Creating Mini-Research Spaces in Problem Based Learning Curriculum using Abstraction

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***Abstract*—When Problem-Based Learning and Computational Thinking are integrated as a teaching-learning pedagogy; they provide a comprehensive platform for both teachers and students, enhancing approaches to teaching and learning respectively. Abstraction being one of the aspects of computational thinking, can help computer science engineers to model a system design problem with social context and provide a mini-research space for further exploration. This study proposes a research question to explore on the lines of how computational thinking's abstraction can impact students' ability to solve research-based problems in PBL scenarios. And also, how can it guide to build effective models. Abstraction is used a research intervention in the process. With Conceptual Change theory as a conceptual framework, this work compares the influence of abstraction on modeling problems in research space. Multi method is used as a research methodology for the study and self-selection is used as a sampling technique from the students who took a modeling course jointly offered by an industry Knit Space and KLE Technological University. Scenarios from arts and culture play a major impact in designing such problem scenarios. Library of Babel and Guernica were given as modeling problems which also have the social context and historical connection aspects. 50 student answer sheets were evaluated qualitatively and quantitatively for the study analysis. With appropriate descriptive measures, statistical methods like paired t-tests, student feedbacks, in-vivo coding and process coding, the collected data was analyzed for results and discussion. Along with statistical measures, this study discusses the themes generated from the study with an emphasis on research in curriculum design. The results positively align towards the conclusion that abstraction trigger points can aid in building research-based models.**

***Keywords*—abstraction; computational thinking; curriculum; problem-based learning; research space.**

ICTIEE Track: Curriculum Development

ICTIEE Sub-Track: Incorporating Research Opportunities into the Curriculum to Encourage Student Engagement in Research

I. INTRODUCTION

CURRICULUM development is a process of designing and realizing an educational framework that is empirically grounded and also that is pedagogically validated (Schneiderhan et al., 2019). A good curriculum must integrate theoretical insights, best practices, research-based syllabus, practical data and encourage the achievement of learning outcomes effectively. Curriculum also needs continuous improvement to ensure it is relevant and effective for the contemporary learning environment. The course faculty constantly checks if the designed curriculum meets the state-of-the-art needs (Soto, 2015). There has been constant research in the space of curriculum development to incorporate learning theories, psychology behind learning, pedagogical approaches, assessment practices and curriculum evaluation.

While the curriculum was mostly about learning, today, even for an undergraduate program, there is a flavor of research that students are expected to know (Wang et al., 2021). It is required from the faculty end to create a program that is relevant, effective, and meets the needs of stae-of-art requirement. While students learn, it is also important how they learn so that they can become a lifelong learner which is a requirement for the professional world. Students must understand principles so that they can apply the knowledge to the long-term and real-world problems that they will be facing ahead. Research-based curriculum helps students to engage in evidence-based practices. Students are expected to be critical thinkers and problem solvers and have the ability to transfer knowledge. They must have the aptitude to generate new insights and build solutions. And all of this is possible if they are trained from a research perspective. This requires an appropriate pedagogy to be selected for the classroom delivery. One such pedagogy that supports this is Problem-Based Learning (PBL).

PBL, originally developed in the medical field (Barrows, 1998), has been adapted across many disciplines to meet specific educational needs. Its core principles help students develop critical thinking and tackle complex problems. Research has provided useful insights and frameworks (Hegade, 2019) for creating engaging and effective learning environments (Tan, 2021). PBL involves students in real-world scenarios, encouraging active problem-solving and making the learning experience more meaningful. It connects theoretical knowledge to those practical applications that help

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students see the relevance of what they learn. PBL also creates an interactive environment that prepares students for their future careers (Warnock & Mohammadi-Aragh, 2016). It has been integrated with Computational Thinking (CT) to improve problem-solving skills and structured reasoning, with abstraction playing a key role in CT.

Abstraction in CT simplifies complex scenarios by keeping only the necessary information (Lyon & Magana, 2020). This process in turn helps in decomposition and algorithms. From a research perspective, abstraction can help to focus on the key information and help in understanding the right theories. They provide insights and a pathway for the development of models. When theories and principles are understood, it enables the transfer of knowledge to other contexts. Not all problems clearly provide abstractions. The inherent complicated contexts might make it difficult to explore. In such cases, we need comprehensive approaches to understand and address the abstractions. Designing models can help in the process. Models are abstract representations of systems and processes. They simplify complex real-world scenarios, allowing for analysis, simulation, and problem-solving (Aho & Ullman, 1992).

This paper combines the components of abstraction as an approach for a model design to understand and enhance research in curriculum development. The paper further is organized as follows. Section 2 presents the literature survey. Section 3 presents the research question and research design along with the model. Section 4 presents the results and data analysis. Section 5 presents the discussion and section 6 concludes the paper.

II. Literature Survey

This section presents a survey of the literature along lines of curriculum development, research in curriculum, problem-based learning, computational thinking, abstraction, and modeling. Each sub-domain has been studied individually in various contexts, but there is a natural connection that ties them together. While some studies may not directly highlight this relationship, they all share a common emphasis on problem-solving. This shared focus highlights the importance of understanding how these areas intersect and contribute to practical learning approaches. The literature review concentrates mainly on the field of computer science, exploring how problem-solving is addressed and applied within this domain. It aims to uncover insights that demonstrate the interconnectedness of these areas and their relevance to engage in effective learning and skill development.

The evaluation of the curriculum development process has been thoroughly discussed (Hussain et al., 2011), and the functions of curriculum development have been deliberated upon (Michael Connelly, 1972). Theories and research related to curriculum have also been explored (Van Tassel-Baska, 2000). Curriculum serves as a blueprint for learning, ensuring that students gain the knowledge and skills necessary for future success. To achieve this, curriculums must offer meaningful learning experiences (Soto, 2015). Various curriculum development practices have been compared (Kelting-Gibson, 2005), and effective curriculum design involves integrating feedback from educators, students, and industry stakeholders, ensuring the curriculum remains current and relevant (Ornstein & Hunkins, 2017). Periodic evaluation of the curriculum is crucial for addressing the evolving needs of the education system and society (Posner, 2004). Furthermore, frameworks such as six-step approaches have been developed to guide curriculum design (Thomas et al., 2022). To meet the changing demands of the industry, it is essential for engineers to develop research skills, which enhance problem-solving and critical thinking abilities (Dewey, 1986).

Problem cases and scenarios play an important role in influencing how students learn and apply knowledge (Wood, 2012). Studies have shown that PBL environments significantly shape learning processes and outcomes, exploring what students learn and how they learn it (Hmelo-Silver, 2004; Yew & Goh, 2016). The foundations and benefits of PBL have been well-documented, with its application ranging from individual courses to entire institutions, showing positive impacts at every level (Baden & Major, 2004; Chen et al., 2021). Research has found that PBL encourages effective learning behaviors, such as critical thinking and problem-solving skills (Ghani et al., 2021; Nadeak & Naibaho, 2020). It has also been combined with other educational frameworks to enhance student outcomes and has been studied in relation to learning styles, particularly in developing cognitive abilities (Islamiat et al., 2024). In computing education, PBL has proven practical and beneficial, preparing students for real-world challenges (O'Grady, 2012).

When paired with CT, PBL becomes even more effective in equipping students with the skills they need. CT is a method of thinking that aids in the development of skills such as decomposition, abstraction, pattern recognition, and algorithmic thinking (Wing, 2006). CT mirrors human problem-solving processes (Lu & Fletcher, 2009), and its definition and acquisition have been explored from multiple perspectives (Selby & Woollard, 2013). As a valuable framework, CT has been shown to improve problem-solving abilities across various disciplines (Jonassen & Gram-Hansen, 2019). Abstraction, a core component of CT, has been discussed in terms of its development and its application to simplify complex problems (Cetin & Dubinsky, 2017; Qian & Choi, 2023). Research on abstraction in educational settings has focused on how it can help students better manage complexity (Jeong, 2016) and how it contributes to effective knowledge construction (Gautam et al., 2020). The integration of abstraction in the CT framework has been examined to enhance problem-solving and creative thinking (Hu, 2011).

The importance of modeling in computational thinking is emphasized throughout the literature, particularly in understanding algorithms and solving complex problems (Van, 1991). Modeling is integral to logical reasoning, decision-making, and the creation of effective solutions (Page, 2007). The process of modeling has also been explored in the context of computational systems (Sztipanovits & Karsai, 1997), and abstraction plays a critical role in simplifying models and facilitating problem-solving (Gregor et al., 2013).

PBL and components of CT have been researched from several perspectives. Abstraction and its influence in knowledge construction has been studied (Hegade et al., 2023). Effectiveness of CT and the usage of metaphors in it have been deliberated (Aryan et al., 2023). Effectiveness of reflections in PBL and CT while using abstraction has been researched and pondered over (Urankar et al., 2024). The study that attempts to understand the technological evolution in teaching, discusses on how a classroom is about enriching experience and creating a mini-research space has a significant contribution to it (Hegade et al., 2022).

This review presents the value of integrating PBL, CT, and abstraction in curriculum development. Combining these methodologies creates an environment that leans towards critical thinking and problem-solving skills which also channelizes towards research-driven learning.

III. Research Design

This section presents the research design along the research question, context, model, problem design, approach and other associated specifics.

A. Philosophical Assumptions

This study adopts pragmatism (Morgan, 2014) as its interpretive framework, which integrates quantitative and qualitative methods to explore practical issues. Pragmatism focuses on real-world relevance and flexibility in selecting methods that address the research problem effectively. The study's ontology views abstraction, curriculum development, and models as essential tools, with their effectiveness in PBL for research-based curricula being evaluated. A multi-method methodology is employed, combining qualitative and quantitative approaches. The study's axiology is informed by perspectives of both the researcher and participants, with knowledge constructed through an inductive approach.

B. Research Question

Exploration and research is evident when we provide abstractions. Using abstraction can guide towards research. The problem in the context is to design an effective problem-solving process using abstraction that enables research mind set in the students.

The research questions for the study are formulated as follows:

RQ: How do instructions using computational thinking’s abstraction influence research-based problem-solving PBL scenarios where students build models?

As we use multi method, we further break this into two questions with quantitative and qualitative focus.

RQ1: What patterns and trends emerge from the descriptive statistics on students’ problem-solving performance when abstraction is introduced in their PBL assignments?

RQ2: What insights do students provide about their experiences with using abstraction to model problems and its impact on their understanding and approach to problem-solving in PBL scenarios?

The study aims to explore with and without explicit usage of abstraction as an intervention point while students build models for problems that are abstract in nature. The nature of the problems selected requires research and deeper understanding.

As we have two case studies solved by same group of students, we formulate the hypothesis for the paired t-test as follows:

H_0: There is no significant difference between two groups

H_1: There is a significant difference between two groups

C. Context of the Study

The study involved students who had completed their second year of computer science engineering from KLE Technological University, Hubli. They participated in a summer audit course jointly offered by Knit Space and the university. The course spanned for 50 contact hours, divided between 25 hours of offline sessions and 25 hours of online self-learning assessments. It focused on model thinking for computer science graduates, using PBL as the primary teaching method, incorporating CT elements. The course included various graded activities and assignments, with abstraction playing a key role in the design of case studies and assessments.

D. Sampling Method

Ninety-six students were enrolled in the course. Out of these, fifty students agreed to be part of the study. Before starting the study, informed consent was obtained from these fifty students, ensuring they understood the study and agreed to participate. They were informed that their responses would be used solely for research purposes. A self-selection sampling method was employed to select the fifty students (Wainer, 2013). This involved inviting all students to participate, and those who were interested and agreed to be part of the study were included. This is a common method where individuals choose to participate in a study voluntarily. The written responses of all fifty students were analyzed to understand their thoughts and opinions. This analysis provided insights into the topic under study.

E. Conceptual Change Theory - Conceptual Framework

The study uses conceptual change theory as its conceptual framework. Conceptual Change Theory and abstraction are related in the learning process on how students restructure their understanding of concepts. Conceptual Change Theory is a framework that explains how learners revise or replace their existing understanding of a concept with new information or experiences that contradict their prior knowledge (Chi et al., 1994). It is relevant in situations where students have misconceptions that need to be addressed for deeper learning (Denis et al., 2015). The theory has the elements of preconceptions, cognitive conflicts, accommodation, assimilation, and beliefs (Liljedahl, 2011). Abstraction facilitates the process of conceptual change by helping learners refine and generalize essential aspects of new concepts. This allows for the transformation of their cognitive structures and deeper learning.

F. Study Model

The model used for the study is presented below in Figure 1. The syllabus is segregated to understand the concepts, principles, and applications. Usually, principles help to understand the concept better and they can be applied to other concepts as well within the same course or other. They help to design abstractions. Scenarios are designed to realize principles. Models are designed using these scenarios directly or they undergo abstraction and conflict change first. In both cases, research is a prominent part of the model design. Case studies are designed in such a way that students need to explore the area before they arrive at the models.

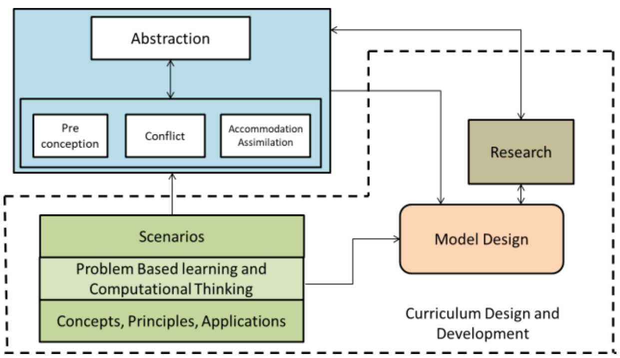

Fig. 1: Model for abstraction research using the conceptual change theory

Preconceptions are existing knowledge. Accommodation is to resolve the cognitive conflict and it involves rethinking and restructuring their understanding to incorporate the new information. Assimilation is when learners integrate new information into their existing cognitive framework without significantly altering their preconceptions.

G. Problem Design

Two problem scenarios (also interchangeably used as case studies) were designed to test the influence on models. The selected case studies were library of Babel and Painting Guernica where both of them have ample abstractions in them. Each of them was evaluated for ten marks.

Question 01: Go to the site 'Library of Babel' - https://libraryofbabel.info/ and explore. Design a model that represents this system. Write a short description of the platform, followed by its model and description of the model.

Question 02: Explore the painting Guernica by Pablo Picasso. What does it represent? Write its abstractions. There are many elements/metaphors in the painting that stand as an abstraction of life lessons. What else can the painting also indicate? Use this abstraction knowledge to model a system.

The first question asked the students to build the model for Library of Babel and second one explicitly stated to abstract the painting and then model it. Question 2 had several explicit trigger points. Both the problems have the same level of complexity and require the same amount of effort. Both the problems require research to set the context and arrive at principles.

The Library of Babel and Guernica, both do look like unrelated to computer science but they provide productive ground for exploring computational concepts. The Library of Babel, with its infinite permutations of text, can be a powerful tool for understanding randomness, algorithms, and data structures. Students can analyze how information is organized and retrieved within this infinite library, which can be mapped to real-world challenges in data science and information retrieval. For instance, they can develop algorithms to search for specific patterns or sequences within the text, or analyze the statistical properties of the text to gain insights into the nature of language and information. It has scope for ample research space.

Similarly, Guernica, with its fragmented and abstract imagery, can be used to study pattern recognition, image processing, and artificial intelligence. Students can analyze the painting's composition, identify patterns, and develop algorithms to reconstruct or analyze the image. They can experiment with different image processing techniques, such as filtering, segmentation, and feature extraction, to uncover hidden patterns and meaning within the painting. When we apply CT to these artistic and literary works, students can discover new research areas that bridge the gap between the humanities and computer science.

IV. Results and Data Analysis

This section presents the results and data analysis of the two modeling exercises that students carried with the underlying principles of decomposition and abstraction. The data analysis is presented in the sections of quantitative and qualitative.

A. Quantitative Analysis

The Table 1 below presents the descriptive statistics for the two case studies.

TABLE I
DESCRIPTIVE STATISTICS OF CASE STUDIES

Descriptive	Case study 1	Case study 2
N	50	50
Missing Values	0	0
Mean	6.70	7.57
Median	6.25	7.25
Standard Deviation	1.93	1.69
Variance	3.71	2.85
Minimum Value	3.50	4.50
Maximum Value	10.00	10.00
Skewness	0.0561	-0.106
Strd. Error Skewness	0.337	0.337
Kurtosis	-0.137	-1.11
Std. error kurtosis	0.662	0.662
Shapiro-Wilk W	0.921	0.938
Shapiro-Wilk p	0.003	0.012

Of the 50 data values present for each group, there were no missing values. Small standard deviation and variance from the above table indicate that the data points in a case study score are clustered closely around the mean. Smaller values mean that they are relatively similar to each other and there is a consistent pattern in the data. They are tightly grouped and specify high reliability or precision. The skewness values of the two datasets are 0.0561 and -0.106. For the first dataset, 0.0561 is close to zero, indicating a nearly symmetric distribution. The data points are evenly distributed around the mean, with a slight positive skew. This means there is a slightly longer tail on the right side of the distribution. For the second dataset, -0.106 is also close to zero but with a negative sign, indicating a slightly negative skew. The distribution has a slightly longer tail on the left side.

Kurtosis values of both are negative given by -0.137 and -1.11 and this indicates that both datasets are platykurtic. This means the distribution has thinner tails compared to a normal distribution and has fewer extreme outliers. -0.137 value suggests a slightly platykurtic distribution and -1.11 value indicates a more pronounced platykurtic distribution, meaning there are even fewer extreme values. For case study 1, The Shapiro Wilk W value is 0.921 which indicates a reasonably good fit to a normal distribution (Razali & Wah, 2011). But the p-value is 0.003, which is very low and hence we reject the null hypothesis. Therefore, despite the good fit indicated by the W value, we conclude that the data in case study 1 is not normally distributed. Similarly, for case study 2, W value is 0.938 and p is 0.012. The data in case study 2 is also not normally distributed. Since both case studies exhibit non-normal distributions, we use non-parametric statistical tests for analysis. These tests do not rely on the assumption of normality. The histogram with density for case study 1 data can be seen in Figure 2 below.

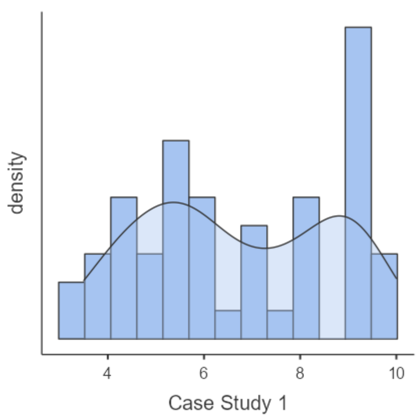

Fig 2: Histogram for case study 1

Histogram with density for case study 2 can be seen in Figure 3 below.

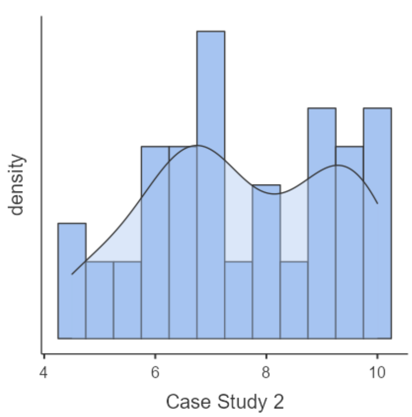

Fig 3: Histogram for case study 2

The histograms for Case Study and Case Study 2 illustrate clear differences in score distributions. Case Study 2 demonstrates a higher mean score (7.57 compared to 6.70 in Case Study 1), signifying improved performance when explicit abstraction trigger points were introduced.

The theoretical quantiles versus the standard residuals graph (Q-Q plot) for both case studies together can be seen in Figure 4 below. It helps to visually compare the quantiles of the observed data with the quantiles of the theoretical distribution. If the data points fall close to a straight line on the Q-Q plot, it suggests that the observed data follows the theoretical distribution. The Q-Q plot, combining residuals from both case studies, offers a comparative visual analysis of the data distributions. Deviations from normality, confirmed by the Shapiro-Wilk test results (p-values of 0.003 and 0.012 for Case Studies 1 and 2, respectively), substantiate the choice of non-parametric analysis.

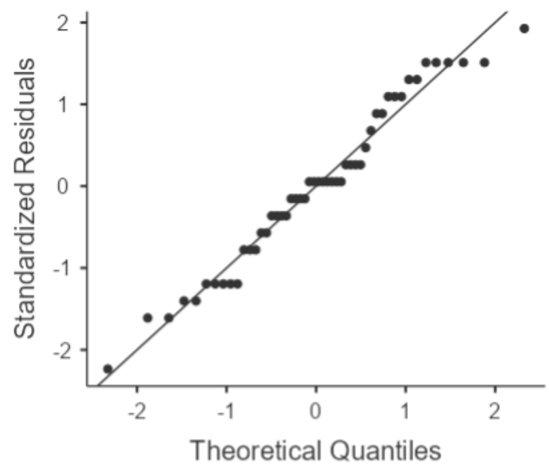

Fig 4: Q-Q plot for two case studies combined

A non-parametric Wilcoxon paired samples t-test was carried out on the data (Cuzick, 1985). The results are presented in Table 2 below.

TABLE II
WILCOXON TEST RESULTS

Attribute	Value
Statistic	331
P value	0.022
Tied pairs	4

W value of 331 is the test statistic calculated by the Wilcoxon signed-rank test. A higher W value generally suggests a larger difference between the paired samples. A positive W value generally suggests that the observations in one group tend to be larger than those in the other group. While the test provides information about the direction of the difference between the two related groups, its principal interpretation lies in the p-value. A p-value 0.022 is highly significant. The p-value of 0.002 is smaller than the common significance level of 0.05. This means that we reject the null hypothesis. Therefore, based on this test, we can conclude that there is a significant difference between the two related groups considered for the study even after having 4 tied common pairs (Refer to Hypothesis in Section III, B). Given a p-value of 0.022, which is less than the commonly used significance level of 0.05, we can reject the null hypothesis. The results suggest that the differences between the two samples are not likely to be due to chance. There is a meaningful difference between the two groups.

A feedback question was asked for both case studies measuring the model effectiveness on a five-point Likert scale (Joshi et al., 2015). For case study 1, the question was "You explored Library of Babel with a model perspective. How effective was it in terms of learning?" The result is presented in Figure 5 below.

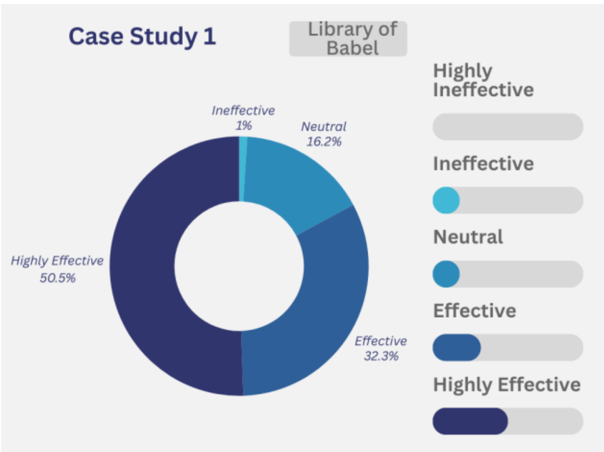

Fig 5: Feedback for Library of Babel case study

For case study 2, the question was "You explored Guernica with a model perspective. How effective was it in terms of learning?" The results of 50 students are presented in Figure 6 below.

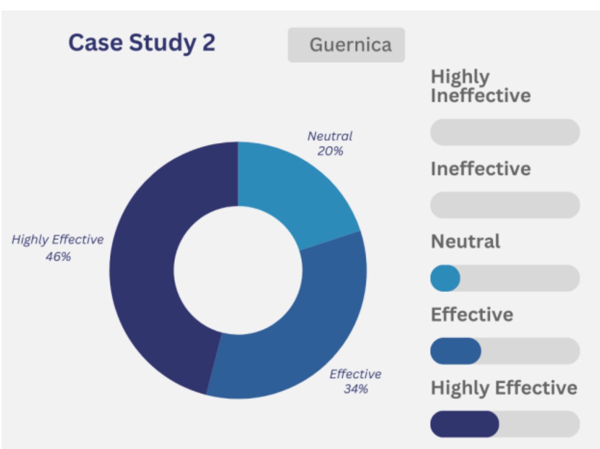

Fig 6: Feedback for Guernica case study

As we can see from both figures, the learning effectiveness of both case studies is the same varying in a small margin between effective and highly effective.

B. Qualitative Analysis

The student's answer sheets were coded using in-vivo and process coding methods (Saldana, 2014). In in-vivo, we code from the phrase as is and in process coding, we code based on the conceptual framework. A few examples and samples of the assigned codes for case study 1 are presented in Table III below.

TABLE III
CASE STUDY 1 CODES

Phrase	Code
It uses concepts to store	CONTEXT
I think the philosophy of the model is everything we want is possible in the world but it is our job to discover, invent	INVENT
Share the discovery and engage in discussions	ENGAGE
It is an infinite library	INFINITE
Arrangement of galleries	ARRANGEMENT
Fastest means to search	PROCESS
Map query to browsing actions	PROCESS
Search for given string as various possibilities	DESIGN
Due to large functionality, it was divided into parts	DECOMPOSE
Extracts the relevant sections	RELEVANCE
It uses a deterministic algorithm	DETERMINISTIC
It explores themes of infinity, randomness, and the search for meaning within chaos.	THEMES
Symbolizes the paradox of infinite knowledge	METAPHOR
In an infinite universe, there is chance of exists a seemingly endless library	INFINITE
It's a vast interconnected structure	INTERCONNECTED
Endless maze of possibilities and confusion	MAZE

Few sample assigned codes for case study 2 are presented in Table IV below.

TABLE IV
CASE STUDY 2 CODES

Phrase	Code
Depicts the suffering and chaos	CHAOS
emphasizes how civilians are affected by conflict	CONFLICT
Everything has a metaphor and a theme	THEME
Investigate the historical context and events	CONTEXT
Destructive impact of war	IMPACT
Interconnectedness of elements conveys shared experiences.	SHARED
Symbolic representations and their connections	CONNECTIONS
Vibrant flowers symbolize growth and the human capacity to find beauty even in tragedy.	METAPHORS
Symbolize various historical events	TIMELINE
Blends world history and art.	BLEND
Analyze the modern warfare technologies	RELATE
Destroy the culture and infrastructure	CULTURE
There are a lot of hidden symbols	ABSTRACT
Themes cocoon the core messages of the artwork, providing a high-level understanding of its significance.	BEYOND
Contemporary and historical contexts	CONTEXTS
Deeper understanding of abstract themes	ANALYZE

It can either reduce stress, that is innovation, or raise stress, that is destructive capability	RELATE

V. Discussion

The quantitative results validate that there is a significant difference between both the case studies. Using abstraction is positively different and effective with higher scores. Along with that, with the qualitative analysis, several themes originated from the in-vivo and process coding.

Case Study 2 promoted higher-order thinking as compared to Case Study 1. If a faculty intends to achieve higher-order learning outcomes, then the mechanism used for Case Study 2 can serve the purpose. Consider, for example, the code CONTEXT, which appears in both case studies. However, the level at which context is achieved is higher in Case Study 2. In this case, students compared classic and contemporary contexts or tagged a label to it. The codes are derived based on the conceptual framework and the research question.

When we observe the codes generated for both case studies, the codes in Table III are more basic, focusing on individual elements such as INFINITE, ARRANGEMENT, and PROCESS. These reflect the identification of components but do not go deeper into their interconnections. The Table IV shows more complex and higher-order codes such as CONFLICT, IMPACT, and THEME. These indicate a more sophisticated analysis, with students engaging in higher-order thinking by linking multiple components and understanding their relationships. This difference in the level of coding illustrates how the use of abstraction and trigger points in Case Study 2 gave a deeper level of cognitive engagement. The models produced in Case Study 2 were more interconnected, showing that students could not only identify individual components and also understand their interactions within a larger context. This was evident from the student answer scripts that were evaluated.

Apart from the codes, if we look into the themes that emerge from the study, the trigger points in Case Study 2 played a critical role in leading students to engage in further research. Trigger points are specific prompts designed to guide students' focus towards key components of the problem that guide them towards the deeper inquiry. In Case Study 2, these trigger points helped students to explore the problem in depth and encouraged them to explore related areas, including historical and social contexts. This made students conduct additional research to better understand the complexities of the problem. The use of these structured prompts facilitated a comprehensive understanding, which allowed students to link concepts and ideas across different domain and to elaborate the models under study.

As Case Study 1 lacked the same degree of structured reflection and trigger points has led to limit the depth of student engagement. In Case Study 2, students connected metaphors and features to larger systems and historical timelines, which gave them more complex models. When students thought more deeply about the topic, they were able to see the bigger picture. This helped them create better models and understand the topic more fully. This shows that using trigger points is a good way to guide students' learning and research.

Conclusion

This study shows that using abstraction in PBL and CT can help students think better, learn more deeply, and solve problems more effectively. When students were given clear guidelines and examples (trigger points), they were able to create better models and understand the topics more thoroughly. This was especially true for the second case study, where students performed better and reflected more deeply on the subject matter. Students connected to different ideas and explored complex systems and abstraction helped them improve their learning outcomes. Both quantitative and qualitative data support the idea that abstraction is a valuable tool for creating a research-oriented learning environment. This study recommends that integrating abstraction into the curriculum can help students develop critical thinking and creativity, enabling them to tackle real-world problems by creating mini research spaces.

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