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Exploring the Impact of Contextual Framing and Construct-Level Complexity on Engineering Problem-Solving Performance: A Study on Electrical Circuit Course

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Wade Goodridge is a tenured Associate Professor in the Department of Engineering Education at Utah State University. His research often has a focus on what drives us to learn, how we learn and how well we do it, and what can improve that learning. This work is often directed with a spatial thinking emphasis. Dr. Goodridge has investigated different learning modalities (fully online, hybrid, blended courses), cognitive and metacognitive learning processes (self-regulation, engineering problems solving, neural efficiency in engineering problem solving) learning motivators (engineering self-efficacy), and effective and personalized engineering education interventions (tactile engineering curriculum, physical teaching models, XR environments and AI informed systems of delivering and monitoring engineering learning). Dr. Goodridge has created a valid and reliable instrument to assess spatial ability in blind and low vision (BLV) learners thus opening new areas of research centered on tactile spatial ability. He has created tactile and visual learning tools and has offered professional development experiences on how to improve the education of tomorrows engineers.

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Foeday Zinnah is a graduate researcher and a second-year Ph.D. student in the Department of Engineering Education at Utah State University. He holds a master's degree in soil and water sciences from the Hebrew University of Jerusalem and a bachelor's degree in civil engineering from the University of Liberia. His research interests focus on engineering workforce development, particularly the role of non-degree credentials and work-based learning in shaping STEM career pathways. He is also interested in e-learning management and the use of diverse learning methods to enhance learning outcomes for both traditional and non-traditional learners. Additionally, Foeday brings professional experience in youth and community development, nonprofit leadership, and online learning management in higher education.

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Sehrish Jabeen, Utah State University

Sehrish Jabeen is currently a Ph.D. student and Graduate Research/Teaching Assistant. She brings over three years of teaching experience across K–16 educational settings, along with seven years of professional experience in the field of information technology, where she worked in the banking sector. Her research interests include mathematical well-being, mathematical modeling and problem-solving, and the application of Cognitively Guided Instruction (CGI) in mathematics education. Through her work, Sehrish aims to explore how instructional practices and learning environments can support students' mathematical thinking and students engagement with mathematics.

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Abstract

Active Learning, Problem-solving and Designing are core competencies in engineering education and serve as the foundation for engineering students' skills development. To effectively cultivate these skills, instructional strategies and learning materials must be carefully designed, particularly in the formulation and the presentation of problem statements that promote active learning.

This study investigates the impact of contextual framing, defined as the situational context in which a problem is embedded, and the construct-level complexity, which refers to the number of steps or components required to solve a problem, on students' performance during engineering problem-solving activities. This study was conducted on an undergraduate sophomore level engineering course. The analysis encompasses 363 problem-solving samples drawn from four distinct problems administered in a "Fundamental Electronics for Engineers" course at a research-intensive university in the western part of the United States.

Each problem-solving event was qualitatively evaluated by two independent researchers using a rubric presented by Docktor et al. (2016) in recent literature. The resulting assessments were analyzed both descriptively and inferentially to then determine the statistical significance of the impact of contextual framing and construct-level complexity found in students' representative samples of problem-solving performance. Deeper inferential analyses were also conducted to explore engineering approaches and their specific applications. The findings from this study help engineering educators infer that gradual and sequential increases in both contextual framing and construct-level complexity may be positively associated with improved students' performance while abrupt or simultaneous increase is associated with reduced performance. This is, likely, due to increased cognitive load.

The outcomes of this study align with a constructivist learning theory, which posits that learners construct knowledge more effectively when they can derive meaning from their experiences. Incremental complexity facilitates this constructivist process by enabling students to internalize concepts progressively. Additionally, the study can also assist instructors in cultivating an engineering learning environment as suggested in Carol Dweck's Growth Mindset (2007). It does this, by fostering students to engage in increasingly challenging tasks that foster motivation, resilience, and a constructive attitude toward problem-solving. Overall, this study advocates for the intentional sequencing of problem difficulty and contextual framing as a means to cultivate robust problem-solving skills and improve overall learning outcomes in the education of tomorrow's engineers.

Keywords: *problem-solving, electrical engineering, constructive learning, active learning*

Introduction

Engineering involves the systematic application of knowledge of the physical world through mental processes to solve real-world open-ended problems [1], [2]. The central point, therefore, in Engineering Education is training cognitive agents (or what prominent cognitive scientists Andy Clark refers to as cognizers) to be better thinkers and problem solvers [1] – [6]. Students, in general, become better thinkers and learners when they are cognitively engaged and challenged in the learning and problem-solving processes [6] – [8]. However, it can be hard for an instructor to comprehend how to design or develop rule-based, knowledge-rich, and well-structured academic problems [9], [10] that can continuously enhance and develop students' thinking and problem-solving abilities. For engineering educators, Gentner (2002), and Fischer's (1980) seminal works provide both a philosophical and methodological perspective for analyzing and comprehending human cognitive processes in problem-solving activity [11], [12]. King and Kitchener (2004) described that the current learning and assessment mechanisms for problem-solving activities only develop 'functional level' ability and are unable to teach students to reach their 'optimal level' of problem-solving performance [13]. This study, therefore, urges educators to redesign or rethink engineering problems based on construct-level and contextual framing, seeking to reduce the developmental gap that can sometimes be observed within an engineering instructional setting [13]. This stepped redesign of engineering problems aligns with Fischer's skill development theory [12]. Moreover, the intentional sequencing of problem design may also help students to reach their optimal level of performance and begin to rewire their brain's neural formations, and neural activity (known as positive neuroplasticity) [13], [14].

This research, therefore, initiates a study into the dynamic changes in students' cognitive processes that are resultant to scaffolded increments of problem-solving components, constructs, and context. To guide the scaffolding of construct-level complexity and associated contextual framing, this study draws on cognitivist, constructivist, and pragmatic learning theories. A fundamental principle found in Constructivist learning theory is that the students construct meaningful understanding of the concepts in their mind through the learning and problem-solving process [15], [16]. Pragmatism is a situational or contextual learning approach in which people comprehend the components of the problem and solve the problem based on specific applications of the concepts within a given situation [15], [16]. Cognitivism, and in particular cognitive development theory, describes the development of the human thinking process through interactions they have within the environment [16] – [18].

Along with Fischer's skill development theory, neo-Piagetian Cognitive development theories, such as Pascual-Leone, Case, Fischer, Demetriou, also provide developmental or chronological advancement in mental processing models [18]. These models can leverage a philosophical basis (not defined in terms of age) that can be used in instruction and problem-design for Engineering classrooms. Many existing learning materials target different levels of subjective difficulty for their problems (i.e., easy, medium, & hard), but there is still an advantage to understand the problem levels based on the problem components, constructs, and context.

Jonnasen (2000) identified that the research in instruction designs rarely focuses on problem-solving processes [9], and he posits that these results in limited understanding of the proper design of problems. Although existing problem typology frameworks (such as, Cynefin, TIPP, Jonassen's problem design theory based on structuredness, complexity, and abstractness) are useful, their analysis lacks knowledge component usage levels, and problems embedded in a situation. So, there is still a need for in-depth investigations into how we design and develop problems that are often echoed in seminal and current research in cognitive science, especially in engineering education. This study therefore provides a guideline to design problem statements and to augment students and future STEM professional's problem-solving performance and to design a cognitively autonomous learning environment.

The Study

This study was conducted by sampling engineering students' homework solutions for four selected and distinct problems in a sophomore-level class at a public land-grant university in the western part of the United States. The course was given in the Spring of 2025. These selected problems vary in terms of components, constructs, and contextual framing. The construct-level complexity is defined as the steps, components, and concepts required to solve a problem. The word 'construct' stems from the definition of constructivism or construction of meaning based on acquired knowledge during a learning process and how the constructed knowledge is implemented to solve a problem [3],[4],[6],[15]. Conceptual understanding developed during proficient engineering problem-solving generates inherent meaning and connects with other constructs or concepts (steps) or knowledge-components in problem solvers' minds [15]. Contextual framing is the representation of the problems within a comparatively complex setting. The complexity of contextual framing can be generated from a novel setting or from the integration of multiple simple situations or arrangements.

Jonassen (2000) and Kluwe (1995) defined problem complexity in terms of the need for more cognitive operations within a problem-solving space [9], [19], because both the increase in construct levels and the simplification of contextually complex problems require greater cognitive operations than a problem focused on a single construct and simple contextuality. Along with the learning theories (i.e., cognitivist, constructivist, and pragmatic), Jonassen and Kluwe's definition of problem complexity also influences the problem design phenomenon (construct-level and contextual framing) of this research as well as the study design [9], [19].

The selected problems of this study are categorized based on the construct and context characteristics. Structurally, these problems are similar and are built upon one over the other. The construct-level categorizations are CL1 for level one, CL2 for level two, and CL3 for level three. The context can be comparatively simple (CS) or comparatively complex (CC). The problem context is comparatively simple - meaning familiar - if the problem-solving context is taught or shown during the class or in the textbook. The problem context is comparatively complex if problem-solving is not shown in the classroom or in the textbook and the problem is embedded in different contexts. For instance, solving a Fibonacci series through coding is a simple problem, but the same Fibonacci concept can be embedded within a climbing staircase situational context, a very common computer science problem. With this context being so different, many students may find it comparatively challenging compared to coding Fibonacci series. In this study, the first problem, CL1-CS, is within a single construct-level (i.e., method of DC circuit analysis), and a simpler or familiar contextual frame. The second problem, CL1-CC, is also single-construct-level or method of DC circuit analysis, but is set within comparatively difficult or unfamiliar context. Specifically, the problem statement is presented in 'Wheatstone Bridge' format. The third problem, CL2-CS, requires combining two knowledge components or steps (i.e., method of DC circuit & inductor analyses) together, and are within the familiar settings shown in the classroom. Finally, the students need to follow three distinct steps (i.e., method of DC circuit, inductor & capacitor analyses) to get a solution for the fourth problem. This fourth problem is comparatively complicated. Therefore, the final one is categorized as CL3-CC. This CL3-CC problem-solving circuit requires understanding of the 'cascading switching' phenomenon. Therefore, problem solvers not only need to understand the working procedures of individual circuit components but also are required to learn how the 'cascading switching' shapes the analysis. The four problem types are described below to illustrate the systematic variation in construct-level complexity and contextual framing.

- **CL1-CS problem:** CL1-CS problem (shown in **Figure 1**) is a simple series-parallel circuit problem with two sources (one voltage and another current source). The formation of the circuit is very familiar to the problem-solvers under this study setting. The problem is designed to apply just one broader concept, the 'Superposition Theorem'. No additional advanced concepts are required to be implemented other than simple circuit analysis. The problem-solvers, in this study context, had freedom to think and reason differently and integrate their other knowledge.

Problem Statement: Using superposition, find the current through R_1 for the network in Fig. 1.

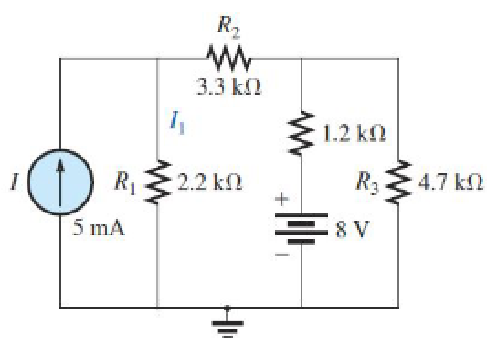

Fig. 1.

Figure 1: Construct Level 1 and Comparatively Simple Context (CL1-CS Problem)

- **CL1-CC problem:** CL1-CC problem (illustrated in **Figure 2**) is a single concept (Norton circuit) type of problem situated within Wheatstone Bridge circuit. The problem, even though conceptually simple, sits within a contextual (unfamiliar) setting that makes the problem comparatively hard. Problem-solvers need to simplify or rethink the circuit, before proceeding with a solution. After simplification of the circuit, no additional advanced conceptual application is required to solve the problem. The contextual framing, therefore, may have impact on the cognitive processes.

Problem Statement: Find the Norton equivalent circuit for the network external to the resistor R in Fig. 2.

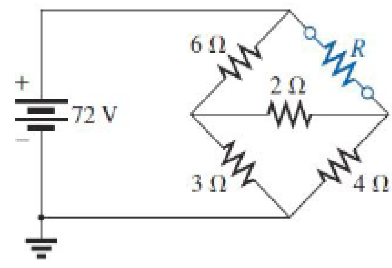

Fig. 2.

Figure 2: Construct Level 1 and Comparatively Complex Context (CL1-CC Problem)

- **CL2-CS problem:** The CL2-CS problem (in **Figure 3**), situated in a simpler or familiar context, requires problem-solvers to apply two major steps or knowledge components for the generation of their solutions. In the first step, the problem-solvers need a fundamental understanding of the working procedure for a R-L circuit. In the second step, they can apply the electrical circuit analysis principles (i.e., Norton, Thevenin, Mesh, Nodal analysis) to solve the problem. As the problem requires more than one major concept to solve the circuit is designed into a familiar context, thus resulting in the CL2-CS problem designation.

Problem Statement: For Fig. 3:

a. Describe how you would determine the value of the time constant (τ) ?
b. Determine the mathematical expressions for i_L and v_L following the closing of the switch.
c. Determine i_L and v_L after one time constant.

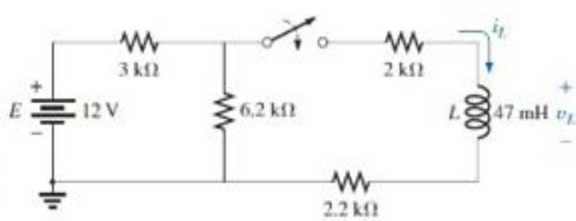

Fig. 3

Figure 3: Construct Level 2 and Comparatively Simple Context (CL2-CS Problem)

- **CL3-CC problem:** CL3-CC problem is the most complex one in this study. Figure 4 provides the circuit diagram and the problem statement. This problem tests students' problem-solving ability at three hierarchical conceptual levels. The three major concepts of problem-solving steps are interrelated with one another. The major concepts are understanding of the transient response for the capacitive circuit, the energizing and discharging process of inductors and the foundations of circuit analysis (i.e., Thevenin, Norton, Mesh Analysis etc.). Failure to correctly apply any one step often results in an incorrect solution. The circuit arrangement is comparatively complex, as revealed in **Figure 4**. Therefore, the problem is designated as a CL3-CC problem.

Problem Statement: A DC circuit containing different components (i.e., capacitive and inductive elements, switches, voltage and current sources, and resistors) is illustrated as follows (in Fig. 4)

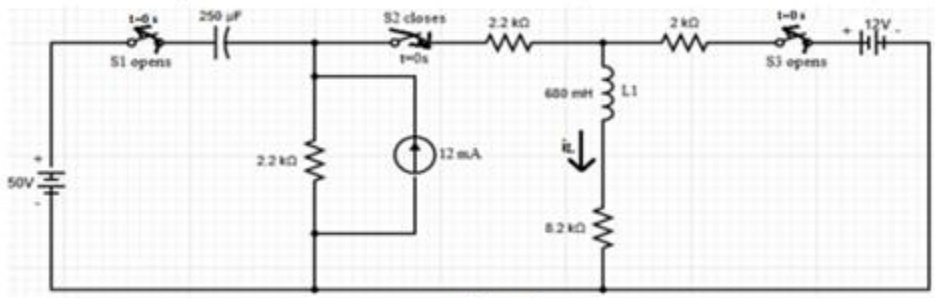

Fig. 4

a. S1 and S3 switches have been closed for a long time. Now, when t=0s, the S2 switch is closed at the same instance that S1 and S3 are opened to avoid any current interruption through the coil, L1. Derive the mathematical expression for the current i_L after the closure of the S2 switch.
b. If 680mH inductor is inserted in between 8.2KΩ resistor and inductor L1 in Fig. 4 , how will this affect the resulting i_L - t curve? Explain and show proof of your response through calculations.

Figure 4: Construct Level 3 and Comparatively Complex Context (CL3-CC Problem)

Study Context

This study is designed for students attending a foundational and general engineering class, Fundamental Electronics for Engineers at a Carnegie R1 University. Typically, foundational and general engineering classes are attended by all engineering students, except those who specialize in that specific domain. Therefore, all students of this class are from Biological, Mechanical, Aerospace, Civil and Environmental engineering as well as computation sciences department. No students from Electrical Engineering specialization are attending this class. This context reduces the motivational or interest biases from problem-solving design study. These students are in their second or third year of engineering or STEM disciplines. Before attending this course, most students also attended physics and other STEM courses (i.e., physics, chemistry, mathematics, fundamental computer science) in their K-12 levels and have adequate problem-solving experience. They also share similar socio-cultural learning environment during their pre-college years. Some students work in university laboratories and engineering industries. Moreover, students are taught AC and DC concepts in their class and provided with instructions, text and video materials related to AC and DC circuit problems. In general, most students are familiar with the concepts and processes of solving problems designed for this study.

Research Question and Objectives

This research is guided by the following question: How does the change in construct-level and contextual framing within a problem statement impact problem-solving performance? The major objectives of this study are to (1) demonstrate how engineering educators can design problem-solving activities based on construct-level complexity and contextual framing instead of more subjective measures, like, easy, medium and hard; (2) understand why certain problems are perceived as more difficulty by students; (3) integrate learning theories, such as, constructivism, cognitivism and pragmatism, together for designing instructions or course activities, and (4) provide engineering instructors tools for assisting targeted students. For instance, students failing in construct level 1 or simpler context should be supported differently than students who can solve construct level 3, and contextually complex problems. While the former needs support in basic understanding of engineering concepts, the latter can benefit more from challenging or open-ended problems.

Data Collection and Analysis

To conduct this study, the researchers collected 396 de-identified responses (samples) from the Fundamental Electronics for Engineers classes (sections 001 and 002) during the Spring 2025 semester from a data governing body at the University. Due to the Family Education Rights and Privacy Act (FERPA), the researchers did not directly access LMS data. Throughout the data collection process, the researchers maintained all IRB protocols and guidelines. The researchers followed step-by-step processes (shown in Figure 5) by analyzing the data to answer the research question of this study. The data analysis process is shown in detail in **Figure 5**.

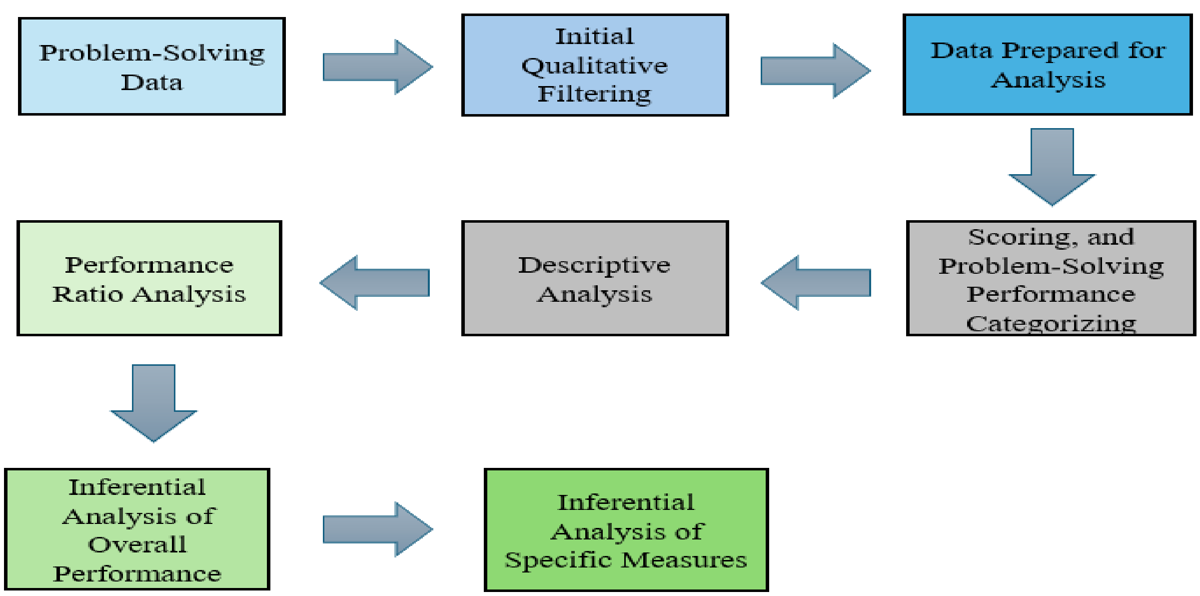

Figure 5: Data Analysis Process Diagram

Data was initially qualitatively analyzed for its intelligibility and interpretability (inclusion and exclusion criteria). From this initial analysis, 33 data samples filtered out, as they were unintelligible and non-interpretable problem-solving events. This resulted in the remaining 363 problem-solving samples that were usable for further processing. Then, the researchers analyzed the distribution of the collected data across four problem types, such as CL1-CS, CL1-CC, CL2-CS, and CL3-CC. **Figure 6** is a pie chart showing the number of problem-solving data from each problem type along with their percentages within the total data size (n=363). Based on the figure, it is apparent that the four problem types are almost evenly distributed (CL1-CS= 27%, CL1-CC=25%, CL2-CS=26%, and CL3-CC=22%) across the total problem-solving samples.

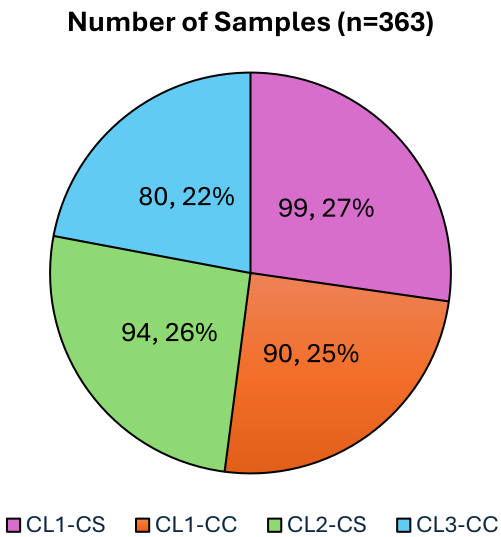

Figure 6: Distribution of Problem Solutions Across Problem Types

The scoring process was completed by two independent researchers, possessing similar expertise in both problem-solving and engineering education. Each problem solution was scored based on modified version of Docktor et. al.'s rubrics, which implemented 0-5 point Likert scales [20]. The dimensions of the rubrics were: Useful Descriptions, Engineering Approach, Specific Applications of Engineering, Mathematical Procedures, and Logical Progression [20]. A score 0 represented almost no, or minimum performance, and a score of 5 meant the problem-solvers demonstrated superior functioning on each measure [20]. After scoring the problem solutions, the researchers discussed their scoring procedures among themselves. Scoring discrepancies were discussed until consensus arrived, resulting in a 100% agreement [21]. Researchers then developed an Excel sheet containing pseudonyms of problem samples, scores of individual measures, and their aggregated scores. The total score of individual problems, therefore, could lie between 0 and 25. For example, a score of 1 representing just above no performance would multiply by 5 measures, yielding a final score of 5.

Researchers determined a threshold value for classifying solutions in terms of two categories: “proficient” and “limited” problem-solving samples. If the problem-solving samples scored sixty percent or above, they were considered to fall in the proficient category. The limited sample category was assigned if they received less than sixty percent. The researchers chose the threshold value of 60% as it is the standard cutoff point because it is used in many US institutions as a minimal or “D” level passing threshold in a class [22] – [24]. Therefore, this selected threshold point is consistent with the academic grading standards, policies, and practices in the United States [22] – [24]. After scoring each solution for 5 measures, an aggregated total was computed for each problem solution. The scoring range, therefore, for each solution is 0 to 25. Finally, the research team conducted the descriptive, ratio, and inferential analysis to answer the research question of this study.

Results

The findings or the results of the paper are discussed in four separate sections to illustrate how the changes of problem-solving construct-levels and contextual framing within the problem statements impacted the problem-solving performance. The findings mentioned here are associated with descriptive and performance ratio analysis, inferential statistical analysis of overall performance and specific engineering operation measures during problem-solving:

- **Descriptive Analysis of Problem-Solving Performance**

The researchers first performed descriptive analysis on problem-solving samples based on the total score received by sample solutions (i.e., 0-25) and solution categories (i.e., Proficient and Limited). This descriptive analysis provided a general understanding of the problem-solving data produced for this study.

Descriptive statistical analysis for the problem-solving samples (shown in Table 1) targeted the problem types, the average, and the standard deviation/interquartile range (IQR) of the solution categories, such as proficient and limited samples. The overall problem-solving sample ($n=363$) has average, $M = 13.66$, standard deviation, $SD = 6.94$, and interquartile range, IQR= 12.00. The total number of proficient samples (>=60%) is 175, and the limited samples (<60%) are 188. Their averages are 19.95 and 7.80, standard deviations are 2.63 and 3.89, and IQRs are 4.00 and 7.00, respectively. From this general descriptive analysis, it is found that proficient samples performed better than limited samples across all problem types (i.e., CL1-CS, CL1-CC, CL2-CS, and CL3-CC). The average gap between CL1-CS and CL3-CC was found to be much bigger compared to others, indicating a general understanding of the impact of construct-level and contextual framing on students’ problem-solving performance. Moreover, the interquartile range (IQR), and the statistical methods used to understand sample distribution also demonstrated that limited samples were more spread out than proficient samples, in almost all cases. The interquartile range (IQR) was calculated by subtracting the first quartile (Q1) from third quartile (Q3).

This work (shown in **Table 1**) developed a general understanding which provides a shallow but introductory overview. However, it does not provide details on whether the effect of the study's variables on student problem-solving performance is genuine, or random. For detailed analysis, problem-solvers' proficiency ratios and non-parametric inferential statistics (for both broader-level and pairwise problem types) were conducted in the following sub-sections. The inferential statistics contain both broader-level and local-level pairwise analyses for overall, and the specific measures: Engineering Approach and Specific Applications of Engineering measures. They were chosen, because these two measures which are mentioned in the Docktor et. al.'s rubrics are more relevant to this study context.

Table 1: Descriptive Statistical Analysis of Problem-Solving Samples

Problem Types	**Sample Size (n) of Problem Types**	**Overall Problem-Solving Sample (n=363, *M*=13.66, *SD*=6.94, *IQR* = 12.00)**							
		Proficient Samples (>=60%) (n=175, *M* =19.95, *SD* =2.63, *IQR*=4.00)				**Limited Samples (<60%) (n=188, *M* =7.80, *SD* =3.89, *IQR*=7.00)**			
		n	***M***	***SD***	***IQR***	**n**	***M***	***SD***	***IQR***
CL1-CS	99	67	20.06	2.72	4.50	32	7.50	4.64	8.50
CL1-CC	90	42	20.10	2.53	2.00	48	7.40	4.38	8.25
CL2-CS	94	48	20.00	2.68	3.25	46	8.41	3.46	5.75
CL3-CC	80	18	19.06	2.55	3.50	62	7.82	3.38	4.00

n: Sample Size*; M*: Mean or Average; *SD*: Standard Deviation; *IQR*: Interquartile Range (Q3-Q1)

- **Ratio Analysis of Problem-Solving Performance**

The researchers then conducted a ratio analysis of proficient and limited samples for each engineering problem type. On a broader level, the ratio of proficient to limited sample size is 0.93. This value describes that there are more limited solutions than proficient solutions, but the sample difference of both categories is very slim. **Table 1** shows the actual sample size for proficient and limited categories.

The researcher additionally conducted individual problem type analysis. The pictorial overview of individual problem-type analysis is shown in **Figure 7** below. This figure clearly demonstrates the ratio of proficient and limited solutions for CL1-CS, CL1-CC, CL2-CS and CL3-CC categories. For single construct level and simple contextual framing, the ratio of proficient to limited is 2.09 (67.68 : 32.32). This value describes that there is one limited solution per two proficient solutions in CL1-CS cases. However, the change of one additional construct level and contextual framing results in noticeable changes in performance. Contextual framing changes have more impact on problem-solving performance than the inclusion of one construct, or knowledge component (more steps) in the problem-statement. The inclusion of one-construct level in the problem statement drops the finding of proficient solution CL2-CS down to 1.04 (51.06 : 48:94). This informs the researcher that there are an even number of proficient and limited solutions in CL2-CS. With a contextual framing change the proficient ratio drops further down to 0.88 (46.67 : 53.33). Finally, the combination of changes in two additional constructs, or knowledge components, and the changes in contextual framing results in substantial decrease in proficient performance. The value is about 0.29 (22.50 : 77.50). This ratio value indicates that the combined multilevel constructs, and contextual change imposes detrimental impact on problem-solvers' performance, resulting in 77.50% of scores falls towards the limited categories.

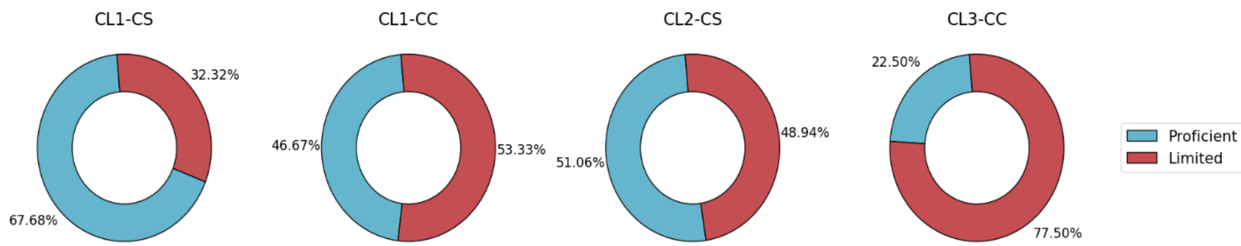

Figure 7: Ratio Analysis of Proficient and Limited Problem-Solving Samples Across Problem-Types

Overall, the findings indicate that there is certainly an impact of construct-level and contextual framing on problem-solving performance for different problem types. The descriptive analysis (above), and the ratio analysis of proficient to limited performance across all problem types instigate researchers to conduct in-depth inferential statistical analysis. This is done because researchers want to observe if the findings are by chance, or if the impact of construct levels and contextual framing of problem-solving performance is genuine.

- **Inferential Analysis of Overall Problem-Solving Performance**

As mentioned earlier, the scoring of this study is ordinal (a form of categorical data) or ranked in nature (0-5). Therefore, the normality tests (such as Shapiro-Wilk or Kolmogorov-Smirnov tests) were not performed to check the data distribution. In such cases, an omnibus Kruskal-Wallis H-test, and Mann-Whitney U test are more suitable for the inferential analysis. As a result, the Kruskal-Wallis H-test was first conducted to understand whether there is a significant difference in performance rank due to the change in construct-levels and contextual framing across the total scores obtained in the CL1-CS, CL1-CC, CL2-CS, and CL3-CC problems. A Kruskal Wallis H-test can be performed in non-normal distributed data, eliminating the worry of checking normality in the data. The statistical analysis illustrated that there is a significant difference in problem-solving performance because of the impact of construct-level and contextual framing, $H(3)=31.164$, p-value = 0.000 (< 0.05), with a medium or moderate level of overall effect size (ϵ^2) = 0.078. This shows that almost 8% of the variance in problem-solving performance is attributed to the differences between four problem categories, separated by the construct-level and contextual framing characteristics.

To identify more nuanced details of the impact of construct-level and contextual framing on the overall scores (performance) of problem-solving, a pair-wise non-parametric Mann-Whitney U test (or, Wilcoxon Rank-Sum Test) for four problem-solving samples (CL1-CS, CL1-CC, CL2-

CS and CL3-CC) was performed. **Table 2** summarizes the test results of the pair-wise non-parametric Mann-Whitney U test. The table contains six non-parametric statistical analyses and rank-biserial correlation (effect size, r) values.

Table 2: Summary of Non-Parametric Mann-Whitney U Tests for Pairwise Sample Comparison

Samples for Pairwise Comparison		Statistical Analysis		
Sample 1	**Sample 2**	**U Statistic**	**p-value**	**Effect Size (r_{rb})**
CL1-CS	CL1-CC	5380.5	0.014*	+0.208
CL1-CS	CL2-CS	5365.5	0.066**	+0.153
CL1-CS	CL3-CC	5839.0	0.000*	+0.474
CL1-CC	CL2-CS	3922.5	0.395**	-0.073
CL1-CC	CL3-CC	4489.0	0.005*	+0.247
CL2-CS	CL3-CC	5065.5	0.000*	+0.347

Significance Level, α:*<0.05; **>0.05

From six statistical analyses shown in **Table 2**, the transition of contextual framing (simple to comparatively complex or unfamiliar context) results reveal statistically significant differences in problem-solving performance regardless of the problems' construct-levels. Among three contextual framing changes, the least significant is found when there are no construct-level changes in testing samples CL1-CS vs CL1-CC, U=5380.5, p-value = 0.014 (< 0.05), with effect size, r_{rb}, = +0.208. The effect size r_{rb}, for ordinal data is calculated through a rank-biserial correlation calculation and corrected using Kerby Simple difference [25]. This effect sizes describes that there are 60.4% chance of getting a higher score in CL1-CS than CL1-CC [25]. The highest significant impact occurred when there were two levels of the construct changes as well as the changes in the contextual framing, U=5839.0, p-value = 0.000 (< 0.05), and yielded a comparatively moderate effect size, r_{rb} =+0.474 [25]. The test is performed within the CL1-CS and CL1-CC samples. The effect-size states that there is 73.9% chance that a problem-solution from CL1-CS is higher than CL3-CC [26]. These findings provide an important insight into designing engineering problems in instructional settings: the changes of contextual framing (even for a simple concept) reduce the overall proficiency in problem-solving performance.

The second observation is that single changes of construct-levels do not produce a considerable level of statistical significance in problem-solving performance. For instance, a Mann-Whitney U test for samples CL1-CS and CL2-CS did not produce significant results when α < 0.05. However, increasing two construct-levels drops down the overall problem-solving performance significantly. The non-parametric test conducted on CL1-CC vs CL3-CC on overall problem-solving scores demonstrated a significant difference in problem-solving performance, U= 4489, p-value = 0.005(< 0.05) with an effect size of +0.247.

Overall, the contextual framing results in problem-solving performance differences regardless of the changes in the construct-level. Single changes at the construct-level do not create significant differences in overall performance, but changes at two construct-levels have a significant impact on overall problem-solving performance.

The pairwise statistical analysis of the impact of construct-level and contextual framing on problem-solving performance (shown in **Table 2**) enabled researchers to explore further in-depth, specifically students' engineering approaches and specific applications of engineering. This was of interest, as these measures are more relevant to the engineering problem-solving activities.

- **Inferential Analysis of Specific Operations of Engineering Measures**

The researchers first conducted a Kruskal-Wallis H-test for both the Engineering Approach and Specific Application of Engineering measures. The engineering approach reflects students' general conceptual strategy, whereas the specific application of Engineering captures the contextualized use of those concepts. These non-parametric statistical analyses were conducted to determine whether the changes in construct-levels and contextual framing have an impact on engineering specific operations during problem-solving, resulting in performance differences across all problem types in this study. The statistical analysis (shown in **Table 3**) identified significant differences in performance in both cases with moderate to small effect size. In both analyses, p-value is less than 0.05 with effect size ($\in^2$) as 0.059 and 0.045, respectively.

Table 3: Summary of Omnibus Kruskal-Wallis H-tests for Engineering Approach and Specific Application of Engineering Measures

Measures	**H-Statistic**	**p-value**	**Effect Size ($\in^2$)**
Engineering Approach	24.246	0.000 (< 0.05)	0.059
Specific Application of Engineering	19.631	0.000 (< 0.05)	0.046

The pairwise non-parametric statistical analyses were further performed for four problem-solving samples (CL1-CS, CL1-CC, CL2-CS and CL3-CC) for both Engineering Approach and Specific Application of Engineering measures. Throughout these analyses, six non-parametric Mann-Whitney U Tests are performed for each problem-solving measure. **Figure 8(a)**, and **8(b)** demonstrated the inferential statistical analyses in terms of p-value of Engineering Approach, and Specific Application of Engineering measures respectively, and **Figure 9** provides the comparative analysis of the effect size (biserial correlation, r_{rb}) of these two measures.

Engineering Approach: Of these six pairwise statistical analyses for Engineering Application, the CL3-CC problem is found to be statistically significant (< 0.05) when compared with the other three-problem types (CL1-CS, CL1-CC, and CL2-CS), shown in deep blue color in **Figure 8 (a) and 9**. This shows that a combined two-level increase in construct-level and contextual framing changes resulted in a significant decrease in problem-solving performance with p-values less than 0.05, and effect size, 0.409 and 0.322, respectively.

Another interesting observation is that students generally do not have problems with the overall engineering approach in the single-construct-level problems, shown in CL1-CS ($\mu = 3.54, \sigma = 1.68$) vs CL1-CC ($\mu = 2.99, \sigma = 1.91$) statistical analysis ($p > 0.05$) with effect size 0.15. This means that they can identify the major engineering concepts to solve the problem when construct level is one, regardless of the context. The statistical analysis of the overall performance of CL1-CS vs CL1-CC identified that the difficulty in generating solutions for single-construct-level problems is due to the contextual changes does not generally stem from the students' understanding of overarching conceptual utility. The difficulty may, rather, arise from other measures, such as task interpretation [27], [28], specific applications of engineering [29], [30], or logical progressions. This finding indicates that the general conceptual understanding issues may be far less relevant in designing complex engineering problems containing single concepts than other issues. This is because students' incorrect responses may arise from other cognitive activities rather than the general understanding of engineering. This finding also matches with the earlier Fibonacci example presented in the argument of this study. Students generally have no problem with the Fibonnaci series alone as the concept of the single-construct problem but do have more difficulty understanding the same problem in different contexts.

The researchers also observed that the changes in single-construct-level generally have a dissimilar impact on engineering approaches during problem-solving. There is no statistical significance, $p=0.147$ (> 0.05) in CL1-CS ($\mu = 3.54, \sigma = 1.68$) vs CL2-CS ($\mu = 3.24, \sigma = 1.56$) statistical analysis (effect size, $r_{rb} =0.11$) seen when problems given followed this pattern. This means that single-construct-change changes have virtually equal impact on the engineering approach. Therefore, the work indicates that engineering students either have equal or no problem with identifying or using the general engineering approaches when there is a single increase in the solution construct.

All these observations discussed so far suggest that the engineering students also did not find the utilization of the general concept difficult when the problem stays within single construct level. Additionally, the overarching engineering approaches were equally challenging when the problems became a little complicated (changes of one construct-level), but they may face difficulty in utilizing the general engineering concept when the construct level rises to two steps (single-step or knowledge component to three-steps or knowledge components) with different contextual framing.

Specific Application in Engineering: The six pairwise non-parametric statistical analyses for Specific Application in Engineering illustrate that any construct-level or contextual changes results in impact on Specific Application in Engineering during problem-solving. This is shown in the deep blue color in **Figures 8 (b) and 9**. The pairwise statistical analysis conducted for CL1-CS vs CL1-CC, CL1-CS vs CL2-CS, CL1-CS vs CL3-CC, and CL2-CS vs CL3-CC reveals statistically significant results (<0.05). Of all these statistical analyses, the combined effect of construct-levels and the change of contextual framing have more impact on the specific application of engineering, where the CL1-CS ($\mu = 3.2, \sigma = 1.91$) vs CL3-CC ($\mu = 1.9, \sigma = 1.48$) analysis has a p-value=0.000 with an effect size, $r_{rb} = + 0.401$. Also this holds where CL2-CS ($\mu = 2.62, \sigma = 1.95$) vs CL3-CC ($\mu = 1.9, \sigma = 1.48$) analysis has p-value=0.022 with an effect size, $r_{rb} = + 0.198$. These findings support the expertise and findings in development literature which discusses new students starting at a Naivette level (no knowledge of a domain) and slowly progressing towards a mastery level (possess steady, standard and ideal judgement, and are acknowledged as expert by the domain relevant community) with time and practice [31].

Another interesting observation from this work is that the inherent complexity of the problems results in similar performances across specific applications of engineering concepts. The non-parametric statistical analysis of CL1-CC vs CL3-CC demonstrated that the performance differences between CL1-CC ($\mu = 2.47, \sigma = 2.06$) and CL3-CC ($\mu = 1.9, \sigma = 1.48$) samples are not statistically significant, p=0.121 (>0.05) with effect size, $r_{rb} = + 0.136$. This analysis proves that the students found contextual or specific application of engineering equally difficult. This occurs because the students did not develop the appropriate level of expertise to perform at that level when learning.

Overall, the statistical analysis for Specific Application in Engineering produces an important observation. Engineering students generally face difficulty in the contextual or specific application of engineering concepts, as predicted during the analysis of the overall engineering approach. Therefore, the instructors may find students applying Kirchhoff's Voltage Law (KVL) quite easily for general cases, but students have difficulty when the application of the same KVL is embedded within a problem as a sub-operational element. The students also feel surprised when they discover the relations in sub-operational levels that they missed in a problem-solving context.

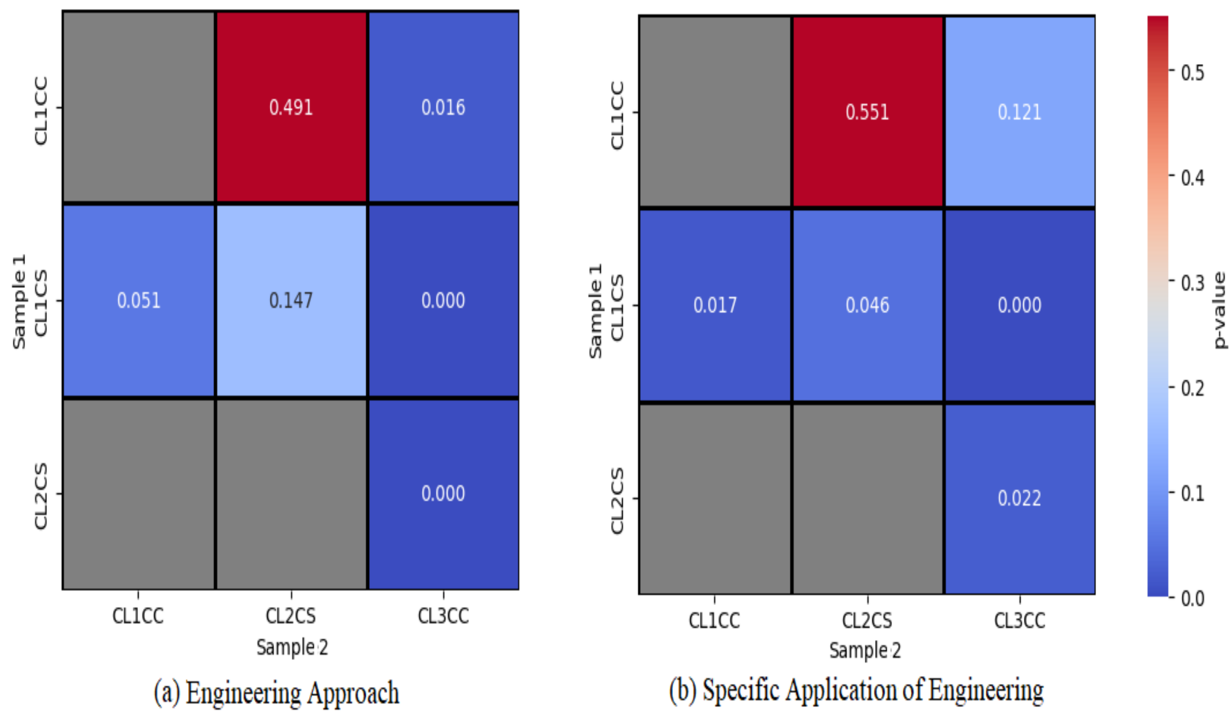

Figure 8: Non-Parametric Mann-Whitney U Test for Pairwise Sample Comparison – (a) Engineering Approach, and (b) Specific Application of Engineering Measures

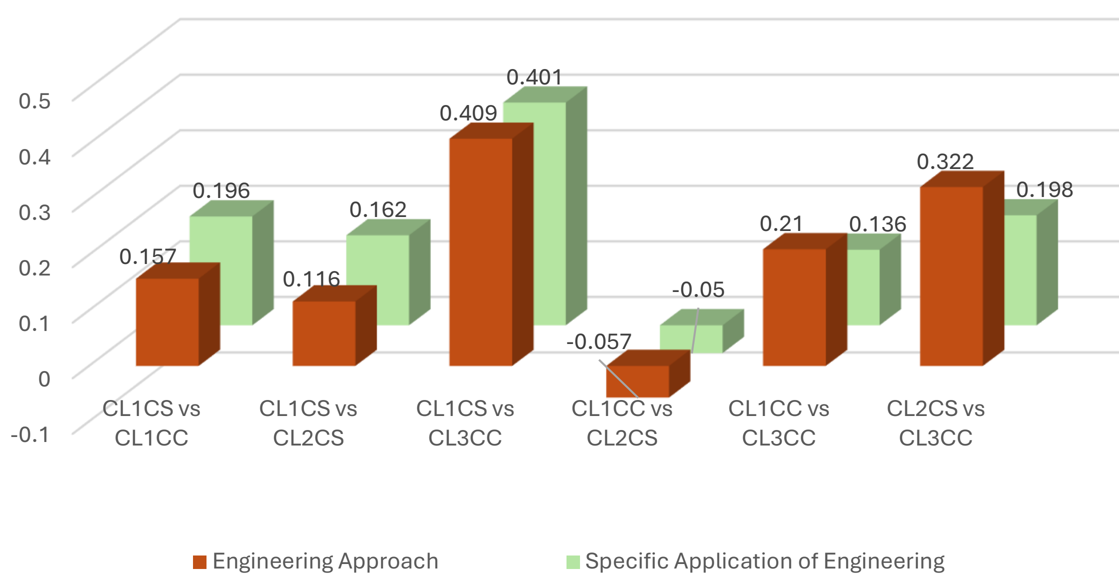

Figure 9: Rank Biserial Correlation (Effect Size, r_{rb}) - Engineering Approach and Specific Application of Engineering Measures

Conclusion and Brief Discussion

The study shows that the changes of construct-level and contextual complexity have many important effects on problem-solving performance. First, these changes reduce students' overall proficiency rate. The two-construct-level changes and contextual framing changes are found to have a significant impact on overall problem-solving performance. Single-construct-level changes have minimal impact.

When researching specific cases, it is found that engineering students generally do not have problems with applying major engineering concepts in the solutions for single-construct-level problems, but with the rise in the number of constructs, they do see difficulty, and a detrimental impact is observed in solutions. The students may also find that single construct-level problems are difficult due to task interpretation, specific application of engineering, mathematical, and/or logical flaws [27], [28], [32], [33].

Finally, this study also found that students have difficulty applying concepts in specific or contextual use cases, which aligns with expertise development literature [6], [31]. Students also face challenges in applying specific engineering concepts when instructors embed problems in unfamiliar or comparatively more difficult or complex contexts.

This study has several important implications in terms of understanding engineering problem design and instructional practices. From this study, it is found that there can be an objective approach for designing problems based on the understanding of the construct-level, and contextual framing. This understanding of problem-solving construct-level and contextual framing can result in intentional sequencing and increasing complexity in problem design, to make students feel progressively more challenged. This would be similar to advancing obstacles within a game. Moreover, Lawanto and colleagues (2023) identified that students mostly over or under evaluate their problem-solving activities, as many lack self-regulation in actions [34], [35]. Therefore, intentional sequencing and increasing complexity strategies in designing academic rule-bound problems result in less stress and more cognitive engagement and subsequent self-evaluative confidence in problem-solving skill development. This chronologically challenging problem-set design idea is also aligned with Carol Dweck's growth mindset theory [36] and Fischer's skill development theory [12] of designing an educational engineering environment that cultivates motivation, resilience, persistence, and continuous growth. Additionally, the proposed problem development technique can be utilized in professional industrial training to train new STEM professionals.

Limitations and Future Directions

This study is a part of a broader study to understand and design engineering problems. The researchers have not yet conducted an in-depth qualitative analysis of the solutions. Some 'Think-a-Loud' protocols or 'Interview Session' may offer valuable insights into students' experiences. Researchers are thus also planning to collect students' experiences through interviews for in-depth analysis. Similar work should be conducted in other fields of engineering knowledge outside of electronics. However, it is expected that the analytical processes of the problems will remain the same. Moreover, the study did not attempt to observe the correct outcomes of the solutions. Rather, the researchers observed the solution generating processes. These results, therefore, would be better affirmed if these statistical outcomes were based on problems with the same concepts. Nonetheless, this does not impede the researchers from observing and gaining valuable insights that match the experiential observations and findings in existing literature. This study also provides a valid way to design and develop a problem more objectively. Moreover, this study also discussed only two specific measures (i.e., Engineering Approach and Specific Application of Engineering) of the problem-solving process. Future studies will observe more measures, such as task-interpretation, mathematical and logical progression differences among problem types.

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