Uncovering the Hidden Layers of Thinking: Extended Computational Thinking (CT) Strategies in Problem-Based Classrooms Learning

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Abstract—**This study explores how broadened computational thinking (CT) models can support and enhance students' approaches to problem solving within problem-based learning (PBL) settings. To evaluate the proposed model, the researchers introduced a structured framework that included clear metacognitive prompts, guidance for collaborative work, and support for iterative design. This framework was implemented with 70 undergraduate engineering students participating in a six-week PBL cycle. Evidence gathered over three semesters showed notable gains in students' CT performance, more balanced group participation, reduced unnecessary task switching, and smoother workflow patterns. Regression findings indicated that equitable involvement, idea generation, and overall PBL process efficiency were strong predictors of growth in CT scores. Students' use of plan-monitor-evaluate (PME) strategies further suggested deeper metacognitive activity. Overall, the results show that extended CT scaffolding enables PBL groups to produce stronger and more numerous outcomes, while also refining the reasoning and teamwork practices required to achieve them. These insights can help educators design PBL environments that foster more effective thinking and reinforce students' understanding of the value of their collaborative and reasoning processes.**

Keywords— **Innovative Pedagogies and Active Learning; Project-Based and Problem-Based Learning (PBL)**

I. INTRODUCTION

Integrating Computational Thinking (CT) into STEM instruction is reshaping the way students approach challenging problems, break them into workable parts, and refine their solutions through repeated improvement. Earlier influential studies identified CT as a core framework for supporting abstraction, decomposition, and the creation of algorithms within computing contexts (Wing, 2006; Grover & Pea, 2013). More recent studies indicate that CT also includes reasoning that develops from design projects, collaborative inquiries, and reflective decision-making activity (Weintrop et al., 2016). Problem-Based Learning (PBL) is set up in such a way that the breadth of CT can blossom. As a student participates in a problem-based environment, he/she must cooperate with his/her peers and come to a consensus about what the problem is, how best to proceed towards solving the problem, and how to modify their approach once their ideas have been confronted with new complexities. Although PBL has been shown to foster the development of higher-order thinking (Hmelo-Silver, 2004), much of the assessment in these environments still centers around evaluating the students' final products, which means that many elements of a student's thinking process, such as how they gauge their comprehension, interact with other students, adjust their techniques, etc. are less likely to be visible but have an important impact on a student's growth in CT. As learning analytics and process-tracing have developed, they have shown a growing importance in capturing not only the internal processes that take place within the student when solving problems but also the collaborative processes that occur when students work together. The studies identified by the authors above have demonstrated that the results of the students are not where The meaning of the Process and the Path taken to get to a particular end is just as important if not more important than the Final Product. These emerging findings indicate a critical need for a Framework that considers all three Components of CT - the Cognitive/Collaborative/ Metacognitive as one cohesive Whole, rather than three Isolated Pieces. The framework introduced by this research will further develop on this Theme and provide a clearer visual representation of Students' Reasoning and Coordination when working in a PBL Environment, by including Metacognitive

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Prompts and Scaffolded Collaboration as well as Iterative Design Support and Data collected through Multiple Sources/Methods within the Classroom Setting. The study will examine how students Plan for the completion of Problem-Based Learning Projects, Share Ideas or Work through a Task before reaching their Final Solution, Manage the Completion of the Assigned Tasks, and Refine their Solutions Before Submitting Them for Evaluation. Utilizing this model, the original research then attempts to address the following three main questions about how to utilize extended computational thinking strategies when working with undergraduate engineering students:

1. What impact does using extended computational thinking strategies have on how well students are able to solve problems and the overall nature of their problem-solving processes compared to traditional problem-based learning?
2. What types of connections exist between the degree of equity within groups of students working together on collaborative projects, their degree of engagement in metacognitive activity during problem-solving, and the amount of improvement students demonstrate in their computational thinking abilities?
3. To what extent can the examination of student work products provide reliable measures for predicting improvements in students' computational thinking skills and competencies?

The model incorporates a range of methods, including quantitative measures, the analysis of qualitative data, and the process of tracing how students approach solving problems, to provide a more complete perspective on the development of computational thinking skills in a problem-based learning environment. The results of this research will serve as valuable resources for educators, curriculum designers, and education research scholars in creating learning environments that promote both the visible and invisible aspects of computational thinking.

II. LITERATURE REVIEW

Research on project-based and problem-based learning (PBL) has shown that both types of learning positively impact students' ability to develop Computational Thinking (CT). Meta-analyses of these studies suggest that projects and problems can help increase students' abilities to decompose problems, create algorithmic reasoning, and develop higher-order cognitive skills in many STEM settings, provided that the students are engaged in real-world open-ended tasks (Zhang et al., 2024; Zhang et al., 2023). The studies demonstrate that students' growth in CT is typically the most significant when they are required to articulate their reasoning and make iterative design choices rather than simply focus on producing a correct final product. In addition to contributing to the literature regarding CT development, there has been an increased interest in understanding how CT develops over time. Researchers have begun to explore how students use CT to solve problems not just at the end of the problem-solving process, but throughout the entire problem-solving process. Empirical studies that utilize process tracing and multimodal learning have provided insights into how students use CT when they plan, explore, revise, and evaluate their work using different strategies (Pan et al., 2023; Hartmann et al., 2022). These studies provide detailed information about how students transition between using various CT practices such as abstraction, debugging, and iterative refinement. The present study also builds on the findings from the empirical studies mentioned above and uses workflow and interaction data to examine how students engage in CT behaviors. Research about collaboration has brought us a new way to view CT development in tandem with PBL through LLAs for CLAs. Several new studies of CLA have identified patterns in which collaboration impacts group performance and the ability for students to engage in deeper reasoning (Catasus et al., 2025; Esterhazy et al., 2025). Additionally, there has been evidence that by sharing their knowledge and resources with one another, students will create a much higher level of CT (Yang, Yuan & Chen, 2024; Yang, Yuan, Zhu & Jiao, 2024). Through metacognitive development, collaboration and CT are related through the processes of monitoring, evaluating, and regulating the behaviours associated with managing complex problem solving, diagnosing errors in one's thinking, and amending strategies when necessary (Gamby, Kersaint & Waters, 2022; Halmo, Eddy & Brownell, 2024). Given that in PBL situations students must work repeatedly with uncertainty and iterating solutions, developing metacognitive abilities is critical to supporting learning through productive strategic progress and preventing unproductive trial-and-error cycles. From this collection of studies, it is evident that CT within Authentic Learning comes from a combination of several types of activity, including Cognitive Problem Solving, Collaborative Coordination, and Metacognitive Regulation. While there has been much investigation into each of these areas separately, there has been less focus on how they may interact to create an integrated framework that better reflects the “Hidden Layers” of Student Thinking. The growing ease with which we can gather Multimodal Data through Digital Technology means that there is now the potential for very Created Approaches to be considered, although some of these approaches may prove difficult or impossible to implement in Classrooms. At the same time, there are many practical challenges associated with the use of a Multimodal Process-Oriented Approach, including the challenge of managing and analyzing large datasets, the need for Instructor/Teacher training, and the need for Protective Measures for Individuals' Personal Data. The limitations posed by these obstacles demonstrate the necessity for frameworks that effectively balance the said limitations on the one hand and provide Teachers/Teaching Assistants with information and advice concerning how to observe and help their students develop CT, without the need for instructors to be able to provide expert understanding of all technical aspects of the framework. In light of this context, this Research Study, which demonstrates how to apply developed CT Framework, is based on existing research literature and will address the need for Additional Integrated Classroom Ready Methods of Exploring Students' Problem Solving Processes through a Combination of

Cognitive, Collaborative, Metacognitive and Process Level Indicators.

III. Methodology

The Proposed methodology of Problem based Learning includes several steps. This section starts with the overview of the Framework.

A. Research Framework Overview

The research presented here employs an extended version of the Computational Thinking (CT) framework within the scope of a Problem-based Learning (PBL) environment. The purpose of this extended framework is to highlight all areas of the CT process that are generally neglected using conventional CT assessments, including how cognitive, collaborative, metacognitive and workflow-related elements are utilized throughout the process of solving problems.

While most CT assessments place a significant emphasis on evaluating the final product, this framework also emphasizes the importance of understanding the processes behind the final product and documenting how students organize and develop their CT skills. The cyclical nature of the PBL-based process shows that after you create a PBL task, collect multiple forms of data, analyze the use of CT skills during the process of solving a problem, provide students with feedback, and finally provide students with the opportunity to reassess and re-engage with the process of solving the problem.

B. Experimental Design

1) Participants and Setting

The research participants were 70 undergraduate engineering students from a 3rd-year Interdisciplinary Engineering course, who worked in teams of 4-5 over a 6-week project cycle. This course included programming, electronics and applied system design elements within an authentic environment for the development of critical thinking skills (CT).

To clarify the conditions of this research study, the engineering problems addressed within the classrooms were very similar to those described here. As part of the course, each team was given two open-ended engineering design challenges which required them to combine hardware and software components. Such challenges included:

1. Building an environmental sensing system that included live-data processing;
2. Designing a control algorithm for a simulated robotic system; and
3. Using MATLAB/Simulink to develop the optimal configuration of a power management system.

All three tasks included a process to break them down into smaller and more manageable sections, to conduct iterative testing, to identify any faulty assumptions and continually communicate and collaborate with each other. Each team was provided with a physical and digital workspace in which to conduct their collaborative activities and document their interactions.

2) Learning Environment Setup

To enable collaborative planning and iterative refinement of their projects, the course utilized Microsoft Teams for group discussions, planning and process documentation alongside Miro boards for sharing information and documents. There are several software programs that can be used for project modelling and implementation, namely MATLAB/Simulink and Python. The course used Event log systems and audio/video recordings to record the time-stamped actions and comments made by students while working on projects collaboratively as a team. Process mining software has been used to recreate the processes that students followed to complete their projects based on the digital evidence available to the course. The tools were valuable in providing an accurate overview of how students moved between different tasks, developed their project ideas and worked collaboratively with peers in their groups. While digital tools were used to capture project-related data, the framework has been developed to provide approximations of the previously mentioned indicators based upon classroom observation, thus making the framework suitable for implementation in environments where the use of digital technology is limited.

C. Data Sources and Collection Methods

Several complementary forms of data were gathered for this study, including:

1. Student work samples such as code files, design diagrams, written reports, and project planning materials.
2. System event logs documenting when students carried out actions in the shared development workspace.
3. Interaction records consisting of transcripts of group conversations and chat exchanges.
4. Measures of collaboration, including counts of individual contributions, speaking turns, and chat messages.
5. Metacognitive prompts intended to guide planning and self-monitoring at designated points during the project.

Bringing these sources together made it possible to examine students' CT practices from both Outcome and Process perspectives and to gain a detailed view of how these practices shifted as teams moved through the different phases of a CT-focused project.

D. Extended CT Strategy Operationalization

To make the internal and collaborative dimensions of Computational Thinking more visible, several teaching approaches were incorporated into the course, including:

1. Layered Abstraction - distinguishing core conceptual structures from the specific implementation steps.
2. Detailed Decomposition - dividing the overall task into clear, workable subtasks.
3. Algorithmic Refinement - continually improving the efficiency/accuracy of a solution through iteration.
4. Iterative Evaluation - testing, validating and revising after each stage of development.

Incorporated as part of the course design process through supportive prompts and checkpoints, these strategies were intended to support, rather than disrupt, the flow of projects.

E. Analytical Methods

1) Quantitative Metrics

Four indicators were used to examine collaboration and workflow:

i. Participation Equity Index (PEI):
Measures how evenly team members contributed.

$$\text{PEI} = 1 - \frac{\sum_{i=1}^{n} | p_i - \bar{p} |}{2\bar{p}n}$$

where p_i represents individual participation shares.

ii. Task Transition Rate (TTR):
Frequency of task switching relative to total collaboration time.

$$\text{TTR} = \frac{\text{Number of Task Changes}}{\text{Collaboration Hours}}$$

iii. Idea Contribution Ratio (ICR):
Proportion of unique idea contributions within total interactions.

$$\text{ICR} = \frac{\text{Unique Ideas}}{\text{Total Interactions}}$$

iv. Process Efficiency (E):
Ratio of value-adding actions to total observed actions.

$$E = \frac{\text{Value-Adding Actions}}{\text{Total Actions}}$$

How to use this in class: Although formulae were used in the analysis, teachers could also estimate these indicators without having access to these types of sophisticated tools. Some examples of how a teacher might estimate these indicators are:

1. The number of times a student takes a speaking turn or does form work can be used as indicators of their level of participation.
2. When teams switch from one task to another or start over on a task, those occurrences can be counted as an estimate of team production time (Time to Rework).
3. Counting the number of unique ideas generated can be used for assessing team creativity (Idea Creation Rate).
4. Process efficiency can be estimated by counting the number of times a team needs to repeat, throw away or modify a step.
5. As a result, this framework is flexible enough to be applicable in classrooms where access to analytics software is limited.

2) Qualitative Analysis

To code the metacognitive statements, the researchers assigned them to preestablished categories based on the rules for using metacognitive code. Collaborative talk was analyzed using discourse analysis to determine the patterns of idea generation, justification, and negotiation.

F. Validation and Reliability

Qualitative data were double coded by two professional coders; the level of agreement between the coders for the qualitative data was significant (Cohen's κ = .84). The process mining model was validated by comparing it to historical data from previous courses; therefore, the workflow interpretation is deemed reliable.

G. Ethical Considerations

Consent was obtained from all participants for audio/video recording and the storage of logs. Identifying information was removed from the data before conducting analyses, and data were stored securely in encrypted systems. Collaboration metrics were utilized exclusively to provide instructional insight, and secondarily to offer an overall assessment of student performance.

H. Methodology Diagram

A simplified diagram serves as a conceptual model of how the extended CT Framework combines PBL task design, multimodal trace collection, CT indicator identification, and feedback.

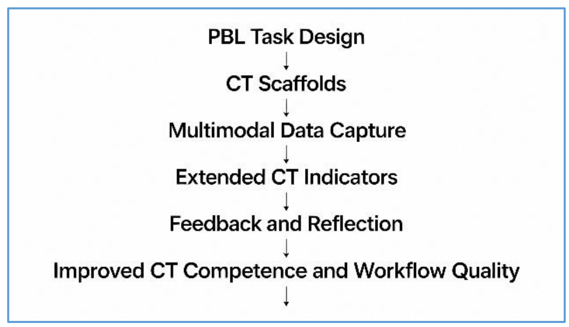

Fig. 1. Overview of Proposed Methodology

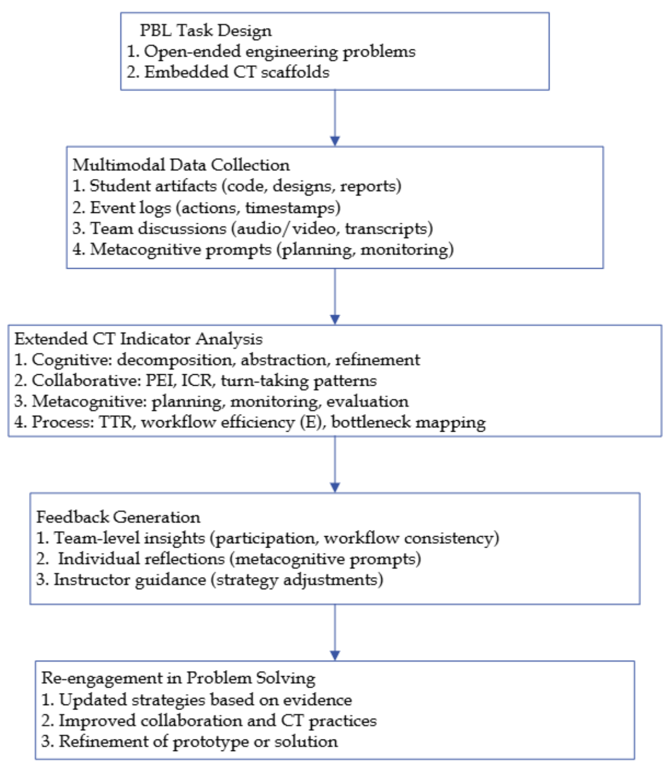

Fig. 2 Detailed Steps of the Proposed Methodology of Problem Based Learning

Table I presents the mapping between CT indicators and data sources, and Table II links learning outcomes to evaluation metrics.

TABLE I
MAPPING OF EXTENDED CT INDICATORS TO DATA SOURCES

Indicator	DESCRIPTION	Primary Data Sources
Participation Equity Index (PEI)	Degree to which contributions are distributed evenly within a team	Event logs, chat transcripts, speaking-turn counts
Task Transition Rate (TTR)	Frequency of switching between tasks relative to collaboration time	Collaboration timelines, workflow logs
Idea Contribution Ratio (ICR)	Proportion of unique ideas within total interactions	Discussion transcripts, chat messages
Process Efficiency (E)	Ratio of value-adding actions to total observed actions	Process mining outputs, action logs

TABLE II
MAPPING OF LEARNING OUTCOMES TO EVALUATION METRICS

Learning Outcome	ASSOCIATED METRIC(S)	Analysis Type
Problem Decomposition	Depth and clarity of task breakdown	Qualitative coding
Collaboration Quality	PEI, ICR	Quantitative indicators
Metacognitive Engagement	Frequency of planning, monitoring, and evaluation statements	Qualitative coding
Process Optimization	Process Efficiency (E), Task Transition Rate (TTR)	Quantitative workflow analysis

The process depicted in the Figure 1 is a repeated set of multiple steps-Cyclical, that illustrate how students engage in the critical thinking behaviors of problem-solving, collaborating with peers on engineering tasks, and honing their final solutions while learning. An open-ended engineering task was designed to include several engineering prompts that were strategically spread out to promote Computational Thinking (CT) behaviours. To encourage this behaviour, each open-ended engineering task is designed to be sufficiently vague to require students to dissect, plan, and justify their approach/decisions/actions; this requires the use of CT in everyday problem-solving situations. During the period when students are actively solving an engineering problem, data are gathered from several different sources regarding their problem-solving activity, including materials produced - code, design sketches, etc., analysis of digital evidence generated from collaboration tools, video/audio documentation of students during team meetings, and questions related to the students' initial planning and monitoring throughout the process. All of these sources together will provide a complete picture of the process students went through in order to create a product, as well as the process used to create it. During the subsequent phase of analysis, data will be analyzed via four (4) types of CT Indicators: Cognitive Indicators reflect student development of problem decomposition and idea refinement; Collaborative Indicators illustrate the extent to which team members equally participate and utilize strategies for sharing ideas with others; Metacognitive Indicators describe the extent to which students are planning/cognitive-checking their progress throughout the task process and subsequently evaluating their effectiveness; and Process Indicators compare various team task switches or breakdowns. The combination of these CT Indicators provides insight into students' thought processes, team interaction, and interaction with processes utilized during the completion of the science process. Once the CT Indicators have been identified and analysed, the instructor will provide both group-level feedback regarding the participation pattern and workflow habit of each group and individual-level feedback in terms of encouraging an increased level of reflective thought about their planning (cognitive-checking) and monitoring of their strategy as a result of their use of the CT Indicators. In closing, we saw how, after gathering their group's feedback, student groups typically use that information to revisit their projects and create new plans for working together, optimizing the contribution of each member's ideas, and gaining better understanding of how to think computationally. Moving forward, as student groups work to complete a project, they will take advantage of the lessons they acquired through the interactions of their peers, thereby increasing the overall quality of their solutions (i.e., what they built) and how they think about the way in which they execute their project goals.

IV. RESULTS

The research included 70 undergraduate students assigned to 14 groups over a six-week duration during which the students learned through a PBL approach enhanced by CT Scaffolding. The students completed open-ended data-driven algorithmic modeling challenges such as building Decision Modelling (DM) models, creating a basic simulation and executing multi-step algorithms. Students were required to go through repeated cycles of contingent decision-making, collaborative critical thinking and modifying solutions, supporting the study's aim in exploring CT growth, collaborative patterns of behavior and students' engagement in developing metacognitive strategies. Students improved according to multiple forms of data (CT assessments, collaboration logs, workflow efficiency logs, and reflective writing). Below is a brief summary of each data source's changes in CT performance, collaboration quality, workflow efficiency, and metacognitive activity, with comparisons to other performance levels.

A. Computational Thinking Development

1) Statistically Significant Results

CT proficiency of students grew significantly through the use of the intervention. Prior to the intervention
Pre-Intervention Mean: $M = 61.3$ $SD = 8.4$
Post-Intervention Mean: $M = 78.9$, $SD = 7.6$
The resulting t-test from the paired samples was found to be a statistically significant difference $t\ (67) = 14.21$, $p < .001$, $d = 1.21$, indicating a high level of effect size and substantial learning growth.

B. Collaboration Measures

To provide educators with further clarity about each of the analytic measures. Each Measure is presented in a conceptual way that is usable and understandable for the purpose of Educators.

1) Participation Equity Index (PEI)

Through the PEI, we can see how equally members of a team are participating in conversation and tasks (1.0 = Perfectly Equal participation from every member).

i. On Pre-Intervention: PEI = 0.68
ii. On Post-Intervention: PEI = 0.84
iii. Change: $\Delta = +0.16$
iv. $t(13)=4.27$
v. $p < .001$

The increase of this PEI means that the scaffolding method used in CT processes (e.g., Structuring Roles, Explicit Planning) aided in reducing disparities of team member participation, and encouraged a much higher level of equitable participation among members of the team.

2) Task Transition Rate (TTR)

The TTR measurement depicts the average number of times a team switched from one task to another during the time they were working together. A lower number indicates that members of the team were focusing on the same single task for a longer period of time.

On Pre-intervention the TTR was reported at 1.87 transitions/hr. On Post-intervention, it was reported at 1.23 transitions/hr.

The data indicates that students are engaged in a more stable manner, working together more clearly, and setting a clearer direction as to where to take the group effort.

3) Idea Contribution Ratio (ICR)

The ICR is calculated as the number of new unique ideas relative to all interactions (i.e., new concepts added through the discussion), and therefore it should not be confused with the proportion of repeated or confirmed ideas.

Overall, teams after CT scaffolding produced a greater density of unique ideas (0.47), which means that they were able to engage each other in more rich and engaging conversations, which in turn resulted in a stronger collaborative process.

C. Process Efficiency

This measure of process efficiency can be calculated as follows:

$$E = \frac{\text{Value-Adding Actions}}{\text{Total Actions}}$$

Prior to intervention, E = 0.54

After intervention, E = 0.71

The improvement of 31% between the two conditions indicates that team workflows were streamlined and included fewer actions that reflected confusion, redundancy, and instead included actions that contributed to constructive problem solving. Practitioners who wish to determine a similar efficiency metric can perform the same type of observation described above: coding of task-relevant vs. non-task-relevant actions without analytical tools.

D. Metacognitive Engagement

The qualitative coding of the reflective analyses of students' thoughts showed an increase across the three metacognitive dimensions, including:

i. Planning statements (43% increase)
ii. Monitoring statements (38% increase)
iii. Evaluation statements (29% increase)

The inter-rater agreement between researchers coding the data was very good ($\kappa = 0.84$; ICC = 0.88).

Examples of representative excerpts illustrating these changes include:

Planning - "To avoid redoing all of our work later, we should create a map to track all of our major decision points before we begin coding."

Monitoring - "We need to verify that our algorithm continues to handle all of the edge cases after making this change."

Evaluation - "Our model functions, but it is taking longer than we would like; can we streamline the decision tree and speed it up?"

CT scaffolds encourage students to demonstrate more sophisticated self-regulated and strategic abilities at every stage of the project.

E. Regression Analysis: Predicting CT Gains

To investigate how collaboration &process indicators relate to CT development (or improvements) a multiple regression was conducted:

$$CT_{\text{gain}} = \beta_0 + \beta_1(\text{PEI}) + \beta_2(\text{ICR}) + \beta_3(E) + \epsilon$$

Regression results of predictors were statistically significant:

i. Participation equity ($\beta_1 = 5.21$, $p = .002$)
ii. Idea contribution ratio ($\beta_2 = 3.87$, $p = .011$)
iii. Process efficiency ($\beta_3 = 4.45$, $p = .006$)

The model accounted for 68% of the variance. ($R^2 = 0.68$) indicates that when combining these three factors together they are strong contributors to developing (or improvement) of CT.

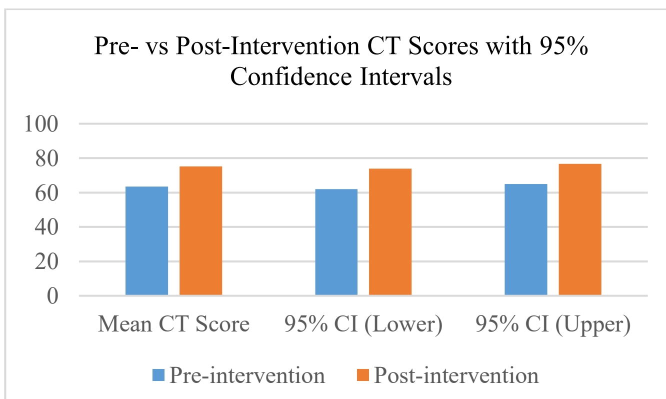

Fig. 1. Pre/post CT scores with 95% CI bands

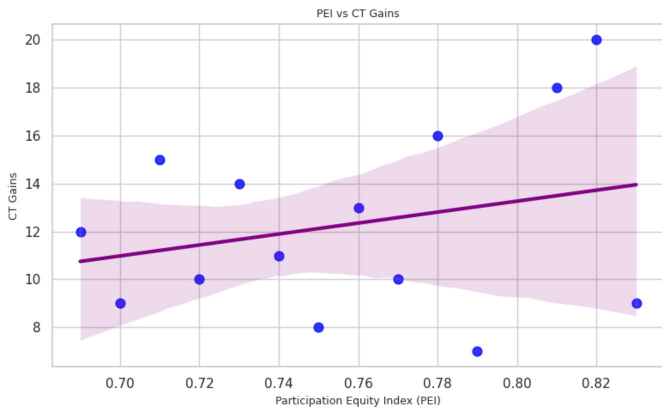

Fig. 2. PEI vs. CT gains (scatterplot with regression line)

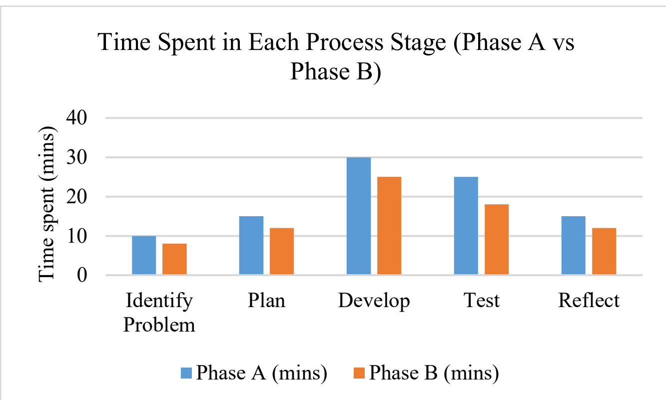

Fig. 3. Process-mining overlays showing bottleneck reduction

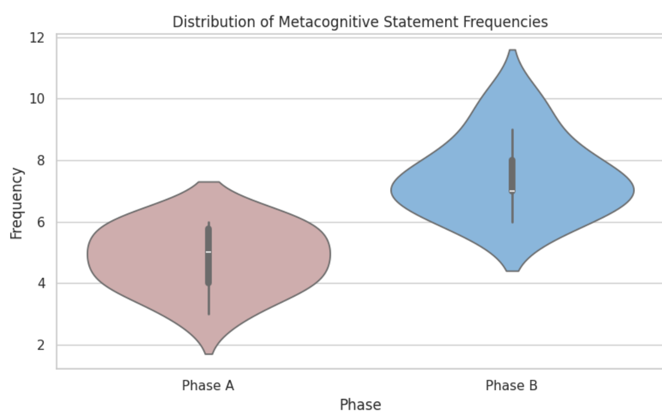

Fig. 4. Violin plots of metacognitive statement distributions

F. Team-Level Differences in Performance

To compare how improvement differed between teams based on how well they performed at the time of intervention as measured by CT scores, the teams were divided into three groups - high, medium, and low.

1) Benefits from Using CT Grains

High-performing Teams: There were moderate benefits from using CT (made "moderate" improvements between 4-12 points with a overall of about 12 points) therefore these teams would benefit from refining these CT practices over time, but were likely working on CT to keep building their foundational CT hisory.

Medium-performing Teams: There were the greatest benefits from using CT to develop ideas with a total of 20 points average increase on CT scores meaning these teams responded really well to scaffolded activities and collaboration building CT.

Low-performing Teams: Team gained a total of 13 points because of improvements in their structure and strategies to support collaboration among their team members.

2) Collaborative Indicators

PEI: All teams showed improvement on their PEI scores and low-performing teams showed the highest percentage of improvement on PEI therefore the scaffolding helped to balance out the team members and minimize the imbalance of participation.

ICR: Medium-performing teams showed the highest improvement in idea generation.

Efficiency(E): All teams showed improvements on their efficiency scores although high-performing teams started out with a slightly higher baseline.

The major findings from this analysis indicate that all teams will experience improvements in CT through scaffolding, developing much more significant improvements for mid-range performing teams and more balance in collaboration for the low-performing teams.

G. Interpretation

The combined outcomes demonstrate that including PBL elements in conjunction with Extended CT have produced considerable benefits in the areas of technology, teamwork & collaboration as well as on the metacognitive level. These combined outcomes displayed a large effect size indicating a large impact in terms of increased equity of participation; increased number of ideas generated; and improved processes/operations within the classroom. In addition to improvements in collaboration, even greater than those achieved using PBL, collaboration was found to be a powerful predictor of increased CT score improvements. This outcome highlights that organized group routines play an essential role in learning environments that rely heavily on computational work. Since the study was carried out at a single institution and relied on digital log data to capture collaborative activity, the results should be applied cautiously to settings that lack comparable technological systems or instructor preparation. Table III summarizes students' views prior to starting the case study. The responses indicate that most participants felt prepared for both the technical and teamwork demands of the project, although a smaller portion reported uncertainty about planning, using the required tools, and making sense of complex information. In general, the table shows varied but mostly positive levels of initial confidence.

H. Limitations

The work has several constraints that should be recognised. Since it draws on data from a single institution, the findings may not translate neatly to programmes with different resources or teaching practices. Much of the analysis also depends on digital records of student activity, meaning that settings without similar tools may find it difficult to apply the same approach.

In addition, the framework relies on instructors being comfortable interpreting workflow patterns and collaboration evidence, which may require more training than is typically available.

TABLE III
PRE-CASE STUDY QUESTIONS

Pre-Case Study Question	5	4	3	2	1
I feel ready to break large, open-ended engineering problems into smaller tasks.	1	5	11	24	59
I am comfortable using abstraction to make complex design work easier to handle.	3	5	10	27	55
I can recognise the different roles each person might take on in group work.	2	6	8	24	60
I expect to take part actively and offer ideas during team discussions.	3	5	9	25	58
I feel sure of my ability to read and understand technical materials like schematics and code.	2	7	13	22	56
I am able to map out the early stages of a project before we begin building or testing.	3	7	17	26	47
I believe I can keep track of my own progress during multi-step engineering tasks.	3	5	13	21	58
I can describe the thinking behind the choices I make in my engineering work.	1	9	15	26	49
I know how to use tools such as Teams or Miro to help plan with my group.	3	8	17	27	45
I am confident that my team will work well together throughout the project.	3	7	14	23	53

Table IV shows the responses gathered after the case study. Overall, the scores are higher on almost every point. Students noted that they had become better at separating complex tasks into smaller parts, improving their ideas through repeated adjustments, and maintaining focus during team work. The results indicate that the project supported growth in both their technical decision-making and their capacity to collaborate effectively with others.

TABLE IV
POST-CASE STUDY QUESTIONS

Post-Case Study Question	5	4	3	2	1
I am now better at breaking down engineering problems into clear parts.	60	23	9	5	3
I strengthened my skill in improving algorithms or design ideas through repeated revisions.	58	25	10	4	3
I shared ideas more often and in a more useful way than I did previously.	57	26	11	3	3
Our team worked together more evenly throughout the project.	59	24	10	4	3
I was able to stay on task with fewer unnecessary shifts between activities.	56	27	10	5	2
I improved at recognising when a method needed to be changed.	61	22	10	4	3
I kept track of my own progress more deliberately during the project.	58	25	9	5	3
I became more confident using tools like MATLAB, Simulink, Python, and Miro.	57	24	12	4	3
I can describe how our workflow developed from the beginning to the end.	55	28	10	4	3
I can carry the abilities gained from this project into future engineering work.	59	23	11	4	3

Table V outlines students' comments on their experience with the case study. Many noted that the overall setup, guidance, and support built into the tasks were useful. They also reported that the digital platforms helped them organize their group activities. The responses show that students felt the setting encouraged balanced involvement, careful handling of shared project information, and steady improvement in working through engineering challenges together.

TABLE V
FEEDBACK QUESTIONNAIRE

Feedback Question	5	4	3	2	1
The case study guidelines made the steps of the PBL process clear.	58	24	11	4	3
The CT approaches—abstraction, decomposition, and iteration—helped me learn.	57	26	10	4	3
Platform like Teams helped us manage our group work well.	56	27	10	5	2
The open-ended format pushed me to think more deeply and be more creative.	59	24	9	5	3
The feedback I received showed me how to strengthen my CT abilities.	58	23	12	4	3
The amount of time given for each phase of the work felt appropriate.	55	29	10	4	2

The CT measures (PEI, TTR, ICR, Efficiency) represented our workflow well.	60	23	9	5	3
The setting supported fair involvement from everyone on the team.	57	25	11	4	3
The digital records collected during the project were handled responsibly.	56	26	10	5	3
The case study helped me improve how I approach engineering problems with others.	58	25	9	5	3

Conclusion

The results of this research indicate that the use of a broader scaffolding of CT extended over an entire semester has a positive effect on student learning in PBL contexts. Substantial gains were evident in CT skills for participants, collaboration was more evenly distributed and the rate of ideas generated increased significantly. Students' metacognitive reflections demonstrated improvement in planning, monitoring and evaluating the concepts of their groups through collaboration on PBL projects. The study indicates that collaboration quality and strategic regulation support the development of CT in addition to a student's cognitive abilities. The research was conducted within a single institution; however, the majority of the indicators could have been assessed through classroom observation, allowing for more flexibility in application of the framework. The extended CT framework provides educators with an excellent way for capturing hidden reasoning processes of students, which facilitates higher-level strategies in solving complex problems. Future research should focus on broader uses of the framework and future technological automation of the key analytic components of the framework.

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