Exploring Cognitive Processes in Engineering Problem-Solving: A Case from Fundamental Electronics for Engineers Class

Mr. Rifatul Islam Himel, Utah State University

Rifatul Islam Himel is a doctoral candidate in Engineering Education at Utah State University (USU), Logan, Utah, US. His doctoral research focuses on understanding human cognition in engineering problem-solving. He holds a Bachelor's degree in Electrical and Electronics Engineering and a Master's degree in Electronics and Telecommunication Engineering. With over six years of professional experience in the Information Technology industry and a strong background in teaching and research, Rifatul brings a unique interdisciplinary perspective to his work. His research interests include Human and Machine Cognition, Applied Artificial Intelligence in Engineering Education, Information Processing, and the study of Consciousness.

Dr. Oenardi Lawanto, Utah State University

Dr. Oenardi Lawanto is a professor in the Department of Engineering Education at Utah State University, USA. He received his B.S.E.E. from Iowa State University, his M.S.E.E. from the University of Dayton, and his Ph.D. from the University of Illinois at Urbana-Champaign. Dr. Lawanto has a combination of expertise in engineering and education and has more than 30 and 14 years of experience teaching engineering and cognitive-related topics courses for his doctoral students, respectively. He also has extensive experience in working collaboratively with several universities in Asia, the World Bank Institute, and USAID to design and conduct workshops promoting active-learning and life-long learning that is sustainable and scalable. Dr. Lawanto's research interests include cognition, learning, and instruction, and online learning.

Dr. Yashin Brijmohan, Utah State University

Yashin Brijmohan is a registered professional engineer who is currently appointed as Chairman of Engineering Education Standing Technical Committee of the Federation of African Engineering Organizations, Executive committee member of the Commonwealth Engineers Council, Board Member of the UNESCO International Centre for Engineering Education, and Co-Chair of the Africa Asia Pacific Engineering Council.

He was the founding Executve Dean of Business, Engineering and Technology at Monash South Africa, former Vice President of the World Federation of Engineering Organizations, and led several committees in the engineering profession.

Yashin has both leadership and specialist experience within the engineering power industry and education sectors and is known for his thought leadership in capacity building and engineering education.

Dr. Wade H Goodridge, Utah State University

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.

Dr. Zain ul Abideen, Utah State University

Zain ul Abideen holds a Ph.D. in Engineering Education from Utah State University, where he also served as a Graduate Researcher. He is a computer engineer and earned his bachelor's degree in computer engineering and master's degree in engineering, and brings over a decade of experience in teaching and research with undergraduate engineering students. He actively contributes to several technical committees and serves as a reviewer for leading journals and international conferences. His doctoral research focused on cognitive engagement, AI in education and engineering design, self-regulated learning, and mobile learning. His work seeks to deepen our understanding of how these elements influence learning and success in engineering education. With a strong commitment to educational advancement and a robust academic background, Zain is recognized as a dedicated and emerging scholar in the field of engineering education.

Mr. Foeday Zinnah, Utah State University

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.

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.

Exploring Cognitive Processes in Engineering Problem-Solving: A Case from Fundamental Electronics for Engineers Class

Abstract

This full empirical research paper explores the structural distinction of cognitive processing associated with Proficient and Limited Problem-Solving events within the context of Fundamental Electronics course and a focus of Engineering Education. The proficient and limited problem-solving events were differentiated in this study from the solution samples based on the failure cutoff point used in many US institutions. As a part of the ongoing dissertation study, this paper only reviews the background, research objectives, and the emergent results of cognitive processes in engineering problem-solving. Studies identified that there is an interplay between dynamic information processing in the human mind, and the intricacy of the problem-solving tasks. Studies also found that the qualitative differences of the pre-existing knowledge structure, or cognitive schemas are correlated with the student cognitive processing and problem-solving performance. In fact, this idea is the foundation for the information processing model of cognitivism theory. Therefore, the cognitive mechanisms students engage in while problem-solving is found to be very context-specific rather than agent-specific. To understand these dichotomous structural differences in cognition during problem-solving events, this study employs multi-level qualitative methods for over 363 problem-solving events drawn from the foundational Engineering course titled "Fundamental Electronics for Engineers". The initial qualitative investigation and scoring are performed based on modified five measures procedure mentioned in Docktor et al.'s (2016) rubrics. To identify uniformity in the findings and to observe more nuanced differences in the cognitive processes associated with the problem-solving performance, the data are collected from four problem types (one retrieval, two diagnosis, and one strategy problems). For in-depth qualitative investigation, a combination of inductive and abductive reasoning is employed to generate cognitive processing maps associated with the problem-solving activities from eighteen selected events. These problem-solving events belong to only the first two problem types, retrieval and diagnosis. The common themes between two dichotomous groups, Proficient and Limited Problem-solving events, are identified. The results reveal that there are significant qualitative differences in cognitive processing between dichotomous (Proficient and Limited) engineering problem-solving groups. Proficient problem-solving events are interrelated with better organization, creative synthesis, abstraction, and improvisation, whereas limited problem-solving events contain logical flaws, decontextualized knowledge pieces, cognitive dissonance, and distractive knowledge elements. These findings suggest that the need for targeted instructional interventions, including the development of active learning strategies inside and outside of the engineering classroom. In addition to these findings, this study contributes to cognitive science by reinforcing that human intelligence is dynamically shaped by the interaction of task demands and cognitive states.

Keywords: *Cognitive Process, Problem-Solving, Reasoning, Cognitive Dynamics*

I. Introduction

This full empirical research paper initiated an investigation on understanding cognitive processing in routine rule-bound academic problem-solving activities in the engineering education context. This work presented here is a part of larger study and only provides background, research objectives, and some preliminary quantitative and qualitative findings of human cognitive processes associated with problem solving in the foundational engineering classes, such as, Fundamental Electronics for Engineers. These findings are expected to persist in all levels of academic engineering courses that require framing, reasoning, and solving routine and well-defined problems mathematically.

Psychologist VanLehn considered all human activities to be virtually linked to solving problems [1]. Throughout the history of mankind, humans have solved problems that vary in structuredness, abstractness, complexity, time consumption, knowledge demands, and cognitive efforts or engagements, and goal-orientation [1] – [6]. As civilization progresses, problems become more complicated, nuanced, contextualized, and require high cognitive demands from Andy Clark's modern cognizers, both humans and machines [7]. In solving modern complex problems, humans can utilize their sophisticated and complex cognitive structure through repetitive redescription of their internal knowledge within their mind. This repetitive redescription of internal thought processes solidifies learning and clarifying thinking. In addition, machines can help reshape human thinking and understanding and enhance human functionality throughout the solution generation processes [7]. The concern of underdeveloped cognitive processes becomes critical when students increasingly depend on artificial intelligence, potentially replacing key cognitive efforts required for learning, reasoning, problem solving and decision making [3], [8] – [11]. A recent study found that students who frequently rely on artificial systems (i.e., Generative AI) for writing demonstrated significantly lower neural and cognitive engagement than their counterparts [12]. Lawanto and colleagues defined seven learning episodes based on students' practices of meta-cognition and self-regulation and discussed how meta-cognition and self-regulation influences problem-solving performance [13], [14]. It is possible these practices of metacognition and self-regulation could also be compromised without exercising having an impact on cognitive autonomy. Furthermore, it has been seen that many ill-defined problems require creative endeavors in generating acceptable, and unique solutions [3], benefiting problem-solvers in the long run through the enhancement of their divergent thinking capability. Recognizing these points crystallizes how activities and autonomy are more important than ever before. This work begins to present a deep study opening an understanding regarding cognitive processes associated with all problem-solving types as mentioned by Jonassen [2].

II. The Study

The study was conducted on students submitting solutions for four distinct homework problems. The problems were sampled from a compulsory, sophomore-level, fundamental engineering, Spring 2025, class at a public university in the western United States. The homework problems can be characterized as academic, knowledge-rich, well-defined, and routine in nature [1], [2], [8]. Due to the nature of the study and in an effort to follow IRB protocols established with this work, only the anonymous or deidentified students' problem solutions were collected from a "Fundamental Electronics for Engineers" class. The deidentification process was conducted by a data governing body at the University. The researchers of this study maintained precautions and guidelines prescribed by IRB and FERPA throughout their data collection process. Deidentification of problem-solving events has an additional advantage of reducing any possible bias from the research team regarding known identities. To ensure more naturalistic and real-life cognitive processes associated with problem-solving activities, no pre-informed data collection sessions (i.e., think-a-loud protocol, in-person interview, etc.) were conducted. Therefore, the problem-solvers were allowed to use all the available resources, including books, notes, tutoring centers, generative AIs, or take help from the classmates etc., to demonstrate how they process their cognition in real-life problem-solving settings when all the resources are available. The students of this foundational engineering class submitted their solutions to the assignment's problems via Course Canvas.

III. Study Context

The foundational engineering course selected for this study is designed to be delivered in twelve modules. The modules focus on containing DC and AC networks and digital electronics for electrical engineering non-majors, such as Biological, Mechanical, Aerospace, Environmental, and Civil engineering or Computational Sciences. In each week, the students must complete around 9 to 15 homework problems, with an exception for the last week, so there is a total of 11 homework problem sets submitted. Four problems were carefully chosen from the eleven-homework problem set for this research. The students enrolled in the course are mostly in their sophomore and junior years. Aside from this course, they also have experience in logical and abstract reasoning in their K-12 STEM classes and from other mathematics and engineering courses in the university. Furthermore, the students share similar learning cultures in terms of learning values, beliefs, and practices.

IV. Research Question and Objectives

This study is guided by one major research question: How do cognitive processes structurally differ between proficient and limited problem-solving events? The problem-solving events are defined as Proficient if they receive a score of sixty percent or higher on five measures found in a modified version of Docktor et al.'s rubrics. These five measures are useful description, engineering approaches, specific applications in engineering, mathematical procedures, and logical progressions [15]. Limited problem-solving events scored less than sixty percent. The sixty-percent score is the standard sub-performance passing line or failure cutoff point used in many US institutions and academics for grading students [16] – [18]. The researchers selected this 'sixty percent' as threshold score as the standard measure for assessing problem-solving proficiency to ensure that this study is more consistent with the current US academic grading policies and practices [16] – [18]. Moreover, it is a very widely accepted fact that a cutoff point is required to evaluate the quality of the students' work. For instance, a student receiving a score of 4.0 on their submitted work is qualitatively different from a student who secures a score equivalent to 2.7. As this study is about exploring the cognitive processes associated with dichotomous problem-solving events, a standard failure cutoff point is utilized for dissecting the collected problem-solving data. Moreover, this cutoff point has been proved to be effective for grading students or assessing the quality of students' assignment submissions for decades in the United States, and in the universities of the other countries following the similar scoring standard.

The major objectives of this study are: (1) understanding cognitive processing mechanisms for two distinct (i.e., proficient and limited) types of problem-solving events in educational and training curriculum; (2) informing educators to observe and categorize students based on their problem solutions so appropriate interventions or remedies in their workforce development programs can be implemented (i.e., academic courses, industrial training, hands-on experiences); and (3) developing cognitive adaptive technological solutions for all STEM courses, and programs through personalized feedback. The current general-purpose answer producing generative AI systems based on Chatbots are just answer producing machines (like a solution manual) and are incapable of tutoring students for educational and training context. This creates an ineffective or underperforming crutch for students learning and problem-solving. Even though generative AI can enhance students' understanding with better prompt design, it does not make students think about the problems, associated concepts, or make cognitive efforts. Therefore, engineering students, who use generative AI mindlessly, may not be capable problem-solvers, as they may never be cognitively engaged deep enough with the problems to be mentally skillful. This problem is also an eminent threat to stay competitive in the job market across the world and overall future societal progress.

V. Data Collection and Analysis

Data was collected from 396 de-identified problem-solving events from the Fundamental Electronics for Engineers in the Spring 2025 course (sections 001 and 002). It was de-identified initially by a data governing body. The collected and evaluated solutions were from four distinct problems and characterized based on the PPST framework. One problem is from a retrieval type, two are diagnosis types, and one is strategy problem [19]. A problem-solving event is called a retrieval event when the problem identification and knowledge components for solutions require the yielding of relevant information in the solution[19]. For solving the retrieval problems, the concepts do not need to be changed. On the contrary, diagnosis solutions need certain changes in understanding, interpretation tasks, and generating solutions [19]. Strategy-type solutions require problem-solvers to understand the complex relationship of the knowledge components within a problem and to generate solutions in the stages or in the subsystems [19]. Strategy type problems are the hardest in this study context as the problem-solvers need to make association between concepts. After collecting problem-solving data, the researchers qualitatively screened and filtered the problem-solving events based on their intelligibility and interpretability and reduced the problem-solving events down to 363. **Figure 1** showed the sunburst plot of the distribution of the selected 363 problem-solving events.

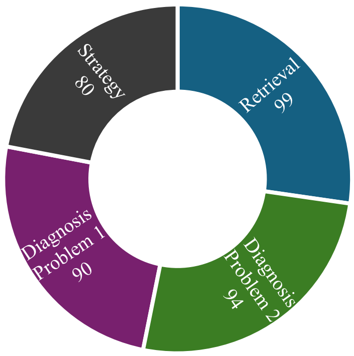

Figure 1. Distribution of Problem-Solving Events (n=363)

In the first phase of multi-level qualitative analysis, the researchers scored problem-solutions based on five measures, mentioned in the slightly modified Docktor et al.'s rubrics [15]. Each measure was scored based on a 0-5 Likert scale (0 represents no cognitive processing, and 5 represents comparatively superior cognitive processing). Then, the researchers calculated overall total scores for individual problem solutions. A solution could only receive a 25 for the best solution (0 and 5 measures × 5 max scores for each measure) and 0 for a no apparent cognitive processing solution. From this total maximum (25) score, the proficient (60% or more) and limited (less than 60%) problem-solving events are separated. After separating the problem-solving events based on the proficiency category, the researcher conducted descriptive and inferential statistical analyses for each problem type (retrieval, diagnosis and strategy) to observe the general cognitive processing differences between proficient and limited problem-solving events.

In the second phase of the data analysis, the researchers implemented thematic analysis through inductive-abductive reasoning in an effort to seek more granular understanding of the cognitive processes associated with problem-solving processes. This was garnered from qualitative data. Both inductive and abductive reasoning were used to confirm that the qualitative analysis provides the best contextual explanation of the knowledge component processes identified in the problem solution. This phase of data analysis ensures a more contextualized, nuanced, and extensive understanding of the cognitive processes beyond quantitative explanations. To conduct the in-depth thematic qualitative analysis, only the retrieval, and the first diagnosis problems were selected. The reasoning for selecting these two problem types (i.e., Retrieval, and Diagnosis Problem 1) is discussed in the finding sections, because the inferential analysis and the associated discussion provide better justification. The inductive-abductive qualitative reasoning ensures the uniformity of the major themes about cognitive processes associated with the problem-solving across problem types. Therefore, a total of 189 (99 Retrieval and 90 Diagnosis Problem-1) problem-solving events were distilled further down to only 18 events through qualitative screening and filtering. In this phase of qualitative screening and filtering processes, the researchers observed the dissimilarity or cognitive variety associated with problem-solving processes, including unique solution generation strategies, creatively synthesizing engineering concepts, adopting fewer steps than necessary, improvisations, visible logical or procedural problems, unnecessary elements in the problem solutions. All similar applications of the concepts, mistakes, or apparent cognitive processing resemblance were filtered out. As the researchers were observing both proficient and limited problem-solving events, the selected 18 problem-solutions used in the second phase of analysis contain correct, partially correct and incorrect solutions. A smaller subset selection from the 363 problem-solving events is justified, because Creswell (2007) suggested that six samples are enough to have theoretical saturations in a similar qualitative study [20]. **Figure 2** demonstrates the allocation of the selected problem-solving (PS) events for in-depth qualitative analysis to identify common themes and their differences associated with Proficient and Limited Problem-Solving (PS) activities.

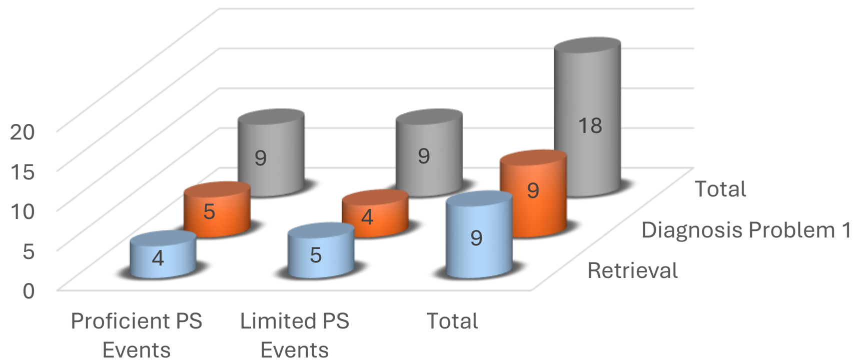

Figure 2. Distribution of Problem-Solving Events and Problem Types for In-Depth Qualitative Study (n=18)

Throughout the multi-level qualitative data analysis process, two independent researchers with similar expertise and experience were involved. They independently performed qualitative filtering, scoring 363 problem-solving data, and inductively and deductively studied 18 problem-solving events throughout the data analysis process. In data analysis steps, they did peer-debriefing and discussion until 100% agreement was reached [21].

VI. Results

The descriptive analysis shown in **Table 1** contains information about the total sample size (n), problem-types, average score (*M*), standard deviation (*SD*), and interquartile range (*IQR*) for overall, proficient, and limited problem-solving events for each problem type (one retrieval, two diagnoses, and one strategy). The overall average of 363 problem-solving samples is 13.66 with a standard deviation of 6.94, and IQR of 12.00. The sample size for proficient problem-solving events is 175, with IQR=4.00, and the limited event is 188 with IQR=7.00. The average

(*M*), standard deviation (*SD*), and interquartile range (*IQR*) for each problem type illustrate the cognitive processing associated with all measures mentioned in slightly modified Docktor et. al.'s rubrics [15]. These values are different for all problem-solving types in proficient and limited problem-solving events. The average proficient performance (>=60%) for all problem types is around 19.06 to 20.10 with IQR of 2.00 to 4.50. The average of the limited performance (<60%) for all problem types is around 7.40 to 8.41, with IQR of 4.00 to 8.50. Proficient performances are comparatively more consistent in cognitive processing than their limited counterparts for all problem types. Table 1 illustrates the descriptive summary of Problem-Solving Events based on the problem types and the competency levels.

Table 1. Descriptive Summary of Problem-Solving Events Based on Problem Types and Competency Levels

Problem Types	Sample Size (n) of Problem Types	Overall Problem-Solving Events (n=363, *M*=13.66, *SD*=6.94, *IQR* = 12.00)							
		Proficient Events (>=60%) (n=175, *M* =19.95, *SD* =2.63, *IQR*=4.00)				Limited Events (<60%) (n=188, *M* =7.80, *SD* =3.89, *IQR*=7.00)			
		n	*M*	*SD*	IQR	n	*M*	*SD*	IQR
Retrieval	99	67	20.06	2.72	4.50	32	7.50	4.64	8.50
Diagnosis Problem 1	90	42	20.10	2.53	2.00	48	7.40	4.38	8.25
Diagnosis Problem 2	94	48	20.00	2.68	3.25	46	8.41	3.46	5.75
Strategy	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)

To support the descriptive analysis of this study, the researchers also conducted pairwise non-parametric Mann-Whiteny U Tests between proficient and limited problem-solving events across all problem types. The standard normality tests (such as Shapiro-Wilk or Kolmogorov-Smirnov tests) were not performed in analyzing the scored problem-solving data, as the data is ordinal in nature. The inferential statistical analysis in this study demonstrated that the performance differences between the proficient and limited problem-solving events is statistically significant (**$p < 0.000$**) with effect size, **$r_{rb} = +1.000$** for all cases. This indicates two important aspects of this study: (1) the cut-off point selected for this study genuinely differentiate problem-solving performance across all problem-types, making the US standard of grading very effective to categorize students based on their quality, and (2) there must be a qualitative distinction of cognitive processes between proficient and limited problem-solving events. **Figure 3** illustrates the statistical analysis and the visualization of data distribution of proficient and limited problem-solving events across all cases.

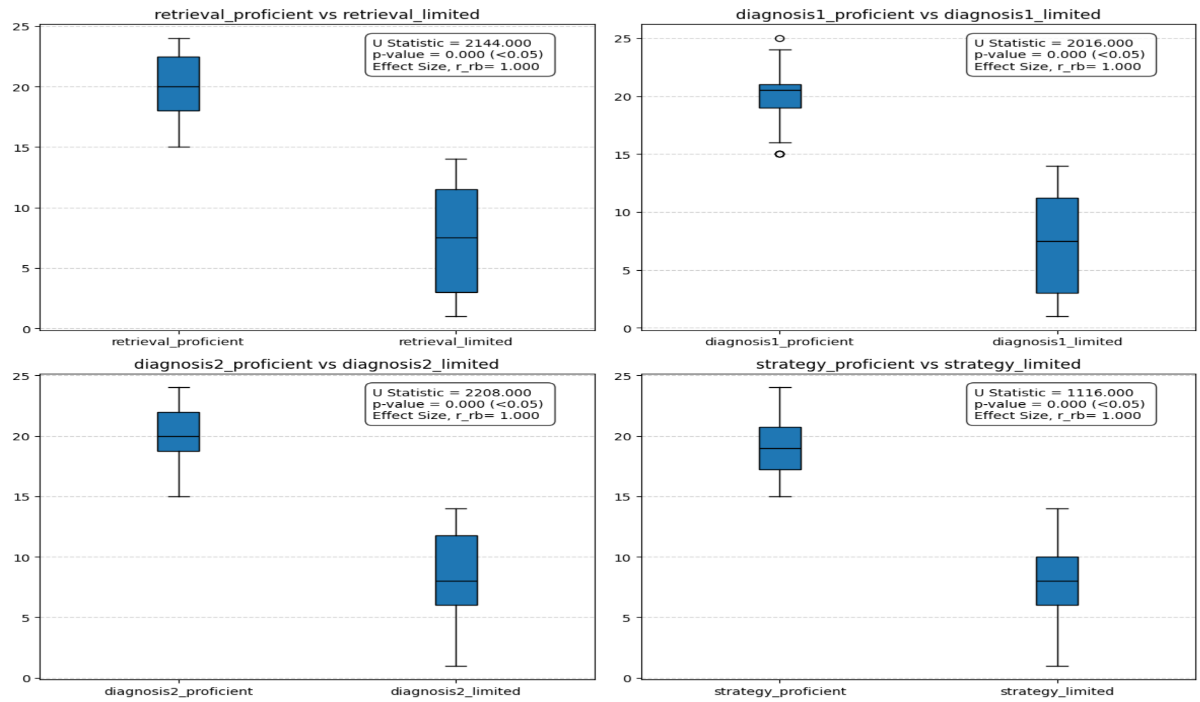

Figure 3. Summary of Non-parametric Mann-Whitney U Test for Proficient and Limited Problem-Solving Comparison for Different Problem Types

Taken together, the descriptive and inferential statistical analyses as well as the data distribution (boxplot) across all problem-solving types, it is evident that proficient and limited problem-solving events are comparatively different in cognitive processes, including in useful description, engineering approach, specific application of engineering, mathematical procedures, and logical progressions, across all problem types.

Solutions in proficient and limited problem-solving groups appear to be more consistent in strategy type problems than any other, indicating that the cognitive processes associated with proficient and limited solution in strategy type problems are mostly similar. Moreover, the deep structure to solve diagnosis 1 and 2 Problems are almost similar (using a circuit analysis theorem to proceed further). Therefore, the researchers only recommend one retrieval and diagnosis problem for the qualitative investigations of cognitive processes associated with problem-solving.

From the in-depth qualitative analysis of the selected eighteen problem-solving events (Figure 2) through inductive-abductive reasoning [22], four common themes emerge for each proficient and limited problem-solving event for both retrieval and the first diagnosis problems (or, Diagnosis Problem 1) through thematic analysis. The combined inductive-abductive reasoning is used for an attempt to generate the best possible explanation of the cognitive processes associated with problem-solving activities within the generated samples [22]. Almost all problem-solving events have more than one theme.

A. Proficient Problem-Solving Events

Problem-Solving Events associated with proficient competency demonstrated four key characteristics across nine problem-solving events (Figure 2). The solutions mostly have better knowledge organizations, creative synthesis between knowledge components, and efficient and improvised knowledge processing across all problem types.

1) Structured and Systematic Thinking*:* Most problem-solving events in the proficient problem-solving categories have demonstrated well-connected, organized, and strategic knowledge utilization and processing in generating solutions. They have minimal overall deviations or errors. Of the selected qualitative data, around 66.7% of the routine solutions within the collected problem-solving events processed engineering concepts in orderly, and systematic manners at both procedural and sub-procedural levels. Smoother transitions were evident between each problem-solving step.

2) Creative synthesis between knowledge components*:* The problem-solving events associated with the proficient competency-level are found to have synthesized multiple engineering concepts contextually and creatively in developing solutions. The approaches to the solutions to these problem-solving events are found to be comparatively unconventional. The solutions demonstrate that the solvers may have firm understanding, such as constraints, associations, and applications, of multiple engineering concepts that can transfer into this creative synthesization. Around 66.7% of the collected events in the second phase of data collection (Figure 2) are under this theme. The researchers also identified that the retrieval problems consisted of 75% creative utilization of engineering concepts, whereas the diagnosis solution consists of 80% innovative amalgamation of concepts. These findings demonstrated that the problem-solvers' ability to be more creative in diagnosis problems than retrieval ones. These findings also match the definition of problem types, as diagnosis problem needs the adjustment of conceptual understanding during solution generation [19]. On the other hand, the retrieval problems (as the name suggests) require minimal, or no changes in engineering concepts to produce solutions.

3) Efficient cognitive processes through abstraction*:* Some proficient solutions were found to contain higher-order or integrated (linked) knowledge structure [23], [24]. The utility of higher-order or compressed knowledge structure streamlines the solution with fewer steps than necessary by leveraging non-contextual natural higher-order or compressed pre-existing abstract knowledge. An example would be the application of larger conceptual chunks in the multiple steps in a solution. In the study, some solutions demonstrated series-parallel resistor calculation of total resistance, star-delta conversion, or source current calculations within a single or two steps, which traditionally require multiple steps to solve the problem. Around 55.6% of the collected problem-solving events demonstrated this theme. This efficient cognitive processing is also prevalent among proficient problem solvers in many higher-level mathematical or engineering courses, where problem-solvers typically utilize advanced compounded formulas instead of simple concepts. The limited problem-solvers typically struggle with foundational concepts, resulting in inability to apply higher-order knowledge structures.

4) Improvised processing of knowledge*:* The problem-solving events associated with the proficient problem-solving category have illustrated valid, contextually appropriate, and comparatively lower-order pre-existing knowledge to compensate for higher-order knowledge during solution generation. Basically, these types of proficient solutions adopt flexible and dynamic cognitive processes that utilize the available mental resources (hierarchically lower order) to generate the most viable and successful outcomes without strictly adhering to or depending on the standard procedures for a solution. Only 11.11% of the collected data demonstrated this theme. These types of cognitive processing are valuable for open-ended or ill-structured problems where the appropriate engineering concepts are not readily available.

B. Limited Problem-Solving Events

The problem-solving events associated with limited competency have demonstrated distorted logical processing among individual one or more deformed knowledge structures, fragmented knowledge in the problem-solvers' minds, incorrect cognitive relations among correct attributes (knowledge components), and the trigger of irrelevant knowledge elements. These themes are found in all limited problem-solving events across the retrieval and diagnosis problem types.

1) Faulty Reasoning from Misstructured Thinking: Many limited problem-solving events contain deformed under constructed knowledge structures, which generate inherent defective logic at local and/or global levels of the problem-solving activities. Most problem-solving data (66.7%) collected in the second phase of data collection contains one or two flawed logical associations between under-constructed knowledge structures. On some occasions, the problem-solvers even appear to forcefully adjust their knowledge within the problem settings, resulting in over-complication of the process to a solution.

2) Decontextualized knowledge pieces or fragmented thinking: Limited problem solutions, on several occasions, processed fragmented or inconsistent applications of knowledge pieces during solution generation. The solution often possesses unutilized or unconnected knowledge pieces (steps) that were never used in other parts of the solution. These decontextualized knowledge components stay as separated entities in both the apparent and dormant states in the problem solution process. The researchers found 22.2% of these cognitive processing activities in the limited problem-solving events. The decontextualized fragmented knowledge processing also aligns with Collins and Gentner's pastiche model or diSessa's knowledge in pieces theory [25].

3) Flaws in Framed-Based Thinking: Some limited problem-solving events demonstrate the emergence of dysfunctional relation generation between well-constructed knowledge structures. This occurs when the problem-solving states are misaligned with the corresponding mathematical expressions, and formulations due to the creation of conflicting associations between two or more correct knowledge components engaged by the problem solver. Around 33.3% of the solutions possess this kind of incorrect association between the error-free knowledge components. In this study, some solutions contain the changes of the circuits' current direction, when calculating the superposition theorem without any valid reason provided to do so. In Gentner's term, this theme can be described as incorrect relation between correct knowledge attributes [26].

4) Cognitive distraction through irrelevant instigation of knowledge elements: In limited problem-solving events, some mental processes trigger additional and irrelevant knowledge-structures, elements, or components that increase cognitive load. These additional or irrelevant knowledge components have the prospects of misdirecting cognitive processes during the development of problem solutions. Around 11.1% of collected solutions contain this problem. This cognitive distraction could be part of the domain-specific intrinsic, and environment extrinsic load place upon the student. Many domain-specific intrinsic, and environment extrinsic load may stem from the problem representations, and adjusted concepts found in the problem-solving context. Some extrinsic load can generate problem-solvers' external issues which are out of the scope of this study.

VII. Brief Discussion and Implications

The descriptive analysis together with emergent qualitative themes reveals that cognitive processing associated with problem-solving activities are significantly different for proficient and limited problem-solving events. The problem-solving competency levels and problem-solving performance also vary based on problem types, supporting the fact that complex actions, knowledge demands and cognitive efforts in problem-solving are highly contextualized. These findings also imply that the manifestation of intelligence is not agent-specific, but task specific. Therefore, the same agent can perform uniquely in different problem-solving tasks. Moreover, the findings also suggest that the existence of resources does not necessarily influence cognitive processes associated with learning, quality of reasoning, cognitive engagement, and problem-solving. Engineering educators need to develop targeted interventions, such as active learning activities in the classroom, problem assignments based on pragmatic philosophy, and social learning for individual topics. For example, students, who are unable to connect engineering concepts related to problem-solving activities, should be instructed or illustrated how the concepts relate to one another. The instructors may want to design more individualistic problem-statements for a group of students, who show those cognitive activities during problem solving. As a result, the students who fail to connect multiple concepts of engineering problems became more capable not only of the given problem but also of other future engineering problems. In fact, multiple studies through Triad framework found that majority students possess inflexibility in connecting concepts [27], [28]. Moreover, another study is conducted by the researchers of this study to show how to design problems based on the understanding of human cognition [29]. These interventions may enable engineering students to cognitively engage with the learning contents, solution generations, and encourage them to put extra mental effort into their learning materials. The instructors can also design the course activities that facilitate the practice of self-reflection, and metacognition in synchronous, asynchronous, and in-person learning environments. It is important to note that this study, by no means, seeks to discourage the use of generative AI in STEM education settings, but rather urges the STEM educators to rethink the limitations it may have.

VIII. Limitations

This study illustrates initial findings of a larger study that focuses on understanding the cognitive processing mechanisms and their structure utilizations during problem-solving. The quantitative and qualitative analyses in this study both highlighted the basic differences between cognitive processing in proficient and limited problem-solving activities in a very limited contextual setting. The convenient sampling or the changing of demographics needed to be explored in the future. Furthermore, the researchers will provide more in-depth details with relevant examples in their future work. In those future works, the researchers will show how cognitive attributes shape proficient and limited problem solvers thinking, and how these attributes' changes result in changes of thinking.

References:

[1] K. VanLehn, "Problem Solving and Cognitive Skill Acquisition," in M.I. Posner (Eds.) *Foundations of Cognitive Science*, 1st ed. Cambridge, MA: The MIT Press, 1993, pp.527-579.

[2] D. H. Jonassen, "Toward a Design Theory of Problem Solving," *Educational Technology Research and Development,* 48(4), 63-85, 2000. https://www.learntechlib.org/p/165433/.

[3] Y. Wang, and V. Chiew, "On the cognitive process of human problem solving," *Cognitive Systems Research,* 11(1), 81–92, 2010. https://doi.org/10.1016/j.cogsys.2008.08.003

[4] Z. Abideen, O. Lawanto, T. Naqash, and A. Minichiello, "A systematized literature review on problem-solving in STEM education exploring the impact of task complexity on cognitive

factors and student engagement,” in *Proc. 2024 ASEE Annu. Conf. & Exposition*, 2024, doi: 10.18260/1-2--46499.

[5] Z. Abideen, S. Jabeen, O. Lawanto, A. Minichiello, and A. Iqbal, “Exploring the relationship between achievement goal orientation and cognitive engagement in engineering problem-solving,” in *Proc. IEEE Frontiers in Education Conf. (FIE), 2025*.

[6] Z. Abideen, S. Jabeen, O. Lawanto, A. Minichiello, and A. Iqbal, “Exploring the impact of the need for cognitive closure on undergraduate engineering students’ cognitive engagement during problem solving,” in *Proc. IEEE Frontiers in Education Conf. (FIE), 2025.*

[7] A. Clark and A. Karmiloff-Smith, "The Cognizer’s Innards: A Psychological and Philosophical Perspective on the Development of Thought," *Mind Lang.*, vol. 8, no. 4, pp. 487–519, Dec. 1993, doi: 10.1111/j.1468-0017.1993.tb00299.x.

[8] O. Lawanto and Z. Abideen, “Routine vs. non-adaptive learning: Examining the impact of metacognitive knowledge and self-regulation on problem-solving,” in *Proc. 2025 ASEE Annu. Conf. & Exposition*, 2025.

[9] Z. Abideen, S. Jabeen, and A. Iqbal, “A systematized literature review on the role of goal orientation in active learning and engagement during problem-solving in STEM education,” in *Proc. IEEE Frontiers in Education Conf. (FIE)*, 2025.

[10] M. Stadler, M. Bannert, and M. Sailer, “Cognitive ease at a cost: LLMs reduce mental effort but compromise depth in student scientific inquiry,” *Computers in Human Behavior*, 160, 108386, 2024. https://doi.org/10.1016/j.chb.2024.108386

[11] J. G. Greeno, A. M. Collins, and L. B. Resnick, “Cognition and Learning.” In D. C. Berliner & R. C. Calfee (Eds.), *Handbook of educational psychology*, Macmillan Library Reference USA; Prentice Hall International, pp. 15–46, 1996.

[12] N. Kosmyna, E. Hauptmann, Y. T. Yuan, J. Situ, X. Liao, A. V. Beresnitzky, I. Braunstein, and Pattie Maes, “Your brain on chatgpt: Accumulation of cognitive debt when using an ai assistant for essay writing task,” *arXiv preprint arXiv:2506.08872*, 2025

[13] O. Lawanto, A. Minichiello, and Z. ul Abideen, "Impeccable Learning: Deep Understanding, Self-Evaluation, and Monitoring for Problem-Solving Success," in *Proc. 2025 ASEE Annual Conference & Exposition*, Montreal, Quebec, Canada, June 22–25, 2025.

[14] O. Lawanto, "Integrating Metacognitive Knowledge and Self-Regulation: Insights from Problem-Solving in Engineering Mathematics Courses," in *Proc. 2025 ASEE Annual Conference & Exposition*, Montreal, Quebec, Canada, June 22–25, 2025.

[15] J. L. Docktor, J. Dornfeld, E. Frodermann, K. Heller, L. Hsu, K. A. Jackson, A. Mason, Q. X. Ryan, and J. Yang, "Assessing student written problem solutions: A problem-solving rubric with application to introductory physics," *Phys. Rev. Phys. Educ. Res.*, vol. 12, no. 1, p. 010130, May 2016. doi: 10.1103/PhysRevPhysEducRes.12.010130.

[16] T. R. Guskey, “The case against percentage grades,” *Educational Leadership*, *71*(1), 68–72, 2013.

[17] J. Cain, M. S. Medina, F. Romanelli, and A. M. Persky, "Deficiencies of Traditional Grading Systems and Recommendations for the Future," *American Journal of Pharmaceutical Education,* vol. 86, no. 7, Oct. 2022, https://doi.org/10.5688/ajpe8850.

[18] J. Schneider, and E. Hutt, "Making the grade: a history of the A–F marking scheme," *Journal of Curriculum Studies*, 2014. 46(2), 201-224.

[19] L., Shakhman, and M. Barak, "The Physics Problem-Solving Taxonomy (PPST): Development and Application for Evaluating Student Learning," *Eurasia Journal of Mathematics, Science and Technology Education, 15*(11), em1764, 2019. https://doi.org/10.29333/ejmste/109266

[20] J. W. Creswell, Qualitative Inquiry and Research Design: Choosing Among Five Approaches, 2nd ed. Thousand Oaks, CA, USA: Sage Publications, 1998.

[21] Z. U. Abideen, "Cognitive Dynamics in Undergraduate Engineering Education: Effects of Need for Cognitive Closure and Achievement Goal Orientation on Cognitive Engagement," *Utah State University, Utah State Research and Scholarship*, 2025. doi: 10.26076/52e3-0b05.

[22] D. Barrett and A. Younas, "Induction, deduction and abduction," *Evid. Based Nurs.*, vol. 27, no. 1, pp. 4–5, Jan. 2024, doi: 10.1136/ebnurs-2023-103859.

[23] M. S. Sabella and E. F. Redish, "Knowledge organization and activation in physics problem solving," *American Journal of Physics*, vol. 75, no. 11, pp. 1017–1029, Nov. 2007, doi: 10.1119/1.2746359.

[24] R. R. Skemp, "The need for a schematic learning theory," *British Journal of Educational Psychology*, vol. 32, no. P2, pp. 133–142, 1962.

[25] D. Gentner, "Psychology of mental models," in *International Encyclopedia of the Social and Behavioral Sciences*, N. J. Smelser and P. B. Bates, Eds. Amsterdam, The Netherlands: Elsevier Science, 2002, pp. 9683–9687.

[26] D. Gentner and D. R. Gentner, "Flowing waters or teeming crowds: Mental models of electricity," in *Mental Models*, D. Gentner and A. L. Stevens, Eds. Hillsdale, NJ: Lawrence Erlbaum Associates, 1983, pp. 99–129.

[27] M. S. Sabella, "Using the context of physics problem solving to evaluate the coherence of student knowledge," *Ph.D. dissertation, Dept. Phys.,* Univ. Maryland, College Park, MD, 1999.

[28] A. Berger and S. Stewart, "Schema development in an introductory topology proof," in *Proc. 23rd Annu. Conf. Res. Undergraduate Math. Educ.,* S. S. Karunakaran, Z. Reed, and A. Higgins, Eds. Boston, MA, Feb. 27–29, 2020.

[29] R. Himel, O. Lawanto, Y. Brijmohan, W. Goodridge, Z. Abideen, F. Zinnah, S. Jabeen, (in press). "Exploring the Impact of Contextual Framing and Construct-Level Complexity on Engineering Problem-Solving Performance: A Study on Electrical Circuit Course" 2026 ASEE Annual Conference & Exposition, Charlotte, North Carolina, June 21 - 24, 2026