of the scales.

	N° items	ω	α	Source	Mean	Std. Deviation	Skewness	Kurtosis
Academic commitment (AC)	5	0.771	0.766	[1]	4.531	0.556	-1.515	4.247
Belonging to major (SB_major)	5	0.872	0.873	[34]	4.144	0.750	-0.987	1.606
Expectancy for STEM job (Exp_job)	4	0.908	0.929	[22]	3.969	0.777	-0.627	0.666
Expectations for success in STEM (Exp_succ)	7	0.936	0.941	[22]	3.955	0.707	-0.545	0.959
Extrinsic motivation (Ext_mot)	4	0.633	0.687	[11]	4.082	0.684	-0.757	0.986
Intrinsic motivation (Int_mot)	4	0.731	0.687	[11]	3.951	0.610	-0.433	1.373
Membership to STEM (STEM_Memb)	4	0.943	0.933	[9]	3.449	0.887	-0.365	0.366
Percieved value of STEM fields (Val_STEM)	8	0.894	0.924	[22]	3.876	0.681	-0.294	0.509
Self-efficacy (Self_Eff)	5	0.916	0.904	[11]	3.961	0.709	-0.717	1.445
Self-regulation (Self_Reg)	5	0.759	0.773	[39]	3.816	0.665	-0.622	1.337

We estimated hierarchical regression models with *academic commitment* as the dependent variable, entering predictors in a theoretical order. To aid readability, Table 2 shows overall fit indices, and Table 3 presents Model 4's regression results with collinearity statistics. The appendix lists all layered model results.

The baseline model, including gender and scholarship status, explained negligible variance (R^2 = .007, p = .031), suggesting that background characteristics alone have minimal explanatory value. Adding *self-efficacy* and *self-regulation* in M_1 produced a substantial gain in explained variance (R^2 = .272; ΔR^2 = .265, p < .001), with both emerging as strong positive predictors ($\beta \approx$ .36 and $\beta \approx$ .23, respectively). M_2 added *intrinsic motivation*, *extrinsic motivation*, and *perceived STEM value*, yielding a further increase (R^2 = .337; ΔR^2 = .065, p < .001): *intrinsic* and *extrinsic motivation* showed small-to-moderate effects ($\beta \approx$ .09; $\beta \approx$ .12), while *perceived STEM value* was comparatively more substantial ($\beta \approx$ .22). *Self-efficacy* and *self-regulation* remained significant, albeit attenuated ($\beta \approx$ .26; $\beta \approx$ .11). In M_3, introducing *expectations for success in STEM* and *expectancy for STEM job* raised explained variance to 36.6% (ΔR^2 = .030, p < .001). STEM job expectancy showed a robust positive association with commitment ($\beta \approx$ .21), whereas success expectations were smaller ($\beta \approx$ .10, p = .036). Predictors from M_2 largely retained their effects. However, *perceived STEM value* dropped to non-significance once expectations entered the model, consistent with substantial shared variance between valuing STEM and future-oriented academic/labour-market appraisals.

Table 2. Fit indices for hierarchical regression models predicting academic commitment.

Model		R^2	R^2_{adj}	RMSE	AIC	BIC	ΔR^2	p
M_0	gender, scholarship	0.007	0.005	0.555	1586.940	1606.379	0.007	.031
M_1	M_0, Self_Eff, Self_Reg	0.272	0.269	0.476	1295.141	1324.299	0.265	< .001
M_2	M_1, Int_mot, Ext_mot, Val_STEM	0.337	0.332	0.455	1212.665	1256.402	0.065	< .001
M_3	M_2, Exp_job, Exp_succ	0.366	0.360	0.445	1173.276	1226.732	0.030	< .001
M_4	M_3, STEM_Memb, SB_major	0.441	0.434	0.418	1057.913	1121.088	0.075	< .001

The final M_4 (Table 3) added *belonging to major* and *membership to STEM* as context-proximal indicators of academic integration. This block produced the most significant incremental gain after the self-system variables, increasing explained variance to 44.1% ($\Delta R^2 = .075$, $p < .001$), while RMSE, AIC, and BIC decreased monotonically across models (Table 2). *Belonging to major* was the strongest predictor of *academic commitment* ($\beta = .32$, $p < .001$), followed by *expectancy for STEM job* ($\beta \approx .21$, $p < .001$), *self-efficacy* ($\beta = .18$, $p < .001$), *self-regulation* ($\beta = .09$, $p = .004$), and *intrinsic* and *extrinsic motivation* ($\beta = .08$–$.11$, both $p < .01$). *Perceived value of STEM fields* and *expectations for success in STEM* were non-significant once the complete set of predictors was included. A more complex pattern emerged for *membership to STEM*: although it improved overall fit, its partial coefficient was negative ($\beta = –.16$, $p < .001$) despite a positive zero-order correlation with commitment. In supplementary models with only controls and the belonging indicators, membership to STEM was strongly positive when entered alone ($\beta = .28$, $p < .001$), but dropped to a small, non-significant effect once *belonging to major* was added, whereas *belonging to major* remained strongly positive ($\beta = .51$, $p < .001$). Overall, this configuration is consistent with a suppression pattern.

Table 3. Standardized coefficients and collinearity diagnostics for the final model (M_4).

					95% CI		Collinearity Statistics	
Model		β	t	p	Lower	Upper	Tolerance	VIF
M_4	(Intercept)		13.317	< .001	1.366	1.838		
	Gender (Women)		1.780	.075	-0.007	0.142	0.939	1.065
	Scholarship (No)		0.024	.981	-0.054	0.055	0.960	1.041
	Self_Eff	0.175	5.100	< .001	0.084	0.190	0.506	1.975
	Self_Reg	0.092	2.906	.004	0.025	0.129	0.595	1.680
	Int_mot	0.081	2.532	.012	0.017	0.131	0.585	1.710
	Ext_mot	0.104	3.900	< .001	0.042	0.127	0.836	1.196
	Val_STEM	0.015	0.341	.733	-0.059	0.083	0.305	3.280
	Exp_job	0.209	5.430	< .001	0.095	0.203	0.403	2.483
	Exp_succ	0.051	1.161	.246	-0.028	0.108	0.309	3.231
	STEM_Memb	-0.158	-5.132	< .001	-0.137	-0.061	0.627	1.596
	SB_major	0.322	10.702	< .001	0.195	0.283	0.656	1.524

Diagnostic checks for collinearity and parameter stability showed tolerances from .34 to .97 and VIFs from 1.03 to 2.92, even for highly correlated predictors. Adding predictors caused only moderate VIF increases and did not alter coefficient signs or significance. Bootstrapping with 1,000 replications revealed minimal bias, with 95% BCa intervals confirming significance for variables such as self-efficacy, self-regulation, motivation, STEM expectancy, membership, and belonging, as they excluded zero. Variables like success expectations, STEM value, gender, and scholarship included zero. Coefficients, bootstrap estimates, and intervals are in the Appendix.

These results indicate stable associations, supporting the model's robustness and ruling out collinearity or parametric issues.

Discussion

This discussion addresses the research questions using hierarchical modeling to analyze bivariate patterns and joint effects. It also examines redundancy and suppression among related constructs, concluding with methodological contributions, limitations, and practical implications.

The first research question examined how socio-cognitive factors relate to students' engineering commitment. *Self-efficacy, self-regulation, motivation, perceived STEM value, success expectations, and belonging* were positively linked to commitment, while background factors like gender and scholarship explained little variance. These findings support social-cognitive and expectancy–value theories, showing students invest effort and persist when they feel capable, motivated, and see a promising future in their field [5], [23]. In particular, *self-efficacy* and *self-regulation* emerged as key correlates, consistent with prior research linking them to academic performance and persistence [4], [18], [22]. Similarly, value-related beliefs and belonging align with findings that motivation, relevance, and academic integration support STEM persistence [8], [10], [12], [21].

The second research question asked whether certain constructs show stronger or more consistent associations when examined together. The full model (M_4) explained 44.1% of the variance in commitment. In this model, *belonging to a major* was the strongest predictor ($\beta \approx .32$), followed by *expectancy for a STEM job* ($\beta \approx .21$), and *self-efficacy* ($\beta \approx .18$). This hierarchy supports prior studies linking academic fit and program-level belonging with identity and institutional integration as drivers of commitment [2], [10], [12]. The strong effect of *STEM job expectancy* reinforces the importance of future-oriented beliefs, seeing STEM as aligned with long-term goals increases persistence [7], [27], [28]. *Self-efficacy* and *self-regulation* remain central, echoing findings on their role in success and engagement [1], [4], [18]. These results show that analyzing these constructs jointly yields a deeper understanding than isolated analysis.

The third question examined how related dimensions interact, such as *perceived value* vs. *expectations*, and *program-level* vs. *STEM-field* belonging. Several predictors lost significance when more proximal constructs were included. *Perceived STEM value* initially linked to commitment, but this disappeared after adding expectations and employment. Expectations for success also lost significance when belonging was included. This suggests that valuing STEM and expecting success influence commitment mainly through beliefs about good job prospects and feelings of belonging. This pattern aligns with expectancy–value theory, which sees task values and expectations as intertwined [23], [25], though our findings suggest that future expectations and belonging have stronger unique associations with commitment, while value-related beliefs fade when proximal appraisals are considered [27], [43], [44]. Likewise, *STEM-field membership* initially predicted commitment positively, consistent with literature showing that STEM identification boosts motivation and persistence [12]. However, once *program-level belonging* and other socio-cognitive factors were included, the effect of STEM membership turned small and negative, while *belonging to a major* remained strongly positive. This supports prior findings that broad identification is less influential than contextualized belonging, which more directly shapes engagement and persistence [2], [10], [12]. In practical terms, students may identify with STEM in general, but only those who feel integrated into their specific engineering program tend to sustain a strong commitment.

This study shows how hierarchical regression clarifies how socio-cognitive constructs influence academic commitment. Entering predictors in ordered blocks reveals how explained variance changes as beliefs, motivation, expectations, and belonging are added. This approach identifies blocks with unique effects after accounting for shared variance and complements prior SEM research (e.g., [9], [11], [20]). It also aligns with recent multi-block studies on academic and career outcomes [36]–[38], offering a more accessible analytic strategy. A further contribution is the explicit handling of collinearity given the conceptual and empirical overlap among constructs such as self-efficacy, value, expectations, and belonging, coefficient instability is a known risk. Reporting diagnostics (tolerance and VIF) helps ensure results are not distorted by multicollinearity, an often-overlooked issue in survey-based motivation research, particularly when suppression or redundancy effects occur.

Beyond substantive findings, the analytic workflow offers practices to improve institutional research: examining blockwise R^2/R^2adj, error, and information criteria provides more informative model comparisons than p-values alone. Incorporating residual and influence checks, along with BCa bootstrap intervals, helps address common issues in self-report data, such as skewness and outliers. Overall, hierarchical regression emerges not only as a predictive tool but also as a flexible, accessible method for analyzing socio-cognitive structures before advancing to SEM or longitudinal designs.

Limitations must be acknowledged. The study used cross-sectional, self-report data from a large private Chilean engineering school, limiting causal inference and generalizability. High mean scores suggest a successful student subset, potentially reducing variability. The models omit relevant variables, such as prior performance, perceived teaching quality, and course features that may influence commitment. Future research should test these models across diverse settings, integrate longitudinal data on retention and progression, and explore techniques, such as structural equation modeling or latent profile analysis to capture patterns and effects.

Despite limitations, findings inform engineering education. Program-level belonging, such as initiatives that foster student integration into majors, can boost commitment. Evidence indicates that academic fit, identity, and support improve belonging and motivation and lower dropout risks in STEM and non-traditional fields [2], [10], [12]. Effective strategies include cohort-based structures, program-level mentoring, early disciplinary engagement, and inclusive faculty practices that foster recognition. Course design also matters; methods like gamified courses and escape rooms boost engagement and motivation [15], [16], suggesting that belonging can be enhanced through both social and curricular structures. As students consider STEM careers, showcasing pathways through internships, projects, and career talks becomes essential, with research linking perceived opportunities and long-term benefits to motivation and career choice [7], [9], [27], [28]. Finally, self-efficacy and self-regulation can be strengthened through transition courses, workshops, and feedback, consistent with findings linking self-beliefs and regulatory skills to academic success [4], [14], [18], [22]. Recent studies also highlight the value of interventions focused on peer norms, outcome expectations, and instructional improvements based on course evaluation data [19], [45]. Aligning interventions with constructs most strongly associated with academic commitment enables institutions to better use survey-based evidence to promote persistence and timely progression in engineering programs.

Conclusion

This study addressed a gap in research on academic engagement in engineering by hierarchically modeling a set of relevant socio-cognitive beliefs. Based on a sample of engineering students from a Chilean university, the results show that while self-efficacy, self-regulation, perceived value of STEM, and expectations of success are positively related to academic engagement, the sense of belonging to the program is the strongest predictor when all factors are considered together. Along with this, the expectation of obtaining employment in the STEM field emerges as a central factor, highlighting the importance of employability projections as a bridge between academic experience and professional goals.

These findings suggest that everyday integration into the training environment, perceived fit with the program, and perceptions of job opportunities are key factors in the decision to persist in demanding careers like engineering, beyond general identification with the STEM field. For faculty, the weight of program-level belonging ($\beta \approx .30$) favors structured within-major team activities, office hours framed as program-community spaces, and course content explicitly tied to the major's career trajectories. For academic advisors and career services, the role of employability expectations ($\beta \approx .21$) argues for major-specific internships, industry projects, alumni mentoring, and structured professional exploration. For program administrators, investments in cohort structures and program-level tutoring—rather than cross-program initiatives—are most likely to shift the constructs most strongly associated with commitment.

Methodologically, the study offers a transparent and reproducible approach that combines hierarchical analysis, assumption evaluation, collinearity control, and robust inference through bootstrap. This approach can be adapted to other educational contexts and complemented with techniques such as latent profile analysis or structural models to explore differentiated trajectories.

Overall, the results help to better understand how motivational, prospective, and contextual factors interact in shaping academic engagement among Chilean engineering students, and they provide conceptual and analytical tools to design institutional strategies that promote retention and timely progress in these programs.

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Appendix 1. Pearson´s correlations

Variable	1	2	3	4	5	6	7	8	9
1. Self_Eff	—								
2. Int_mot	0.546***	—							
3. Ext_mot	0.268***	0.305***	—						
4. Self_Reg	0.515***	0.521***	0.347***	—					
5. STEM_Memb	0.433***	0.373***	0.241***	0.376***	—				
6. AC	0.476***	0.415***	0.315***	0.419***	0.282***	—			
7. SB_major	0.469***	0.375***	0.250***	0.390***	0.440***	0.534***	—		
8. Exp_job	0.328***	0.323***	0.219***	0.297***	0.467***	0.441***	0.376***	—	
9. Exp_succ	0.535***	0.422***	0.258***	0.419***	0.498***	0.478***	0.473***	0.703***	—
10. Val_STEM	0.408***	0.445***	0.294***	0.421***	0.520***	0.442***	0.419***	0.732***	0.766***

*** $p < .001$

Appendix 2. Standardized coefficients and collinearity diagnostics for all the layered models.

					95% CI		Collinearity Statistics	
Model		β	t	p	Lower	Upper	Tolerance	VIF
M_0	(Intercept)		156.184	< .001	4.501	4.615		
	Gender (Women)		1.526	.127	-0.022	0.173	0.975	1.025
	Scholarship (No)		-1.894	.059	-0.141	0.003	0.975	1.025

M_1	(Intercept)		25.723	< .001	2.487	2.898		
	Gender (Women)		1.844	.065	-0.005	0.163	0.961	1.040
	Scholarship (No)		-1.088	.277	-0.096	0.028	0.970	1.031
	Self_Eff	0.361	11.106	< .001	0.233	0.333	0.728	1.374
	Self_Reg	0.227	6.955	< .001	0.136	0.243	0.722	1.385
M_2	(Intercept)		15.942	< .001	1.765	2.261		
	Gender (Women)		0.915	.360	-0.043	0.118	0.947	1.056
	Scholarship (No)		-0.399	.690	-0.071	0.047	0.964	1.037
	Self_Eff	0.255	7.480	< .001	0.148	0.253	0.604	1.656
	Self_Reg	0.110	3.219	.001	0.036	0.148	0.606	1.651
	Int_mot	0.085	2.462	.014	0.016	0.139	0.588	1.701
	Ext_mot	0.118	4.069	< .001	0.049	0.142	0.841	1.189
	Val_STEM	0.215	6.819	< .001	0.125	0.226	0.708	1.411
M_3	(Intercept)		15.068	< .001	1.639	2.130		
	Gender (Women)		0.895	.371	-0.043	0.115	0.945	1.058
	Scholarship (No)		-0.444	.657	-0.071	0.045	0.964	1.037
	Self_Eff	0.217	6.123	< .001	0.116	0.225	0.536	1.867
	Self_Reg	0.115	3.433	< .001	0.041	0.151	0.604	1.656
	Int_mot	0.091	2.702	.007	0.023	0.144	0.587	1.703
	Ext_mot	0.117	4.130	< .001	0.050	0.140	0.840	1.190
	Val_STEM	-0.004	-0.077	.939	-0.077	0.072	0.312	3.206
	Exp_job	0.211	5.218	< .001	0.094	0.208	0.410	2.439
	Exp_succ	0.097	2.101	.036	0.005	0.148	0.314	3.187
M_4	(Intercept)		13.317	< .001	1.366	1.838		
	Gender (Women)		1.780	.075	-0.007	0.142	0.939	1.065
	Scholarship (No)		0.024	.981	-0.054	0.055	0.960	1.041
	Self_Eff	0.175	5.100	< .001	0.084	0.190	0.506	1.975
	Self_Reg	0.092	2.906	.004	0.025	0.129	0.595	1.680
	Int_mot	0.081	2.532	.012	0.017	0.131	0.585	1.710
	Ext_mot	0.104	3.900	< .001	0.042	0.127	0.836	1.196
	Val_STEM	0.015	0.341	.733	-0.059	0.083	0.305	3.280
	Exp_job	0.209	5.430	< .001	0.095	0.203	0.403	2.483
	Exp_succ	0.051	1.161	.246	-0.028	0.108	0.309	3.231
	STEM_Memb	-0.158	-5.132	< .001	-0.137	-0.061	0.627	1.596
	SB_major	0.322	10.702	< .001	0.195	0.283	0.656	1.524

Appendix 3. Bootstrap Coefficients for M_4

						95% CI*	
Model		Unstandardized	Bias	Standard Error	p*	Lower	Upper
M_4	(Intercept)	1.607	0.002	0.192	< .001	1.217	1.956

	Gender (Women)	0.066	-0.001	0.036	.055	-0.004	0.141
	Scholarship (No)	2.818×10^{-4}	1.331×10^{-4}	0.027	.958	-0.050	0.054
	Self_Eff	0.137	1.729×10^{-4}	0.029	< .001	0.077	0.193
	Self_Reg	0.078	8.395×10^{-4}	0.027	.017	0.017	0.127
	Int_mot	0.074	-2.428×10^{-4}	0.032	.021	0.008	0.135
	Ext_mot	0.085	6.928×10^{-4}	0.025	.004	0.037	0.135
	Val_STEM	0.012	-3.462×10^{-4}	0.038	.768	-0.064	0.093
	Exp_job	0.149	4.406×10^{-4}	0.031	< .001	0.091	0.208
	Exp_succ	0.038	-0.002	0.036	.241	-0.027	0.109
	STEM_Memb	-0.099	-1.620×10^{-4}	0.020	< .001	-0.141	-0.062
	SB_major	0.239	5.027×10^{-6}	0.025	< .001	0.188	0.284

Note. Bootstrapping based on 1000 replicates.
Note. Coefficient estimate is based on the median of the bootstrap distribution.
* Bias corrected accelerated.