Identifying Competency Gaps Among Engineering Students in a Post K-12 Setting Through the Use of Clustering Algorithms

John Raymond B. Barajas, Pee Jay N. Gealone, Marben S. Ramos, Nico O. Aspra, Arpon T. Lucero, Jr., Oliver M. Padua

Abstract— **This paper leverages on the power of clustering algorithms to determine potential deficiencies in mathematics competencies of incoming first year engineering students who are graduates of the recently implemented K to 12 program. To achieve this objective, a total of 23 prerequisite mathematics competencies in Algebra, Advance Algebra, Plane and Spherical Trigonometry, Analytical Geometry, and Solid Mensuration common to engineering programs offered in the country were identified from the approved policies, standards, and guidelines published by the Commission on Higher Education. A survey instrument was developed to assess the self-rated proficiencies of participating respondents in these competencies using a 5-point liker scale (5 being the highest). Results of the clustering analysis showed the formation of four distinct groups of students based on their self-rated proficiencies: (1) above average, (2) average, (3) below average, and (4) poor. It was found that participants generally gave low self-ratings to Advanced Algebra and Analytic Geometry prerequisites. Although it is expected for non-STEM graduates of the K to 12 program to struggle in engineering programs, further analysis of the clusters revealed that about half of the STEM respondents self-rated their proficiencies in the below average and poor clusters. Though it may be argued that this finding may need to be explored further in the absence of ground truth labels, diagnostic examination scores garnered by the participants validate this observation. In conclusion, this study highlights the need for universities to implement targeted intervention programs to address the identified deficiencies and ensure the success of their enrollees in engineering programs.**

I. INTRODUCTION

Recently, the Philippines has implemented the K-12 curriculum, requiring two additional years of education before students can be admitted to higher educational institutions (HEIs). The "Enhanced Basic Education Act of 2013" (Republic Act No. 10533) requires grades 11 and 12 students to choose from four tracks: academic, technical-vocational-livelihood (TVL), arts and design (AD), sports, and information and communications technology [1]. For students who choose the academic track, they must specialize in one of four academic strands: accountancy, business, management (ABM), humanities and social sciences (HUMSS), general academic (GA), and science, technology, engineering, mathematics (STEM) [2]. Ideally, K-12 graduates aspiring to pursue an engineering degree should complete kindergarten, six years of primary education (Grades 1 to 6), four years of junior high school (Grade 7 to 10), and two years of senior high school (Grades 11 to 12) in the STEM academic strand. However, this implemented shift has limited the flexibility in screening and selecting qualified applicants to engineering programs among the HEIs in the country.

For instance, the Commission on Higher Education Memorandum Order (CMO) no. 105 series of 2017 mandates that all HEIs accept K-12 graduates for college admission tests or assessments, regardless of the track or strand they graduated from [3]. This is with a caveat that acceptance to the chosen program is still subject to the applicant passing the set admission standards by an HEI. However, this policy has resulted in a potential issue for the engineering programs offered by these HEIs, as it is beyond their control to ensure that accepted applicants have completed the required prerequisites for their revised engineering curricula [4]. This lack of applicant entry control means that students may be allowed to enroll in courses without the necessary foundational knowledge (e.g., applicant has taken up pre-calculus courses), resulting in gaps in their proficiencies, and a potential mismatch between their abilities and the requirements of their chosen degree [5]. To address this issue, it is therefore crucial for HEIs to establish a comprehensive profiling system for the mathematics proficiencies of its enrollees and implement intervention programs tailored to their specific deficiencies. By doing so, HEIs can ensure that its students have the necessary knowledge and skills to succeed in their chosen fields.

J. R. Barajas is with the Bicol University College of Engineering Chemical Engineering Department, Legazpi City, Albay, Philippines (email: jrbbarajas@bicol-u.edu.ph).

P. J. Gealone is with the Bicol University College of Engineering Electrical Engineering Department, Legazpi City, Albay, Philippines (email: pjngealone@bicol-u.edu.ph).

M. Ramos is with the Divine Word College of Legazpi, Legazpi City, Albay, Philippines and is presently the Dean of the School of Engineering and Computer Studies. He also serves as a professional lecturer with Bicol University College of Engineering, Legazpi City, Albay, Philippines (email: marbz_ramos@dwc-legazpi.edu).

N. Aspra is with the Bicol University College of Industrial Technology Mechanical Technology Department, Legazpi City, Albay, Philippines (email: nico.aspra@bicol-u.edu.ph).

A. Lucero, Jr. is with the Bicol University College of Engineering Chemical Engineering Department, Legazpi City, Albay, Philippines (email: ajdlucero@bicol-u.edu.ph).

O. Padua is with the Bicol University College of Engineering Civil Engineering Department, Legazpi City, Albay, Philippines (email: ompadua@bicol-u.edu.ph).

In an attempt to contribute a potential solution to this problem, this work pilot-tested an instrument which aimed to map the mathematics deficiencies of participating first-year engineering students. The deployed instrument asked the participants to rate their proficiencies on 23 prerequisite competencies taken from the pre-K12 approved CMOs for the programs in Chemical Engineering, Civil Engineering, Electrical Engineering, Geodetic Engineering, Mechanical Engineering, and Mining Engineering [6]-[11]. To make the analysis of the results more meaningful, the collected survey data was clustered using agglomerative hierarchical clustering techniques to categorize the participants in accordance with their identified deficiencies. To validate the identified clusters, a diagnostic examination centering on the prerequisites was also given to the participants. Results of the diagnostic examination verified the existence of four clusters grouped according to the identified deficiencies of the participants.

II. METHODOLOGY

The employed methodology in this work is divided into three phases: instrument development (*Phase I*), clustering of survey data (*Phase II*), and diagnostic examination (*Phase III*). Details on how each phase was implemented are discussed in the succeeding sections.

A. Phase I: Instrument Development

To assess the mathematics deficiencies of first-year engineering students, a self-evaluation instrument was developed and administered to willing participants. The primary objective of this instrument is to solicit self-ratings of the participants in the 23 prerequisite competencies detailed in Table I. To achieve this, the self-evaluation instrument was anchored on five domains as suggested in reviewed literature [12]-[14].

TABLE I. IDENTIFIED PREREQUISITE COMPETENCIES

Competency Code[a]	**Description of Competency[b]**
A_1	Simplify and manipulate algebraic expressions
A_2	Determine the solution sets of algebraic equations, exponential and logarithmic equations; and inequalities
A_3	Apply algebraic concepts and techniques to solve word problems
A_4	Identify the domain and range of a given relation/function
AA_1	Determine the solution sets of inequalities
AA_2	Determine the solution sets of systems involving quadratics
AA_3	Apply advance algebra concepts and techniques to solve word problems
AA_4	Perform operations and manipulations on matrices and determinants
AA_5	Solve systems of linear equations using matrices and determinants
AA_6	Find the sum of elements in arithmetic and geometric sequences
T_1	Define angles and their measurements using degrees and radians
T_2	Evaluate the sine, cosine, tangent, cosecant, secant, and cotangent functions
T_3	Prove the properties and identities of trigonometric functions
T_4	Define and evaluate inverse trigonometric functions
T_5	Solve trigonometric equations
T_6	Solve problems involving right triangles using trigonometric function definitions for acute angles
T_7	Solve problems involving oblique triangles by the use of the sine and cosine laws
AG_1	Set up equations given enough properties of lines and conics
AG_2	Draw the graph of the given equation of the line and the equation of the conic section
AG_3	Analyze and trace completely the curve, given their equations in both rectangular and polar coordinates, in two-dimensional space
SM_1	Calculate the area of plane figures using appropriate formulas
SM_2	Calculate the surface areas and volumes of various types of solids using appropriate formulas
SM_3	Determine the volumes and surface areas of solids using other methods such as the theorems of Pappus

[a] A – Algebra; AA – Advance Algebra; T – Plane and Spherical Trigonometry; AG – Analytic Geometry; SM – Solid Mensuration

[b] Competency descriptions were taken from approved CMOs [6]-[11].

Specifically, a participant is asked to honestly rate from a scale of 1 to 5 (where 5 is highest) their *comprehension*, *efficiency*, *confidence*, *reasoning*, and *willingness* on a competency – resulting to a total of five questions to each of the identified competencies. The self-rated score of a participant on a competency is then calculated as the arithmetic average of the self-ratings in these five domains (see Figure 1 for the framework used to develop the self-evaluation instrument). With a Cronbach's alpha coefficient of 0.9845, reliability analysis of the self-evaluation instrument demonstrated high internal consistency, indicating a high level of reliability [15]. This high coefficient is not surprising, given that the same reflection questions were used for all 23 prerequisite competencies.

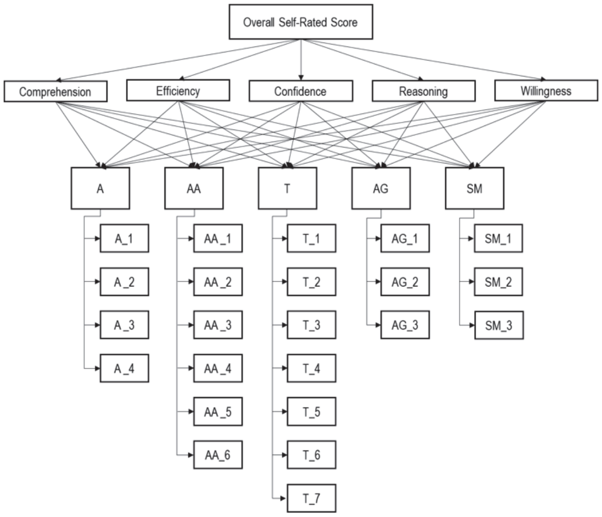

Figure 1. Framework Used for the Self-Evaluation Instrument.

B. Phase II: Clustering of Survey Data

To ensure a systematic and meaningful analysis of the survey data, four agglomerative hierarchical clustering algorithms were implemented, namely: (1) single, (2) average, (3) complete, and (4) Ward's method [16]-[23]. As ground truth labels were not available, the Calinski and Harabasz score as the internal validation criterion to evaluate the quality of the clustering results [24]. The algorithm that yielded the highest Calinski and Harabasz score was selected, with the expectation that the resulting clusters would be more compact and well-separated.

C. Phase III: Diagnostic Examination

To ensure an objective and reliable validation procedure for the clustering results, a panel of five (5) domain experts was commissioned to develop a 50-item multiple choice diagnostic examination covering the 23 prerequisite competencies. The exam was designed with a balanced level of difficulty, with three (3) easy, four (4) medium, and three (3) hard questions for each of the following subjects: Algebra, Advanced Algebra, Plane and Spherical Trigonometry, Analytical Geometry, and Solid Mensuration. Since the speed of answering the questions was not a focus of this work, the examination was given a maximum of three (3) hours to provide enough time for the participants to answer the questions. The diagnostic scores of the participants were then calculated by dividing the number of correct answers by the total number of items in the exam, expressing the scores of the participants in percentage.

III. RESULTS AND DISCUSSION

A. Demographic Profile of Respondents

The demographic profile of the participants is summarized in Table II. A total of 554 useful responses from willing participants were recorded. Consistent with the trend in engineering programs, male students constituted the majority of the sample (58.7%), while a substantial number of female students were also included (41.3%). Notably, nearly 1 in 5 respondents came from non-STEM backgrounds, of which the majority have taken specialized tracks in ABM, GAS, and TVL. This demographic information of the participants suggests that a considerable number of first-year engineering students may exhibit deficiencies in the prerequisite competencies due to possible mismatch in their academic background.

B. Overall Self-Rated Scores

Before identifying clusters of participants who may have deficiencies in the 23 identified prerequisite competencies, this study initially evaluated the overall self-rated scores of the participants on these competencies. Figure 2 displays the overall self-rated scores and its distribution by academic strand. Results indicate that STEM students generally have higher mathematics knowledge than non-STEM students. This is not surprising, as precalculus subjects such as Algebra, Advance Algebra, Plane and Spherical Trigonometry, Analytic Geometry, and Solid Mensuration are already covered in the junior and senior high school years of K12 STEM students. Conversely, non-STEM students had a lower mean overall self-rated scores than STEM students.

Comparing the means of these two groups using Welch's T-test for unequal sample sizes, resulted in a T-statistic of 6.78 and a P-value of less than 0.000001. Although the self-rated scores of STEM and non-STEM students are relatively close, these statistical results suggest that the difference between the means of the two groups is highly significant. However, it should be noted that the whiskers on the boxplot for STEM participants reached as low as 2.0, and at least the first quartile of this group reported overall self-rated scores lower than the average self-rating of 3.0. This observation then indicated that a significant number of STEM first-year engineering students may also have deficiencies in the identified prerequisite competencies similar to that of non-STEM first-year engineering students.

C. Selection of Clustering Algorithm

Table III presents the summary of the clustering algorithms implemented in this work. With a Calinski and Harabasz (CH) score of 244.67, it was found that the Ward's method with *n clusters* of two (2) had the most compact and well-separated clusters. The Ward's method was therefore chosen as the agglomerative hierarchical clustering algorithm to be employed in this work.

TABLE II. RESPONDENT PROFILE

Demographics	**Frequency**	**Percentage (%)**
Age (years)		
17	11	2.0
18	370	66.8
19	173	31.2
20	9	1.6
21	2	0.4
Sex (Birth)		
Male	325	58.7
Female	229	41.3
Academic Strand		
ABM	28	5.1
Arts and Design	2	0.4
GAS	38	6.9
HUMSS	4	0.7
ICT	1	0.2
Non-K12	3	0.5
STEM	460	83.0
TVL	18	3.2

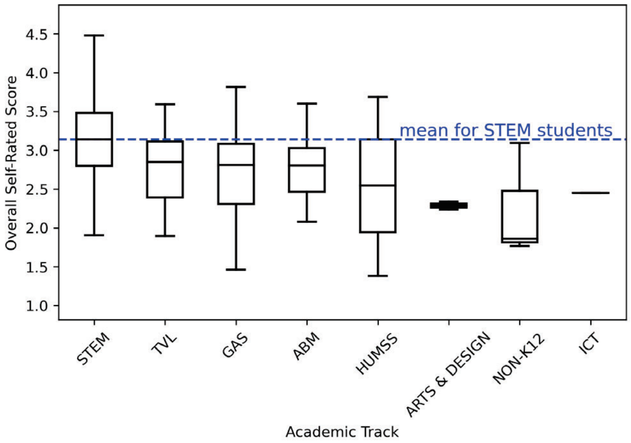

Figure 2. Box-plot of Self-Rated Scores Grouped by Academic Strand.

TABLE III. CALINSKI AND HARABASZ SCORES

Clustering Algorithm	***n clusters***	**CH score**
Single	2	4.46
Average	2	19.67
Complete	2	198.54
Ward's Method	2	244.67

D. *Interpretation of Clusters*

Figure 3 shows the clusters formed using the Ward's method, which are clearly separated into two distinct groups at a delta of 60. To gain a deeper understanding of these clusters, a further division was made at a delta of 22 resulting to a total of four distinct groups. Descriptive statistics of the overall self-rated scores for these four groups are summarized in Table IV. Based on these findings, the formed clusters could then be interpreted as follows:

- *Engineering Students with Above Average Proficiency (Group 1, 65 Students):* With a mean overall self-rating score of 3.94, this cluster represents students who are expected to demonstrate mastery of the identified pre-requisite mathematics competencies.

- *Engineering Students with Average Proficiency (Group 1, 151 Students):* With a mean overall self-rating score of 3.44, this cluster represents students who are expected to demonstrate minimal deficiencies in the identified pre-requisite mathematics competencies.

- *Engineering Students with Below Average Proficiency (Group 2, 258 Students):* With a mean overall self-rating score of 2.91, this cluster represents students who are expected to demonstrate substantial deficiencies in the identified pre-requisite mathematics competencies. This group of students may need supplementary classes to address gaps in the prerequisite competencies.

- *Engineering Students with Poor Proficiency (Group 2, 80 Students):* With a mean overall self-rating score of 2.16, this cluster represents students who are expected to be strongly deficient in the identified prerequisite mathematics competencies. This group of students are advised to undergo a bridging course before entering the engineering program they have been accepted into.

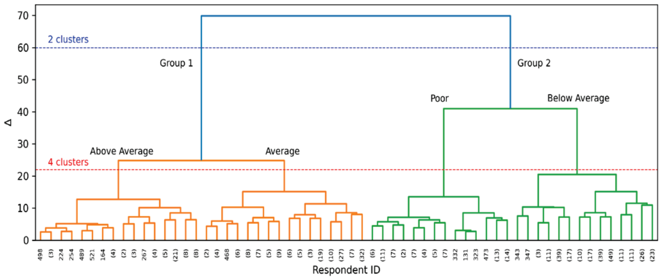

Figure 3. Results of Hierarchical Clustering Using Ward's Method.

TABLE IV. OVERALL SELF-RATED SCORE STATISTICS OF CLUSTERS

Cluster	**count**	**%**	**mean**	**std**	**min**	**max**
Above Average	65	11.7	3.94	0.30	3.42	4.68
Average	151	27.3	3.44	0.21	2.89	4.03
Below Average	258	46.6	2.91	0.24	2.27	3.44
Poor	80	14.4	2.16	0.27	1.00	2.63

E. *Validation of Clusters through Diagnostic Examination*

In order to validate the interpretation of the formed clusters and gain further insights from the analyzed survey data, this study also conducted a 50-item multiple choice diagnostic examination covering the 23 identified prerequisite competencies. Since ground truth labels were not available, the diagnostic exam scores garnered by the willing STEM and non-STEM participants were used as a basis for comparison. As shown in Figure 4, the results of the diagnostic examination are in agreement with the analysis of the self-rated scores grouped by cluster. Moreover, consistent with the findings on self-rated scores, participants who indicated *above average* and *average* competencies also obtained the highest scores in the diagnostic examination. Therefore, these results provide confirmatory evidence for the identified clusters, and these further validate the reliability of the cluster interpretation derived.

F. *Distribution of Academic Track in the Clusters*

An analysis of the distribution of academic tracks of the participants grouped according to the identified clusters revealed significant findings. As depicted in Figure 5, it is not surprising that most non-STEM students fall under the *below average* and *poor* proficiency clusters since the identified mathematics competencies were not taken up in their tracks [25]. However, it is noteworthy that (1) around 15 non-STEM students expressed *average* proficiency in mathematics competencies, and (2) about half of the participating STEM students expressed *below average* and *poor* proficiency in the same set of prerequisite competencies. While the former observation suggests that some non-STEM students may have already taken up extra classes to enhance their mathematics proficiency, the latter is a definite cause for concern. This finding strongly highlights the need for intervention programs, such as extra classes and bridging courses, to be offered to willing and accepted applicants to engineering programs in HEIs to address their deficiencies in these prerequisite competencies [26]-[27].

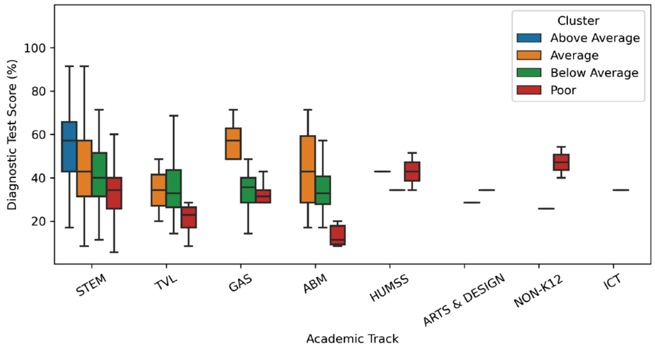

Figure 4. Box-plot of Diagnostic Scores Grouped by Cluster.

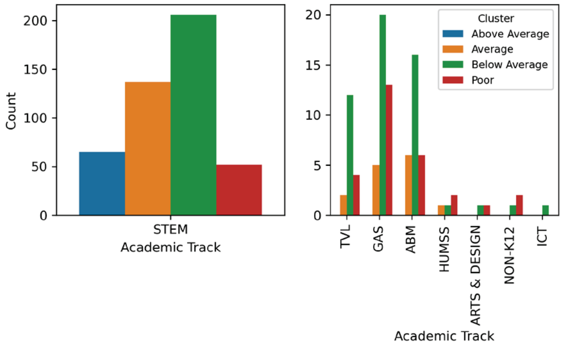

Figure 5. Distribution of Academic Tracks Based on Clusters Formed.

G. *Mapping of Deficiencies in Prerequisite Competencies*

As the primary contribution of this work, this study presents a working map of deficiencies in the identified prerequisite competencies as perceived by STEM and non-STEM students. As shown in Figure 6, the following insights could then be drawn:

- Students under the *above average* and *average* clusters would demonstrate proficiency in the identified prerequisite competencies, with Solid Mensuration competencies identified to have the highest self-rated scores.
- Students under the *below average* and *poor* clusters signified substantial deficiencies across all prerequisite competencies, with Advance Algebra competencies identified to have the lowest self-rated scores.
- In all clusters, Advance Algebra and Analytic Geometry competencies garnered the lowest self-rated scores.

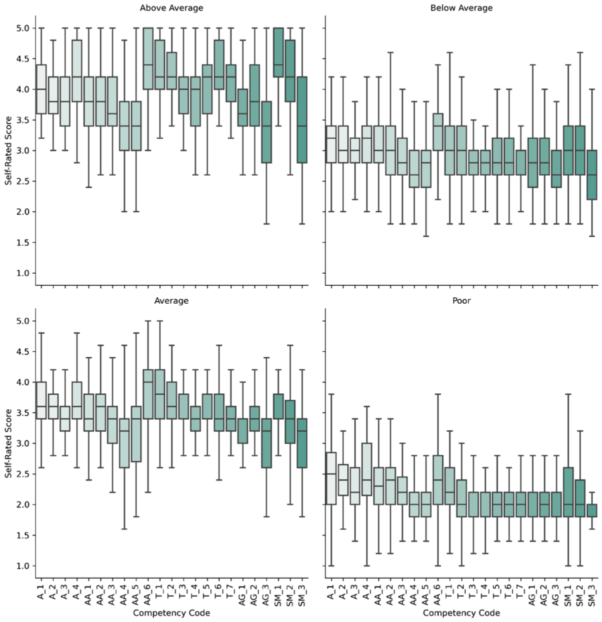

Figure 6. Box-plot of Competency Self-Rated Scores Grouped by Cluster.

G. *Practical Implications of Findings*

The findings of this study emphasize the critical need for targeted intervention programs to address the identified gaps in prerequisite competencies for both STEM and non-STEM students. This study further provides substantial evidence that simply being on the STEM track does not guarantee proficiency in competencies that are prerequisite to enrolling in engineering programs. It is also alarming to note that approximately half of the STEM participants have substantial deficiencies in the identified prerequisites, as confirmed by both self-ratings and diagnostic examination scores. Parallel to what is reported in reviewed literature [26]-[27], these gaps negatively impact the academic success of future engineering students in HEIs, as the identified competencies serve as foundational skills that are necessary for the successful completion of engineering courses.

To ensure therefore that future engineering students are equipped with the necessary competencies, intervention programs such as extra classes and bridging courses must be designed to address deficiencies in the identified prerequisite competencies. These programs can be tailored to the needs of individual students and tweaked to provide them with the necessary support to enhance their proficiency in the identified competencies [26]. By doing so, students are given the chance to hone the foundational skills necessary to succeed in engineering programs and, ultimately, their careers.

IV. FUTURE DIRECTIONS

A team of experts in the field of mathematics, engineering, and education is currently finalizing the course design and instructional materials for an intervention program that is aimed to address the deficiencies in prerequisite competencies identified in this study. The development of this bridging course is seen as a huge step in institutionalizing an admission policy that will equip aspiring engineering students with the necessary competencies needed for the successful completion of an engineering degree. It is further hoped that this intervention program will serve as a model for other HEIs in addressing similar challenges in their respective institutions.

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