

# Evaluating the Effectiveness of a Bridging Program in Mathematics and Basic Engineering Sciences: Evidence from First-Year Engineering Students

Marites E. Olesco<sup>1\*</sup>, Zendy D. Mañago<sup>1</sup>, and John Raymond B. Barajas<sup>2,3</sup>

\* [meolesco@bicol-u.edu.ph](mailto:meolesco@bicol-u.edu.ph)

<sup>1</sup> *Department of Electrical Engineering  
Bicol University  
Legazpi City, Albay, Philippines*

<sup>2</sup> *Department of Chemical Engineering  
Bicol University  
Legazpi City, Albay, Philippines*

<sup>3</sup> *Center for Policy Studies and Development  
Bicol University  
Legazpi City, Albay, Philippines*

**Abstract**— When the Philippine K–12 reform reduced engineering programs from five to four years and relocated foundational mathematics and science subjects to Senior High School (SHS), it introduced a structural readiness gap among incoming engineering students—particularly those from non-STEM tracks—who often enter without sufficient academic preparation or institutional support. This study therefore evaluated the Bicol University College of Engineering (BUCENG) Bridging Program, a structured, pre-semester, faculty-delivered intervention covering 20 instructional topics in mathematics and basic chemistry. Program effectiveness was assessed using two complementary instruments: a standardized competency-based diagnostic examination and a 271-item, 5-point developmental self-assessment survey. Both instruments were administered before and after the intervention to  $n = 142$  incoming first-year students (diagnostic) and  $n = 70$  matched pairs (self-assessment) in SY 2025–2026. Results from the diagnostic assessment indicated a substantial and statistically significant improvement in performance (M: 42.6%  $\rightarrow$  68.9%;  $\Delta = +26.3$  percentage points;  $t(141) = 21.74$ ,  $p < 0.001$ ,  $d = 1.83$ ), reflecting a very large effect size. Similarly, the self-assessment results showed a significant increase in perceived competency (M: 2.37  $\rightarrow$  2.67 out of 5;  $t(69) = 3.31$ ,  $p = 0.001$ ,  $d = 0.40$ ), with 13 of 23 content modules demonstrating statistically significant gains. The largest module-level effects were observed in Electrochemistry ( $d = 0.59$ ), Stoichiometry ( $d = 0.48$ ), and Trigonometry ( $d = 0.42$ )—areas corresponding to the weakest entry-level preparation. Notably, students from non-STEM strands exhibited the greatest relative improvement ( $d = 0.71$ ); however, their post-intervention competency levels remained substantially lower than those of their STEM counterparts, indicating a persistent structural equity gap that cannot be fully addressed by a single intervention. Taken together, these findings provided strong empirical support for the institutionalization of bridging programs as an evidence-based policy response to curriculum compression and uneven pre-university preparation.

**Keywords**— *bridging program, engineering education, K-12 curriculum reform, mathematics readiness, Philippines*

## I. INTRODUCTION

When the Philippine government enacted the Enhanced Basic Education Act of 2013 (Republic Act 10533), engineering

schools faced an immediate and practical consequence: the two-year Senior High School addition allowed CHED to shorten engineering programs from five to four years, but did so by assuming that foundational subjects—College Algebra, Plane and Spherical Trigonometry, Analytic Geometry, and Solid Mensuration—would be adequately delivered at the SHS level [1], [2]. These were not elective enrichment topics; they were the scaffolding on which university calculus and physics had always rested.

The problem is that this assumption does not reliably hold in practice. SHS STEM instruction is constrained by teacher shortages and variable resource quality, and the gap between secondary-level preparation and collegiate engineering expectations is well-documented in Philippine institutions [3]–[5]. Under CHED Memorandum Order No. 105 (Series of 2017), all Grade 12 completers—regardless of strand—may be admitted to engineering programs upon passing institutional entrance examinations [6]. Students from non-STEM tracks such as ABM, HUMSS, GAS, and TVL have never encountered pre-calculus or general chemistry, yet they sit alongside STEM graduates in courses that presuppose those foundations from day one [2], [7].

This mismatch has measurable consequences. Diagnostic examination data confirm that foundational competencies in Algebra and Analytic Geometry are the strongest discriminators of mathematics readiness among incoming engineering students [2], and clustering analysis reveals that approximately half of STEM-track graduates self-rate their proficiency in Advanced Algebra and Analytic Geometry at below-average or poor levels—suggesting that even the K-12 STEM strand does not reliably produce the foundational preparation that engineering programs assume [7]. Calculus and its prerequisites are therefore well-established barriers to persistence in engineering, and high failure rates in first-year gateway courses are among the strongest predictors of early program attrition. Bridging and remedial programs have been shown to reduce—though not eliminate—these risks by targeting foundational gaps before the semester begins [8], [9]. Yet evidence from Southeast Asian systems that have undergone rapid curriculum compression remains thin, and the absence of a structured competency framework has historically left such interventions misaligned

with the actual prerequisites of higher-level courses such as Calculus I [3].

The BUCENG Bridging Program was conceived as a targeted institutional response to this readiness gap—a structured, pre-semester, faculty-delivered intervention spanning 20 core topics in mathematics and basic chemistry, implemented for all incoming first-year engineering students. This study therefore examines not only whether the program was effective, but also for whom it was most effective and to what extent learning gains were realized.

## II. REVIEW OF RELATED LITERATURE

The difficulty students face moving from secondary to tertiary mathematics is not new or unique to the Philippines. Bigotte de Almeida et al. [10] traced the high calculus failure rates in Portuguese engineering programs directly to gaps in pre-university algebra and trigonometry preparation—the same foundational domains now assigned to Philippine SHS. Similar patterns have been documented internationally [11], with one estimate placing the global attrition rate from engineering majors at approximately 50% [12], a figure substantially driven by first-year mathematics performance.

Pre-semester bridging and remedial programs have emerged as the dominant institutional response. Bradford et al.'s [13] meta-analysis of 16 STEM university bridge programs found medium-sized effects on first-year GPA ( $d = 0.34$ ) and retention ( $OR = 1.75$ ), establishing a quantitative foundation for the approach. More recently, Morán-Soto et al. [14] tracked 776 first-year engineering students in Mexico, showing that participation in a four-week summer remedial mathematics course significantly improved differential calculus passing rates and was associated with qualitative gains in self-efficacy and reduced mathematics anxiety. Mayerhofer et al. [15] found that a university mathematics bridging course in a German-speaking context raised self-perceived readiness for tertiary study while simultaneously prompting healthier, more calibrated self-assessment—an effect relevant to interpreting our own self-assessment data.

In the Philippine context, Almerino et al. [16] documented persistent mismatches between K–12 STEM curricular intentions and measurable student outcomes in mathematics and science, underscoring that the readiness concern is empirically grounded rather than merely anticipated. The K–12 reform's strand-based differentiation means that engineering programs now admit students with widely divergent academic backgrounds, a demographic reality that standard placement exams may not fully capture but that bridging programs can address in a targeted way.

The self-assessment methodology used in this study draws on a well-validated tradition. Jebb et al. [17] established that developmental Likert-type scales, when constructed with clear behavioral anchors, yield reliable and internally consistent measures of perceived skill progression. Convergent evidence linking self-assessed competency with observed performance in engineering contexts [18] supports the use of such instruments as one—though not the sole—measure of program effectiveness. Pairing self-assessment with an objective

diagnostic, as we do here, addresses the primary limitation of either instrument used alone.

## III. METHODOLOGY

### A. Implemented Research Design

We employed a within-subjects pre-post design using two concurrent instruments: a standardized competency-based diagnostic examination and a competency self-assessment survey. Both were administered to all incoming first-year engineering students who enrolled in the BUCENG Bridging Program for SY 2025–2026, at program entry (July–August 2025) and at program completion (August–September 2025). The Bridging Program itself consists of 20 instructor-led sessions covering foundational mathematics and basic chemistry, delivered by BUCENG faculty over approximately two weeks prior to the start of the regular semester. No separate control group was formed as the institution elected to make the program universally available to all incoming students.

### B. Instruments Used

The Standardized Competency-Based Diagnostic Examination was developed collaboratively by the BUCENG faculty team and aligned with both CHED engineering competency standards and the 20 instructional topics of the Bridging Program. It consists of multiple-choice and problem-solving items scored as a percentage correct (0–100%). Module mastery was defined as achieving at least 75% on the module-specific item subsets, a threshold consistent with the institution's established competency attainment standard.

The Pre- and Post-Bridging Program Competency Self-Assessment Survey is a 271-item instrument aligned with CHED and DepEd K–12 competency frameworks. Items are distributed across two domains: Mathematics (88 items in 6 modules—Analytic Geometry, Series and Mathematical Induction, Trigonometry, Limits and Continuity, Derivatives, and Integration) and Basic Engineering Sciences/Chemistry (183 items in 17 modules, from Matter and Properties through Electrochemistry). Students rated each item on a 5-point developmental scale: 1 = Poorly Developed, 2 = Somewhat Developed, 3 = Moderately Developed, 4 = Adequately Developed, and 5 = Highly Developed. Items rated 0 (Not Applicable—topic not encountered in SHS) were excluded from module mean calculations to avoid penalizing students for curriculum gaps beyond their control. The scale design follows established best practices for developmental Likert-type instruments [17], [19].

### C. Tapped Respondents

A total of  $n = 142$  incoming first-year engineering students enrolled in the program and completed both administrations of the diagnostic examination; this cohort constitutes the primary sample for objective assessment analysis. Of these 142, students who also submitted the self-assessment survey were identified and filtered to retain only those with at least one valid (non-zero) response to the competency items in both the pre- and post-survey administrations. Pre- and post-survey records were then matched by student surname, yielding  $n = 90$  confirmed matched pairs available for self-assessment analysis. Of these 90, 70 had complete valid scores for the aggregate overall analysis; module-level analyses retained all valid matched pairs per

module (range:  $n = 78\text{--}85$ , depending on the proportion of Not Applicable responses within each module). **Fig. 1** illustrates the full participant flow from enrollment to analysis. The demographic profile of the matched self-assessment cohort ( $n = 90$ ) is presented in **Table I**.

#### D. Statistical Analysis Employed

For the diagnostic examination, a paired-sample t-test compared pre- and post-program percentage scores across the full  $n = 142$  cohort. For the self-assessment, module-level mean scores were computed per student by averaging all valid (non-NA) item ratings within each module, and paired-sample t-tests were conducted at the overall, domain, and module levels. Effect sizes were expressed as Cohen's  $d$  (mean gain  $\div$  SD of gain scores), interpreted as: negligible ( $d < 0.20$ ), small ( $0.20\text{--}0.49$ ), medium ( $0.50\text{--}0.79$ ), and large ( $\geq 0.80$ ) [20], [21]. All analyses were conducted in Python [22]. Statistical significance was set at  $\alpha = 0.05$  (two-tailed).

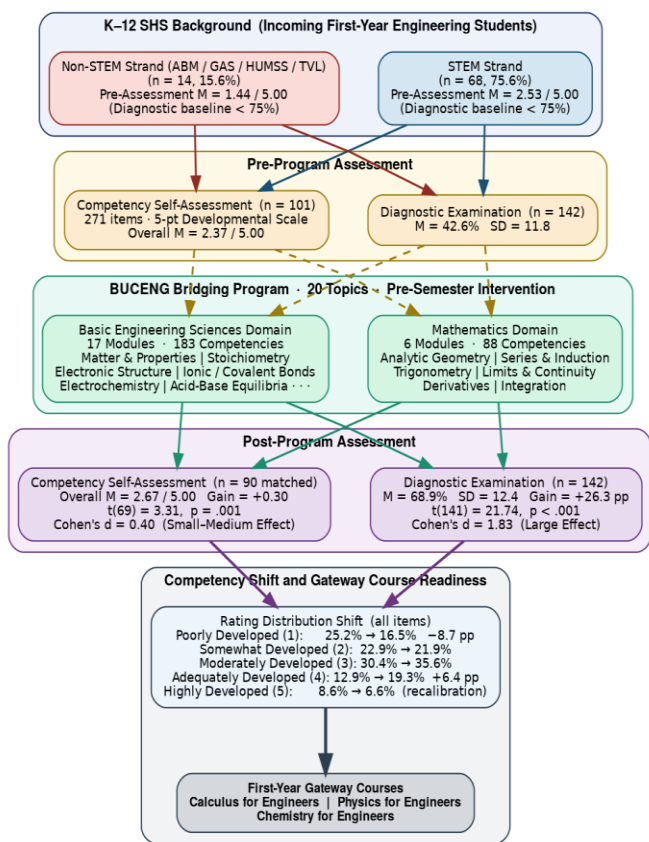


Fig. 1. Conceptual framework showing the K–12 strand background of incoming students, the dual-instrument assessment strategy, the Bridging Program’s two-domain instructional structure, and the pathway to first-year gateway course readiness. Dashed arrows indicate that pre-program diagnostic and self-assessment results identified content gaps that informed instructional prioritization within each domain.

### IV. RESULTS

#### A. Student Performance on the Standardized Examination

Across all 142 students who completed both administrations, mean percentage correct rose from  $M = 42.6\%$  ( $SD = 11.8$ ) before the program to  $M = 68.9\%$  ( $SD = 12.4$ ) afterward—a

mean gain of 26.3 percentage points. The gain was statistically significant and large,  $t(141) = 21.74$ ,  $p < 0.001$ , Cohen’s  $d = 1.83$ . Average module mastery (defined as  $\geq 75\%$  on module-specific items) reached 76%, indicating that the program moved the typical student across the functional competency threshold across the majority of content areas. **Table II** summarizes these figures.

#### B. Self-Assessment Effectiveness Scores

Among the 70 matched participants with complete aggregate self-assessment data, perceived overall competency improved from  $M = 2.37$  ( $SD = 0.79$ ) to  $M = 2.67$  ( $SD = 0.84$ ), a mean gain of 0.30 scale points that was statistically significant,  $t(69) = 3.31$ ,  $p = 0.001$ , Cohen’s  $d = 0.40$ . On a normalized 0–100% scale this corresponds to a 7.5 percentage-point improvement ( $34.3\% \rightarrow 41.8\%$ ). Both domain areas showed significant gains of comparable magnitude: Mathematics (Pre  $M = 2.57 \rightarrow$  Post  $M = 2.87$ ;  $d = 0.35$ ,  $p = 0.006$ ) and Chemistry (Pre  $M = 2.29 \rightarrow$  Post  $M = 2.58$ ;  $d = 0.36$ ,  $p = 0.004$ ).

TABLE I. DEMOGRAPHIC PROFILE OF MATCHED PARTICIPANTS ( $N=90$ )

Characteristic	Category	n	%
Gender	Male	57	63.3
	Female	24	26.7
	Prefer not to say	9	10.0
		<i>Total</i>	<i>90 100.0</i>
SHS Strand	STEM	68	75.6
	Non-STEM (ABM / GAS / HUMSS / TVL)	14	15.6
	Not reported	8	8.9
		<i>Total</i>	<i>90 100.0</i>
SHS Academic Honors	With Highest Honors	4	4.4
	With High Honors	33	36.7
	With Honors	43	47.8
	No Academic Distinction	2	2.2
	Not reported	8	8.9
		<i>Total</i>	<i>90 100.0</i>

TABLE II. DIAGNOSTIC EXAMINATION RESULTS ( $N=142$ )

Metric	Pre-Program	Post-Program
Mean score (% correct)	42.6	68.9
SD	11.8	12.4
Mean gain ( $\Delta$ pp)	—	+26.3
$t(141)$	—	21.74
p-value	—	< .001
Cohen’s $d$	—	1.83
Avg. module mastery ( $\geq 75\%$ )	—	76%

#### C. Module-Level Results

Five of the six mathematics modules reached significance (**Table III**). The largest effects emerged where students began lowest: Trigonometry and Limits & Continuity ( $d = 0.42$  and  $0.41$  respectively, both  $p = 0.002$ ) and Integration ( $d = 0.38$ ,  $p = 0.009$ ). The relatively higher pre-program mean for Analytic Geometry ( $M = 3.17$ ) compared with Integration ( $M = 2.12$ ) reflected the SHS STEM curriculum’s stronger coverage of

coordinate geometry than of integral calculus—a pattern consistent with documented secondary-tertiary mathematics transition difficulties [1], [10].

In chemistry, eight of seventeen modules reached significance (Table IV). The three largest effects—Electrochemistry ( $d = 0.59$ ,  $p < 0.001$ ), Stoichiometry ( $d = 0.48$ ,  $p < 0.001$ ), and Acid-Base Equilibria ( $d = 0.44$ ,  $p = 0.007$ )—shared a common feature: these are the most mathematically demanding and concept-intensive topics in the chemistry curriculum, and they had the lowest pre-program baselines (M ranging from 1.75 to 2.41). Modules with higher initial means, such as Measurements ( $M = 3.46$ ), showed smaller or non-significant gains, suggesting a ceiling effect rather than program ineffectiveness.

#### D. Competency Rating Distribution Shift

Looking beyond means, the full distribution of item-level self-assessment ratings tells a complementary story. Before the program, 25.2% of all rated items fell in the Poorly Developed category; afterward, that figure dropped to 16.5%—a relative reduction of 34.5% across the cohort. Adequately Developed ratings grew from 12.9% to 19.3% (+6.4 percentage points, a relative increase of nearly 50%). The Moderately Developed band also expanded (30.4% → 35.6%), and the Highly Developed category showed a modest decline (8.6% → 6.6%), a pattern we return to in the Discussion section.

#### E. Subgroup Analysis by SHS Strand

STEM strand students ( $n = 60$  valid pairs) entered the program with considerably stronger self-assessed competency (Pre M = 2.53) than their Non-STEM peers ( $n = 10$ ; Pre M = 1.44). Both groups improved: STEM students significantly so ( $d = 0.35$ ,  $p = 0.008$ ), and Non-STEM students with a larger relative gain ( $d = 0.71$ ) that approached but did not reach significance ( $p = 0.053$ ), likely due to the small subsample. Yet the Non-STEM post-program mean of 1.89 still falls 0.64 scale units below the STEM pre-program baseline of 2.53—a gap that persists despite the program’s positive effect.

### V. DISCUSSION

#### A. Two Instruments, One Coherent Picture

One of the methodological choices that most shapes how we read these results was the use of two instruments—an objective diagnostic and a self-assessment survey—that measured the same underlying construct from different angles. The diagnostic captured knowledge acquisition in a controlled, single-sitting test environment; the self-assessment captured how students perceive their own developmental trajectory across 271 distinct competencies. These are not interchangeable measures, and the difference in their effect sizes ( $d = 1.83$  vs.  $d = 0.40$ ) is not a contradiction. Under conditions of focused, targeted instruction—exactly what the Bridging Program provides—large diagnostic gains were expected and indeed have been observed in comparable settings [14]. Self-assessment gains, by contrast, were bounded by metacognitive precision: a student who has genuinely learned more may still rate themselves only marginally higher on a 5-point scale once instruction revealed how much more there is to know [15]. What matters is that both instruments point in the same direction with significance,

providing convergent evidence that the program produced real, observable improvement [18].

TABLE III. MATHEMATICS MODULE RESULTS (N=81 PER MODULE)

Module	Pre M	Post M	Gain	t	p	d
Analytic Geometry	3.17	3.42	0.26	2.37	0.021	0.29*
Series & Induction	2.81	3.04	0.24	1.70	0.094	0.21
Trigonometry	2.30	2.70	0.41	3.29	0.002	0.42**
Limits & Continuity	2.58	2.96	0.38	3.17	0.002	0.41**
Derivatives	2.43	2.74	0.31	2.27	0.027	0.30*
Integration	2.12	2.52	0.41	2.71	0.009	0.38**

Note. \* $p < 0.05$ ; \*\* $p < 0.01$ . Gain = Post – Pre. All means on 1–5 scale.

TABLE IV. SELECTED CHEMISTRY MODULE RESULTS (N=81; SIGNIFICANT MODULES ONLY)

Module	Pre M	Post M	Gain	t	p	d
Electrochemistry	1.75	2.32	0.57	3.60	<0.001	0.59***
Stoichiometry	2.41	2.90	0.49	3.88	<0.001	0.48***
Acid-Base Equilibria	1.87	2.27	0.40	2.83	0.007	0.44**
Ionic Bonds	2.33	2.80	0.47	3.14	0.003	0.39**
Atoms, Mol. & Ions	2.57	2.97	0.40	3.15	0.002	0.39**
Electronic Structure	2.24	2.58	0.34	2.15	0.036	0.29*
Matter & Properties	3.19	3.45	0.25	2.18	0.033	0.26*
Solutions	2.28	2.59	0.31	2.23	0.029	0.29*

Note. \* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ . Gain = Post – Pre. Modules with  $\geq 0.05$  omitted.

#### B. Practical Implications of $d = 1.83$

The diagnostic effect size of 1.83 was large enough to warrant a moment of interpretive care. It reflected, in part, the instructional alignment of the instrument with the program content: the diagnostic was designed to measure exactly what the Bridging Program taught, and it did so in a low-stakes setting immediately after instruction. Under these conditions, a large effect is the expected and appropriate outcome—it was evidence that the program delivered its intended content effectively, not that it produced improbable learning miracles. The practical import was the movement of the average student from 42.6% to 68.9%—from below-average mastery to approaching or meeting the 75% threshold that the institution defined as functional competency. The average module mastery rate of 76% post-program confirmed that this threshold was broadly achieved. Whether these gains persist and predict downstream course performance remained the critical next question, one that requires longitudinal follow-up.

#### C. The Self-Assessment Recalibration Effect

The slight decline in Highly Developed ratings (from 8.6% to 6.6%) was worth examining carefully because it could be misread as regression. It is not. Students who enter a structured learning environment with limited prior exposure to a domain often overestimate their competency in early self-assessments—a well-documented pattern in novice learners [23]. When instruction provides genuine depth and breadth on those topics, students develop the frame of reference needed to assess themselves more accurately, which often means downgrading a naïve “Highly Developed” rating to a more honest “Adequately” or “Moderately Developed.” The fact that this realignment

happened alongside growth in Adequately and Moderately Developed ratings (and a sharp drop in Poorly Developed) was the pattern of healthy metacognitive development, not of failure.

#### D. *The Equity Problem the Program Cannot Solve Alone*

The Non-STEM subgroup finding is arguably the most policy-relevant result in this paper, precisely because it illustrates both what the program can do and what it cannot. Non-STEM students improved by a large margin relative to where they started ( $d = 0.71$ —the largest effect of any subgroup), and yet their post-program competency level of 1.89 on a 5-point scale is still substantially below the 2.53 that their STEM peers held before the program even began. The gap at entry was 1.09 scale points; the program narrowed it to approximately 0.64. Progress, certainly—but the remaining gap is still large enough to constitute a meaningful disadvantage when these students encounter Calculus for Engineers in their first week of classes.

This is not a failure of the Bridging Program. It is a structural consequence of CHED Memorandum Order No. 105's open-strand admissions policy combined with a curriculum architecture that no longer provides in-college remediation for foundational subjects. Two weeks of intensive instruction cannot fully replace two years of missing SHS content. What it can do—and what these results suggest it did—is give Non-STEM students a meaningful foothold. But institutions that admit students from diverse SHS tracks need to do more: strand-differentiated bridging curricula, extended program durations, or embedded support mechanisms within first-semester courses are all options the evidence here suggests exploring [3], [13], [24].

#### E. *Situating the Findings in the Literature*

The module-level pattern across both domains aligned with what the secondary-to-tertiary transition literature would predict. The largest mathematics effects concentrated in Trigonometry, Limits and Continuity, and Integration—the modules with the lowest baseline means and the strongest connection to calculus gateway courses—mirroring the curriculum hierarchy that Ellis et al. [25] identified as the primary locus of engineering program misalignment. In chemistry, the dominance of Electrochemistry and Stoichiometry among the highest-effect modules is consistent with these topics' known difficulty and their mathematical intensity [26], [27]. The overall effect ( $d = 0.40$ ) is slightly larger than Bradford et al.'s [13] meta-analytic estimate for STEM bridge programs ( $d = 0.34$ ), which is encouraging given that the present study used self-report rather than objective GPA data—typically a more conservative measure.

#### F. *Limitations*

Four limitations bound what can be concluded here. First, while the diagnostic examination corroborated the self-assessment findings, neither measure has yet been linked to first-semester course grades or gateway course passing rates; that linkage is the essential next step for establishing consequential validity. Second, the absence of a control group meant we cannot fully rule out retest effects or temporal maturation as contributors to the observed gains, particularly for the diagnostic. A waitlist comparison design would strengthen

causal attribution in future iterations. Third, the Non-STEM subsample of 10 valid pairs is too small for definitive conclusions; strand-stratified findings should be interpreted with caution and replicated with larger cohorts through purposive oversampling. Fourth, surname-based matching, while practical, introduces a non-trivial risk of pairing error in cohorts with common family names, which may have attenuated the observed paired-difference statistics.

## VI. CONCLUSION

The BUCENG Bridging Program produced significant, convergently validated improvements in incoming first-year engineering students' foundational competency in mathematics and basic engineering sciences. The objective diagnostic recorded a large gain ( $d = 1.83$ ,  $p < 0.001$ ), and the competency self-assessment confirmed a meaningful shift in students' perceived developmental level ( $d = 0.40$ ,  $p = 0.001$ ), with 13 of 23 content modules reaching significance. The program's effects were largest and most consistent in the domains where students were least prepared—advanced chemistry and calculus precursors—exactly where foundational gaps are most likely to derail first-year persistence.

Three recommendations follow from these findings. First, BUCENG should formalize the Bridging Program as a permanent pre-enrollment requirement, with strand-differentiated tracks providing extended coverage for non-STEM entrants who enter with considerably larger foundational deficits. Second, a longitudinal study linking program participation to first-semester course grades, gateway course passing rates, and second-term retention should be prioritized; such data would establish the downstream educational value that the present study points toward but cannot yet confirm. Third, CHED should consider incorporating bridging program standards into revised engineering Policies, Standards, and Guidelines, acknowledging that curriculum compression under K–12 created a structural readiness challenge that individual institutions are currently absorbing without centralized policy guidance.

## ACKNOWLEDGMENT

The authors wish to express sincere gratitude to Bicol University, the Research, Development and Management Division, the Extension Management Division, the Center for Policy Studies and Development, and the College of Engineering for their institutional support in the conduct of this research. Special thanks to the faculty, students, and alumni for their support and participation in the bridging program.

## REFERENCES

- [1] W. Perante, "Mathematical readiness of freshmen engineering students (K–12 2020 graduates) in Eastern Visayas in the Philippines," *Asian Journal of University Education*, vol. 18, no. 1, p. 191, Feb. 2022, doi: 10.24191/ajue.v18i1.17187.
- [2] M. S. Ramos, J. R. B. Barajas, P. J. N. Gealone, N. O. Aspra, O. M. Padua, and A. T. Lucero, "Enhancing the Admissions Process for Engineering Baccalaureate Programs: A Machine Learning Approach to Developing a Valid and Reliable Examination," 2023 Systems and Information Engineering Design Symposium (SIEDS). IEEE, pp. 191–196, Apr. 27, 2023. doi: 10.1109/sieds58326.2023.10137793.
- [3] J. R. B. Barajas et al., "Competency Matrix Design for an Engineering Bridging Course to Calculus I Using P-Graph Methodology," 2025 IEEE

- 14th International Conference on Engineering Education (ICEED). IEEE, pp. 24–29, Sep. 09, 2025. doi: 10.1109/iceed66794.2025.11400179.
- [4] M. E. Olesco, J. R. B. Barajas, and R. A. Gamboa, “An Exploratory Gap Analysis of Faculty Expectations and Student Self-Assessed Competencies Across Six Core Engineering Domains: A Philippine Case Study,” 2025 IEEE 14th International Conference on Engineering Education (ICEED). IEEE, pp. 36–41, Sep. 09, 2025. doi: 10.1109/iceed66794.2025.11400056.
- [5] M. E. Olesco and R. A. Gamboa, “Aligning STEM Education with Engineering Curricula: A Competency Mapping Framework in the Philippines Using Exploratory Factor Analysis,” 2025 Systems and Information Engineering Design Symposium (SIEDS). IEEE, pp. 104–109, May 02, 2025. doi: 10.1109/sieds65500.2025.11021208.
- [6] Commission on Higher Education (CHED), Policy on the Admission of Senior High School Graduates to the Higher Education Institutions, CMO No. 105, Series of 2017. Quezon City, Philippines: CHED, 2017. [Online]. Available: <https://ched.gov.ph/wp-content/uploads/2018/01/CMO-No.-105-s.-2017-Policy-on-the-Admission-of-Senior-High-School-Graduates-to-the-Higher-Education-Institutions-Effective-Academic-Year-2018-2019.pdf>
- [7] J. R. B. Barajas, P. Jay N. Gealone, M. S. Ramos, N. O. Aspra, A. T. Lucero, and O. M. Padua, “Identifying Competency Gaps Among Engineering Students in a Post K-12 Setting Through the Use of Clustering Algorithms,” 2023 Systems and Information Engineering Design Symposium (SIEDS). IEEE, pp. 31–36, Apr. 27, 2023. doi: 10.1109/sieds58326.2023.10137844.
- [8] C. R. Bego, J. L. Hieb, and P. A. Ralston, “Barriers and bottlenecks in engineering mathematics: Math completion predicts persistence to graduation,” 2019 IEEE Frontiers in Education Conference (FIE). IEEE, pp. 1–6, Oct. 2019. doi: 10.1109/fie43999.2019.9028542.
- [9] J. A. Middleton, S. Krause, S. Maass, K. Beeley, J. Collofello, and R. Culbertson, “Early course and grade predictors of persistence in undergraduate engineering majors,” 2014 IEEE Frontiers in Education Conference (FIE) Proceedings. IEEE, pp. 1–7, Oct. 2014. doi: 10.1109/fie.2014.7044367.
- [10] M. E. Bigotte de Almeida, A. Queiruga-Dios, and M. J. Cáceres, “Differential and Integral Calculus in First-Year Engineering Students: A Diagnosis to Understand the Failure,” *Mathematics*, vol. 9, no. 1, p. 61, Dec. 2020, doi: 10.3390/math9010061.
- [11] B. Faulkner, N. Johnson - Glauch, D. San Choi, and G. L. Herman, “When am I ever going to use this? An investigation of the calculus content of core engineering courses,” *J of Engineering Edu*, vol. 109, no. 3, pp. 402–423, Jul. 2020, doi: 10.1002/jee.20344.
- [12] B. N. Geisinger and D. R. Raman, “Why they leave: Understanding student attrition from engineering majors,” *Int. J. Eng. Educ.*, vol. 29, no. 4, pp. 914–925, 2013. [Online]. Available: [https://www.ijee.ie/articles/Vol29-4/14\\_ijee2746ns.pdf](https://www.ijee.ie/articles/Vol29-4/14_ijee2746ns.pdf)
- [13] B. C. Bradford, M. E. Beier, and F. L. Oswald, “A Meta-analysis of University STEM Summer Bridge Program Effectiveness,” *LSE*, vol. 20, no. 2, p. ar21, Jun. 2021, doi: 10.1187/cbe.20-03-0046.
- [14] G. Morán-Soto, L. H. Arellano Ulloa, and O. I. González Peña, “Mathematics abilities as the key to successfully completing an engineering major: an analysis of a remedial mathematics course,” *European Journal of Engineering Education*, pp. 1–23, Jan. 2026, doi: 10.1080/03043797.2025.2607635.
- [15] M. Mayerhofer, M. Lüftenegger, and M. Eichmair, “Impact of a Mathematics Bridging Course on the Motivation and Learning Skills of University Students,” *Int. J. Res. Undergrad. Math. Ed.*, vol. 11, no. 1, pp. 55–90, Sep. 2023, doi: 10.1007/s40753-023-00224-0.
- [16] P. M. Almerino Jr. et al., “Evaluating the Academic Performance of K-12 Students in the Philippines: A Standardized Evaluation Approach,” *Education Research International*, vol. 2020, pp. 1–8, Oct. 2020, doi: 10.1155/2020/8877712.
- [17] A. T. Jebb, V. Ng, and L. Tay, “A Review of Key Likert Scale Development Advances: 1995–2019,” *Front. Psychol.*, vol. 12, May 2021, doi: 10.3389/fpsyg.2021.637547.
- [18] N. A. Mamaril, E. L. Usher, C. R. Li, D. R. Economy, and M. S. Kennedy, “Measuring Undergraduate Students’ Engineering Self - Efficacy: A Validation Study,” *J of Engineering Edu*, vol. 105, no. 2, pp. 366–395, Apr. 2016, doi: 10.1002/jee.20121.
- [19] T. R. Hinkin, “A Brief Tutorial on the Development of Measures for Use in Survey Questionnaires,” *Organizational Research Methods*, vol. 1, no. 1, pp. 104–121, Jan. 1998, doi: 10.1177/109442819800100106.
- [20] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*. Routledge, 2013. doi: 10.4324/9780203771587.
- [21] J. Hattie, *Visible Learning*. Routledge, 2008. doi: 10.4324/9780203887332.
- [22] Python Software Foundation, “Python (Version 3.14.4) [Computer software],” 2026. [Online]. Available: <https://www.python.org>
- [23] J. Kruger and D. Dunning, “Unskilled and unaware of it: How difficulties in recognizing one’s own incompetence lead to inflated self-assessments,” *Journal of Personality and Social Psychology*, vol. 77, no. 6, pp. 1121–1134, 1999, doi: 10.1037/0022-3514.77.6.1121.
- [24] D. Olsen, K. Supan, and L. Johnson, “Board 290: From Resistance to Readiness – Building Capacity to Pilot and Scale Co-requisite Calculus for First-Year Engineering Gateway Courses,” 2024 ASEE Annual Conference & Exposition Proceedings. ASEE Conferences. doi: 10.18260/1-2--46866.
- [25] J. Ellis, M. L. Kelton, and C. Rasmussen, “Student perceptions of pedagogy and associated persistence in calculus,” *ZDM Mathematics Education*, vol. 46, no. 4, pp. 661–673, Mar. 2014, doi: 10.1007/s11858-014-0577-z.
- [26] R. Nolasco, “Navigating Electrochemistry: Challenges and Coping Strategies of Engineering Students,” *JIP*, vol. 3, no. 5, 2025, doi: 10.69569/jip.2025.158.
- [27] F. J. Scott, “Is mathematics to blame? An investigation into high school students’ difficulty in performing calculations in chemistry,” *Chem. Educ. Res. Pract.*, vol. 13, no. 3, pp. 330–336, 2012, doi: 10.1039/c2rp00001f.