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Computational Learning Analytics in First-year Engineering: Examining Student Attitudes, Persistence, and Experience

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1. Introduction

The growing availability of computational methods in education research including statistical modeling, natural language processing (NLP), and machine learning (ML) has expanded opportunities to analyze, interpret, and improve the learning experience [1]. Within engineering education, where complex problem-solving and persistence are central [2], computational methods offer a scalable mechanism to understand how students develop their sense of identity and belonging. These affective dimensions are often as critical as technical competencies in shaping long-term success [3]. Previous research has consistently shown that early student experiences in engineering courses influence not only academic outcomes but also students' intentions to remain in the field. Students who feel a strong sense of belonging and confidence in their abilities, and who perceive alignment between their values and those of the engineering profession, are far more likely to persist in graduation and pursue engineering careers [4].

However, identifying which students are struggling with belonging, motivation, or confidence early in the semester remains a significant challenge. Instructors teaching large, multi-section introductory engineering courses often receive vast amounts of both quantitative and qualitative feedback that are difficult to interpret in a timely manner. Traditional assessment methods of exam grades, attendance, and end-of-semester evaluations rarely provide the level of granularity needed to intervene effectively [5]. Computational learning analytics methods, specifically logistic regression for supervised pattern recognition across multi-variable survey data, and NLP techniques (sentiment analysis, keyword extraction, topic modeling) for scalable interpretation of open-ended text, can bridge this gap by identifying patterns in survey data and written reflections that signal disengagement or difficulty long before it is reflected in performance metrics [6]. Both logistic regression and NLP are established components of the broader AI and machine learning toolkit: logistic regression is a supervised learning algorithm widely applied in educational data mining [5], while NLP automates language understanding tasks that would otherwise require time-intensive human judgment at scale.

This study applies these accessible computational methods, namely logistic regression and classical NLP, as analytical instruments to interpret student survey and feedback data from a first-year engineering design course offered at a Hispanic-Serving Institution (HSI) in the U.S. Southwest. HSIs serve a vital role in broadening participation in engineering by providing access and culturally relevant learning environments for Latinx and other underrepresented students [7][8]. Yet there remains limited research on how computational learning analytics can be applied in these contexts to encourage inclusive and responsive instruction. By integrating predictive modeling with NLP-driven sentiment and thematic analysis, alongside demographic disaggregated examination of student experiences, this study introduces a data-informed framework that captures both quantitative and qualitative dimensions of student experience across diverse populations.

This research employs a mixed-methods framework examining data from 102 first-year engineering students through five complementary analytical phases: paired-samples t-tests, sequential logistic regression, NLP analysis (VADER sentiment analysis [9], TF-IDF keyword extraction [10], and LDA topic modeling [11]), demographic-disaggregated NLP [12], and cross-method integration. This study is guided by the following research questions:

1. To what extent do students exhibit statistically significant changes in attitudes toward engineering from the beginning to the end of the course?
2. To what extent do post-course attitudes predict students' STEM persistence, as measured by their intention to major in engineering?
3. What themes and sentiments emerge from students' open-ended feedback, and do these patterns vary across demographic groups?
4. How do quantitative and qualitative findings converge to provide complementary insights into students' attitudes, experiences, and persistence-related outcomes?

The rest of the paper is organized as follows: Section 2 discusses the relevant literature, Section 3 the methodology, and Section 4 the results. Afterward, section 5 discusses the results, section 6 discusses the limitations, and we conclude the paper in section 7.

2. Literature Review

2.1 Sense of Belonging in Engineering

A sense of belonging has consistently been recognized as a critical factor influencing persistence and success in engineering education [13]. It encompasses students' feelings of acceptance, connection, and fitness within their academic and professional communities. Carberry, Lee, and Ohland [4] emphasized that students' confidence in design and teamwork activities is directly associated with engineering self-efficacy as a strong determinant of persistence. Likewise, Godwin and Kirn [3] demonstrated that identity formation and belonging are shaped by early classroom experiences, mentorship, and peer interactions. These findings underscore that belonging is not merely an outcome, but a dynamic process influenced by institutional culture, representation, and instructional practices.

Research specific to gender and race/ethnicity has further illuminated the centrality of belonging for retention in engineering. Good, Rattan, and Dweck [14] demonstrated that sense of belonging predicts women's representation and persistence in mathematics-intensive fields, with belonging threats contributing to gender disparities. Rainey [15] found that the relationship between belonging and decisions to major in STEM varies by race and gender, with belonging playing a particularly critical protective role for students from groups underrepresented in STEM. For historically underrepresented students in engineering such as those at Hispanic-Serving Institutions (HSIs) creating environments that support belonging and affirm identity is essential for increasing retention and closing equity gaps [16].

The role of course design and pedagogy in fostering belonging has been documented extensively. Walton and Cohen [17] demonstrated through randomized interventions that even brief social belonging exercises can have lasting effects on academic outcomes, particularly for African American students. In engineering specifically, Tonso [18] found that collaborative learning environments and team-based projects can foster belonging by creating communities of practice where students develop engineering identities through authentic participation. Early identification and intervention, supported by AI-driven analytics, can offer timely insights into how these affective constructs evolve across the semester, enabling responsive pedagogical adjustments.

2.2 AI and Learning Analytics in Higher Education

Learning analytics has emerged as a rapidly growing field dedicated to improving education through the analysis of large-scale student data. Siemens [1] defined learning analytics as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (p. 1380). AI and ML models have been used to predict academic performance, detect at-risk learners, and provide adaptive, personalized learning pathways [5] [19].

More recent research has extended these methods beyond cognitive outcomes to explore affective, motivational, and behavioral aspects of learning. Winne and Baker [20] argued for the integration of self-regulated learning theory with learning analytics to understand not just what students do but why they do it. D'Mello and Graesser [21] demonstrated that automated detection of affective states including confusion, frustration, and engagement can predict learning outcomes and inform adaptive interventions. Pardo [22] applied learning analytics to examine student engagement patterns in blended learning environments, showing that analytics can identify early warning signs of disengagement.

In engineering education specifically, learning analytics has been applied to predict persistence and retention. Aulck, Velagapudi, Blumenstock, and West [23] used machine learning on institutional data to predict student dropouts, achieving high accuracy while identifying socioeconomic factors as critical predictors. Gray and DiLoreto [24] examined learning analytics in engineering courses, finding engagement metrics such as resource access and forum participation predicted performance. This study contributes to this evolution by applying learning analytics to socio-emotional constructs such as belonging, confidence, and identity, thereby expanding the domain of AI from performance metrics to holistic indicators of student wellbeing and persistence.

2.3 NLP and Sentiment Analysis for Educational Insights

Traditionally, qualitative feedback from students requires manual thematic coding as a process that is both time-intensive and prone to subjective interpretation [25]. With the emergence of transformer-based NLP models such as BERT [26] and GPT [27], automated sentiment classification, entity recognition, and thematic clustering now provide scalable and highly interpretable insights into student experiences. These models can detect recurring affective signals such as frustration, satisfaction, or disengagement, allowing instructors to respond more effectively to student needs.

In educational contexts, NLP has been increasingly applied to analyze student feedback, discussion forums, and reflective writing. Wen, Yang, and Rosé [28] used sentiment analysis and topic modeling to examine discussion forum posts, identifying patterns in collaborative learning that predicted course outcomes. Kovanović [29] applied automated analysis of discussion transcripts to measure cognitive presence, finding that NLP methods could reliably identify higher-order thinking. Robinson [30] used sentiment analysis on student course evaluations to identify factors associated with satisfaction, demonstrating that automated methods could complement traditional evaluation metrics.

More recently, researchers have applied NLP specifically to engineering education. Kastner [31] used machine learning to analyze student reflections in a first-year engineering course, identifying themes related to growth mindset and engineering identity. Folayan [32] applied sentiment analysis to student feedback in online engineering courses during the COVID-19 pandemic, revealing concerns about hands-on learning and isolation. Integrating text-based insights with survey-derived quantitative data provides a richer, multi-modal understanding of the student learning environment [33]. In this study, NLP methods are used to extract sentiment and thematic trends from open-ended reflections, offering understanding regarding students' experiences which in future can be transformed into actionable feedback to instructors.

2.4 Demographic Differences in Engineering Student Experiences

Understanding how engineering experiences vary across demographic groups is essential for designing equitable, responsive pedagogy, particularly at Hispanic-Serving Institutions. Research on first-generation college students has consistently documented the unique challenges and assets this population brings to engineering. Engle [34] found that first-generation students face structural barriers, including financial constraints, family responsibilities, and limited access to college-preparatory resources, yet they demonstrate high motivation and resilience. Pascarella [35] documented that first-generation students experience lower academic and social integration in their first year but benefit substantially from interventions that explicitly teach college navigation skills. In engineering specifically, Gibbons and Woodside [36] found that first-generation students particularly value explicit instruction in time management, study strategies, and professional norms.

Gender disparities in engineering education and persistence have been extensively documented. Sax [37] found that mathematical self-concept became increasingly salient in shaping women's STEM aspirations over the college years, with women more likely to opt out of STEM despite equivalent or superior performance. Godwin, Potvin, Hazari, and Lock [38] developed an identity-based model predicting engineering career choice, finding that recognition (feeling recognized as an engineer by others) was particularly important for women. Walton, Logel, Peach, Spencer, and Zanna [39] demonstrated that social-belonging interventions reduced gender gaps in science by addressing stereotype threats and feelings of not belonging.

For Hispanic/Latinx students in engineering, cultural factors including family obligations, financial responsibilities, and navigating predominantly white institutional cultures shape persistence decisions. Rodriguez, Lu, and Bartlett [40] examined engineering identity development among Latinx students at HSIs, finding that culturally validating pedagogies and seeing oneself reflected in the curriculum supported identity development and belonging. Hurtado and Carter [16] found that sense of belonging was particularly critical for Latina/o students' adjustment and retention, with peer interactions and supportive faculty relationships as key predictors.

Few studies, however, have applied NLP-based text analysis to systematically compare open-ended feedback across demographic groups in engineering education, most computational approaches aggregate student text data without disaggregating by gender, first-generation status, or other identity markers. This gap is critical because assumptions that experiences are universal may mask differential impacts of pedagogical approaches, while assumptions that groups inherently differ may reinforce deficit narratives. This study employs demographic-disaggregated NLP analysis to empirically examine whether themes, sentiments, and priorities in student feedback vary by first-generation status and gender, using an asset-based interpretive framework [41] that considers differences as reflecting diverse strengths and contexts rather than deficits.

2.5 Research Gap and Contribution

While applications of AI in investigating student experiences have expanded significantly, most prior studies have focused either on quantitative prediction [19] [5] or qualitative text mining in isolation [28] [29]. Few have developed integrated frameworks that link predictive modeling of student attitudes with sentiment analysis to examine belonging, confidence, and identity. Existing learning analytics research has largely focused on cognitive outcomes (grades, retention) rather than affective development, and most NLP studies analyze discussion forums or course evaluations rather than end-of-semester reflective surveys capturing students' holistic course experiences. This study addresses these gaps by constructing an integrated multi-method framework that combines: (1) paired-samples t-tests examining pre-post attitude changes, (2) sequential logistic regression testing whether post-course attitudes predict persistence beyond demographics and baseline attitudes, (3) NLP analysis applying sentiment analysis (VADER), TF-IDF keyword extraction, and topic modeling (LDA) to 327 open-ended responses, and (4) demographic-disaggregated analysis by first-generation status and gender to assess equity implications. By merging demographic and attitudinal predictors with text-based sentiment mining and ensuring findings apply across diverse populations, this research provides an innovative, data-informed approach to understanding student affective development in first-year engineering courses. Methodologically, it demonstrates that traditional machine learning and classical NLP methods (TF-IDF, sentiment analysis) can yield robust, interpretable insights with typical First Year Engineering (FYE) course enrollments (N~100-300), making sophisticated mixed-methods analysis accessible to engineering education researchers without requiring "big data" or advanced machine learning. It provides evidence that course experiences shape engineering persistence more than demographics or pre-course attitudes, validating investments in high-quality FYE course design as a lever for equity.

3. Methodology

This study employed a mixed-methods approach combining quantitative survey analysis with qualitative natural language processing to understand first-year engineering student experiences at a Hispanic-Serving Institution. The research design consisted of five complementary analytical phases: (1) retrospective pre-post survey data collection capturing demographic characteristics and attitudinal measures, (2) paired-samples t-tests examining pre-to-post attitude changes, (3) sequential logistic regression modeling predictors of STEM persistence, (4) natural language processing analysis of open-ended student feedback, and (5) demographic disaggregated NLP analysis examining whether experiences varied across student populations. This integrated approach allows triangulation across quantitative predictions and qualitative student voice, providing robust evidence for understanding factors that influence belonging, confidence, identity development, and persistence in engineering.

3.1 Study Context and Participants

We collected retrospective pre-post survey data from a first-year engineering design course at a large public open-access Hispanic-Serving Institution (HSI) in the U.S. Southwest during Spring 2025. Data were collected from 102 undergraduate students enrolled in the Engineering Design Experience (ENGR 1302) course. The sample was predominantly male (82.2%) and Hispanic/Latinx (84.8%), with 24.8% of participants identifying as first-generation college students. ENGR 1302 is a three-credit-hour, project-based introduction to engineering design courses open to first-year students regardless of their intended major. The course is structured around three iterative cycles of the engineering design process, with each cycle expanding in scope from individual product improvement to community impact to global considerations. Students complete hands-on prototyping projects, conduct user interviews, deliver design review presentations, and participate in team-based assignments evaluated through peer feedback. Weekly coursework integrates math modules, reading assignments, and collaborative design work. The course intentionally foregrounds belonging and identity development alongside technical skills, explicitly aiming to help students build community, connect with campus resources, and confirm their academic and career direction making it a particularly appropriate context for studying first-year engineering attitudes and persistence. All data were de-identified prior to analysis in accordance with Institutional Review Board (IRB) approval. All demographic information (gender, ethnicity, and first-generation college student status) was self-reported by students as part of the survey instrument and was not obtained from or linked to institutional enrollment records.

3.2 Instruments and Data Sources

Quantitative Survey Data: Retrospective Pre-Post Design: Attitude and perception data were collected using a retrospective pre-post survey design administered at the end of the semester. Students simultaneously rated their current attitudes (post-course) and recalled their beginning-of-semester attitudes (pre-course) on the same survey instrument. The survey was administered during a regular class session to maximize response rates; however, participation was entirely voluntary, did not constitute a course requirement, and had no impact on students' grades.
This design addresses response-shift bias [42] [43], the phenomenon where students' understanding of constructs changes during the course. For example, students' conception of "engineering confidence" evolves as they gain authentic engineering experience, making beginning-of-course ratings potentially incomparable to end-of-course ratings when collected separately. The retrospective approach ensures that both ratings use a consistent internal reference frame. The survey assessed six constructs on Likert-type scales: engineering value (1-5. Engineering confidence (1-5), engineering identity (1-8), engineering community belonging (0-10), grit/perseverance (1-6), and intent to major in engineering (1-5), adapted from [45] [46]. Additional items measured pre-course attitudes toward mathematics (importance, usefulness, personal importance) and demographic variables (gender, ethnicity, first-generation status).

Qualitative Feedback Data: Students responded to five open-ended questions, soliciting reflections on learning experiences, challenges, and course components. Because each student could respond to up to five independent questions, the total number of responses (327) exceeds the number of participants (102); each response was treated as the unit of analysis for NLP purposes. Response rates varied by question: Q72 (most important learning) 88.6%, Q97 (what to continue) 82.9%, Q98 (what should improve) 54.3%, Q73 (unclear concepts) 49.5%, and Q99 (additional feedback) 36.2%. The five questions were designed to capture different dimensions of student experience:

- Q72: "What was the most important thing you learned in this course?" (90 responses)
- Q73: "What concepts or topics were unclear or confusing?" (51 responses)
- Q97: "What should the course continue doing?" (85 responses)
- Q98: "What should the course improve?" (55 responses)
- Q99: "Do you have any additional feedback?" (37 responses)

Pre-Post Attitude Changes: To examine changes in student attitudes over time, paired-samples t-tests were conducted comparing pre-course and post-course measures across five constructs: engineering value, confidence, engineering identity, community belonging, and intent to major. Effect sizes were calculated using Cohen's d, with thresholds of 0.2, 0.5, and 0.8 interpreted as small, medium, and large effects, respectively.

3.3 Sequential Logistic Regression

To further examine predictors of STEM persistence, sequential (hierarchical) logistic regression [44] was conducted with post-course intent to major in engineering as the outcome variable. Persistence was operationalized as an intent score of ≥ 4, corresponding to "probably yes" or "definitely yes." Four hierarchical models were tested: Model 1 included demographic variables (gender and first-generation status); Model 2 added pre-course attitudes; Model 3 incorporated math-related perceptions; and Model 4 included post-course attitudes. This approach assessed whether each block contributed significant explanatory power beyond prior models, with particular emphasis on whether post-course attitudes explained persistence beyond baseline characteristics.

3.4 Natural Language Processing Analysis

Natural language processing techniques were applied to the 327 open-ended text responses to systematically analyze student feedback at scale. The analysis consisted of three complementary methods: 1. Sentiment Analysis: Using VADER (Valence Aware Dictionary and sEntiment Reasoner [9], each response was classified into positive, negative or neutral categories based on compound sentiment scores, with thresholds of ≥ 0.05 for positive, ≤ 0.05 for negative, and intermediate values for neutral sentiment. 2. Keyword Extraction: TF-IDF (Term-Frequency-Inverse Document Frequency) vectorization identified the top 15 distinctive keywords for each question. Preprocessing included stop word removal, lemmatization, and filtering (min_df=2, max_df=0.8) to identify substantive content words. TF-IDF scores quantified keyword importance, with higher scores indicating terms that were both frequent within a question and distinctive to that question. 3. Topic Modeling: Latent Dirichlet Allocation (LDA; [11]) with k=3 topics per question identified latent thematic structures representing coherent word clusters, revealing major themes in student feedback such as math integration challenges, teamwork appreciation, and hands-on learning value. The number of topics (k=3) was selected based on coherence score optimization: models were fit for k=2 through k=6, and k=3 consistently yielded the highest mean topic coherence (C_v scores) while producing interpretable, non-redundant themes. This value also aligns with the relatively constrained response length of the open-ended prompts (median 12 words), where a higher topic count risks overfitting sparse text. Visual inspection of topic-word distributions confirmed that the three resulting topics were semantically distinct and substantively meaningful across all five questions.

3.5 Demographic-Disaggregated NLP Analysis

To assess demographic variation in student experiences, NLP analyses were conducted separately by demographic groups using parallel pipelines. Disaggregation was limited to comparisons with sufficient sample sizes across five open-ended questions (327 responses total): first-generation status (26 first-generation vs. 79 continuing-generation students; ≈81 vs. 246 responses) and gender (18 female vs. 83 male students; ≈58 vs. 269 responses). Ethnicity-based comparisons were excluded due to insufficient non-Hispanic sample size (n=16; ≈50 responses), consistent with recommended minimum cell sizes for text analysis [25]. For each eligible comparison, responses were segmented by demographic attributes while preserving question-level structure (Q72, Q73, Q97, Q98, Q99), and identical NLP procedures were applied independently to each group: VADER sentiment classification (positive/neutral/negative), TF-IDF keyword extraction [KMV1.1] (top 15 keywords per question: min_df=2, max_df=0.8; consistent preprocessing), and normalized theme prevalence analysis for six predefined themes [KMV2.1] (math integration, teamwork, hands-on projects, design process, time management, systems/deliverables). TF-IDF treats each token as a distinct term and does not group synonyms or semantically related words. To partially address this, keyword interpretation was supplemented by LDA topic modeling, which identifies latent themes across co-occurring word clusters and is therefore less sensitive to exact word choice. Group differences were assessed using chi-square tests for sentiment distributions with Cramér's V effect sizes, absolute TF-IDF score differences for shared keywords (>0.05 considered substantive), and independent-samples t-tests for theme prevalence (mentions per 100 responses) with Cohen's d reported, focusing on robust effects given subgroup size constraints. All findings were interpreted through an asset-based framework [41] that considers differences as reflecting diverse experiences and structural contexts rather than student deficits.

4. Results

This section presents findings from five complementary analyses. Results are organized as follows: sample characteristics (4.1), pre-post attitude changes (4.2), sequential logistic regression (4.3), NLP analysis (4.4), and integration of findings (4.5).

4.1 Sample Characteristics: At course entry, ENGR 1302 students reported generally positive baseline attitudes across most constructs. All baseline measures were collected using a retrospective pre-course self-assessment administered at the end of the semester.

Table 1: Sample Demographics (Percentages based on N=102. All demographic data were self-reported)

Characteristic	Category	n	%
Gender	Male	84	82.4%
	Female	18	17.6%
Ethnicity	Hispanic/Latinx	86	84.3%
	Non-Hispanic	16	15.7%
First-Generation Status	First-Generation	25	24.5%
	Continuing-Generation	77	75.5%

4.2 Pre–Post Attitude Changes (Addressing RQ1): Paired-samples t-tests indicated statistically significant improvements across four of the five measured constructs (Table 2).

Table 2: Paired T-Test Results for Pre-Post Attitude Changes

Construct	Pre M (SD)	Post M (SD)	Δ	t	df	p	d	Interpretation
Engineering Confidence	3.50 (1.01)	4.24 (0.77)	+0.74	-7.52	85	<.001	0.77	Medium-large effect
Engineering Belonging	5.80 (2.53)	7.10 (2.15)	+1.30	-6.55	83	<.001	0.68	Medium effect
Engineering Identity	5.27 (1.13)	5.73 (1.17)	+0.46	-2.69	68	.009	0.31	Small effect
Intent to Major	4.16 (1.17)	4.51 (0.91)	+0.34	-3.56	79	<.001	0.38	Small effect; ceiling noted
Engineering Value	4.35 (0.76)	4.38 (0.76)	+0.03	-0.56	85	.578 not significant	0.06	Negligible; ceiling effect

Table 3: Outcome Variable Distributions (Post-Course Changes).

Outcome	n with Individual Score Increase	%	Description
Confidence Improved	65	61.9	Increase in engineering confidence
Engineering Belonging Improved	52	49.5	Increase in engineering community belonging
Identity Strengthened	38	36.2	Increase in engineering identity
Overall Positive Change	33	31.4	Improvement in ≥3 constructs
Engineering Value Improved	27	25.7	Increase in perceived engineering value
Intent to Major Strengthened	21	20.0	Increase in intent to complete engineering major

The n with Individual Score Increase' reflects the number of students whose post-course score exceeded their pre-course score on that construct (i.e., a person-level binary comparison, not a group-level average). Percentages are calculated from the number of respondents with complete pre- and post-course data for each construct

4.3 Sequential Logistic Regression: Predicting STEM Persistence (Addressing RQ2)

Sequential logistic regression was conducted to predict STEM persistence, defined as post-course intent ≥ 4. Engineering persistence intention from Fall to Spring was observed in 84.8% of students. This measure reflects students' self-reported intention at course end and does not capture actual re-enrollment or long-term degree completion, a limitation addressed in Section 6. Model 1 (demographics only) demonstrated limited predictive power (accuracy=60.0%, AUC = 0.615). Model 2, which added pre-course attitudes, improved fit (accuracy = 71.4%, AUC = 0.742), with a significant likelihood ratio test, $\chi^2(6) = 14.51$, $p = .024$. Model 3, incorporating math perceptions, did not yield additional improvement. Model 4, which included post-course attitudes, substantially improved predictive performance (accuracy = 82.9%, AUC = 0.914) over all prior models ($\Delta R^2 = +0.807$, $p < .001$), correctly classifying 91.4% of cases. Key predictors are shown in Table 4. Post-course engineering value and post-course intent were the strongest positive predictors, while demographic variables exhibited minimal effects. Notably, although paired t-tests indicated no significant mean change in engineering value across the sample (Section 4.2), post-course value level remained a strong predictor of persistence reflecting that individual variation in value scores at course end, even within a high-scoring sample, meaningfully differentiates students likely to persist. Negative coefficients on baseline intent, pre-course confidence, and math importance before the course should not be interpreted as low baseline attitudes predicting poor persistence; rather, given the high base persistence rate (84.8%), these reflect ceiling dynamics whereby students entering with already-maximum attitudes had less statistical room to score in the persistent range post-course, while those with moderate baseline scores showed the greatest likelihood of meeting the persistence threshold.

Table 4: Key Predictors in Model 4: STEM Persistence Model

Predictor	β	OR	Direction	Interpretation
Post-course Engineering Value	+1.46	4.32	↑	Strongest positive predictor of persistence.
Post-course Intent to Major	+1.39	4.03	↑	High post-course intent strongly predicts persistence
Baseline Intent to Major	−0.95	0.39	↓	Moderate initial intent more likely to persist (ceiling effect)
Pre-course Confidence	−0.87	0.42	↓	Lower baseline confidence predicts greater persistence gains
Math Importance Before Course	−0.66	0.52	↓	Complex relationship; moderate pre-course math valuation predicts persistence
Demographic Variables	—	—	—	Minimal effects across all demographic predictors

Here, the outcome is Post-course Intent ≥ 4 and β = unstandardized logistic regression coefficient; OR = odds ratio. Model accuracy = 82.9%, AUC = 0.914, Nagelkerke $R^2 = 0.113$.

Table 5: Sequential Logistic Regression Model Comparison.

Model	Predictors	n Pred	Accuracy	AUC	Pseudo R^2	Nagelkerke R^2	Interpretation
Model 1	Demographics	2	60.0%	0.615	-0.552	-1.049	Poor (below baseline)
Model 2	+ Pre-Attitudes	8	71.4%	0.742	-0.398	-0.706	Improved but still limited
Model 3	+ Math Perceptions	11	68.6%	0.739	-0.393	-0.694	No meaningful improvement
Model 4	+ Post-Attitudes	16	82.9%	0.914	0.079	0.113	Excellent performance

Here, the outcome is STEM Persistence defined as post-course intent ≥ 4.

4.4 Natural Language Processing Analysis (Addressing RQ3)

Demographic-disaggregated NLP examined whether qualitative feedback patterns differed by first-generation status and gender among ENGR 1302 students. First-generation students contributed approximately 81 responses and continuing-generation students approximately 246, with female students contributing 58 and male students 269, proportions consistent with the overall sample composition, indicating no systematic dropout from open-ended prompts by any demographic group. Sentiment distributions were also nearly identical: responses were overwhelmingly neutral and descriptive with very low negative sentiment, and chi-square tests indicated no demographic differences (Table 6). Notably, the "confusion" prompt (Q73; see Appendix A for full question text) elicited 0% negative sentiment across groups, this pattern may reflect a constructive feedback orientation, though it could alternatively indicate social desirability effects students may have been reluctant to express negative sentiment in a course-administered survey. Genuinely psychologically safe environments would be expected to elicit both positive and negative responses freely; the near absence of negative sentiment warrants cautious interpretation.

TF-IDF keyword analysis revealed that 'math' was the highest-ranked distinctive keyword in Q73 ('What concepts or topics were unclear or confusing?'), appearing three times more frequently than the next-ranked term, indicating math integration as students' primary area of confusion. The same theme ranked among the top improvement targets in Q98 ('What should the course improve?'), and this pattern held consistently across all demographic groups with no significant differences in math keyword prevalence (Table 7). Theme's prevalence results likewise showed strong cross-group consistency: six of seven themes did not differ by first-generation status, and none differed by gender (Table 8). The only statistically reliable difference was that first-generation students emphasized time management more frequently than continuing-generation students, consistent with differing out-of-class constraints rather than deficit patterns. Overall, findings indicate that the course elicited shared priorities across student groups, especially improving math–engineering connections while highlighting a focused opportunity to strengthen explicit time-management supports.

Figure 1: Sentiment Distribution by Survey Questions

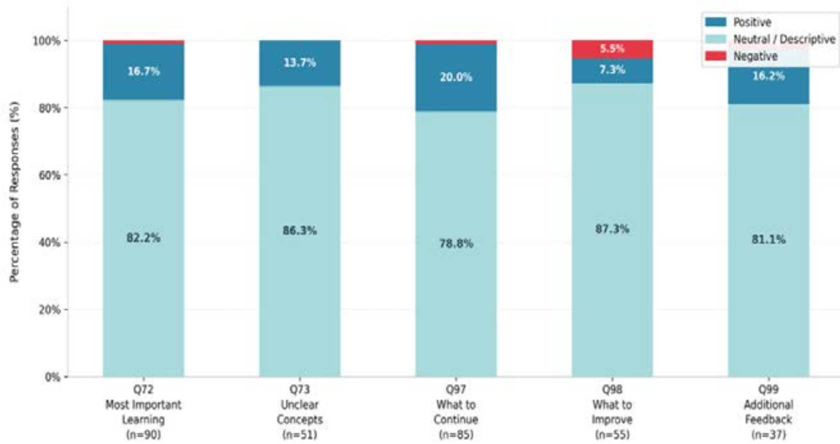

Table 6: Sentiment Distribution by Demographic Groups

Group	n (students)	n (responses)	Positive	Neutral	Negative	χ²	p	Cramér's V
First-Gen Status						0.78	.667	0.05
First-Generation	26	81	13.6%	84.6%	1.5%			
Continuing Generation	79	246	15.4%	83.2%	1.5%			
Gender						0.35	.839	0.03
Female	18	58	15.7%	82.6%	2.2%			
Male	83	269	14.5%	83.9%	1.5%			

Table 7. Math keyword prevalence by demographic group

Group	Q73 TF-IDF	Q73 Rank	Q98 TF-IDF	Q98 Rank	t-test	p	Cohen's d
First-Gen Status					0. 33	.7 41	0.0 9
First-Generation	0.108	#1	0.062	#4			
Continuing Generation	0.104	#1	0.059	#4			
Gender					0. 41	. 685	0. 11
Female	0.102	#1	0.064	#3			
Male	0.107	#1	0.058	#4			

Table 8. Theme prevalence by first-generation status (mentions per 100 responses)

Theme	First-Gen	Continuing-Gen	Difference	t	p	Cohen's d
Math Integration	32.3	31.7	+0.6	0.09	.928	0.02
Teamwork/Collaboration	28.5	29.0	-0.5	-0.15	.881	0.04
Hands-On Projects	24.6	25.6	-1.0	-0.28	.779	0.08

Design Process	22.3	23.5	-1.2	-0.31	.760	0.09
Time Management	**19.7**	**11.5**	**+8.2**	**2.18**	**.035***	**0.48**
Webworks/Systems	15.4	14.8	+0.6	0.12	.907	0.03
Deliverables Clarity	12.3	13.0	-0.7	-0.14	.891	0.04

LDA topic modeling of the 327 open-ended responses identified six recurring themes across the five survey questions. Math integration emerged as the dominant theme in Q73 ('What was unclear or confusing?'), with students expressing concern about connecting course content to prior math knowledge. Teamwork and collaboration were the most frequently cited theme in Q97 ('What should the course continue doing?'). Hands-on projects appeared prominently in Q72 ('What was the most important thing you learned?'), with students describing the value of building physical prototypes. Design process understanding emerged across Q72 and Q97 as students articulated growth in their engineering thinking. Time management appeared in Q98 ('What should the course improve?'), particularly among first-generation students. Webworks/systems deliverables were flagged in Q98 and Q73 as sources of procedural confusion.

4.5 Integration of Findings (Addressing RQ4)

Convergent results across five analyses (descriptive, pre-post tests, sequential logistic regression, NLP, and demographic-disaggregated NLP) answer the four research questions and tell a consistent story about attitude development and persistence among ENGR 1302 students at an HSI. RQ1 was supported: significant gains were observed in confidence (medium-large effect), belonging (medium), identity (small), and intent to major (small), while engineering value showed no significant change due to ceiling effects. RQ2 produced the strongest finding: post-course attitudes predicted persistence with excellent performance, far outperforming models based on demographics, pre-course attitudes, or math perceptions alone, with post-course engineering value and intent emerging as the strongest predictors and demographic variables exhibiting minimal effects. RQ3 showed mostly universal experiences: sentiment distributions and keyword patterns did not differ significantly by first-generation status or gender, with math integration emerging as the dominant concern across all groups; the only statistically reliable difference was first-generation students' greater emphasis on time management, reflecting differing out-of-class constraints rather than deficit patterns. RQ4 was addressed through triangulation across three independent analytical streams, each converging on the same conclusions: (1) math integration emerged as the most robust cross-method priority, appearing as both a statistical predictor in quantitative models and the highest-ranked concern in qualitative student feedback with universal prevalence across all demographic groups; (2) confidence gains in pre-post tests aligned with students' qualitative appreciation for project-based learning and with confidence's role as a persistence predictor; and (3) belonging improvements documented quantitatively aligned with prominent teamwork themes in qualitative feedback and with belonging's predictive relationship to intent strengthening.

5. Discussion

This mixed-methods study demonstrates that a first-year engineering course at an HSI can meaningfully shift students' affective trajectories and that these course-shaped attitudes strongly relate to persistence. Pre-post analyses indicated significant gains across four constructs, with the largest improvements in confidence and belonging showing medium-to-large effect sizes. Natural language processing of open-ended responses identified math-engineering integration as students' dominant concern. Sequential logistic regression provided the central equity finding post-course attitudes predicted persistence with excellent performance, vastly outperforming models based on demographics or pre-course characteristics. Models using only demographics or baseline attitudes showed poor predictive power, some performing worse than baseline, while adding post-course attitudes dramatically improved performance to excellent levels. This demonstrates that what students internalize during the course matters far more than their demographic backgrounds or initial attitudes, reframing persistence as cultivated through course experiences rather than predetermined by student characteristics.

These findings extend and corroborate prior work in several important ways. The confidence and belonging gains observed here align with Walton and Cohen's demonstration that social-belonging interventions produce lasting academic benefits, and with Godwin and Kirn's identity-based motivation framework showing that early course experiences shape engineering role identity. That post-course attitudes predicted persistence far better than demographics replicates and strengthens Hurtado and Carter's [16] finding that sense of belonging drives retention among Latinx students more than background characteristics; the present study extends this by demonstrating that belonging measured at course end predicts persistence in a sequential logistic regression framework, showing its incremental predictive value beyond demographics and pre-course attitudes. The dominance of math integration as both a statistical predictor and qualitative concern converges with Sax et al.'s finding that mathematical self-concept is a central driver of STEM persistence decisions, particularly for underrepresented students. That classical NLP and logistic regression rather than large language models or big data produced robust, interpretable findings with N=102 responds directly to Baker and Inventado's call for learning analytics methods that are accessible and actionable for typical institutional datasets.

The multi-method design was essential to the strength of these conclusions in ways that no single method could have achieved on its own. Paired t-tests established that attitude change was real and statistically significant but could not explain what drove it or whether it mattered for outcomes. Logistic regression showed that post-course attitudes predicted persistence with high accuracy, but it could not reveal what students were actually experiencing or which course elements they valued. NLP of open-ended responses provided the student voice that quantitative models cannot capture, revealing that math integration was not only a statistical predictor but students' own top-expressed concern, in their own words. The demographic-disaggregated analysis then confirmed that these patterns were not artifacts of a single subgroup's experience but were universal, strengthening confidence that the findings are equitable and generalizable within this HSI context. This triangulation, in which three independent analytical streams converged on the same conclusion about math integration, confidence, and belonging, is precisely what justifies the interpretive claims made here and provides a stronger evidentiary foundation than any single method could.

Demographic-disaggregated NLP supported universality: sentiment and themes showed remarkable consistency across first-generation status and gender, with all groups emphasizing math integration as a priority. The only reliable difference was first-generation students' greater emphasis on time management, interpreted as reflecting differing life constraints (balancing work and family) rather than deficits. Together, convergent findings support practical priorities for equity-oriented first-year engineering at HSIs: strengthen math-engineering connections through explicit linkages and contextualized instruction; sustain collaborative hands-on projects that build confidence and belonging; and provide universal supports like time-management scaffolds that benefit all students. Most critically, findings validate that investing in high-quality course design rather than selecting students based on demographics represents the most powerful lever for promoting equity and persistence in engineering pathways.

6. Limitations

This study should be interpreted in light of several limitations: results come from a single Southwestern public HSI with a predominantly Hispanic/Latinx and male sample, limiting generalizability and reducing power for subgroup comparisons; attitude change was measured using a retrospective pre–post design that reduces response-shift bias but may introduce recall bias; the overall sample (N= 102; 327 text responses) was sufficient for medium-to-large effects but may miss small or intersectional differences; the high persistence base rate complicates model fit and yielded negative pseudo-R^2 in baseline models, though post-attitudes still showed strong predictive performance; outcomes were proximal (post-course intent) and self-reported rather than long-term behavioral retention, and no control group or randomization was used, so causal claims about specific course elements are not warranted; finally, NLP findings reflect responses to the specific prompts and parameter choices used. Additionally, TF-IDF keyword extraction does not account for synonymy: students expressing the same concern through different word choices (e.g., 'math,' 'algebra,' 'calculus') would appear as distinct terms, potentially underestimating the prevalence of any single theme. LDA topic modeling partially mitigates this by grouping co-occurring terms, but future work could apply word embedding or semantic similarity methods to more robustly capture synonym clusters. Sentiment findings should be interpreted with caution given potential social desirability bias; students completing a course-administered survey may underreport negative experiences regardless of actual psychological safety. Future work should replicate across institutions, collect true premeasures, incorporate behavioral and longitudinal outcomes, expand subgroup samples for intersectional analysis, and test targeted interventions experimentally.

7. Conclusion

This research demonstrates that first-year engineering courses can fundamentally reshape diverse students' trajectories. By investigating what students gain during the course: their confidence in engineering competence, their sense of belonging to engineering communities, their developing engineering identities, and their perceived alignment between personal values and engineering practice, we can predict persistence with higher accuracy, vastly outperforming predictions based on who students are when they arrive. This validates that persistence is not predetermined by demographic background or initial attitudes but rather is cultivated through responsive teaching that builds confidence and belonging for all students. As computational learning analytics become increasingly accessible to education researchers and practitioners, this study offers a replicable methodological framework that combines the scalability of quantitative modeling and NLP with the depth of qualitative inquiry to understand not just whether students succeed but why and how, supporting data-informed, inclusive, and responsive teaching practices that can improve retention and equity in engineering pathways at HSIs and beyond. The path forward requires sustained commitment to measuring and fostering the affective outcomes: confidence, belonging, identity that our findings prove are both highly responsive to course design and powerfully predictive of persistence, thereby advancing both individual student success and the broader mission of diversifying the engineering profession to reflect and serve all communities.

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Appendix A: Survey Instruments

Part 1: Quantitative Attitude Scales

Students rated the following constructs twice on the same instrument once recalling their beginning-of-semester attitudes (retrospective pre) and once rating their current end-of-semester attitudes (post):

1. Engineering Value (3 items, 1–5 scale): "Compared to other activities, how important is it for you to be good at engineering?"; "In general, how useful is what you learn in engineering?"; "For me, being good in engineering is important."

2. Engineering Confidence (4 items, 1–5 scale): Students rated confidence in (a) designing a system or process based on realistic constraints; (b) creating prototypes to test an idea; (c) searching for innovative ways to do things; (d) improving a design to make it more efficient.

3. Engineering Community Belonging (3 items, 0–10 scale): "I see myself as part of the engineering community at UTEP"; "I feel that I am a member of the engineering community at UTEP"; "I feel a sense of belonging to the engineering community at UTEP."

4. Grit/Perseverance (6 items, 1–5 scale, adapted from the Short Grit Scale): "I have achieved a goal that took years of hard work"; "I finish whatever I begin"; "I have overcome setbacks to conquer an important challenge"; "Setbacks don't discourage me"; "I am a hard worker"; "I am diligent."

5. Intent to Major in Engineering (1 item, 1–5 scale): "Do you intend to complete a major in engineering?" (1 = Definitely not to 5 = Definitely yes)

Part 2: Open-Ended Feedback Questions

The following five open-ended prompts were included at the end of the survey instrument. Responses formed the corpus for all NLP analyses (N = 327 responses total):
Q72: “What was the most important thing you learned in this course?” (n = 90; response rate 88.6%)
Q73: “What concepts or topics were unclear or confusing?” (n = 51; response rate 49.5%)

Q97: “What should the course continue doing?” (n = 85; response rate 82.9%)
Q98: “What should the course improve?” (n = 55; response rate 54.3%)
Q99: “Do you have any additional feedback?” (n = 37; response rate 36.2%)