NetLogo Models for Pattern Recognition in Problem Based Learning

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Abstract*— Problem-based learning and computational thinking, when integrated as a teaching-learning pedagogy, can provide a platform for both teachers and students to explore how to teach and how to learn effectively. Pattern recognition, one of the key aspects of computational thinking, can assist computer science engineers in modeling problem scenarios through accommodation and assimilation. This study proposes a research question to analyze the effectiveness of pattern recognition in modeling the problem scenarios using Schema Theory as a conceptual framework. A multi-method approach was adopted as the research methodology, and self-selection was used as the sampling technique among students who enrolled in the model thinking course jointly offered by industry Knit Space and KLE Technological University. Technology plays a significant role in designing such problem scenarios. For this study, two problems were designed using NetLogo, and reflection points were provided for students to design models for each problem. NetLogo is a platform that offers various simulation models across multiple domains. Both the problems selected emphasized on the pattern recognition. The Paths and Wolf-Sheep models were used for the study. The study analyzed 50 student answer scripts using both qualitative and quantitative methods, after an informed consent to use the data for the research study. Through appropriate descriptive measures and statistical techniques, such as paired t-tests, student feedback, in-vivo coding, and process coding, the collected data was thoroughly examined to derive results and discussion points. Alongside statistical measures, the study also explored themes generated from the findings, with a focus on technology's role in the process. The results align positively with the conclusion that pattern recognition significantly aids in building better models.

***Keywords*—computational thinking; pattern recognition models; problem based learning; technology**

ICTIEE Track: Technology Enhanced Learning
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I. INTRODUCTION

THE pedagogical approaches are traditionally rooted in learning theories for knowledge construction and skill development. Based on the timely needs, the pedagogies have evolved incorporating the state-of-the-art needs of teaching and learning. Rooted in the constructivist theory, Problem-Based Learning (PBL) is a pedagogical approach where learners construct knowledge by engaging with real-world scenarios and problems. As a student-centered method, PBL emphasizes problem-solving, critical thinking, self-directed learning, and collaborative learning. Research supports that PBL stimulates higher order thinking skills (Moallem, 2019). Theoretical frameworks such as situated learning, constructivism and cognitive apprenticeship reinforce the rationale for PBL, highlighting the importance of authentic contexts and social interaction in knowledge construction. PBL enhances student’s ability to develop and apply modeling skills by encouraging them to design, implement, and refine models that address real-world problems.

Originating from the medical domain (Barrows, 1998), PBL ever since has been prolonged and adapted across various disciplines to meet their respective needs. From engineering to social services, it has been adapted into several areas while the principal objective remains the same - to make students as problem solvers and lifelong learners. The professional world increasingly demands individuals capable to solve complex problems, think critically, and collaborate effectively, which aligns with the core principles of PBL. The effectiveness and advantages of PBL have been extensively discussed, alongside guidelines for creating engaging classroom experiences (Tan, 2021). With the problem designed using the real-world contexts and actively making students involve in problem-solving, PBL bridges theoretical and practical knowledge, augmenting a deeper understanding of concepts. In the regards, PBL creates an interactive learning environment, preparing students for future professional roles (Warnock & Mohammadi-Aragh, 2016).

PBL has been integrated with Computational Thinking (CT) to enhance problem-solving and structured reasoning skills. Alongside exploring 'how to teach,' it is essential to understand 'how students learn' to address the specific needs of computer science education. CT is a way of thinking and can help in developing specific skillsets of decomposition, abstraction, pattern recognition and algorithms (Wing, 2006).

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Pattern recognition, a critical aspect of CT, involves identifying recurring patterns and trends within data and problems. This process simplifies complex issues, generalizes solutions, extracts meaningful information, and facilitates effective problem-solving (Basawapatna et al., 2011). Pattern recognition simplifies the problem by aiding one to recognize the similarities and to make informed decision and hence also in the process of modeling. Computer science deeply emphasizes modeling, which allows for analyzing complex real-world systems through simplified abstractions. Models simplify complexity and they enable better understanding of system behavior under numerous conditions. They reveal trends and values within a system, assisting in further optimization. Recognizing key elements of a model helps develop both holistic and detailed understandings of the system, improving its analysis and functionality.

To build accurate models, recurring structures and trends within data must be identified; this is essentially pattern recognition. Models abstract and represent complex systems by capturing these recognized patterns. Pattern recognition and modeling go hand in hand, each reinforcing the other and closely connected to problem-solving.

Pattern recognition and CT are widely recognized for their role in problem-solving and their combined application in PBL environments mostly remains underexplored. Existing research lacks focus on how explicit pattern recognition triggers can enhance modeling capabilities in PBL contexts. There is also limited work and evidence on the integration of these approaches with simulation tools like NetLogo to support learning outcomes. This study addresses these gaps by examining the effect of explicit pattern recognition on model-building in PBL and exploring how technology can be used to support learning outcomes.

The paper is further organized as follows: Section 2 presents the literature survey, Section 3 outlines the research question and design along with the model, Section 4 discusses results and data analysis, Section 5 covers the discussion, and Section 6 concludes the paper.

II. Literature Survey

This section provides a literature survey on the areas of PBL, CT, pattern recognition, and modeling, the domains related to this work proposal. While these sub-domains have been explored individually within specific contexts, an inherent relationship exists among them. Although not all works explicitly highlight this relationship, they are united by their common emphasis on problem-solving. The reviewed works and papers predominantly originate from the computer science domain.

Using problem cases and scenarios significantly impacts the process of learning and transferring knowledge (Wood, 2003). What and how students study in PBL has been extensively discussed (Hmelo-Silver, 2004). The process and its impact on learning have been systematically studied (Yew & Goh, 2016). PBL has been explored from multiple perspectives, assessing its effectiveness and addressing implementation challenges. It has been implemented at various levels, from individual courses to institutional curricula, with its long-term benefits evaluated at each level (Chen et al., 2021). The adoption of PBL has consistently resulted in effective learning behaviors (Ghani et al., 2021) and has been investigated for its role in enhancing critical thinking skills (Nadeak & Naibaho, 2020).

Structured approaches in PBL significantly enhance knowledge acquisition and construction, enabling students to effectively build and organize their understanding (Netekal et al., 2022). Reflection and pattern recognition within PBL contexts have been shown to improve learning outcomes, accentuating their importance in enhancing deeper learning and cognitive development (Torgal et al., 2024). Integrating CT techniques into PBL has proven to be effective in enhancing student’s problem-solving abilities and overall learning process (Aryan et al., 2023). Several variants of PBL have been explored including one day many problems approach (Hegade, 2019). Effectiveness of game based learning in PBL has been deliberated (Hegade et al., 2023).

While the integration of PBL with other learning frameworks, such as learning styles and thinking abilities, has been explored (Islamiat et al., 2024), the interaction between PBL, CT, pattern recognition, and modeling remains underexplored. In the computing domain, PBL's practicality and specific needs have been addressed (O’Grady, 2012), but the combination of these four elements has rarely been investigated in the literature.

CT is widely recognized as a critical skill required for the digital age (Barr et al., 2021). It encompasses key components such as abstraction, decomposition, pattern recognition, and algorithms (Wing, 2006). Thinking computationally involves adopting an approach to problem-solving and resonating with human reasoning processes (Lu & Fletcher, 2009). The teaching, acquisition, and definition of CT have been discussed from diverse perspectives, with criteria developed to define its scope (Selby & Woollard, 2013). CT is a powerful framework for enhancing problem-solving across disciplines (Jonasen & Gram-Hansen, 2019), but while CT and PBL have been explored in combination to assess their effectiveness, the broader integration with pattern recognition and modeling has not been sufficiently explored.

Pattern recognition, a core component of CT, has been widely studied in the mathematical domain (Yasin & Nusantara, 2023). Since mathematics is fundamental to computer science, these findings are relevant to the field. Techniques for recognizing patterns and their applications have been discussed (Basawapatna et al., 2011). Research has also highlighted the importance of pattern identification (Leonard et al., 2022) and its broader implications (Liu et al., 2006). Developing CT skills through pattern recognition has been explored (Caldero et al., 2015), but its connection with PBL and modeling approaches remains limited.

Combining PBL, CT, pattern recognition, and modeling creates an influential learning environment. PBL provides authentic challenges, while CT equips students with problem-solving skills. Pattern recognition helps identify underlying structures, and modeling allows for experimentation and prediction. This paper, therefore, proposes a framework combining these perspectives and to add up, we go for technology influenced solution as it plays a major role in the education system (Cloete, 2017). The process of designing case studies, using simulations, and identifying patterns can be significantly enhanced when technology is used as a medium in the study. NetLogo has proven to be an effective environment for such purposes (Sklar, 2007), making it a suitable choice for our research work.

III. Research Design

This section presents the research design along with the research question and other required details.

A. Philosophical Assumptions

The interpretive framework guiding this study is pragmatism (Putnam, 1995), which supports the integration of both quantitative and qualitative approaches. Pragmatism emphasizes deriving truth and meaning through practical relevance and real-world application, offering flexibility to prioritize solutions that best address the research problem over adherence to specific methodologies. The study's ontological perspective is that pattern recognition and models are essential tools, and evaluating their effectiveness within the context of PBL can yield valuable insights. An inductive approach underpins the knowledge construction, reflecting on the perspectives of both the researcher and participants, which shape the study’s axiology. A multi-method methodology is employed, combining qualitative and quantitative techniques to provide a holistic understanding of the research problem. This approach blends numerical data with in-depth insights into students' learning, resulting in a comprehensive and nuanced analysis.

B. Research Question

The research question for the study is

RQ: “How does integrating pattern recognition from computational thinking influence students' problem-solving and model-building in PBL scenarios?” We further divide this into two sub-questions one for the quantitative study and another for qualitative study.

Sub-Questions:

RQ1: How does the integration of pattern recognition affect the measurable outcomes of students’ problem-solving in PBL scenarios?

RQ2: What insights can be gathered from students’ experiences and reflections on working with PBL scenarios that incorporate pattern recognition?

The study aims to explore the impact of using pattern recognition explicitly as a trigger point, compared to its absence, while students build models for the given scenario. Quantitative aspects will be measured through model-building performance metrics, while qualitative aspects will be assessed through student reflections and observations. The same set of 50 students will be solving two exercises which will be our two study groups.

C. Hypothesis

To examine the impact of explicit pattern recognition on students' model-building performance and learning outcomes, the study compares scenarios with and without explicit pattern recognition. The following hypotheses are formulated:

H_0: There is no significant difference between the two groups.

H_1: There is a significant difference between the two groups.

D. Context of the Study

The study focuses on students who have completed their second year in Computer Science Engineering at KLE Technological University. The participants took part in a summer course jointly offered by Knit Space and KLE Technological University as an audit course. The course consisted of 50 contact hours, split evenly between 25 hours of offline and 25 hours of online engagement. It covered the significance of model thinking and its relevance for computer science graduates. The 50 data points represent the individual scores assigned to student’s modeling tasks based on their model descriptions, pattern identification, and the models they created. Student reflections were collected at the end of each modeling exercise, providing insights into their thought processes and learning outcomes. The course was taught using PBL as the primary pedagogy, with elements of CT integrated throughout. It included several graded activities and assignments, and technology was employed to design case studies and assessments.

E. Sampling Methods

The course was attended by 96 students, of which 50 participated in the study. Informed consent was obtained from all participants, and they were provided with detailed information on how their data would be used for research purposes. The sampling method employed was self-selection (Wainer, 2013), a non-probability sampling technique where individuals voluntarily choose to participate in a study. An open invitation was extended to the students, and those who expressed interest and agreed to participate were included in the study.

F. Schema Theory - Conceptual Framework

This work utilizes schema theory as a conceptual framework (Widmayer, 2004). Schema theory, which is closely related to cognitive processes of organizing and analyzing information, shares a strong connection with pattern recognition. According to schema theory, knowledge is structured in the form of mental frameworks, known as schemas, which help individuals interpret and respond to new information by organizing it into existing patterns. Pattern recognition refers to the ability to identify and categorize these recurring structures within data. Together, these concepts guide the problem-solving process. Schemas serve as a framework for recognizing patterns and providing interpretation, while pattern recognition refines and strengthens these schemas, facilitating better understanding and decision-making (Derry, 1996).

G. Study Model

The model used for this study is presented in Figure 1. Based on the selected concept, a problem is identified that contains inherent patterns. This problem can be modeled by analyzing its operations and behavior, or it can be approached using elements of pattern recognition and schema theory, which include schemas, assimilation, and accommodation. These elements are depicted in the model below.

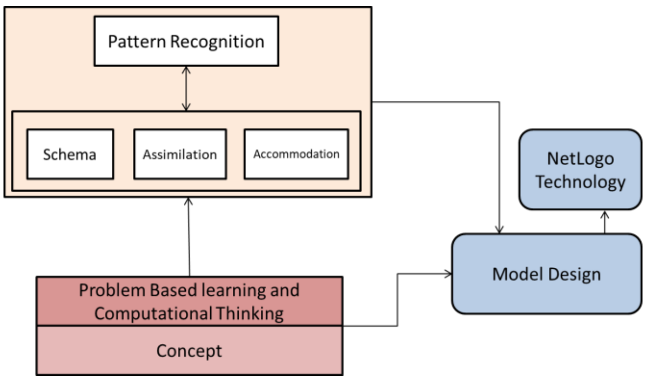

Fig. 1: Model for pattern recognition using the schema theory and technology support

Assimilation involves fitting new information into existing schemas, while accommodation refers to modifying existing schemas to incorporate new information. The NetLogo tool is used to implement and study the model described.

H. Problem Design

Two problem scenarios (also referred to as case studies) were designed to test the influence on model building. The selected case studies were drawn from the NetLogo simulation tool (Tisue & Wilensky, 2004). The problems within the tool are inherently linked with patterns and provide detailed descriptions of each model. While the models used for assessment were introduced to the students, other models were covered during class sessions. Students were familiar with the NetLogo environment but not with the specific problems given for assessment. The simulator offers a social context for the problems, helping students understand the complex dynamics of the social ladder.

Question 01: Do you know how the paths emerge from the commonly traveled routes? From the NetLogo simulator, navigate to the model 'Paths' under Social Science. Study the model (description and rules are present at the end of the same page of simulator) and understand the different parameters associated. Write a short description of the platform, followed by its model and description of the model.

Question 02: Model the Wolf Sheep Predation from the NetLogo simulator. First, identify the possible patterns that exist in the system. Then, use these patterns knowledge to design a model for the process. Write a short description of the platform, followed by its model and description of the model.

The first question asked the students to build the model and second one explicitly stated to identify the patterns and later model it.

I. Technology: NetLogo

The NetLogo tool offers hundreds of models across various domains. It is free to use and publicly available, allowing faculty to select models based on specific learning requirements and design assessments aligned with intended learning outcomes. NetLogo is a powerful environment for understanding the complex dynamics of different systems and modeling real-life phenomena (Chiacchi et al., 2014). The tool simplifies the role of the facilitator by providing an interactive platform for exploration, which is crucial for problem-based learning. Without such tools and technology, supporting higher-order thinking skills would be challenging. NetLogo helps to go beyond the basic problem comprehension and support achieving higher cognitive level. It is a helpful tool to understand abstractions of the complex concepts.

IV. Results and Data Analysis

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

A. Quantitative Analysis

The solutions presented by the students were graded for the quantitative study. The grading was based on predefined criteria that assessed model-building performance and the application of pattern recognition. Descriptive statistics, including mean, median, and standard deviation, were calculated to summarize the performance data. 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	6.44	7.78
Median	6.00	8.00
Standard Deviation	1.32	1.16
Variance	1.73	1.34
Minimum Value	4.00	5.50
Maximum Value	9.50	10.00
Skewness	0.255	0.131
Strd. Error Skewness	0.337	0.337
Kurtosis	-0.597	-0.311
Std. error kurtosis	0.662	0.662
Shapiro-Wilk W	0.951	0.939
Shapiro-Wilk p	0.038	0.012

Of the 50 data points for each group, there were no missing values. The small standard deviation and variance, as shown in the table above, indicate that the data points in each case study are closely clustered around the mean. Smaller values suggest that the data points are relatively similar to each other, demonstrating a consistent pattern. This tight grouping indicates high reliability and precision. The skewness values of the two datasets, 0.255 and 0.131, are both close to zero, suggesting that both distributions are approximately symmetrical. However, the dataset with a skewness of 0.255 may have a slightly longer tail on the right, indicating a very mild positive skew.

The kurtosis values for both datasets are negative (-0.597 and -0.311), suggesting that both distributions have lighter tails than a normal distribution, with fewer extreme values. For case study 1, the Shapiro-Wilk W value is 0.951, indicating a reasonably good fit to a normal distribution (Razali & Wah, 2011). However, the p-value is 0.038, which is low, leading us to reject the null hypothesis. Therefore, despite the W value suggesting a good fit, we conclude that the data in case study 1 is not normally distributed. Similarly, for case study 2, the W value is 0.939 and the p-value is 0.012, meaning the data in case study 2 is also not normally distributed.

Since both case studies exhibit non-normal distributions, non-parametric statistical tests were used for analysis, as these tests do not rely on the assumption of normality.

The box plot for Case Study 1, shown in Figure 2 below, indicates that most scores are clustered in the lower half, with less variation in the higher scores."

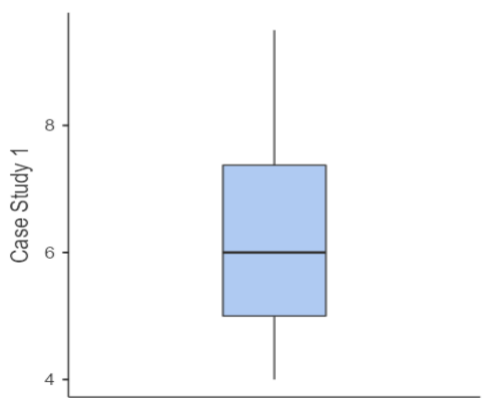

Fig 2: Box plot for case study 1

The box plot for Case Study 2, shown in Figure 3 below, indicates a wider spread of scores, with most scores concentrated in the higher range.

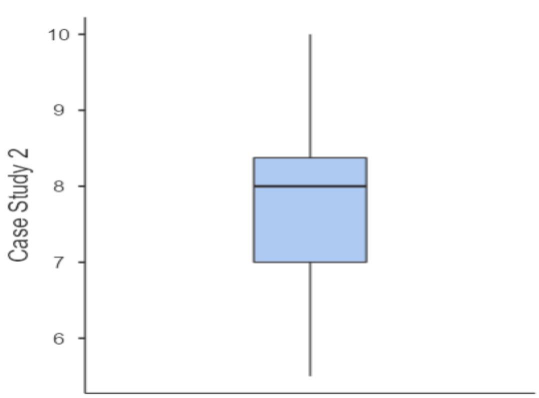

Fig 3: Box plot for case study 2

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

TABLE II
WILCOXON TEST RESULTS

Attribute	Value
Statistic	37.5
P value	< 0.001
Tied pairs	8

The W value of 37.5 is the test statistic calculated by the Wilcoxon signed-rank test. While the test indicates the direction of the difference between the two related groups, its primary interpretation is based on the p-value. A p-value less than 0.001 are highly significant. Since the p-value is less than 0.001, which is much smaller than the common significance level of 0.05, we reject the null hypothesis (refer to H_0 from section III, C). Therefore, based on this test, we can conclude that there is a highly significant difference between the two related groups considered in the study, even with 8 tied pairs.

A feedback question was asked for both case studies, measuring model effectiveness on a five-point Likert scale (Joshi et al., 2015). For case study 1, the question was, "You explored 'Paths' on NetLogo with a model perspective. How effective was it in terms of learning?" The results are presented in Figure 4 below.

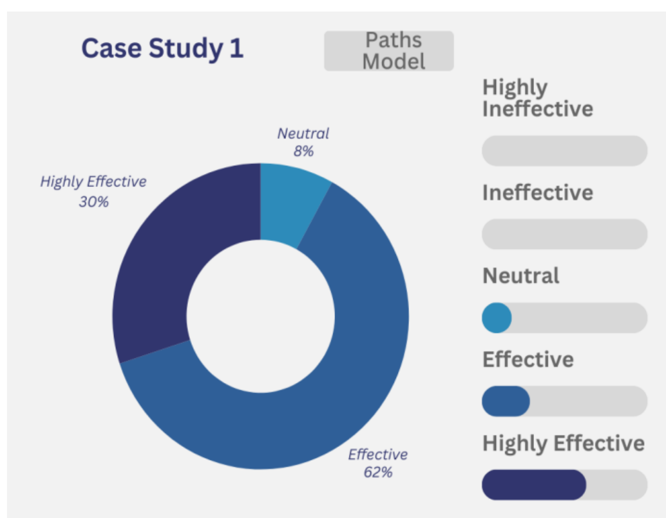

Fig 4: Feedback for paths model case study

In Figure 4, we observe that for the feedback question on Case Study 1, 30% of the students rated the model as “highly effective,” 62% as “effective,” and 8% as “neutral.” “Highly effective” indicates substantial learning outcomes and engagement, “effective” suggests a good level of understanding and application, and “neutral” represents moderate impact.

For case study 2, the question was “You explored Wolf-Sheep on NetLogo with a model perspective. How effective was it in terms of learning?” The results of 50 students are presented in Figure 5 below.

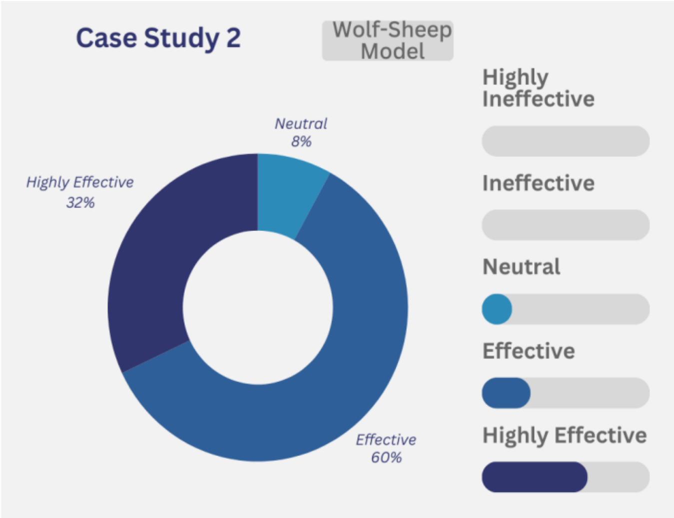

Fig 5: Feedback for wolf-sheep model case study

Similarly, in Figure 5, we observe the feedback results for Case Study 2.

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

B. *Qualitative Analysis*

The students answer sheets were coded using in-vivo and process coding methods (Saldana, 2014). In in-vivo coding, the data is coded directly from the participants' phrases, while in process coding, the coding is based on the conceptual framework. A few examples of the assigned codes for case study 1 are presented in Table III below. As an example, ‘No further changes in path’ was coded as SATURATION. ‘Point of interest is temporary’ was coded as DYNAMIC. The coded words were supported by the Schema Theory.

TABLE III
CASE STUDY 1 CODES

Phrase	Code
Move in a path which is already travelled	FOLLOW
Reach a random destination	RANDOM
Evolve based on movement	EVOLVE
Begins with random movement	INITIATE
Ideal set of routes	IDEAL
Human settlement patterns	SETTLE
Formation of organized structures	STRUCTURAL
Individual actions lead to complex patterns	COMPLEX
Interaction between walkers and paths	INTERACTION
Observe the algorithm	OBSERVE
Every phenomenon follows a particular process to achieve it	ALGORITHM
No further changes in path	SATURATION
Rivers emerge through natural process	INHERENT
Worlds route, boundaries are created by humans	MAN MADE
Don’t take shortest path, instead take most used	DESIGN
Point of interest is temporary	DYNAMICS

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

TABLE IV
CASE STUDY 2 CODES

Phrase	Code
Cycle continues and goes on	CYCLE
Changes effect behavior and outcomes	EFFECT
Evolve based on movement	EVOLVE
Understand ecological principles	PROCESS
Version of producer consumer problem	ABSTRACTION
Simulates the interaction	BEHAVIOUR
Cyclic population dynamics, stable equilibrium and extinction events under unfavorable conditions	PRINCIPLES
Impact of different parameters on these patterns	IMPACT
The presence of grass allows for more balanced interactions	INTERACTION
Observe the changes in the system	OBSERVE
The oscillatory nature arises from the dynamic feedback	INHERENT
If production of grass is less, then sheep population decreases	CONDITION
Different ecological outcomes	PROCESS
Prey predators follow a cycle	CYCLE
Model behaves and whether it remains stable	DESIGN
Balance between these components	DYNAMICS

V. DISCUSSION

The quantitative results validate that there is a significant difference between both methods. Along with that, several themes originated from the in-vivo and process coding.

Categories emerged from the patterns identified by the students. While one student identified primary, secondary, and tertiary producers in the second case study, another identified four different situations. When patterns were explicitly mentioned, it was observed that students tried to group them together. Students were able to identify patterns of resource depletion, equilibrium states, extinction scenarios, etc. They also tried to identify the impact of different parameters on each pattern, rather than on each scenario. This generic thinking can aid in the transfer of knowledge (Hmelo-Silver, 2004).

Abstraction was present in the second case study. Students identified the producer-consumer problem, LV model, cycles, and oscillations, etc., in the second case study (Wood, 2003). There was a discussion about the balance between the components, which was not observed in case study 1. The model in the second case study had more elements compared to the model designed for case study 1. When patterns are recognized, it helps in learning principles, which is beneficial in the learning process (Wing, 2006). The first case study helped students identify algorithms, while the second one helped them identify principles.

The second case study can achieve higher-order thinking and realize more than level 3, as described by Bloom's taxonomy (Bloom, 1956) or SOLO taxonomy (Biggs & Collis, 1982). If a faculty intends to achieve higher-order learning outcomes, then the mechanism used for case study 2 can serve this purpose. When students discuss reinforcing and balancing cycles, they are thinking beyond the given problem and have reached the construct level (Jonassen & Gram-Hansen, 2019). If they can map to similar problems and design models, as happened in case study 2, they are evaluating and constructing. Even when we observe the codes generated for the two case studies, the codes in Table IV represent higher-order thinking than those in Table III. This shows how students' thinking progressed in response to both case studies (Selby & Woollard, 2013).

Conclusion

Pattern recognition plays an important role in designing effective case studies, which assists in deeper engagement and understanding in learning environments. This paper highlights the significance of modeling in PBL and CT, showing how technology, specifically NetLogo, acts as a powerful tool to enhance these processes. As PBL and CT provide the theoretical foundation, tools like NetLogo bring these concepts to life, enabling the creation of complex, reflective problems that go beyond basic actions. When we select appropriate tools and incorporate well-designed trigger points, faculty can significantly enhance learning outcomes and achieve higher levels of cognitive complexity. The critical role of integrating technology and thoughtful design in educational settings can effectively enhance the learning effectiveness.

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