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Developing a Word Code File to link Learning Outcomes to Graduate Attributes in an Engineering Curriculum*

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Graduate attributes (GA) have been integrated into curricula at many universities around the globe, as higher educational institutions seek to make their graduates more employable. The International Engineering Alliance released VERSION 4 of a document listing 11 GA that engineering students need to demonstrate through their educational career. Equally important are learning outcomes (LO) that clearly indicate what is expected of students to demonstrate or achieve during a specific module or course. The purpose of this article is to present a technique that may be used to develop a word code file that enables one to link LO to GA. This code can then be used with AI or quantitative data analysis programs to provide a network map of the GA, thereby providing evidence of their integration within a curriculum. A mixed-methods approach is used focusing on a 280-credit Diploma in Electrical Engineering. The technique focuses on pre-processing the LO of the curriculum, creating a frequency count of the words used, and drawing on the definitions of the attributes to create a word code file. This file lists the 11 GA where key verbs or nouns are associated with each attribute. Applying this file to all the LO in an Electrical Engineering curriculum revealed how the attributes are integrated, with Problem analysis being the dominant attribute. It is hoped that this word code file may be used with other engineering curricula to obtain a clearer picture on the integration of GA.

Keywords: IEA; integration; KH Coder; ChatGPT

1. Introduction

"I know of no single formula for success. But over the years I have observed that some attributes of leadership are universal and are often about finding ways of encouraging people to combine their efforts, their talents, their insights, their enthusiasm and their inspiration to work together" [1]. Queen Elizabeth II uttered these words indicating that some attributes of leadership are universal in finding ways of integration to ensure successful collaboration. This is also true of engineering students, who need to demonstrate key graduate attributes (GA) that are universal in nature and which can enable their successful integration into industry today.

Many countries that have subscribed to the Washington, Sydney and Dublin Accords have sought to integrate GA into their engineering curricula to ensure a quality standard of education for their students. The attributes listed by the International Engineering Alliance (IEA) often forms the basis for this integration that seeks to improve the employability of engineering graduates and to reduce the gap between higher education and industry [2]. The successful acquisition, or demonstration, of these attributes by engineering students is therefore critical to their professional success.

How though can one determine if the 11 GA of the IEA have been succesfully integrated into a curriculum? A proposed technique lies in analysing the learning outcomes (LO) of a curriculum, and linking them to the GA. LO are at the centre of learning in numerous institutions of Higher Education [3]. Although there is no universally accepted definition of LO, various meanings exist that point to them as statements of what a student is expected to know by the end of a programme, module or course. When designing a course, LO need to be aligned with the teaching strategies and assessment mechanisms to ensure consistency among the educational methodologies [4]. GA need to be added to this alignment, as they cannot reside in isolation from each other.

The purpose of this article is to present a technique that may be used to develop a word code file that enables one to link LO to GA. This file can then be used with AI (e.g., ChatGPT) or quantitative data analysis programs (e.g., KH Coder) to provide a network map of the GA, thereby providing evidence of their integration within a curriculum. The article starts with a discussion on the importance of coding and its requirements in a data-driven world. The sequential steps used to develop the word code file is then given. The study context follows along with the methodology and key results in terms of network maps and a frequency table.

2. The Importance of Coding and its Requirements in a Data-driven World

In today's data-driven environment, coding has emerged as a fundamental competency essential across diverse disciplines, particularly within the realm of engineering education. The exponential

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increase in digital data cultivates a pressing need for the ability to process, analyze, and interpret extensive datasets efficiently. Coding serves as a pivotal instrument that bridges the gap between raw data and insightful information, enabling researchers and practitioners to transform unstructured data into structured knowledge [5].

Coding enables systematic analysis of both qualitative and quantitative data. It helps researchers identify patterns, establish relationships, and draw conclusions that inform decision-making processes. In the context of engineering education, coding skills empower students and educators to engage with complex datasets, fostering a deeper understanding of LO and educational effectiveness [6, 7].

In this study, KH Coder [8] was employed to analyze word frequencies and relational patterns between LO that were captured from study guides in an electrical engineering curriculum. Its strengths include the ability to visually map co-occurrence networks of words to indicate key illustrative verbs and nouns that point to the core syllabus of the curriculum. Furthermore, it can map relationships between GA (defined by the IEA) based on a word code file that may be created using the verbs and nouns derived from the word frequency list and co-occurrence network of words. These attributes should be embedded in a curriculum [9], which can be ascertained by using the LO, word code file and KH Coder. Additionally, ChatGPT was used to support data preprocessing and interpretation, particularly in generating thematic summaries and identifying latent patterns that may not be immediately visible through manual analysis alone [9, 10]. This combination of tools enabled an iterative and reflexive process of coding, interpretation, and model refinement.

While KH Coder offered the optimal balance between statistical depth and usability for this study, several alternative platforms also support text mining and qualitative data analysis:

- QualCoder: An open-source qualitative data analysis tool supporting various media types and offering comprehensive coding, memoing, and visualization features [11].
- Voyant Tools: A web-based suite ideal for exploratory text analysis and interactive visualization, well-suited for initial reviews of large text corpora [12].
- MAXQDA and NVivo: Commercial software packages with extensive functionality for coding, mixed-methods integration, and data visualization [13].
- RQDA: An R-based qualitative data analysis package that offers integration with statistical computing [14].
- AQUAD: A flexible, free software package supporting various data types and providing tools for sequence and cluster analysis [15].

Each of these tools varies in terms of usability, licensing, analytic depth, and integration with other platforms. However, for structured educational texts such as LO and graduate attribute definitions, KH Coder provides a uniquely suitable feature set [16].

The integration of coding and automated analysis tools enhances transparency, reproducibility, and methodological rigor of educational research. Structured coding frameworks – such as the word code file used in this study – enable researchers to apply consistent criteria across large datasets. When coupled with statistical analysis and visualization, these tools offer a comprehensive picture of curriculum alignment and graduate attribute integration [17].

KH Coder was selected for this study due to its specific strengths in handling large volumes of structured educational text, such as syllabi and LO. Its ability to perform quantitative content analysis and generate interpretable co-occurrence networks made it ideal for exploring the presence and positioning of GA within curriculum documents. Additionally, its open-source architecture and statistical robustness ensured that the analyses conducted were both replicable and transparent [16].

By applying a custom-built word code file based on the LO of an engineering curriculum, the research team was able to assess the extent to which the GA of the IEA were embedded. This methodology provided a defensible and data-driven basis for evaluating the integration of professional competencies in higher education curricula [2, 9].

3. Sequential Steps used to Create the Word Code File

The word code file is created using ten (10) sequential steps, as listed next.

Step 1: Capture the LO from each study guide in Google Sheets. A request was sent via email to relevant staff members in the department of Electrical Engineering to please upload the LO of their study guides using a Google Sheet link. A deadline was stipulated to complete this step.

Step 2: Verify that all LO have been captured. The researchers then confirmed that all modules in the Diploma program were captured in the Google Sheet and that most of the LO in each module met the important criteria of containing a verb and a noun. If this criteria were not met with a given

Table 1. Linking the 11 GA of the IEA to the RAI strategy

Graduate attribute (* represents the letters GA)	RAI strategy	Reasons for the link
*1_Eng_knowledge	Recall	Engineering knowledge is seen to be quantitative in nature, corresponding to Knowledge and Comprehension in Bloom's Taxonomy
*2_Problem_analysis	Application	Qualitative in nature requiring students to analyse an engineering problem
*3_Design_solutions	Insight	Qualitative in nature requiring students to create an engineering solution
*4_Investigation	Application	Qualitative in nature requiring students to apply scientific techniques to gather data
*5_Tool_usage	Application	Qualitative in nature requiring students to use different tools to gather and analyse data
*6_Engineer_world	Insight	Qualitative in nature, requiring students to evaluate the impact of their solutions on the world
*7_Ethics	Application	Qualitative in nature, requiring students to adhere to ethical standards when creating solutions
*8_Individual_collaborative	Application	Qualitative in nature, requiring students to demonstrate self-efficacy and collaborative skills
*9_Communication	Application	Qualitative in nature, requiring students to apply communication skills
*10_Project_management	Insight	Qualitative in nature, requiring students to evaluate the various processes of project management
*11_Lifelong_learn	Insight	Qualitative in nature, requiring students to engage in critical thinking and self-assessment

module, then the staff member responsible for that module was contacted via email to verify their LO.

Step 3: Pre-process the LO. Extra spaces, inverted commas, symbols and full stops were removed from each learning outcome. Multiple outcomes appearing on the same line were split so that each outcome was listed on a separate line ending with a semicolon.

Step 4: Downloading the LO to a WORD file to verify the number. The outcomes were downloaded to a WORD file where numbered bullet points were applied. This helped to determine the exact number of LO, and to verify that multiple outcomes did not exist on each separate line. Errors were corrected in the WORD file and in the Google Sheet. The "Find" option in WORD was used to locate the semicolons, with the number of occurrences shown needing to match the number of bullet points to verify the reliability of the data.

Step 5: This WORD file was then uploaded to KH Coder, where a frequency of words was determined along with a co-occurrence network of words. This helped to determine the top verbs and nouns used in the LO, as well as their relationships.

Step 6: Link the IEA GA to the RAI strategy (Recall, Application, Insight). This strategy may be correlated to Bloom's Taxonomy, as discussed by Swart and Delport [18]. This proposed link is shown in Table 1 along with associated reasons. For example, Problem analysis requires more application than recall, as students need to call of their acquired knowledge to correctly analyze a problem.

Step 7: Illustrative verbs associated with each level of Bloom's Taxonomy (correlated to the RAI strategy) are now linked to each GA. The basis for selecting these verbs was based on research published in 2018 [3]. Nouns were also used to ensure that relationships are maintained. For example, the verb "communicate" would reside under GA9_Communication. However, it will yield no relationship to another attribute if its complementary words are not specified in the word code file. In this case, a complementary word is "project" (a noun), which is placed under GA10_Project_management. The verb and relevant complementary words (nouns) must reside in the text being analyzed for the relationship between attributes to be determined. These verbs and nouns were drawn from the frequency of words obtained from KH Coder. These words were verified by ChatGPT, that was also used to determine a list showing the frequency of words. This helped to verify the reliability of the results.

Step 8: Draft the first version of the word code file. This involved listing the 11 GA along with illustrative verbs corresponding to the RAI strategy and to the various levels of Blooms Taxonomy.

Step 9: Run the word code file and determine shortcomings. The word code file was loaded into KH Coder with the WORD document where the LO were listed. A co-occurrence network of codes was generated, which helped to determine which GA were present and their relationships.

Step 10: Refine the word code file. The word code file was then refined by adding additional verbs and nouns from the IEA's VERSION 4 document. This helped to improve the link between the 11 GA and the LO contained in the curriculum. Table 2 shows the final word code that was developed.

Many verbs are used for GA1_Engineering_know-

Table 2. Word code file

No.	Graduate Attribute (IEA)	Representative illustrative (action) verbs and nouns
1	Engineering Knowledge	explain | identify | describe | list | define | discuss | relate | state | convert | derive | label | select | choose | duplicate | compile | configure | interface | write | translate
2	Problem Analysis	interpret | calculate | solve | infer | diagnose | apply | analyse | conclude | extrapolate | differentiate | distinguish | classify | categorize
3	Design/Development of Solutions	design | create | develop | produce | draw | integrate | construct | combine | evaluate | confirm | simplify | propose | sketch | form
4	Investigation	test | perform | determine | search | measurement | measure | experiment
5	Modern Tool Usage	operate | navigate | compute | tools | software | autocad | excel | web | matlab
6	The Engineer and Society	sustainability | justify | safety | responsibility | responsible | health | society
7	Ethics	ethics | norms | professionalism | adhere | comply | compliance | diversity | inclusivity
8	Individual and Team Work	collaborate | organise | team | group | organize | individual | leader
9	Communication	communicate | presentation | report | document | instruct
10	Project Management and Finance	manage | execute | monitor | allocate | optimise | budget | plan | project
11	Lifelong Learning	self-assess | reflect | independent | critical | self-direct | self-regulate | critically

ledge, which requires students to explain, define, derive or translate information. Conversely, more nouns are used for GA7_Ethics, such as ethics, norms, diversity and inclusivity.

4. Study Context

The Diploma in Engineering Technology in Electrical Engineering is a nationally registered qualification on the South African National Qualifications Framework (NQF Level 6), requiring a minimum of 280 credits (equivalent to 2,800 notional hours of learning). This program is currently offered by the Central University of Technology (CUT) in South Africa. It aims to provide a robust vocational and technological foundation for students who wish to enter the engineering profession at the technician level. The qualification emphasizes industry relevance, focusing on practical application, problem-solving, and the integration of theoretical and hands-on competencies pertinent to the modern engineering workplace.

The program spans a minimum of two academic years, structured over four semesters. Students must complete foundational modules such as Mathematics, Programming, Basic Digital Literacy, and Engineering Fundamentals before advancing to more complex topics, including Electronic Applications, Digital Systems, Electrical Machines, Control Systems, and Energy Systems. Additionally, Academic Literacy and Communication Studies are prerequisites for graduation, aligning with the broader graduate attributes defined by the IEA.

The qualification consists of 20 core modules, each worth 14 credits, distributed evenly over the four semesters. The program concludes with Design Project III, a capstone module that requires students to integrate technical knowledge, utilize software tools, and apply project management skills to develop a working engineering prototype and present their findings.

The program aims to ensure that graduates demonstrate proficiency in solving broadly defined engineering problems, effective communication, lifelong learning engagement, and ethical operation within societal, economic, and environmental contexts. Furthermore, it aligns with the graduate attributes required for registration with the Engineering Council of South Africa (ECSA) as a Candidate Engineering Technician. Students are expected to work both independently and collaboratively, manage and develop projects, apply engineering tools and methods, and demonstrate readiness for further academic or professional advancement.

5. Methodology

A mixed-methods approach was used in this study. Quantitative data (in the form of a frequency table of words for the LO) and qualitative data (relationships between the GA) were determined using ChatGPT 4.0 and KH Coder. Recent studies have demonstrated the effective use of KH Coder for quantitative content analysis, enabling researchers to identify themes and construct co-occurrence networks from large textual datasets, while ChatGPT 4.0 has been employed to enhance thematic analysis by generating codes, subcodes, and themes, thereby improving the efficiency and consistency of qualitative data interpretation [19, 20].

This study involved using an iterative data analysis technique. This is 'a reflexive process in which the researcher visits and revisits the data, connects them to emerging insights, and progressively refines his or her focus and understandings' [21]. The iterative data analysis process includes steps such as data familiarization, initial coding to label and categorize segments based on recurring themes, focused coding to refine and consolidate codes into broader themes, and theme development to organize coded data into coherent frameworks [22]. In this study, researchers aimed to familiarize themselves with the LO of an Electrical Engineering curriculum. They further preprocessed the outcomes by removing extra spaces, symbols and full stops and by ensuring that each outcome is listed on a separate line ending with a semicolon. A frequency table of words was then created using ChatGPT 4.0 and KH Coder. Initial coding was then done to categorize specific verbs and nouns under the 11 GA of the IEA. This word code file was then applied in KH Coder to create a co-occurrence network of codes. Attributes that were missing from the network were then refined in terms of adding more verbs or nouns to the work code file based on the frequency table of words and on the IEA VERSION 4 document. This helped to consolidate the GA within the word coding file which was then used to create a coherent framework (or network map) and a crosstab analysis showing the integration of the GA across the curriculum.

6. Results

The department of Electrical Engineering has 314 LO spread across 20 modules in their 280-credit Diploma. Five of these modules are termed "service modules" focusing on academic and digital literacy and mathematics. A contrast between some of the top 10 verbs used in the LO for all modules and those limited to the field of study are shown in Table 3. The first and second columns represent data from ChatGPT 4.0., while KH Coder was used to obtain the data for the third column. Contrasting the three columns reveals that the verb "discuss" occurs consistently 15 times. However, the verb "solve" occurs 14 times for all the modules and only 7 times when excluding the service modules from the analysis. A close analysis of the LO for Mathematics indicated that this verb occurs several times in their study guides. In total, the frequency of occurrence changes significantly for 4 verbs (perform, apply, solve and define) when removing the service modules from the analysis. This is noteworthy, as one may assume that students are solving many engineering-related problems in the curricula, while in fact, they are only solving mathematical calculations. The close similarity between the results from KH Coder and ChatGPT 4.0 ensures a measure of reliability.

Table 3. Some of the top 10 verbs used in the LO for the 280-credit Diploma

Verb	ChatGPT – all modules	ChatGPT – excluding service modules	KH Coder – all modules
analyze	37	36	36
design	36	36	36
explain	31	28	31
identify	27	25	27
describe	26	25	26
perform	17	8	15
apply	16	9	18
discuss	15	15	15
solve	14	7	14
define	13	9	13

The co-occurrence network of words is shown in Fig. 1. This indicates the most occurring words and their relationships. The modularity of the LO are emphasized where specific conclusions may be drawn. Modularity is defined as a property of a complex system, whereby the system is decomposed into several subsystems [23]. The frequency of using a specific word is evident by the size of the circles. Larger size circles indicate that the specific word is used often in several LO, either within a single module or across multiple modules. In this case, the LO may be decomposed into several key topics that provide insight into the core syllabus of the curriculum. The subgraph indicates clusters of related terms that can be grouped into thematic areas of the curriculum, thereby highlighting the modular structure of the learning outcomes.

The following deductions are made:

1. The core curriculum focuses on (starting on the left and working clockwise around the network):
   (a) AC circuits (voltage / currents / parallel / series);
   (b) Circuit design (amplifier);
   (c) Power factor;
   (d) Phasor and block diagrams;
   (e) Vector calculations;
   (f) Control systems;
   (g) Resonance;
   (h) Time and frequency signals;
   (i) DC analysis and load lines;
   (j) Differential equations;
   (k) Communication technology;
   (l) Logic expressions; and
   (m) Arduino projects.
2. Key verbs include "explain" and "analyze" which verifies the frequency of words given in Table 1.
3. Verbs such as explain, discuss, and describe link to GA1 (Engineering knowledge).
4. GA5 (Tool usage) is evident in the word program (top of the network).
5. GA10 (Project management) is evident in the word project (bottom left of the network.

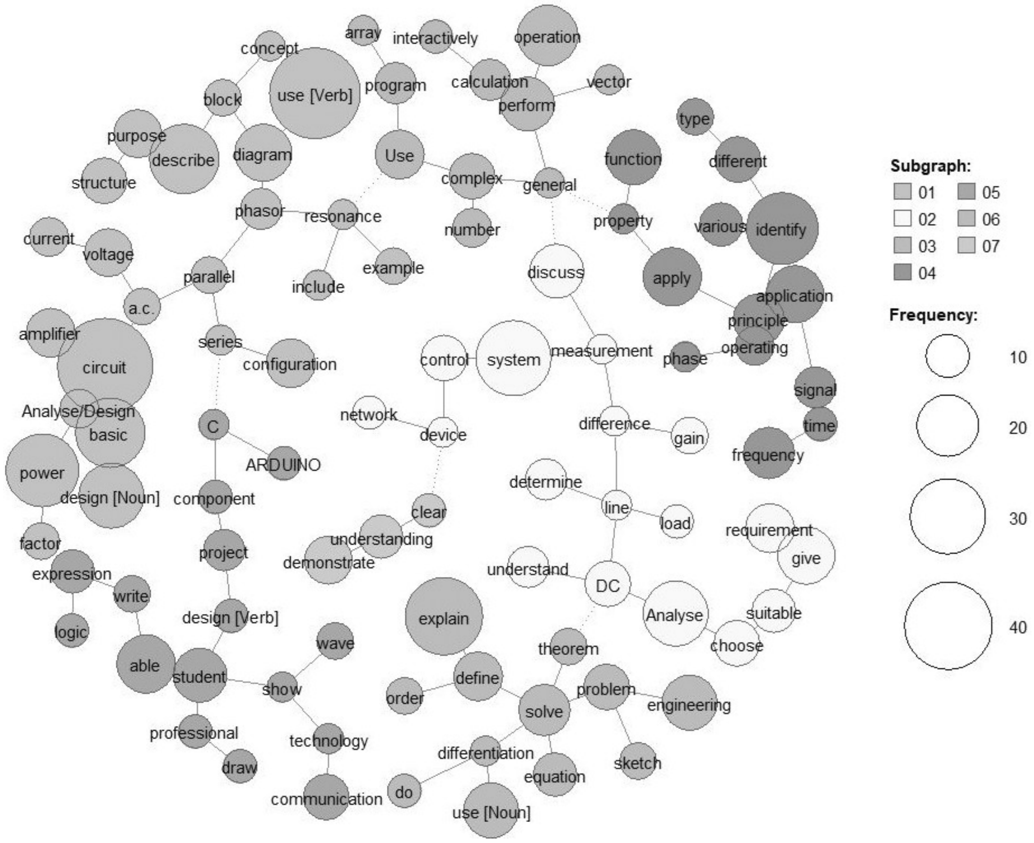

Fig. 1. Co-occurrence network of words for the 280-credit Diploma in Electrical Engineering.

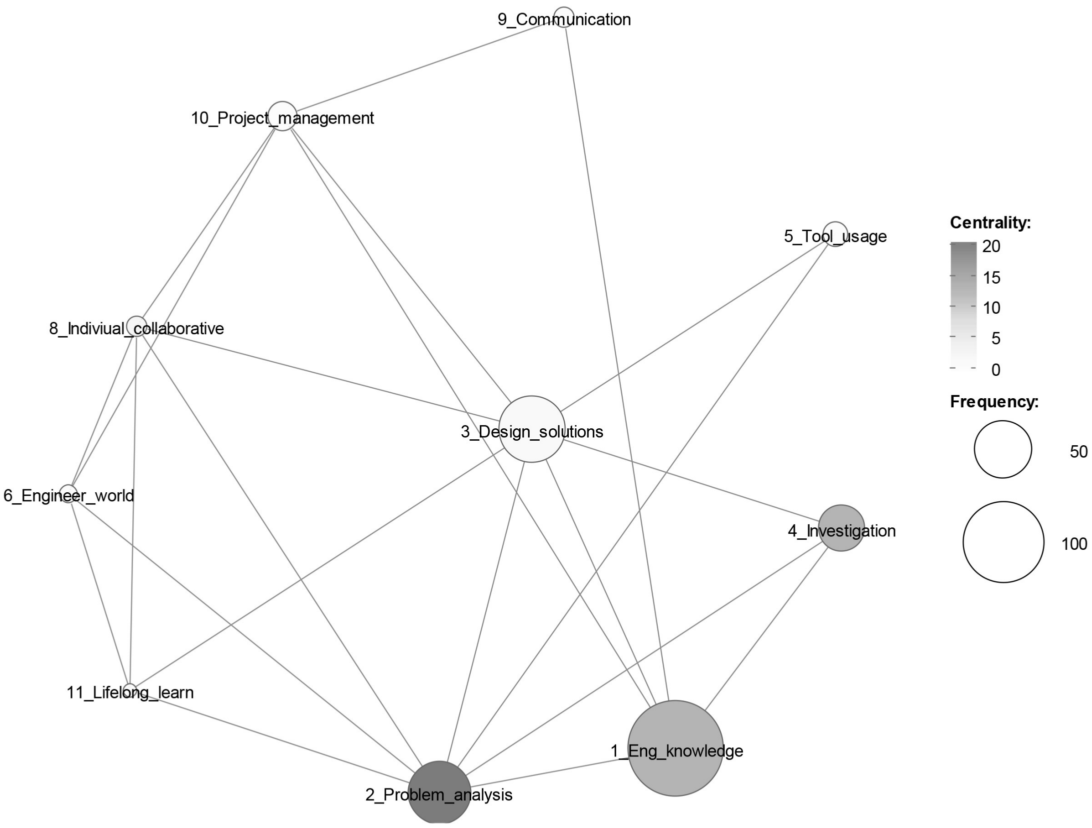

Fig. 2. Co-occurance network of graduate attributes for the 280-credit Diploma in Electrical Engineering.

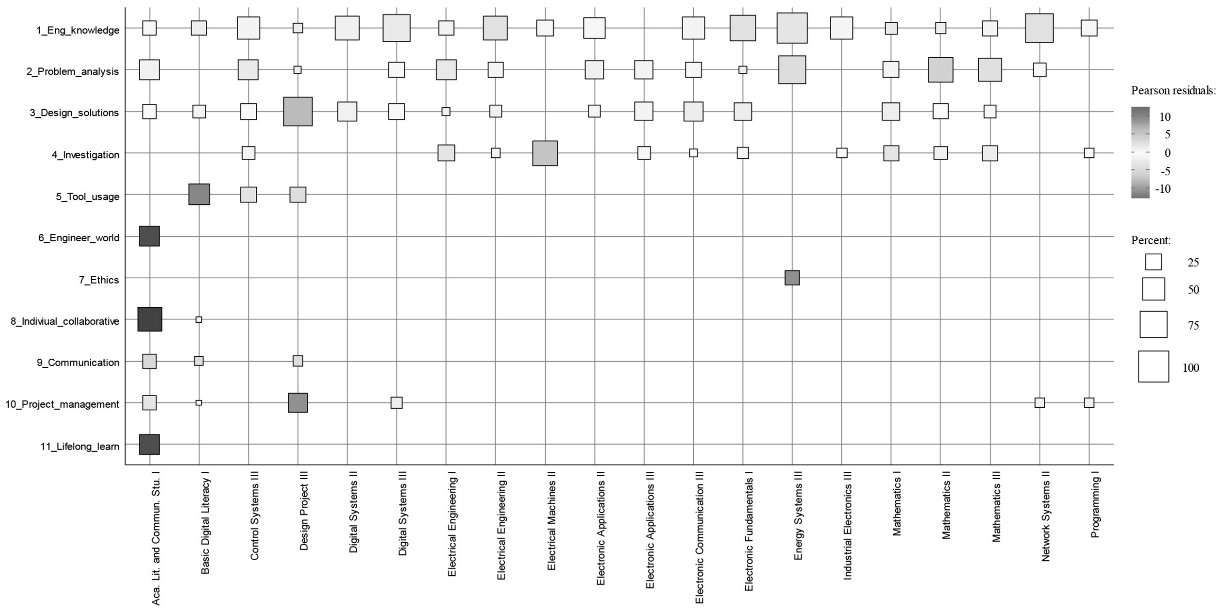

Fig. 3. Crosstab analysis indicating the occurance of the graduate attributes across the 20 modules within the 280-credit Diploma in Electrical Engineering.

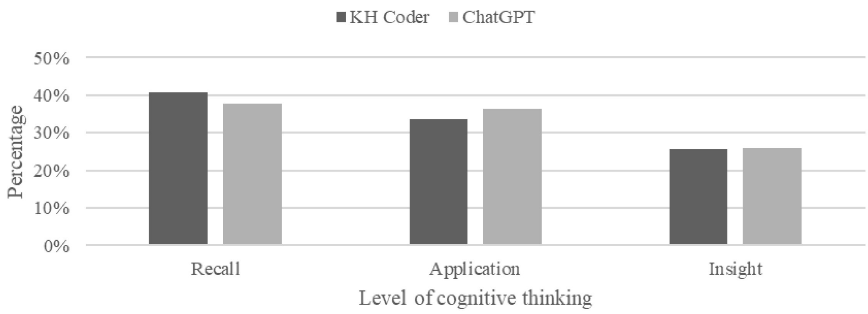

Fig. 4. Different levels of cognitive thinking derived from the attributes prevalent in the 280-credit Diploma of Electrical Engineering.

The co-occurrence network of GA is shown in Fig. 2, which is derived from the word code file that was developed. The betweenness of the attributes is emphasized with Problem analysis (GA2) being central to the map as it links strongly to seven other attributes. Design solutions (GA3) link moderately to seven other attributes. One attribute is missing, namely Ethics (GA7).

Fig. 3 illustrates a Crosstab analysis showing where each GA occurs in each of the 20 modules that make up the 280-credit Diploma. Crosstab analysis is used to describe the relationship between two categorical variables, where one variable is defined as a row and the other variable as a column [24]. In this case, the rows represent the 11 GA and the columns the 20 modules. The size of the square indicates the strength of the relationship as a percentage, while the grayscale indicates the standardized Pearson residual that is used to validate the positive or negative impact of each attribute. No negative relationships were found to exist. The dominant attributes are seen to be Engineering knowledge (GA1), Problem analysis (GA2), Design solutions (GA3) and Investigation (GA4) which occur repeatedly across many modules. The different levels of cognitive thinking, associated with Blooms Taxonomy and derived from the illustrative verbs contained in the LO, are shown in Fig. 4. The similarity between the data analysis from KH Coder and ChatGPT provides a measure of reliability. KH Coder indicates that Recall is dominate (40,7%), followed by application (33,5%) and insight (25,7%).

7. Discussions

Fig. 2 indicated that ten (10) attributes are present in the 280-credit Diploma. The missing attribute is GA7 (Ethics). This suggests that the IEA's attributes are partially integrated into the curriculum. Embedding graduate attributes into a curriculum remains challenging [25], but not impossible as ongoing consultation and awareness of what is required can help to meet this challenge. In this case, awareness of specific words associated with ethics needs to be incorporated into the LO, either by creating new ones or modifying existing ones. From the IEA document on Graduate Attributes Professional Competences (VERSION 4), words such as ethics, norms, compliance, laws, diversity and inclusion could be used [26].

The dominant attribute is GA1 (Engineering knowledge) followed closely by GA2 (Problem analysis) and GA3 (Design solutions). This is indicated by the size of the circle which relates to the frequency or usage of words associated with this attribute. This suggests that the curriculum to closely linked to the main goal of engineering, which is to solve problems using available science and mathematics. The goal of engineering is often to solve a particular problem based on the available science, methods, and techniques rather than just to increase knowledge [27]. Of course, students would first need to know the science (Engineering knowledge) before they can apply it.

GA3 (Design solutions) is strongly linked to seven (7) other attributes, which is excellent. The higher the number of attributes that are linked to solution design, the higher the probability of knowledge integration. Effective solution design requires individuals with different levels of expertise to integrate knowledge from a wide range of domains, and to transcend extreme perspectives and swiftly navigate the paradoxes [28]. One also needs to firstly identify and investigate a problem to fully understand it, before drawing on scientifically acceptable theories to design a solution that will meet ethical standards and codes of practice. This links closely to the iUSE principle [29] related to problem solving.

GA10 (Project management) is linked to five (5) other attributes, which is excellent. Successful engineering project managers must be well-rounded individuals with a strong foundation in engineering and technical principles, as well as demonstrated leadership qualities [30].

GA11 (Lifelong learning) has the lowest frequency of occurrence. This attribute requires students to be socially engaged with their communities [31], which would require an ongoing commitment and engagement. However, this attribute could be further linked to other attributes by modifying specific learning outcomes to include specific words such as self-reflection, self-assessment and self-regulated learning. Lifelong learning requires a commitment to ongoing education, which is inherently self-directed [32].

Fig. 3 showed that GA1 (Engineering knowledge) is dominant in Energy Systems III which is a concern as quantitative knowledge is a priority for first year modules, and not for final year modules. Biggs and Tang [33] state that quantitative stages of learning occur first, after which learning changes qualitatively. GA2 (Problem analysis) is dominant in Energy Systems III which is good as problem analysis should dominate higher-level modules where more qualitative knowledge is required. GA3 (Design solutions) is dominant in Design Project III which is good as the module features design-based learning. GA4 (Investigation) is dominant in Electrical Machines III where much laboratory work would be done. The rest of the attributes are only evident in 30% or less of the modules, while GA7 (Ethics) is found in Energy Systems III. However, the strength of the relationship is weak and therefore does not warrant inclusion in the co-occurrence network of codes.

Fig. 4 highlighted that the dominate level of cognitive thinking is Recall which links with the two lower levels of Bloom's Taxonomy (Knowledge and Comprehension) while Insight links to the two top levels (Synthesis and Evaluation), as suggested by Swart and Delport [18]. This correlates well with Table 3 where a top 10 verb was found to be "apply". Insight would include the verb "design", which is evident in Table 2. The percentage associated with Recall and Application suggests that students are being exposed to both qualitative learning (deep learning or higher-order cognitive thinking) and quantitative learning (surface learning or lower-order cognitive thinking). This is excellent, as 45% of the curriculum (9 out of 20 modules) resides as NQF level 5, where students should be exposed to more quantitative stages of learning on which students can further build in their second year of student (NQF level 6 modules).

8. Conclusions

The purpose of this article was to present a technique that may be used to develop a word code file that enables one to link LO to GA. This file was developed by linking illustrative (or action) verbs and nouns to the 11 GA of the IEA. This file and a WORD document listing each LO of an Electrical Engineering currciulum was applied to KH Coder and ChatGPT to ensure a measure of reliabilty of the results.

While the findings indicate strong integration of most GAs, particularly Engineering Knowledge, Problem Analysis, and Design Solutions, some limitations were noted. The Ethics attribute (GA7) was absent in the co-occurrence network, suggesting a lack of explicit representation in the current LO. This highlights the need for ongoing refinement of learning materials and further engagement with curriculum designers to ensure complete alignment with accreditation expectations.

The significance of this work lies in its dual contribution: methodologically, it offers a structured, iterative process for curriculum analysis, and practically, it equips educators with a tool for continuous quality assurance in engineering education. The comparative consistency between results from KH Coder and ChatGPT adds validity to the approach, reinforcing its potential for broader adoption. A limitation of the study is its focus on a singular curriculum in Engineering. Applying the proposed technique, or word code file, to other Engineering disciplines may further enhance its validity. It may even be refined to include additional verbs and nouns that may lead to it being more comprehensive in nature.

Ultimately, the study emphasizes a critical takeaway: data-driven coding techniques can reveal the silent architecture of a curriculum, ensuring that graduate attributes are not merely aspirational ideals but embedded realities. Institutions can use this technique to close the loop between LO and GA, thereby enhancing graduate readiness for complex, ethical, and interdisciplinary challenges in engineering practice. Alignment must therefore be established between outcomes, attributes and assessments. Successful student integration into industry can therefore be achieved if evidence exists that all relevant GA have been integrated into a curriculum.

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