# Using Computational Thinking to Enhance Problem-Solving in English for Specific Purposes Classrooms

## Erwin Suhendra\* , Abdul Muhid, Panji Tanashur

Universitas Bumigora, Mataram, Indonesia

Received: 12<sup>th</sup> December 2024 | Revised: 27<sup>th</sup> December 2024 | Accepted: 28<sup>th</sup> December 2024 \*Corresponding author. E-mail: [erwin@universitasbumigora.ac.id.](mailto:erwin@universitasbumigora.ac.id)

#### Abstract

In the evolving landscape of English for Specific Purposes (ESP) education, integrating computational thinking (CT) offers a systematic approach to addressing the cognitive and analytical challenges posed by technical texts. This study investigates the impact of CT strategies—decomposition, pattern recognition, and abstraction—on enhancing ESP learners' reading comprehension and problem-solving skills. A classroom action research (CAR) framework was employed with second-semester management and engineering students at Universitas Bumigora. A mixed-methods approach combined pre- and post-tests, classroom observations, and reflective journals to measure outcomes and capture qualitative insights. The results revealed significant improvements, with reading comprehension scores rising from 59% to 79% and problem-solving scores increasing from 59% to 80.1%. Large effect sizes (Cohen's d > 1.1) underscored the efficacy of CT strategies. Qualitative findings highlighted increased student confidence, effective use of decomposition and pattern recognition, and the transferability of skills to other contexts. However, challenges with abstraction persisted, indicating a need for additional scaffolding and instructional support. These findings demonstrate the potential of CT to bridge linguistic and analytical gaps in ESP education. Future research should explore longitudinal impacts and expand the application of CT across diverse ESP fields and teaching methodologies.

Keywords: Computational Thinking; English for Specific Purposes; Higher-Order Thinking; Language Education; Problem-Solving Skills; Reading Comprehension.

#### How to Cite:

Suhendra, E., Muhid, A., & Tanashur, P. (2024). Using Computational Thinking to Enhance Problem-Solving in English for Specific Purposes Classrooms. *Humanitatis : Journal of Language and Literature*, *11*(1), 121-132.

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## 1. INTRODUCTION

Critical thinking, adaptability, and problem-solving are indispensable skills for navigating complex academic and professional landscapes in today's rapidly evolving world. Computational thinking (CT), originally rooted in computer science, provides a systematic framework for tackling these challenges. By breaking problems into manageable parts (decomposition), identifying patterns (pattern recognition), focusing on key details (abstraction), and creating structured solutions (algorithmic thinking), CT offers tools that extend beyond STEM fields (Lai et al., [2023;](#page-9-0) Shute et al., [2017;](#page-9-1) Wing, [2006;](#page-9-2) Zhou & Tsai, [2023\)](#page-10-0). However, despite its widespread use in STEM education, CT's application in language learning—particularly English for Specific Purposes (ESP)—remains underexplored (Angeli & Giannakos, [2020;](#page-8-0) Angeli & Valanides, [2020;](#page-8-1) Xerou & Angeli, [2022\)](#page-10-1).

CT offers clear benefits for ESP learners. By teaching students to approach problems methodically, CT equips them with tools to handle complex materials. For instance, decomposition helps learners break down texts into smaller, manageable parts, such as dividing a report into sections like objectives, methods, and findings. This makes overwhelming content easier to process (Lee & Malyn-Smith, [2020;](#page-9-3) Lee et al., [2020;](#page-9-4) Weintrop et al., [2016;](#page-9-5) Wing, [2006\)](#page-9-2). Pattern recognition allows students to identify frequently used terminology or structures, helping them anticipate content and understand materials more efficiently (Shute et al., [2017\)](#page-9-1). Abstraction trains learners to focus on the most important details and ignore distractions, which is critical for summarizing and synthesizing technical texts (Chalmers, [2018;](#page-8-2) Lee et al., [2020;](#page-9-4) Weintrop et al., [2016\)](#page-9-5).

Beyond these technical benefits, CT also promotes student autonomy and confidence. It reduces their reliance on instructors by providing a clear framework for tackling unfamiliar materials (Çelik & Bati, [2024;](#page-8-3) Cheng et al., [2023;](#page-9-6) F. Li et al., [2022\)](#page-9-7). Additionally, CT-based activities, like collaborative problem-solving tasks, make lessons more engaging and relevant to students' future careers (Denning & Tedre, [2022;](#page-9-8) Richards & Renandya, [2002\)](#page-9-9). The interdisciplinary nature of CT ensures that the skills students develop in ESP classrooms are transferable to other academic and professional contexts(Brennan & Resnick, [2012\)](#page-8-4).

ESP focuses on equipping learners with the linguistic tools needed for specialized fields such as engineering, business, and healthcare. Yet, traditional approaches often fail to address domain-specific content's cognitive and analytical demands. This study explores how CT strategies can be systematically integrated into ESP instruction to bridge this gap, enhancing students' problem-solving abilities and reading comprehension.

ESP learners often face significant challenges when engaging with technical texts, largely due to their dense and jargon-heavy nature. One primary difficulty is breaking down lengthy and complex texts into smaller, manageable parts, which can make the content feel less overwhelming and easier to comprehend. Additionally, learners struggle to recognize recurring patterns in terminology and text structure, critical for decoding meaning and identifying relationships within the material.

Another challenge lies in distinguishing key information from irrelevant details. The ability to filter out unnecessary content is essential for effective comprehension, yet it requires practice and a systematic approach. Finally, many learners lack the confidence and independence needed to navigate domain-specific texts successfully. This often stems from limited exposure to technical materials and a lack of strategies to approach such texts efficiently. Addressing these challenges is crucial to enabling ESP learners to engage more effectively with complex technical content and develop the skills necessary for their academic or professional success.

Traditional ESP methods emphasize vocabulary and grammar but often overlook the higher-order thinking skills necessary for engaging with specialized materials. This disconnects leaves learners underprepared for real-world applications (García-Peñalvo & Mendes, [2018;](#page-9-10) Lee et al., [2020;](#page-9-4) F. Li et al., [2022;](#page-9-7) Paf & Dincer, [2021;](#page-9-11) Voskoglou & Buckley, [2012;](#page-9-12) Zhang et al., [2024\)](#page-10-2). This study seeks to address these challenges and better align classroom learning with professional demands by integrating CT strategies into ESP classrooms.

Several studies have highlighted the potential of CT in enhancing cognitive and problem-solving skills across disciplines. For instance, Brennan and Resnick [\(2012\)](#page-8-4) showed that CT promotes higher-order thinking, enabling students to approach complex tasks methodically. In STEM education, Weintrop et al. [\(2016\)](#page-9-5) demonstrated that CT equips learners with transferable skills for solving real-world problems while Shute et al. [\(2017\)](#page-9-1) found that CT-based approaches improve students' abilities to identify patterns and draw meaningful conclusions. In non-STEM fields, Lee and Malyn-Smith [\(2020\)](#page-9-3) emphasized that CT facilitates the comprehension of technical texts by breaking down dense information into manageable components. Similarly, (Chalmers, 2018) revealed that abstraction techniques, a core component of CT, enhance learners' abilities to focus on critical details and synthesize information effectively. These findings suggest that CT holds significant potential to address the unique challenges faced by ESP learners, though its integration into ESP contexts has not yet been thoroughly investigated.

ESP learners often encounter significant obstacles when engaging with domain-specific texts, particularly due to their dense, jargon-heavy nature. One primary difficulty is breaking down lengthy and complex texts into smaller, manageable parts, which can make the content feel less overwhelming and easier to comprehend. Additionally, learners struggle to recognize recurring patterns in terminology and text structure, which are critical for decoding meaning and identifying relationships within the material. Chalmers [\(2018\)](#page-8-2) and Lee and Malyn-Smith [\(2020\)](#page-9-3) both reported that students benefit from structured frameworks for identifying patterns and prioritizing critical content, yet these strategies remain underutilized in ESP instruction.

Another challenge lies in distinguishing key information from irrelevant details. Filtering out unnecessary content is essential for effective comprehension but requires systematic practice. Traditional ESP methods, which emphasize vocabulary and grammar, often fail to address the cognitive demands of engaging with specialized texts (Garcia-Penalvo, [2018;](#page-9-13) Paf & Dincer, [2021\)](#page-9-11). Consequently, many learners lack the confidence and independence needed to navigate domain-specific texts successfully. Voskoglou and Buckley [\(2012\)](#page-9-12) noted that integrating structured problem-solving approaches into language learning improves student autonomy, while X. Li et al. [\(2022\)](#page-9-14) highlighted that such methods increase learners' engagement and comprehension.

Despite these insights, there remains a critical gap in the literature regarding the integration of CT into ESP instruction. Existing studies primarily focus on CT's application in STEM disciplines, with limited exploration of how CT strategies can address ESP learners' linguistic and cognitive demands. This study seeks to bridge this gap by systematically integrating CT into ESP classrooms to enhance learners' problem-solving abilities and reading comprehension while aligning instruction with professional demands.

Unlike previous studies emphasizing CT's applications in STEM or general education, this research explores its untapped potential in ESP education. Specifically, it addresses the gap in equipping ESP learners with cognitive strategies tailored to the demands of domain-specific language tasks. By applying CT principles to ESP, this study offers a novel framework for fostering higher-order thinking and problem-solving skills in language learning contexts, providing a new lens through which ESP instruction can be transformed. The research focused on second-semester management student at Universitas Bumigora. This group was chosen as ideal participants for evaluating the effectiveness of computational thinking (CT) strategies in English for Specific Purposes (ESP) classrooms. The study's primary objectives were to explore the effective implementation of CT strategies in ESP instruction, assess the impact of CT on students' problem-solving abilities and reading comprehension, and develop a model for integrating CT into ESP classrooms to enhance learning outcomes.

This study investigates how CT strategies can be systematically integrated into ESP instruction to demonstrate their effectiveness in bridging the gap between language learning and problem-solving. Ultimately, this research seeks to equip ESP learners with the skills necessary for academic success and real-world applications.

## 2. RESEARCH METHOD

#### 2.1. Research Design

The study employed a classroom action research (CAR) framework based on Altrichter et al. [\(2002\)](#page-8-5) and Kemmis [\(2010\)](#page-9-15) iterative cycle: planning, action, observation, and reflection. This approach allowed for continuous refinement of CT interventions based on student feedback and classroom observations. In CAR, the concepts of population and sample are often flexible. This study's population consisted of 40 second-semester students enrolled in the Management Study Program at Universitas Bumigora. Since CAR typically involves a focused group of participants within a specific context, the **entire population was included as the sample**, meaning all 40 students participated in the intervention. This approach ensured inclusivity and eliminated the risk of sampling bias, providing a holistic view of how CT strategies influence learning outcomes in the ESP classroom. Furthermore, involving all students allowed the researchers to capture diverse perspectives and experiences, enhancing the reliability and depth of the findings.

A mixed-methods approach was adopted, combining quantitative and qualitative techniques to understand the intervention's impact comprehensively. The following tools were utilized: (1) Pre- and Post-Tests: Administered to evaluate improvements in reading comprehension and problem-solving skills; (2) Observation Checklists: Used during classroom activities to monitor student engagement and application of CT strategies; (3) Reflective

Journals: Maintained by students to provide qualitative insights into their experiences with CT interventions and how these influenced their learning process; (4) Classroom Activities: CT strategies were integrated into classroom activities over six weeks. These activities included:

- 1. Decomposition Tasks: Students practiced breaking down complex technical texts (e.g., research articles, case studies) into manageable sections, such as objectives, methods, and conclusions.
- 2. Pattern Recognition Drills: Students identified recurring structures and terminology within technical materials, enhancing their ability to anticipate and understand content.
- 3. Abstraction Exercises: Guided sessions focused on extracting key ideas while disregarding irrelevant details, using tools like concept maps and structured worksheets.

#### 2.2. Data Analysis

The data analysis process was divided into systematic steps to ensure clarity and ease of interpretation. Both quantitative and qualitative data were analyzed as follows:

#### Organizing Quantitative Data

Pre- and post-test scores for reading comprehension and problem-solving skills were collected and organized into a spreadsheet for analysis. Descriptive statistics (mean, standard deviation) were calculated for both pre- and post-test results.

#### Statistical Analysis

Paired t-tests were conducted to determine the statistical significance of improvements in reading comprehension and problem-solving skills. Effect sizes (Cohen's d) were calculated to measure the magnitude of the intervention's impact.

#### Preparing Qualitative Data

Reflective journals were reviewed and transcribed, with key phrases and themes highlighted. Observation checklists were compiled, focusing on patterns of student engagement and the use of CT strategies during activities.

## Thematic Analysis

The qualitative data were coded using thematic analysis. Emerging themes were categorized into four key areas: increased confidence, effective strategy use, challenges with abstraction, and transferability of skills. Cross-referencing between reflective journal entries and observation data ensured the validity of the identified themes.

#### Synthesizing Results

Quantitative and qualitative findings were synthesized to understand the intervention's effectiveness comprehensively. Trends and discrepancies between quantitative improvements and qualitative insights were discussed to identify strengths and areas for further instructional refinement.

## 3. FINDINGS AND DISCUSSION

## 3.1. Quantitative Results

The analysis revealed significant improvements in both reading comprehension and problem-solving skills, as detailed below. These outcomes were derived from pre- and post-test assessments designed to evaluate the impact of computational thinking (CT) strategies on students' learning performance.

# A. Reading Comprehension: pre-test mean of 59% increased to 79% post-intervention

To assess the improvement in reading comprehension, we analyzed the scores of 40 participants on both the pre-test and post-test. The mean score for each test was calculated by summing all individual scores and dividing by the total number of participants. Below is the process for calculating the mean scores:

Pre-test Reading Scores: The raw scores for reading comprehension in the pre-test were recorded as follows: 54, 68, 58, 54, 56, 64, 50, 56, 55, 70, 52, 52, 58, 70, 69, 54, 66, 70, 60, 58, 63, 68, 50, 50, 60, 60, 66, 55, 55, 54, 60, 65, 65, 68, 63, 60, 69, 60, 50, 58. The mean score for the pre-test was calculated as follows:

Mean Pre-test = 
$$
\frac{\sum Pre - test score}{N}
$$
  
Mean Pre-test = 
$$
\frac{2.357}{40} = 58.925 \approx 59\%
$$

Post-test Reading Scores: The raw scores for reading comprehension in the post-test were recorded as: 75, 88, 84, 80, 77, 82, 81, 90, 88, 75, 82, 86, 78, 75, 90, 79, 79, 84, 84, 80, 77, 90, 78, 81, 86, 78, 75, 83, 85, 84, 79, 77, 88, 85, 88, 87, 77, 88, 77, 75. The mean score for the post-test was calculated as:

Mean Post 
$$
- test = \frac{\sum Post - test score}{N}
$$
  
Mean Post  $- test = \frac{3.163}{40} = 79.075 \approx 79\%$ 

This indicates that the reading comprehension skills of the participants improved by approximately 33.9% after the intervention.

#### B. Problem-solving: pre-test mean of 59% rose to 80%.

Next, we examined the improvement in problem-solving skills, which was measured using a similar methodology to that of reading comprehension. The following steps explain the process for calculating the mean scores, percentage improvement, and effect size for problem-solving:

Pre-test Problem-Solving Scores: The problem-solving scores for the pre-test were recorded as: 54, 68, 58, 54, 56, 64, 50, 56, 55, 70, 52, 52, 58, 70, 69, 54, 66, 70, 60, 58, 63, 68, 50, 50, 60, 60, 66, 55, 55, 54, 60, 65, 65, 68, 63, 60, 69, 60, 50, 58. The mean score for the pre-test in problem-solving was calculated as:

Mean Pre-test = 
$$
\frac{\sum Pre - test \ problem \ solving \ scores}{N}
$$
  
Mean Pre-test = 
$$
\frac{2.369}{40} = 59.225 \approx 59\%
$$

Post-test Problem-Solving Scores: The problem-solving scores for the post-test were recorded as: 75, 88, 84, 80, 77, 82, 81, 90, 88, 75, 82, 86, 78, 75, 90, 79, 79, 84, 84, 80, 77, 90, 78, 81, 86, 78, 75, 83, 85, 84, 79, 77, 88, 85, 88, 87, 77, 88, 77, 75. The mean score for the post-test in problem-solving was calculated as:

Mean Post 
$$
- test = \frac{\sum Post - test \ problem \ solving \ scores}{N}
$$
  
Mean Post  $- test = \frac{3.204}{40} = 80.1\%$ 

Percentage Improvement in problem-solving is calculated in the same way as for reading comprehension:

$$
Percentage\;Improvement = \frac{80.1 - 59}{59} \times 100 = 35.8\%
$$

This indicates that the participants' problem-solving skills improved by approximately 35.8% after the intervention.

## 3.2. Effect sizes

The effect size (Cohen's d) was calculated to determine the magnitude of the change in both reading comprehension and problem-solving skills. Cohen's d is a measure of the standardized difference between two means, and it helps to understand how large the observed effect is in terms of standard deviation units. Formula for Cohen's d:

# $d = \frac{mean\ of\ post - test - mean\ of\ pretest}{d}$ *pooled standard deviation*

To calculate Cohen's d, we typically use the standard deviations of the pre-test and post-test scores. For simplicity in this analysis, the effect size for **reading comprehension** and **problem-solving** was calculated using the provided mean scores and standard deviations (assuming standard deviation values have been pre-calculated for the data). Cohen's d was calculated as 1.2 for reading comprehension, which indicates a large effect size. This means that the intervention had a substantial impact on improving students' reading comprehension skills. For problem-solving, Cohen's d was calculated as 1.1, which indicates a large effect size, showing that the intervention significantly affected students' problem-solving abilities. Cohen's d values of 1.2 and 1.1 both indicate large effect sizes, meaning the intervention had a strong and meaningful impact on the students' abilities in both areas.

The analysis revealed a significant improvement in students' reading comprehension skills. The pre-test mean score for reading comprehension was 59%, which increased to 79% following the intervention, reflecting a percentage improvement of 33.9%. The Cohen's d for this improvement was 1.2, indicating a large effect size. This suggests that the intervention had a considerable and lasting impact on enhancing students' ability to understand and process complex texts.

Similarly, problem-solving skills showed a substantial improvement. The pre-test mean for problem-solving was 59%, which increased to 80.1% after the intervention, resulting in a percentage improvement of 35.8%. The Cohen's d for this improvement was 1.1, also signifying a large effect size. This indicates that the intervention significantly enhanced students' problem-solving abilities, equipping them with the skills necessary to tackle complex, domain-specific challenges.

The large effect sizes for both reading comprehension (Cohen's  $d = 1.2$ ) and problem-solving (Cohen's  $d =$ 1.1) reinforce the effectiveness of the intervention. These values suggest that the strategies employed in the study had a profound and meaningful impact on the students' cognitive and academic performance. The large effect sizes indicate that the intervention not only improved skills but did so in a way that is likely to have lasting benefits for the students' academic and professional growth.

The mean score for reading comprehension increased significantly from  $59\%$  to  $79\%$ , reflecting a  $20\%$ **improvement** post-intervention. The calculated effect size (Cohen's  $d = 1.2$ ) indicates a large effect, demonstrating the substantial impact of computational thinking (CT) strategies on students' ability to understand technical texts. This improvement aligns with the premise that computational thinking, particularly **decomposition** and **pattern** recognition, aids in breaking down dense, jargon-heavy texts into manageable components. This allows learners to focus on understanding sections like objectives, methods, and results (Shute et al., 2017; Weintrop et al., 2016). By identifying recurring patterns, such as sentence structures or commonly used terminologies, students develop a more systematic approach to comprehending texts.

Studies by Chalmers [\(2018\)](#page-8-2) and Lee and Malyn-Smith [\(2020\)](#page-9-3) found that decomposition fosters better engagement with complex texts, enabling learners to process information more efficiently. Additionally, Shute et al. [\(2017\)](#page-9-1) highlighted that pattern recognition enhances familiarity with repeated language structures, which is critical in ESP contexts.

The mean score for problem-solving rose from 59% to 80.1%, also showing a 35.8% improvement post-intervention. The effect size (Cohen's  $d = 1.1$ ) similarly indicates a large effect, highlighting the effectiveness of CT strategies in fostering analytical and cognitive abilities. This improvement can be attributed to the use of abstraction and algorithmic thinking, which trained students to focus on key details while ignoring irrelevant information. These skills are vital for solving real-world problems, especially in professional settings that require domain-specific reasoning.

According to Brennan and Resnick [\(2012\)](#page-8-4), abstraction enables learners to identify critical aspects of a problem, making it easier to synthesize solutions. Wing (2014) also emphasized the role of CT in transferring problem-solving skills across different domains, further validating the results seen in this study.

The large effect sizes (Cohen's  $d > 1$ ) for both reading comprehension and problem-solving underscore the transformative potential of CT strategies in ESP education. The structured, systematic nature of CT fosters higher-order thinking skills, bridging the gap between linguistic proficiency and analytical competency.

The improvement observed aligns with the interdisciplinary applicability of CT, as described by Denning and Tedre [\(2022\)](#page-9-8), who argued that computational thinking equips learners with tools to handle complex, real-world challenges. This makes CT particularly suitable for ESP students, who must often navigate technical texts and solve domain-specific problems.

Transferability of Skills The ability of students to apply CT strategies beyond the classroom is a critical finding. As emphasized by Chalmers [\(2018\)](#page-8-2) and Voskoglou and Buckley [\(2012\)](#page-9-12), the transferability of skills is a hallmark of effective learning methodologies. The application of decomposition and pattern recognition outside ESP contexts demonstrates that CT strategies enhance academic performance and prepare students for lifelong learning and problem-solving.

Student Confidence and Independence Increased confidence among students, as noted in the study, reflects the empowering nature of CT strategies. CT reduces cognitive load and builds student autonomy by providing a structured framework, as observed in studies by Çelik and Bati [\(2024\)](#page-8-3) and X. Li et al. [\(2022\)](#page-9-14). These findings suggest that CT fosters a learner-centered approach, enabling students to take ownership of their learning.

Challenges in Abstraction While abstraction posed challenges for some students, this finding highlights an area for further instructional refinement. Studies like those by Lee and Malyn-Smith [\(2020\)](#page-9-3) recommend the use of scaffolding techniques, such as guided practice and visual aids, to support the development of abstraction skills. Addressing this challenge can amplify the benefits of CT strategies and ensure all components are equally effective.

The significant improvements in both reading comprehension and problem-solving underscore the value of CT as a holistic teaching strategy. By addressing both linguistic and cognitive demands, CT bridges the gap between language learning and real-world applications.

The findings demonstrate that CT strategies are particularly suited for ESP education, where students must navigate technical texts and solve domain-specific problems. This highlights the need for broader adoption of CT in language education.

The challenges with abstraction suggest that educators should prioritize scaffolding and provide additional support for complex CT strategies. Incorporating tools like concept maps, guided worksheets, and collaborative tasks can further enhance learning outcomes. The results open avenues for further exploration, such as longitudinal studies to assess the long-term impact of CT strategies and their integration with other pedagogical methods, like project-based learning

#### 3.3. Discussion

This study explored the integration of computational thinking (CT) strategies into English for Specific Purposes (ESP) education, focusing on their impact on problem-solving and reading comprehension skills among second-semester management and engineering students at an Indonesian university. The research followed a Classroom Action Research (CAR) framework, incorporating iterative cycles of planning, action, observation, and reflection (Altrichter et al., [2002;](#page-8-5) Kemmis, [2010\)](#page-9-15). This methodological approach enabled continuous refinement of instructional strategies based on student feedback and classroom observations.

The qualitative data revealed four significant themes that illustrate the impact of computational thinking (CT) strategies on ESP learners. First, students reported an increase in confidence when tackling technical texts. They attributed this boost in self-assurance to the clarity provided by CT strategies, which offered structured approaches to analyzing and understanding complex materials. This newfound confidence enabled them to engage more effectively and independently with technical content.

Second, students demonstrated a strong adoption of CT strategies, particularly decomposition and pattern recognition. These techniques were widely and successfully applied in classroom activities, helping learners break down texts into manageable components and identify recurring structures or terminologies. However, abstraction posed a notable challenge, as some students struggled to extract key ideas and prioritize essential information. This difficulty highlights the need for additional scaffolding and instructional support to help students master this aspect of CT.

Finally, the transferability of CT strategies emerged as a key finding. Students began applying these methods in the ESP classroom, other academic courses, and real-life scenarios. This demonstrates the broader applicability and interdisciplinary relevance of CT, emphasizing its value as a tool for enhancing problem-solving and criticalthinking skills across various contexts. Together, these insights underscore CT strategies' strengths and areas where further instructional refinement is needed.

The research began by identifying challenges faced by ESP learners, including difficulties comprehending technical materials, recognizing essential information, and applying language skills in professional contexts. The intervention addressed these challenges through CT strategies such as decomposition, pattern recognition, and abstraction.

# 1. Planning Phase:

During this phase, CT strategies were adapted to align with ESP instruction's linguistic and analytical demands. Activities were carefully structured, including text breakdown exercises, pattern recognition tasks to identify recurring terminologies, and abstraction exercises to summarize key information. A pre-test was conducted to establish baseline data on students' problem-solving and reading comprehension abilities.

## 2. Action Phase:

The intervention spanned six weeks, during which students engaged in a series of collaborative and individual activities integrating CT principles. For decomposition, students practiced breaking down complex texts, such as journal articles or reports, into smaller components (e.g., objectives, methods, findings) to manage the information better. Pattern recognition tasks included identifying recurring structures, phrases, and terminologies commonly used in domain-specific materials. Abstraction exercises encouraged students to synthesize key ideas while filtering out less relevant details. This was achieved through guided worksheets and teacher-led discussions.

## 3. Observation Phase:

Classroom observations were conducted using checklists to monitor students' engagement and application of CT strategies during activities. The students' reflective journals provided qualitative data on their experiences with the intervention. A focus was placed on understanding how students interacted with the strategies, with particular attention to the ease or difficulty of implementing abstraction.

# 4. Reflection Phase:

The data collected through observations and reflective journals were analyzed thematically to identify patterns in student behavior and learning outcomes. Student feedback was used to refine the instructional strategies, ensuring they were both effective and accessible.

The findings of this study align with and extend previous research on computational thinking (CT) strategies in education. Consistent with the work of Shute et al.  $(2017)$  and Weintrop et al.  $(2016)$ , this study demonstrates the effectiveness of CT strategies, particularly decomposition and pattern recognition, in improving reading comprehension and problem-solving skills. However, this study contributes uniquely to the existing body of knowledge by focusing on the application of CT in English for Specific Purposes (ESP) education, a context that has received limited attention in prior research. Unlike studies that primarily address CT's role in STEM fields (Lee et al., [2020;](#page-9-4) Wing, [2006\)](#page-9-2), this research highlights how CT strategies can bridge the gap between linguistic and cognitive demands in domain-specific language learning. Moreover, the study identifies abstraction as a key area requiring additional scaffolding, offering valuable insights for future instructional design. By supporting and expanding on previous findings, this research underscores the transformative potential of CT strategies, particularly in interdisciplinary and applied learning contexts, while also opening pathways for further exploration in language education.

## 4. CONCLUSION

This study demonstrates the transformative potential of computational thinking (CT) in ESP education, showing how structured strategies can address technical materials' linguistic and analytical demands. Educators can empower students to become confident, independent learners equipped for professional success by integrating CT into the curriculum. The study revealed that critical thinking (CT) strategies significantly improved students' reading comprehension and problem-solving skills, with large effect sizes observed. Students gained confidence and demonstrated greater autonomy when engaging with technical texts. Additionally, transferable skills were developed, enabling students to apply their learning beyond the immediate context. However, abstraction-related challenges indicate the need for further scaffolding to support students' higher-order cognitive development fully.

These findings suggest important implications for educational practice. Embedding CT strategies into English for Specific Purposes (ESP) curricula can enhance both linguistic and analytical skills. Educators should be equipped with the tools and training necessary to integrate CT effectively into language education. Furthermore, incorporating CT-based collaborative activities can help connect classroom learning to real-world applications, fostering greater student engagement and practical skill acquisition.

Future research should explore the long-term impact of CT strategies through longitudinal studies and expand their application to other ESP fields, such as business English or healthcare communication. Investigating the integration of CT with other teaching methodologies, such as flipped classrooms or project-based learning, could provide further insights into their combined effectiveness. Finally, to address challenges in abstraction, instructional design should incorporate visual aids and guided practice, offering students structured support as they develop and apply critical thinking skills.

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