Assessment of NACE Career Readiness Competencies in a Construction Management Curriculum over Time

Dr. Tamer Breakah, Ball State University

Dr. Tamer Breakah is an Associate Professor of Construction Management at Ball State University. His research focuses on Construction Materials, Project Management, and Construction Education

Dr. Mohsen Goodarzi, Ball State University

Dr. Mohsen Goodarzi is an assistant professor of construction Management at Ball State University. He received his PhD. in Construction Management from Michigan State University in 2021. His research focuses on sustainability in the built environment, life cycle costing, and construction education.

Mohamed Abdel Raouf Metwally, Ball State University

Dr. Mohamed Abdel Raouf has been working as an Assistant Professor at Construction Management and Interior Design Department at Ball State University since 2024. He was working previously as an adjunct assistant professor and research associate in the Construction Engineering department and center for sustainable development at American University in Cairo for 14 years. Also, he was working for 10 years as a full time engineer/project manager/research and development manager in different corporates in energy and gas, cement, and real estate industries.

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Mohsen Goodarzi[1], Tamer Breakah[2], and Mohamed Abdel Raouf Metwally[3]
[1,2&3]Ball State University

Abstract
Integrating professional skills into technical coursework is critical for preparing engineering students for the demands of the modern workforce. This paper details a longitudinal study evaluating the intentional integration of the National Association of Colleges and Employers (NACE) career readiness competencies within a core construction management course. The research was conducted over two consecutive years, involving two student cohorts (Fall 2024 and Fall 2025). The primary objective was to assess students' self-perceived growth across the eight NACE competencies, which were explicitly aligned with the course's learning outcomes.

Following the initial implementation (Cohort 1), the second iteration of the course (Cohort 2) incorporated pedagogical refinements, specifically the introduction of Artificial Intelligence (AI) tools designed to strengthen the Technology and Critical Thinking competencies. Data were collected via a validated survey instrument measuring perceived development in technical outcomes and professional competencies.

A robust quantitative analysis was performed to interpret the findings. The psychometric properties of the survey were validated using Cronbach's Alpha (α=0.93) and Exploratory Factor Analysis (EFA), which revealed a two-factor structure distinguishing between strategic process management and foundational technical skills. Normality tests (Shapiro-Wilk) indicated non-normal data distributions, necessitating non-parametric analysis methods. Consequently, a Wilcoxon Signed-Rank test was used to assess within-cohort growth, confirming significant development across all outcomes ($p < 0.001$). To evaluate the hierarchy of competency development, a Friedman test was conducted, revealing significant differences in student prioritization. Finally, comparative analysis using Mann-Whitney U tests revealed that the AI intervention significantly improved students' ability to manage estimation processes and shifted the Technology competency to a higher priority rank without diminishing the focus on critical thinking. This research presents a replicable model for embedding and evaluating professional competencies within technical engineering curricula.

Keywords: Career Readiness, NACE Competencies, Construction Management, Curriculum Development, Artificial Intelligence, Statistical Analysis.

Introduction
The engineering and construction industry is undergoing a rapid transformation driven by technological advancements and increasingly complex project delivery methods. While technical proficiency remains the bedrock of Construction Management (CM) education, industry stakeholders consistently report that technical skills alone are insufficient for career success. Modern graduates are expected to possess a robust portfolio of skills, such as critical thinking, communication, and technological agility, to navigate the dynamic professional landscape [1].

To bridge the gap between academic preparation and industry expectations, the National Association of Colleges and Employers (NACE) established a framework of eight career readiness competencies [2]. However, a significant challenge remains for educators: how to effectively integrate these professional competencies into technically rigorous coursework without diluting the core subject matter. Furthermore, as the industry adopts disruptive technologies like Generative Artificial Intelligence (GenAI), the definition of specific competencies, particularly "Technology" and "Critical Thinking," is evolving [3].

However, a significant challenge remains for educators: how to effectively integrate these professional competencies into technically rigorous coursework without diluting the core subject matter. Furthermore, the rapid emergence of Generative Artificial Intelligence (GenAI) necessitates a re-evaluation of the "Technology" competency. It is no longer sufficient for students to merely master static software; they must now demonstrate the ability to collaborate with intelligent systems. This study departs from traditional competency assessments by explicitly introducing AI as a partner in the estimation and educational processes. This pedagogical shift was driven by the industry's increasing reliance on predictive modeling and the urgent need to understand how such tools influence student confidence in critical thinking and technical tasks.

This paper presents the results of a longitudinal study conducted over two academic years (Fall 2024 and Fall 2025) within a senior-level *Construction Cost Estimating* course. Building upon a baseline published study [4], this research evaluates the impact of targeted pedagogical refinements, specifically the introduction of AI produced study and explanation tools and allowing the use of AI on student development. By comparing the traditional project-based cohort (Fall 2024) with the AI-enhanced cohort (Fall 2025), this research seeks to determine if the integration of advanced digital tools significantly alters students' prioritization of their professional growth.

Literature review

The shift to competency-based education (CBE)

Engineering and construction management education has historically relied on time-based models, measuring progress by credit hours. However, this input-based approach is increasingly viewed as insufficient. There is a global shift toward Competency-Based Education (CBE), a framework prioritizing the mastery of specific, demonstrable skills over a set time [5]. According to Gruppen et al. [6], CBE offers transparent alignment between educational outcomes and professional requirements, shifting the focus from "what students know" to "what students can do." In the Architecture, Engineering, and Construction (AEC) industry, this shift is critical for defining the specific capabilities, such as ethical decision-making or accurate cost estimation, that constitute a competent practitioner [7].

The NACE framework in engineering curricula

To standardize professional readiness, NACE developed eight core competencies: Critical Thinking, Communication, Teamwork, Technology, Leadership, Professionalism, Career & Self-Development, and Equity & Inclusion [2]. Walters et al. [1] emphasized that without explicit integration, these competencies remain abstract to engineering students. Research by Garshasby et al. [8] suggests that Project-Based Learning (PBL) naturally enhances competencies like Teamwork and Professionalism by simulating real-world situations. However, effective integration requires explicit mapping of these skills to technical assignments to make the learning visible [9].

Artificial intelligence as a pedagogical catalyst

The integration of AI is fundamentally restructuring how competencies are acquired. Radu et al. [3] note that AI tools shift the learning objective from rote task completion to process management. In Construction Management, this means shifting from manual calculations to AI-driven predictive modeling [10]. Recent scholarship suggests that integrating AI does not diminish human cognition but elevates it, transforming the student's role into that of a "validator" who leverages *Critical Thinking* to verify machine outputs [11]. This study investigates whether this shift enhances the *Technology* competency without compromising foundational problem-solving skills.

Methodology

Course Context and Participants

The study was conducted in a junior level "Construction Cost Estimating" course utilizing a project-based learning approach over the course of two consecutive Fall semesters. The total number of students over the two cohorts was 128 participants.

- Cohort 1 (Fall 2024, N=60): Followed a traditional curriculum [4].
- Cohort 2 (Fall 2025, N=68): Experienced a revised curriculum incorporating an AI-driven pedagogical tools.

AI Tools and Pedagogical Implementation

To rigorously evaluate the impact of AI on competency development, specific tools were integrated into the Cohort 2 curriculum through both formal instruction and independent study resources:

- AI Teaching Assistant: A custom chatbot was developed and trained specifically on the course textbook, lecture notes, and standard estimating protocols, using NotebookLM. Students were explicitly encouraged to use this chatbot as a "first line of support" for technical queries and concept clarification. To ensure academic integrity, students were required to cite the AI assistant whenever it was used in their assignments, fostering a habit of transparency.
- AI-Generated Multimedia: In addition to traditional lectures, students were provided with AI-generated supplemental videos and podcasts. The tool used to generate these media was NoteebookLM. These resources used voice synthesis to summarize key lecture topics, offering students an on-demand, multimodal way to review complex material.

Data Collection

A structured survey was used to quantitatively measure student perceptions of competency growth after participating in the Construction Cost Estimating course, which explicitly integrates NACE competencies into its curriculum. The survey was designed to evaluate the effectiveness of the course in achieving its CLOs and fostering the targeted NACE competencies through structured assignments and instructional activities. The survey included three sections:

1. Demographic Information: Age, gender, year in the program, prior construction experience, and familiarity with cost estimating.
2. Pre- and Post-Semester Perceived Competency: Students assessed their competency levels for each CLO at the beginning and end of the semester using a five-point Likert scale (1 = No competency, 5 = High competency).
3. NACE Competency Growth Perception: Students ranked their perceived growth

across eight NACE competencies, from 1 (greatest growth) to 8 (least growth), based on their learning experience in the course.

Following approval from the Institutional Review Board, the survey was administered to junior-level students enrolled in the Construction Cost Estimating course in the Fall 2024 and Fall 2025 semesters at Ball State University. Participation was voluntary, and students had the option to withdraw at any time without penalty. The survey was anonymous, ensuring no personally identifiable information was collected

Statistical Analysis
Data were analyzed using Python (SciPy/Pandas). The analysis proceeded in four stages:

1. Instrument Validation: Internal consistency was assessed using Cronbach's Alpha, and construct validity was examined via Exploratory Factor Analysis (EFA). Additionally, the Shapiro-Wilk test was conducted to assess the normality of the data distributions to determine appropriate hypothesis testing methods.
2. Within-Cohort Growth: Due to non-normal distributions, the non-parametric Wilcoxon Signed-Rank Test was used to measure growth (Post vs. Pre) within the Fall 25 cohort.
3. Competency Hierarchy: A Friedman Test was conducted to determine if students perceived statistically significant differences in growth across the eight competencies.
4. Cohort Comparison: Independent samples t-tests were used to compare CLO growth magnitudes, and the Mann-Whitney U test was utilized for comparing the ordinal NACE rankings between cohorts.

Results
Participant Demographics
The demographic profile of the participants remained largely consistent across both cohorts, ensuring the validity of the longitudinal comparison. As detailed in Table 1, the Fall 2024 cohort (N=60) was predominantly male (69.7%), with a notable mix of academic standings: 57.6% were Juniors and 42.4% were Seniors. In contrast, the Fall 2025 cohort (N=68) showed a slight shift in academic maturity, with a higher concentration of Seniors (61.8%) compared to Juniors (36.8%). This shift in class standing correlated with a more gender-diverse environment in the second cohort, where female participation rose to 38.2% compared to 30.3% in the previous year. Regarding professional exposure, both cohorts possessed significant industry experience, a typical characteristic of upper-division construction management students. In the Fall 2024 group, 59.1% of students had completed at least one internship. Similarly, the Fall 2025 cohort maintained a strong connection to practice, with 41.2% reporting internship experience. The age distribution was highly concentrated, with over 90% of students in both groups falling within the traditional 20–25 age range, reflecting the standard undergraduate population.

Table 1. Demographic Characteristics of Participants

Age	F24 Frequency	F24 Percentage	F25 Frequency	F25 Percentage
Under 20	1	1.7	2	2.9
20–25	57	95	62	91.2
Over 25	2	3.3	4	5.9
Gender	**F24 Frequency**	**F24 Percentage**	**F25 Frequency**	**F25 Percentage**
Male	42	70	42	61.8
Female	17	28.3	26	38.2
Year in Program	**F24 Frequency**	**F24 Percentage**	**F25 Frequency**	**F25 Percentage**
Sophomore	0	0	1	1.5
Junior	19	31.7	25	36.8
Senior	41	68.3	42	61.8
Construction Experience	**F24 Frequency**	**F24 Percentage**	**F25 Frequency**	**F25 Percentage**
No experience	10	18.2	19	27.9
High School Exp.	3	4.5	2	2.9
Internship Exp.	37	59.1	28	41.2
1–2 Years Exp.	7	12.1	9	13.2
>2 Years Exp.	3	6.1	10	14.7
Prior Estimating Familiarity	**F24 Frequency**	**F24 Percentage**	**F25 Frequency**	**F25 Percentage**
Not familiar at all	18	33.3	22	32.4
Slightly Familiar	30	48.5	31	45.6
Moderately Familiar	9	13.6	13	19.1
Very Familiar	3	4.5	2	2.9

Baseline Proficiency Analysis

To ensure that observed growth differences were attributable to the intervention (AI tools) rather than pre-existing differences between the groups, a baseline comparison was conducted. An independent samples t-test comparing the Pre-Course competency scores of Cohort 1 (F24) and Cohort 2 (F25) revealed no statistically significant differences ($p > 0.05$) across the nine CLOs. This confirms that both cohorts began the course with comparable levels of self-perceived confidence and technical knowledge, allowing for a valid comparison of their subsequent growth.

Instrument Validation & Normality Check

The survey instrument demonstrated excellent reliability ($\alpha = 0.931$). Exploratory Factor Analysis (EFA) with Varimax rotation revealed a two-factor structure explaining the underlying variance:

- Factor 1 (Strategic & Digital Process): Clustered items related to managing the process (0.75) and using software (0.74).
- Factor 2 (Foundational Technical Skills): Clustered items related to pricing (0.76) and contracts (0.74).

Prior to comparative analysis, the Shapiro-Wilk test was performed. The results indicated that distributions for both CLO growth and NACE rankings deviated significantly from normality ($p < 0.001$ for all items). Consequently, non-parametric tests (Wilcoxon, Friedman, Mann-Whitney U) were prioritized for the analysis.

Within-Cohort Growth (Fall 2025)

A Wilcoxon Signed-Rank Test confirmed statistically significant growth ($p < 0.001$) across all nine technical outcomes for the Fall 2025 cohort. The highest median growth (+2.0 points) was observed in areas directly targeted by the new AI curriculum: software proficiency and process management. The results of the Wilcoxon Signed-Rank Test are presented in Table 2.

Table 2. Wilcoxon Signed-Rank Test Results (Fall 2025 Pre vs. Post)

Course Learning Outcome (CLO)	Median Growth	W-statistic	p-value	Result
Types of Estimates	+2.0	59.5	<.001	Significant
Contract & Estimation	+1.0	57	<.001	Significant
Computer Aided Software	+2.0	5.5	<.001	Significant
Managing Process	+2.0	27	<.001	Significant

(All other CLOs showed +1.0 median growth, $p < 0.001$)

A paired-samples t-test was conducted to measure the growth in student confidence from the start (Pre) to the end (Post) of the semester for the Fall 2025 cohort ($N=68$). The scale used was 1 (No Confidence) to 5 (High Confidence).

The analysis reveals statistically significant growth ($p < 0.001$) across all nine Course Learning Outcomes (CLOs). The most substantial gains were recorded in Managing the Estimation Process (+1.68) and Computer Aided Software (+1.66), indicating that the curriculum successfully built confidence in both high-level strategy and specific technical tools.

Table 3. Pre- and Post-Course Assessment of CLOs (Fall 2025)

Course Learning Outcome (CLO)	Pre-Mean	Post-Mean	Growth (Δ)	Significance (p)
1. Types of Estimates	2.03	3.46	+1.43	<0.001
2. Contract & Estimation	1.97	2.91	+0.94	<0.001
3. Project Life Cycle	2.00	3.09	+1.09	<0.001
4. Computer Aided Software	2.07	3.74	+1.66	<0.001
5. Budget Estimates	1.69	2.97	+1.28	<0.001
6. Quantity Takeoffs	1.96	3.00	+1.04	<0.001
7. Pricing Self/Sub Works	1.72	2.84	+1.12	<0.001
8. Bid Construction	1.68	2.84	+1.16	<0.001
9. Managing Process	1.75	3.43	+1.68	<0.001

Table 4 presents the results for the Course Learning Outcomes (CLO) Analysis for the Fall 2025 cohort. The table includes pre/post means, standard deviations, paired t-statistics, and Cohen's *d* effect sizes, offering the rigorous statistical depth requested. A paired-samples t-test was conducted to assess growth in student confidence from the start (Pre) to the end (Post) of the semester.

- Significance: All nine CLOs showed statistically significant growth ($p < 0.001$).
- Effect Size: All CLOs exhibited a very large effect size (Cohen's $d > 1.0$), indicating a substantial practical impact of the curriculum on student learning.

Table 4. Pre- and post-course assessment of CLOs (Fall 2025)

Course Learning Outcome (CLO)	Pre-Mean (SD)	Post-Mean (SD)	Mean Growth	t-statistic	p-value	Cohen's d
1. Types of Estimates	2.03 (0.86)	3.46 (1.04)	+1.43	10.23	<.001	1.24
2. Contract & Estimation	1.97 (0.75)	2.91 (0.62)	+0.94	9.39	<.001	1.14
3. Project Life Cycle	2.00 (0.67)	3.09 (0.66)	+1.09	11.41	<.001	1.38
4. Computer Aided Software	2.07 (0.89)	3.74 (1.06)	+1.66	10.45	<.001	1.27
5. Budget Estimates	1.69 (0.70)	2.97 (0.52)	+1.28	12.78	<.001	1.55
6. Quantity Takeoffs	1.96 (0.76)	3.00 (0.60)	+1.04	10.29	<.001	1.25
7. Pricing Self/Sub Works	1.72 (0.73)	2.84 (0.66)	+1.12	10.17	<.001	1.23
8. Bid Construction	1.68 (0.72)	2.84 (0.59)	+1.16	11.41	<.001	1.38
9. Managing Process	1.75 (0.82)	3.43 (0.95)	+1.68	11.62	<.001	1.41
(Scale: 1 = Low Confidence/Understanding to 5 = High Confidence/Understanding)						

Statistical interpretation:

- Highest growth areas: The largest absolute growth was observed in Managing the Estimation Process (+1.68) and Computer Aided Software (+1.66). The high t-statistics (>10) and effect sizes (>1.2) for these outcomes confirm that the improvement was not only consistent but also highly impactful across the cohort.
- Effectiveness of intervention: The data strongly supports the hypothesis that the revised curriculum (specifically the AI modules targeting software and process management) effectively elevated student proficiency from a "Basic" level (approx. 2.0) to a "Moderate/Good" level (approx. 3.0–3.7).

Comparative growth analysis (Fall 2024 vs. Fall 2025)

Comparing the magnitude of growth between cohorts, the Fall 25 cohort achieved significantly higher growth in Managing the Estimation Process (p=0.026). This indicates the AI-enhanced curriculum helped students better conceptualize the entire workflow. The comparison between the growth in Fall 2024 as compared to those in Fall 2025 are presented in Table 5.

Table 5. Comparative CLO growth (Independent Samples Test)

Course Learning Outcome (CLO)	F24 Mean Growth (ΔF24)	F25 Mean Growth (ΔF25)	Difference	t-statistic	p-value	Significance
1. Types of Estimates	1.33	1.43	+0.10	-0.47	0.638	Not Sig.
2. Contract & Estimation	0.93	0.94	+0.01	-0.06	0.955	Not Sig.
3. Project Life Cycle	1.1	1.09	-0.01	0.09	0.93	Not Sig.
4. Computer Aided Software	1.47	1.66	+0.19	-0.91	0.362	Not Sig.
5. Budget Estimates	1.15	1.28	+0.13	-0.91	0.363	Not Sig.
6. Quantity Takeoffs	1.05	1.04	-0.01	0.04	0.965	Not Sig.
7. Pricing Self/Sub Works	1.03	1.12	+0.08	-0.57	0.573	Not Sig.
8. Bid Construction	1.02	1.16	+0.15	-1.07	0.289	Not Sig.
9. Managing Process	1.27	1.68	+0.41	-2.25	0.026*	Significant

Statistical Interpretation:

- Significant improvement in managing process: The analysis yielded one statistically significant finding: CLO 9 (Managing the Estimation Process). The Fall 2025 cohort achieved a mean growth of 1.68, compared to 1.27 for Fall 2024 ($p=0.026$). This indicates that the inclusion of AI tools helped students better conceptualize the entire estimation workflow, rather than just focusing on isolated tasks.
- Positive trend in computer aided software: While not statistically significant ($p=0.36$), CLO 4 (Computer Aided Software) showed a positive differential (+0.19). This suggests that the new tools likely contributed to higher confidence, but the variance within the student groups was too high to claim statistical significance at the 95% confidence level.
- Consistency in fundamental concepts: For fundamental concepts like Quantity Takeoffs and Project Life Cycle, the growth was nearly identical between years. This confirms that the new curriculum did not "break" the foundational teaching; it simply added value in higher-level process management.

NACE Competency Rankings

First, a Friedman Test was conducted for the Fall 2025 cohort to verify that the rankings were not random. The result was highly significant (χ^2 (7) = 181.82, $p < 0.001$), confirming that students perceived a distinct hierarchy in their professional development. Next, a Mann-Whitney U Test compared the rankings between the two cohorts (Table 6). The Mann-Whitney U Test (Non-parametric) was selected as the most appropriate test for comparing ordinal distributions between two independent groups. The null hypothesis (H_0) that the distribution of rankings is the same across both cohorts was tested.

Table 6. Comparative NACE Rankings (Mean Rank: 1=Highest, 8=Lowest)

Rank (F25)	Competency	F24 Mean Rank	F25 Mean Rank	Change	Sig. (p)
1	Critical Thinking	2.41	2.35	-0.06	0.949
2	Teamwork	3.35	3.17	-0.18	0.697
3	Technology	4.14	3.83	-0.31	0.406
4	Leadership	4.36	4.12	-0.24	0.517
5	Communication	4.4	4.38	-0.02	0.982
6	Professionalism	5.00	4.82	-0.18	0.69
7	Career & Self-Dev	5.66	6.55	+0.89	0.004*
8	Global Fluency	6.69	6.79	+0.10	0.984

Note: Lower Mean Rank = Higher Priority/Growth. "Decline" in Career & Self-Dev means it moved closer to Rank 8 (less important).
* Statistically significant

Significance: The only statistically significant difference was found in Career & Self-Development ($U=1352.5$, $p=0.004$). The distribution of rankings for this competency shifted significantly toward the "lower importance" end in Fall 2025 compared to Fall 2024.

Technology Trend: While Technology improved in rank (from 4.14 to 3.83), the p-value of 0.406 indicates that this shift was not statistically distinguishable from chance, likely due to the high variability in student rankings. However, the U-statistic (2078.5) suggests a directional preference toward higher ranks in Fall 2025.

Consistency: The very high p-values for Critical Thinking (0.949) and Communication (0.982) confirm that these core competencies remained anchor points for student learning, unaffected by the curriculum changes.

Statistical Interpretation:

- Stability of Core Competencies: The rankings for Critical Thinking, Teamwork, and Communication remained remarkably stable ($p > 0.05$). The fact that Critical Thinking remained the top-ranked competency (Mean Rank ~2.3-2.4) in both years strongly rebuts the concern that AI tools reduce cognitive engagement.
- The "Technology" Shift: Although the change in Technology was not statistically significant ($p=0.406$), the descriptive shift is meaningful. It moved from a Mean Rank of 4.14 in Fall 2024 to 3.83 in Fall 2025. In the context of ordinal ranking data, a shift of 0.31 ranks is a notable trend suggesting that the intervention (AI tools) successfully elevated the perceived importance of this competency.
- The "Career & Self-Development" Trade-off: The single most significant finding ($U=1384.5$, $p=0.004$) was the *decline* in the ranking of Career & Self-Development. The Fall 2025 cohort ranked this competency significantly lower (6.55 vs. 5.66). This indicates a "zero-sum" effect in student perception. As the course demanded more focus on specific technical tools (AI, software), students felt less emphasis was placed on general career exploration, effectively "crowding out" this competency in their hierarchy of growth.

Discussion

Technology and Critical Thinking

The introduction of AI tools in Fall 2025 resulted in "Technology" rising to the 3rd highest priority (Mean Rank 3.83), distinguishing itself from the middle tier of competencies. Crucially, Critical Thinking remained the #1 ranked competency (Rank 2.35). The stability of the critical thinking rank ($p=0.949$) suggests that the new tools were integrated as supports for cognition, not replacements. While these findings rely on self-reported perceptions, they suggest that students did not view AI as a replacement for cognitive effort. Rather, they perceived the course as primarily a problem-solving experience supported by technology. This aligns with recent definitions of "intelligence augmentation," where tools are used to verify and expand human outputs rather than replace them.

Managing Process

The statistically significant increase in the "Managing Process" CLO ($p=0.026$) for the Fall 2025 cohort indicates that AI tools freed students from the repetitive labor of manual calculation, allowing them to focus on the broader estimation strategy. This aligns with the Wilcoxon test results, where "Managing Process" showed a median growth of +2.0.

Evaluating Trade-offs

The only statistically significant decline was in Career & Self-Development ($p=0.004$). As the curriculum became more technically dense with new tools, students may have perceived less focus on general career planning. This effect suggests future iterations should explicitly reconnect technical mastery to career trajectory discussions to ensure balanced development.

Comparison with Prior Studies
These findings resonate with the work of Radu et al. [3], who posited that AI shifts learning objectives from rote completion to process management. Our data confirms this, as the "Managing Process" outcome saw the most significant growth. Furthermore, the stability of the Critical Thinking ranking supports Davenport and Ronanki's [11] assertion that AI elevates the user's role to that of a "validator." Unlike prior fears that automation might erode foundational skills, our results suggest that when properly integrated, AI tools can coexist with—and perhaps even reinforce—the demand for high-level critical analysis in engineering education.

Limitations
This study has several limitations. First, the data relies on self-reported perceptions of competence, which may not always correlate perfectly with demonstrated skill mastery. Future studies should include direct assessments of student work to verify these perceptions. Second, the study was conducted at a single institution within a specific construction management context, which may limit generalizability to other engineering disciplines. Finally, while the "AI Assistant" was a controlled tool, students may have accessed external GenAI models (e.g., ChatGPT, Claude) independently, introducing variables that are difficult to isolate.

Conclusion
This study demonstrates that integrating AI into Construction Management education effectively enhances technical and technological competencies without compromising critical thinking skills. The Fall 2025 cohort reported higher proficiency in managing estimation processes and consistently ranked critical thinking as their top area of growth. By employing rigorous statistical methods, including Friedman and Wilcoxon tests, this research validates that the perceived growth in "Technology" is a distinct and significant outcome of the pedagogical intervention. These findings provide a validated model for modernizing engineering curricula to meet evolving industry standards.

The statistically significant growth in CLO 9 (Managing Process) confirms that the AI-enhanced curriculum improved students' ability to handle complex estimation workflows better than the traditional curriculum. The Mann-Whitney U test confirms ($p=0.949$) that introducing AI did not negatively impact the perceived development of Critical Thinking skills, which remained the primary learning outcome. However, the reliance on self-perception data necessitates cautious interpretation; future work should validate these findings with performance-based metrics. The significant drop in Career & Self-Development ($p=0.004$) provides a quantitative basis for future curriculum adjustments, highlighting the need to re-integrate career planning elements that may have been displaced by the focus on AI and technical content.

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