Implementing Problem-Based Learning in a Computational Thinking Course: An Educational Experience Using TRACE

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Abstract. *This study reports the implementation of Problem-Based Learning (PBL) guided by the TRACE framework in an undergraduate Computational Reasoning course. Students engaged in contextualized problem solving and dashboard development using a simulated dataset. Motivation was assessed via the Instructional Materials Motivation Survey (IMMS) and qualitative reflections. Results show high overall motivation (M = 4.23), with strong engagement, relevance, and satisfaction, while confidence scores suggest refinement areas. PBL and TRACE fostered autonomy, active participation, and Computational Thinking skills. Challenges involved adapting to active learning and managing workload, while results highlight the effectiveness of PBL for engagement and skill development.*

1. Introduction

Computational Thinking (CT), also referred to as Computational Reasoning (CR), is recognized as a foundational competence that supports problem solving, abstraction, decomposition, and algorithmic reasoning across disciplines [Wing 2006, Shute et al. 2017]. Although its adoption in higher education has expanded, teaching CT remains challenging due to heterogeneous student backgrounds, limited programming experience, and difficulties with abstract computational concepts [Grover and Pea 2018, Zhou et al. 2024].

Active learning approaches have been increasingly adopted to address these challenges. Among them, Problem-Based Learning (PBL) promotes student-centered learning and engagement with authentic problems [Hmelo-Silver 2004, Savery 2019, Saad and Zainudin 2024]. Studies in computing education suggest that PBL can enhance motivation, perceived learning, and higher-order thinking skills, particularly in real-world contexts [Wu et al. 2025]. However, existing studies often emphasize learning outcomes while providing limited detail on instructional design and pedagogical implementation.

Recent reviews highlight the need for empirically grounded studies that document not only learning outcomes but also the design and implementation of active learning interventions in computing education [Lin Lv and Liu 2023, Zhou et al. 2024]. Although PBL is widely adopted, relatively few studies describe its implementation through structured pedagogical frameworks, limiting replicability and the accumulation of design knowledge [Saad and Zainudin 2024, Zhang et al. 2024].

Instructional frameworks such as TRACE (Technical Roadmap for Agile Cross-domain Engineering) have been proposed to support the systematic design and analysis of action-oriented learning experiences in computing education [Lana et al. 2025b, Lana et al. 2025a]. TRACE emphasizes alignment between pedagogical intentions, learning activities, data collection, and educational analysis. Nevertheless, empirical evidence on integrating TRACE with PBL in Computational Thinking courses remains limited.

To address this gap, this study reports and analyzes the implementation of PBL guided by the TRACE framework in an undergraduate CT course at the Federal University of Lavras, São Sebastião do Paraíso Campus, Minas Gerais, Brazil. A mixed methods approach was adopted, combining quantitative data from the Instructional Materials Motivation Survey (IMMS) with qualitative student reflections. The intervention consisted of a sequence of PBL activities structured according to the phases and principles of TRACE.

Results indicate high levels of student motivation and positive perceptions of learning outcomes and instructional quality. Qualitative findings suggest that the activities fostered engagement, autonomy, and the practical application of CT concepts, while also revealing challenges related to adaptation to active learning and workload management.

The remainder of this article is organized as follows: Section 2 presents the theoretical background on Computational Thinking, Problem-Based Learning, and the instruments used to assess student motivation in higher education; Section 3 reports the related works; Section 4 describes the research methodology; Section 5 reports the results; Section 6 discusses the assessment of student motivation using the IMMS; Section 7 presents the threats to validity; Section 8 discusses lessons learned and educational implications; and Section 9 concludes the work and provides directions for future research.

2. Background

This section presents the main concepts and evaluation instruments that support this study.

2.1. Integrating PBL and Computational Thinking

PBL is a student-centered approach in which learning emerges through the investigation of contextualized and ill-structured problems that foster self-directed learning, collaboration, and critical reasoning [Wood 2003]. Beyond content acquisition, PBL promotes competencies such as communication, teamwork, and critical evaluation, supporting a shift from lecture-based instruction toward active learning environments [Saad and Zainudin 2024]. Unlike Project-Based Learning (PjBL), which focuses on developing tangible artifacts, PBL emphasizes inquiry and the cognitive processes involved in problem investigation [Savery 2019].

CT is widely recognized as a core competence in contemporary education. According to [Wing 2006], CT comprises problem-solving skills grounded in computer science principles, including abstraction, decomposition, data analysis, and algorithmic reasoning. Later studies further characterize CT as a cognitive process applicable across disciplinary domains [Grover and Pea 2018]. In higher education, CT is commonly associated with decomposition, abstraction, pattern recognition, and algorithmic thinking, enabling students to address multidisciplinary challenges systematically.

Importantly, CT development is not inherently dependent on programming activities. Research suggests that CT can also be fostered through non-programming activities and digital tools focused on abstraction and logical organization [Wing 2006, Shute et al. 2017]. In this context, spreadsheet-based analytical dashboards can support algorithmic reasoning and pattern recognition while reducing the cognitive burden associated with programming syntax. Thus, PBL and CT converge in their emphasis on inquiry, reasoning, and active knowledge construction, promoting deeper understanding and higher-order cognitive skills [Wing 2006, Grover and Pea 2018].

2.2. Assessment of Learning and Motivation in Higher Education

Assessing teaching effectiveness, student learning outcomes, and motivation is central to higher education research. Reliable evaluation instruments are essential to understand how instructional strategies shape students' learning experiences and perceptions. In student-centered contexts, assessment must capture not only content acquisition but also perceived learning gains and motivational engagement.

The IMMS, grounded in Keller's ARCS model, Attention, Relevance, Confidence, and Satisfaction, evaluates students' motivational responses to instructional materials and course design [Keller 1987, Keller 2009]. In this framework, **Attention** refers to the degree to which learners are actively engaged and focused on the material; **Relevance** reflects learners' perception of the content's significance and applicability to their goals; **Confidence** denotes the extent to which learners feel capable of mastering and applying the knowledge; and **Satisfaction** captures learners' sense of fulfillment and positive experience resulting from the learning process. The instrument has been widely applied in diverse educational settings and provides validated evidence for analyzing how instructional strategies influence student engagement and perceived learning experiences.

3. Related Work

The integration of active learning methodologies into computing education has gained significant scholarly attention in recent years, particularly as educators seek strategies capable of fostering higher-order thinking skills such as problem solving, abstraction, and algorithmic reasoning [Grover and Pea 2018]. CT, widely recognized as a fundamental competency for the 21st century, has increasingly been associated with pedagogical approaches that promote student-centered learning environments rather than traditional lecture-based instruction [Wing 2006, Gong et al. 2025].

[Zhang et al. 2024] conducted a meta-analysis of 31 experimental and quasi-experimental studies to examine the impact of Problem- and Project-Based Learning on CT. The results showed a significant positive effect on students' computational competencies and engagement when compared to traditional instruction. The authors conclude that collaborative and inquiry-based designs are effective for fostering CT, while emphasizing the need for greater methodological consistency in future research.

[Nurasiah et al. 2023] investigated the impact of technology-supported PBL on CT in higher education using a quasi-experimental design with 66 students. The findings revealed statistically significant improvements in CT skills, particularly in problem decomposition, abstraction, and algorithmic reasoning. The authors conclude that integrating PBL with technological resources effectively strengthens computational competencies.

Similarly, [Shin et al. 2021] investigated the use of Project-Based Learning as an instructional approach to promote Computational Thinking in undergraduate courses involving computational modeling. Through an empirical classroom-based study, the authors demonstrated that engaging students in authentic, complex problem-solving tasks enhanced their ability to apply computational concepts and reasoning strategies. The study concludes that PBL-oriented approaches foster meaningful learning experiences and strengthen CT skills, particularly when students are actively involved in designing and implementing solutions to real-world problems.

Previous studies [Shin et al. 2021, Nurasiah et al. 2023, Zhang et al. 2024] have highlighted the positive impact of PBL on the development of CT, primarily focusing on learning outcomes such as engagement and skill acquisition. However, many provide limited detail on the pedagogical structures that guide implementation, restricting replicability. In contrast, the present study offers a methodologically transparent account of PBL integration through the TRACE framework, explicitly describing instructional design, assessment strategies, and pedagogical mediation. By adopting a process-oriented perspective, this work contributes to the literature by supporting more replicable, theory-informed practices for active learning in higher education computing contexts.

4. Methodology

The Computational Reasoning course was offered in the second semester of 2025 to three classes (39A, 39B, and 39C), with 32, 29, and 16 students enrolled in the second semester of the Interdisciplinary Bachelor's Program in Innovation, Science, and Technology (BICT) at the Federal University of Lavras, São Sebastião do Paraíso Campus. The practical assignment was designed following PBL and flipped classroom principles. Students initially received training on spreadsheet use and dashboard development, focusing on Microsoft Excel, while face-to-face classes were dedicated to problem solving, data analysis, and collaborative development of analytical solutions.

As a case study, the dataset "Student Habits vs. Academic Performance" was used[1]. The dataset is simulated and not related to Brazilian institutions, representing synthetic records of international students. Its use served a pedagogical purpose, allowing the exploration of variables related to study habits, digital behavior, mental health, and academic performance without ethical concerns associated with real personal data. The dataset, originally in English, was cleaned and standardized by the students, who were also guided to formulate analytical questions based on identified patterns. Based on these analyses, they developed interactive dashboards in Microsoft Excel using pivot tables, slicers, and pivot charts to identify patterns, compare student profiles, and generate insights.

The results supported discussions on how higher education institutions can improve student retention and educational processes, while encouraging students to reflect on how their habits may influence academic performance. The practical assignment was systematically conducted using the TRACE framework (cf. Figure 1), which guided stages such as domain understanding, problem definition, data understanding, solution design and evaluation, tool development, deployment, and communication of results [Lana et al. 2025a, Lana et al. 2025b].

[1] https://www.kaggle.com/jayaantanaath

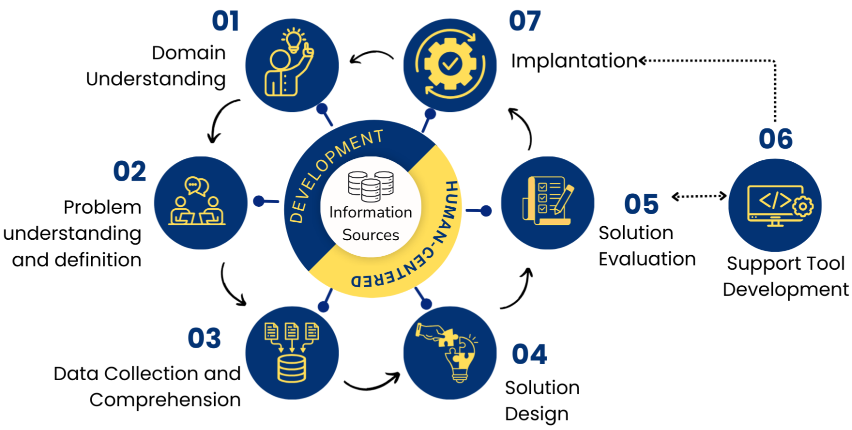


Figure 1. TRACE Framework
Fonte: [Lana et al. 2025a]

The first activity, **domain understanding**, involves acquiring and organizing knowledge about the context in which the solution will be developed and applied. In this study, the domain focuses on analyzing students' habits and their influence on academic performance. Variables such as study hours, attendance, mental health indicators, social media use, and final grades were examined to capture the multidimensional nature of students' daily lives. This analysis supports the identification of behavioral patterns and factors that may influence learning outcomes, engagement, retention, and dropout prevention.

The second stage, problem understanding and definition, involves identifying and structuring the problem to establish a clear and validated statement that considers causes, objectives, constraints, and success criteria. In this study, the central problem was defined as: *to identify how students' habits, digital behavior, and mental health influence academic performance, and how these factors can inform institutional interventions*. To operationalize this problem, seven research sub-questions were formulated. (i) Is there an association between the time devoted to studying and students' academic performance, as measured by final grades? (ii) Does engagement in part-time employment significantly affect academic performance? (iii) Does class attendance show a direct and statistically significant relationship with academic achievement? (iv) Is intensive use of social media associated with lower academic performance? (v) Are mental health indicators correlated with attendance and academic performance? (vi) Does time devoted to digital leisure activities, such as the consumption of streaming platforms (e.g., Netflix), influence academic achievement? (vii) Which behavioral and academic patterns can be identified as potential indicators of risk for low performance and student dropout?

Some variables in the dataset are self-reported, particularly those related to mental health and study time, which may introduce perception and response biases. Additionally, the absence of detailed socioeconomic data and unique identifiers for longitudinal tracking limits the scope of the analysis, restricting long-term inferences and the development of more robust predictive models.

The third stage, data collection and comprehension, involved analyzing a dataset of 1,000 simulated records of international students with more than 15 variables[2]. The goal was to prepare the data for building an analytical dashboard in Microsoft Excel using dynamic tables in Portuguese. The CSV file was imported, translated into Portuguese, and standardized, as some numerical variables were initially interpreted as text (e.g., replacing periods with commas to ensure correct numeric recognition in the Portuguese version of Excel). Missing values with semantic meaning, such as in `study_hours_per_day`, were preserved when relevant for interpretation. Continuous variables, including study hours and social media use, were grouped into ranges to facilitate visualization. Finally, inconsistencies and outliers were systematically checked to improve data quality and reliability. The remaining TRACE stages are addressed in the following sections.

5. Analysis of the Behavioral Profile, Academic Performance, and Risk Factors

The integration of the TRACE framework with the PBL approach in the Computational Reasoning course resulted in the development of analytical dashboards to examine academic performance across student groups. To address the central problem, selected variables from the dataset were analyzed, including study hours, attendance, digital leisure time (social media and streaming), part-time work, and mental health indicators. These variables were chosen because they capture different dimensions of students' routines and demands. Study hours directly reflect academic engagement, while digital behavior may represent potential distractions. Mental health was also associated with performance, whereas attendance showed limited variation in relation to final outcomes. By analyzing these variables jointly, it was possible to identify patterns and outline a broader academic risk profile. The dataset and the resulting dashboard are available on GitHub[3]

5.1. Study Habits and Class Frequency

The dataset analysis revealed a strong positive correlation between study hours and final grades (r = 0.82), indicating that time dedicated to studying is a key factor for academic success. Students with grades above 90 study, on average, 5-6 hours per day, whereas those with grades below 60 study approximately 2 hours daily.

In contrast, attendance showed a weak relationship with academic performance (r = 0.09). Attendance rates remained relatively stable across performance levels, averaging about 84% among students with low and medium grades and 87% among high-performing students. This result suggests that class attendance alone does not ensure academic success without consistent individual study.

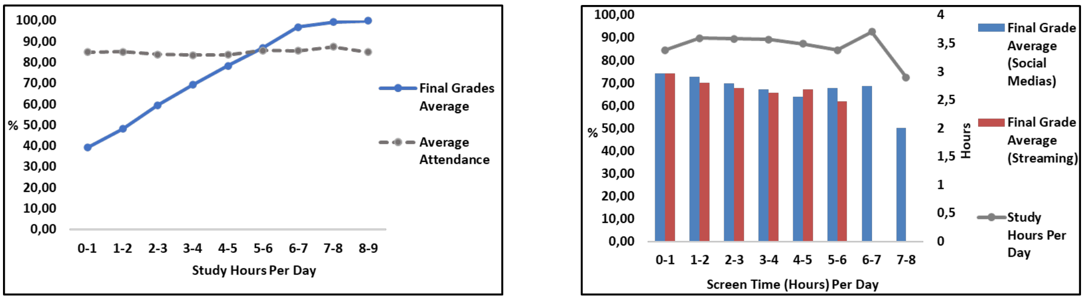
Figure 2a reinforces these findings, showing a clear increase in average final grades as daily study hours rise. From the 3-4 hour interval onward, academic performance improves consistently, with the highest grades concentrated in the 5-6 hour range, while attendance remains nearly constant across intervals.

5.2. Digital Behavior

Regarding digital behavior, the dashboards developed by the students revealed a negative relationship between intensive screen use and academic performance. Both social media

[2] `https://www.kaggle.com/jayaantanaath`

[3] `https://github.com/vininicodemos/Student-Habits-vs-Academic-Performance.git`



(a) Impact of study hours and class attendance on final grades.

(b) Impact of screen time (hours) on final grades.

Figure 2. Analysis of Study Hours, Class Attendance, and Screen Time on Final Grades.

use and streaming consumption, such as Netflix, showed a negative correlation with the final grade (r = -0.17). Students with averages below 60 spend about 4 hours per day on social media or streaming platforms, which substantially reduces the time available for studying.

Figure 2b reinforces these findings, indicating that higher screen time is generally associated with lower academic performance. As screen use increases, study time tends to decrease. The decline in performance appears earlier for streaming consumption, beginning in the 4-5 hour interval, while for social media it becomes noticeable from the 5-6 hour range. In the highest screen-time intervals, particularly 7-8 hours, study time drops sharply, accompanied by a significant reduction in the final average grade, which falls to around 50 points.

5.3. Mental Health

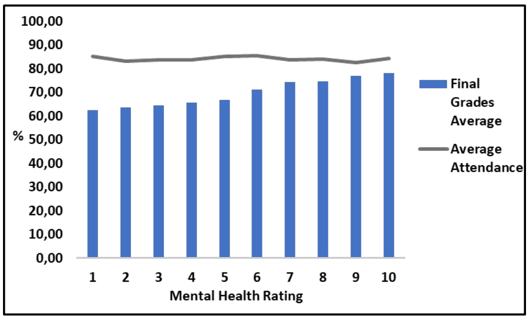
The analysis of psychological well-being and academic results revealed a moderate positive correlation (r = 0.32) between students' reported mental health and their academic performance. Students with the highest averages reported higher well-being levels (scores 7-10), whereas those with lower averages tended to report lower levels (around score 4).

Figure 3a reinforces this pattern, showing that higher psychological well-being is associated with higher final grades. In contrast, attendance remains relatively stable across these conditions; even students with lower mental health scores maintain similar attendance rates.

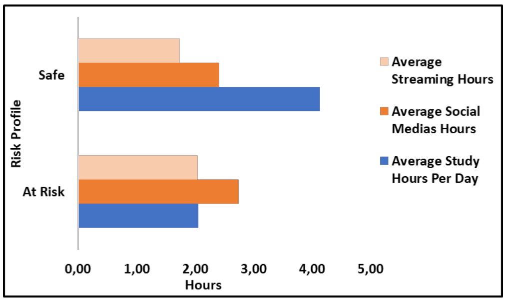
5.4. Risk Profile

Validating behavioral and psychological metrics enables the definition of a "risk profile" to identify students who may require pedagogical intervention. In this study, students were classified as "at risk" when presenting the following characteristics: (i) studying less than 2 hours per day, (ii) reporting a mental health level below 5, and (iii) exhibiting combined screen time (social media and streaming) greater than 4.8 hours per day. Students who did not meet these conditions were classified as "safe".

Figure 3b illustrates the contrast between these groups. Students outside the risk profile generally dedicate more time to studying, even when spending considerable time on social media. In contrast, students classified as at risk tend to combine high screen time with limited study hours, a pattern that is associated with lower academic performance.



(a) Impact of mental health on final grades.



(b) Combining behavioral and psychological metrics into Risk Profiles.

Figure 3. Mental Health and Academic Performance: Combining Behavioral and Psychological Metrics into Risk Profiles

6. Motivational Assessment Results

At the end of the semester, the IMMS instrument was administered via Google Forms and completed anonymously by 45 of the 63 enrolled students (71%). The instrument includes 36 items designed to assess students' motivation toward the Excel dashboard development activity implemented through PBL and guided by the TRACE framework.

IMMS evaluates four motivational dimensions derived from the ARCS model, Attention, Relevance, Confidence, and Satisfaction, which respectively measure engagement with the learning materials, perceived usefulness, expectations of success, and perceived reward after completing the activity [Keller 1987, Keller 2009]. Negatively worded items were reverse scored following the instrument guidelines, and mean scores were computed using a five-point Likert scale.

Overall results indicate a high level of student motivation (M = 4.234; SD = 0.428; 95% CI [4.105, 4.363]; n = 45), with strong internal consistency (= 0.894). Descriptive statistics for each motivational dimension are presented in Table 1. Among the dimensions, Satisfaction (M = 4.400; SD = 0.547) and Relevance (M = 4.380; SD = 0.399) showed the highest scores, followed by Attention (M = 4.248; SD = 0.554). Confidence presented the lowest mean (M = 3.958; SD = 0.499), although still within a positive motivational range.

Table 1. Descriptive Statistics of IMMS Motivational Dimensions

Dimension	Mean	SD	Median	Min	Max	95% CI
Attention	4.248	0.554	4.417	2.833	5.000	[4.082-4.415]
Relevance	4.380	0.399	4.444	3.222	5.000	[4.260-4.500]
Confidence	3.958	0.499	3.889	2.889	5.000	[3.808-4.108]
Satisfaction	4.400	0.547	4.500	2.833	5.000	[4.236-4.564]
Overall	**4.234**	**0.428**	**4.333**	**3.167**	**4.944**	**[4.105-4.363]**

From the perspective of the ARCS model, these results suggest that the intervention was perceived as engaging, meaningful, and rewarding. The comparatively lower value for Confidence indicates opportunities to strengthen instructional elements that support students' perceptions of control and success expectancy, such as clearer task progression, explicit evaluation criteria, and structured formative feedback

[Keller 2009, Hattie and Timperley 2007]. The slightly lower score in the Confidence dimension may be explained by the learning curve associated with new data analysis tools and the transition to a more active and autonomous learning model. In PBL environments, students accustomed to traditional lecture-based instruction may initially experience insecurity when dealing with open-ended and complex problems, temporarily affecting their perceived confidence despite maintaining high engagement levels.

A within-subject comparison using the Friedman test revealed significant differences among the four dimensions (^{2} = 33.29, p ¡ .001, Kendall's W = 0.247). Post hoc analyses indicated that Confidence was significantly lower than the other dimensions, confirming it as the most sensitive component of the motivational profile.

Correlation analysis also revealed moderate to strong positive associations among the dimensions (p ¡ .001), with the strongest relationships observed between Relevance and Satisfaction (r = 0.787) and Attention and Satisfaction (r = 0.756). These results suggest that higher perceived usefulness and engagement are strongly associated with students' satisfaction with the learning experience.

At the item level, the highest scores were associated with perceived value of the activity and positive feelings after completion (items including "Completing this task gave me a sense of accomplishment"), whereas lower scores were related to perceived task difficulty and information density (statements such as "There was so much information that it was difficult to identify and retain the most important points"). Detailing these specific statements helps characterize how the practical dashboard creation directly influenced the different dimensions of student motivation. Overall, the findings indicate that the intervention was motivationally effective, particularly in terms of Attention, Relevance, and Satisfaction, while Confidence represents the main dimension for future instructional refinement.

7. Threats to Validity

Several threats to validity were considered in this study, and mitigation measures were adopted to reduce their potential impact, following the guidelines of [Wohlin et al. 2012]. Regarding **internal validity**, students' prior experience with lecture-based instruction and differing familiarity with spreadsheet tools may have influenced motivation and engagement. In addition, researcher bias may have affected the qualitative interpretation, since the course instructor also conducted the pedagogical mediation. To mitigate these threats, the intervention was systematically structured through TRACE, IMMS responses were collected anonymously, and qualitative evidence was triangulated with quantitative motivational data.

Regarding **construct validity**, the study primarily used the IMMS to assess motivational perceptions rather than direct measures of Computational Thinking skill acquisition, and motivation does not necessarily imply objective learning gains. To mitigate this limitation, IMMS results were complemented with descriptions of the developed dashboards, enabling broader interpretation of engagement and perceived learning experiences.

Concerning **external validity**, the study involved a single cohort of undergraduate students from the Federal University of Lavras and used a simulated international dataset in a specific educational context, which may limit generalizability. To address this threat, the instructional design, TRACE integration, PBL activities, dataset preparation, and evaluation procedures were described in detail to support replication and analytical generalization.

Finally, regarding **conclusion validity**, the relatively small sample size, absence of a control group, and predominance of descriptive analyses may limit stronger causal inferences. To mitigate this threat, measures of central tendency, dispersion, confidence intervals, and internal consistency were reported, and the findings were interpreted in light of established theoretical frameworks and related empirical studies.

8. Lessons Learned and Educational Implications

Lessons learned and educational implications were derived from students' reflective accounts and open-ended responses, which were analyzed and validated by the course instructor, enabling triangulation between student perceptions and pedagogical mediation. Students reported that PBL increased engagement, autonomy, and active participation, while the TRACE framework helped align learning objectives, activities, problem scenarios, and assessment. However, transitioning from instructor-centered approaches to active learning required greater self-regulation and shared responsibility, highlighting the need for scaffolding strategies, especially at the beginning of the course.

Workload management also emerged as a challenge due to task complexity and deadlines. In this context, TRACE supported iterative adjustments in course planning to reduce cognitive overload while preserving learning depth. Overall, the findings suggest that integrating PBL with TRACE strengthens Computational Thinking instruction, supports replicability, and provides methodological guidance for planning, documenting, and evaluating active learning interventions. The combined use of quantitative and qualitative evaluation methods also enabled a broader understanding of motivation, perceived learning, and instructional effectiveness.

9. Conclusion and Future Work

This paper presented an educational experience that integrated Computational Thinking into higher education through PBL guided by the TRACE framework. The approach aimed to address student heterogeneity and the abstract nature of computational concepts by providing a structured roadmap that supported students throughout the problem-solving process. The results indicate that the methodological scaffolding offered by TRACE facilitates effective PBL implementation by aligning pedagogical objectives with learning activities. This structure contributed to greater student engagement and fostered an environment where students reported the practical application and perceived improvement of core Computational Thinking skills, such as abstraction and decomposition.

As an exploratory study, several directions for future research emerge. These include conducting longitudinal studies to measure learning gains and motivation over time, extending the TRACE-PBL approach to other interdisciplinary Science, Technology, Engineering, and Mathematics (STEM) contexts, and investigating computational tools that support the traceability mechanisms of the framework, enabling more immediate feedback for both students and instructors.

Ethical Issues and Artificial Intelligence Use

This study followed the ethical guidelines of the Sociedade Brasileira de Computação (SBC) for educational activities involving minors. Participation was voluntary, all data were anonymized, and the intervention posed no academic or psychological risks. ChatGPT was used solely to support writing and linguistic revision of the manuscript.

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