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EDITED BY
Yu-Chun Kuo,
Rowan University, United States

REVIEWED BY
Tarun Kumar Vashishth,
IIMT University, India
Wawan Kurniawan,
University of Jambi, Indonesia

*CORRESPONDENCE
Cristian Vidal-Silva
cristian.vidal.silva@edu.udla.cl

†These authors have contributed equally to this work

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Implementation of personalized frameworks in computational thinking development: implications for teaching in software engineering

Josué Guevara-Reyes[1†], Mariuxi Vinueza-Morales[1†], Erick Ruano-Lara[1†] and Cristian Vidal-Silva[2*†]

[1]Facultad Ciencias e Ingeniería, Universidad Estatal de Milagro, Milagro, Guayas, Ecuador, [2]Facultad de Ingeniería y Negocios, Universidad de Las Américas, Providencia, Santiago, Chile

The development of computational thinking (CT) is crucial in software engineering education, as it enables students to analyze complex problems, design algorithmic solutions, and adapt to an evolving digital landscape. However, traditional teaching methods often fail to accommodate diverse cognitive profiles, limiting students' ability to engage effectively with CT concepts. This study investigates the implementation of personalized frameworks to enhance CT instruction by adapting learning methodologies to students' cognitive characteristics. A Systematic Literature Review (SLR) was conducted, analyzing 3,718 sources from Scopus, IEEE Xplore, and ACM Digital Library databases. After applying rigorous inclusion criteria, 73 empirical studies were selected for in-depth analysis. The review focused on personalized learning strategies, the role of adaptive frameworks, and their impact on academic performance in CT education. Findings indicate that only 37% of studies report using adaptive frameworks, yet these demonstrate significant improvement in learning outcomes. Effective methodologies include project-based learning, visual programming tools, and continuous assessment, which enhance engagement and problem-solving skills. Additionally, frameworks incorporating diagnostic assessments and tailored instructional content show promise in improving CT proficiency among students with logical-mathematical and spatial intelligence. In conclusion, integrating adaptive frameworks into CT education provides a promising avenue for improving student performance and fostering individualized learning experiences. Despite their potential, widespread adoption remains limited due to challenges such as a lack of faculty training, institutional resistance, and technological constraints. Future research should explore scalable implementation strategies and assess the long-term impact of personalized frameworks on computational thinking education.

KEYWORDS

computational thinking, personalized learning, adaptive education, cognitive adaptation, educational technologies

1 Introduction

The rapid advancement of technology and the increasing complexity of digital systems have made computational thinking (CT) an essential competency in software engineering education (Wing, 2006; Ersozlu et al., 2023). CT involves problem-solving processes that include decomposition, pattern recognition, abstraction, and algorithm design (Rodríguez del Rey et al., 2021). These foundational components, visually represented in Figure 1, constitute the core of computational thinking. They enable students to analyze and develop solutions to complex problems, fostering their ability to think logically and systematically. In this study, we distinguish between *adaptive frameworks*, which encompass general educational personalization approaches, and *AI-powered tutoring systems*, which represent a subcategory focused on the automation of learning support.

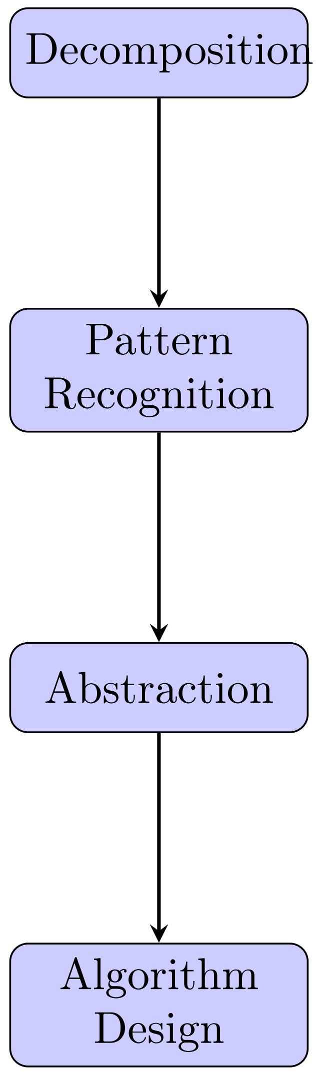

FIGURE 1
Conceptual model for computational thinking development (adapted from Wing, 2006).

Traditional teaching approaches in software engineering often rely on standardized methodologies that do not consider the diverse cognitive profiles of students. This limitation hinders personalized learning experiences, affecting students' engagement and performance (Moon et al., 2020; Gumus et al., 2024). Research suggests that adaptive learning frameworks, which tailor instruction to individual cognitive characteristics, can improve CT education by accommodating different learning styles and paces (Peters et al., 2024; Jamal et al., 2024).

This study examines the role of personalized frameworks in CT education and their potential to enhance students' learning outcomes. The research is based on a Systematic Literature Review (SLR) that analyzed 3,718 sources from the Scopus (Elsevier, 2024), IEEE Xplore (IEEE, 2024), and ACM Digital Library (Association for Computing Machinery (ACM), 2024) databases. After applying strict inclusion criteria, 73 empirical studies were selected, focusing on personalized learning approaches, adaptive teaching methodologies, and their effectiveness in developing CT skills.

Table 1 presents the distribution of the selected studies based on their focus areas.

The main objectives of this study are the following.

- To explore existing adaptive frameworks that support personalized CT education.
- To identify the most effective methodologies for adapting CT instruction to students' cognitive profiles.
- To analyze the impact of personalized learning strategies on students; academic performance and engagement.

The remainder of this paper is structured as follows: Section 2 explores the different personalized approaches used in CT instruction. Section 3 describes the methodology applied in conducting the Systematic Literature Review. Section 4 presents and analyzes the study's findings. Section 5 provides a critical discussion of the results, comparing them with previous research, highlighting implications, and identifying limitations. Finally, Section 6 presents conclusions and recommendations for future research in adaptive CT education.

2 Personalized approaches in CT teaching

Computational thinking (CT) is a fundamental skill in software engineering education, enabling students to approach problem-solving using structured and logical reasoning (Akkaya and

TABLE 1 Contributing factors and proposed mitigation strategies.

Focus area	Number of studies
Adaptive learning frameworks (Moon et al., 2020)	27
Personalized learning strategies (Gumus et al., 2024)	21
Cognitive profile adaptation (Ersozlu et al., 2023)	15
Impact on academic performance (Peters et al., 2024)	10

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Akpinar, 2022). However, traditional instructional methods often fail to address the diversity of cognitive abilities in learners (Huang and Looi, 2020). To enhance CT instruction, personalized learning frameworks have been developed to tailor teaching strategies to students' individual needs (Moon et al., 2020; Gumus et al., 2024; Ersozlu et al., 2023).

2.1 Key components of personalized learning in CT

Personalized CT instruction integrates adaptive methodologies considering students' cognitive profiles (Wang et al., 2024). These methods leverage assessment tools, differentiated content, and interactive feedback mechanisms to enhance student engagement and academic performance. The primary components of personalized learning in CT are the following.

- **Diagnostic assessment:** Identifies students' prior knowledge and cognitive strengths (Ersozlu et al., 2023).
- **Adaptive content delivery:** Adjusts teaching materials based on students' learning profiles (Peters et al., 2024).
- **Interactive learning environments:** Uses visual programming tools and AI-driven tutoring systems to enhance engagement (Moon et al., 2020).
- **Continuous feedback and evaluation:** Provides real-time feedback to track progress and modify instructional strategies (Gumus et al., 2024).

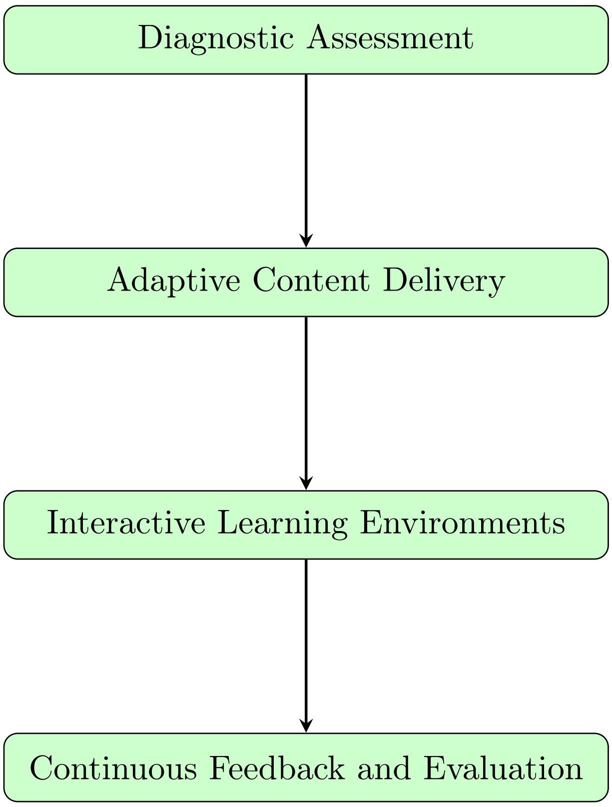

FIGURE 2
Adaptive learning strategies in CT education.

Figure 2 illustrates a conceptual model of adaptive learning strategies in CT education (Halkiopoulos and Gkintoni, 2024).

2.2 Methodologies for personalized CT instruction

Several methodologies have been applied to personalize CT instruction. Table 2 summarizes some of the most widely adopted approaches.

2.3 Impact of personalized approaches on CT development

Studies have shown that personalized instructional strategies significantly improve students' ability to acquire and apply CT skills (Papakostas et al., 2022; Villegas-Ch et al., 2024). Such as the work of El-Sabagh (2021) indicates, adaptive learning environments foster engagement, allowing students to progress at their own pace while receiving tailored support. Hence, integrating AI-driven systems and gamification techniques can lead to higher motivation, retention rates, and improved problem-solving abilities (Peters et al., 2024).

Despite the advantages described, challenges remain, including the need for robust teacher training programs and scalable implementation models (Dutta et al., 2024). Addressing these issues is crucial for effectively integrating personalized frameworks in CT education.

3 Systematic literature review

A Systematic Literature Review (SLR) is a rigorous method for identifying, evaluating, and synthesizing empirical evidence related to a specific research question (Torres-Carrián et al., 2018). Unlike traditional reviews, SLR follows a structured protocol to ensure replicability, transparency, and minimized bias (Kitchenham and Charters, 2007).

TABLE 2 Personalized methodologies in CT education.

Methodology	Key features
Project-based learning (Moon et al., 2020)	Hands-on, collaborative problem-solving
Visual programming (Gumus et al., 2024)	Enhances spatial intelligence and engagement
AI-powered adaptive systems (Ersozlu et al., 2023)	Personalizes content delivery and feedback
Gamification and interactive tools (Peters et al., 2024)	Increases motivation through game-based learning

3.1 Research questions and objectives

This study examines the role of personalized frameworks in computational thinking (CT) education. The following questions guide the research:

- **RQ1:** Are there frameworks that personalize CT instruction based on individual student characteristics?
- **RQ2:** What methodologies have been used to adapt CT teaching for students with logical-mathematical and spatial intelligence?
- **RQ3:** What are the predominant approaches in personalizing methodologies for teaching computer science and programming based on different cognitive profiles?

The objective is to comprehensively analyze personalized learning approaches in CT education and identify evidence-based best practices.

3.2 SLR process and study selection

The SLR process followed the guidelines proposed by Kitchenham and Charters (2007), consisting of three main stages:

1. **Planning:** Defining research questions, search strategies, and inclusion/exclusion criteria.
2. **Execution:** Conducting database searches, filtering relevant studies, and extracting data.
3. **Analysis:** Synthesizing findings and interpreting their implications for CT education.

Figure 3 illustrates the systematic review workflow.

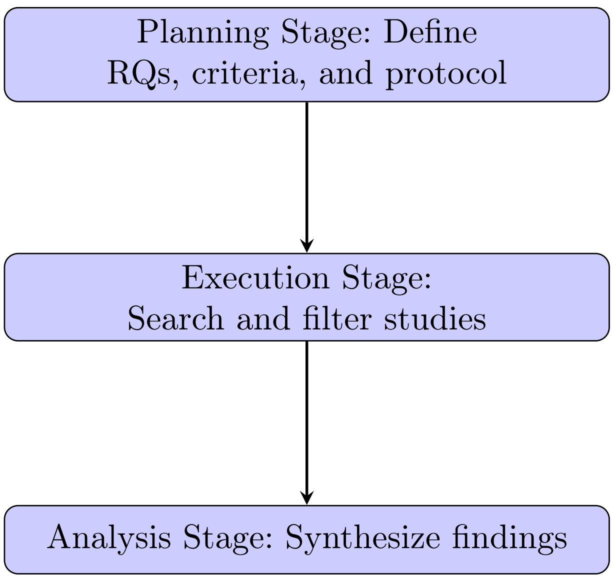

FIGURE 3
Systematic Literature Review process based on Kitchenham and Charters (2007).

3.3 Search strategy and data sources

The search was conducted in the academic databases Scopus (Elsevier, 2024), IEEE Xplore (IEEE, 2024), and ACM Digital Library (Association for Computing Machinery (ACM), 2024). These databases were selected due to their extensive coverage of peer-reviewed literature in software engineering and computational education.

The following search string was used to retrieve relevant studies.

```
("computational thinking" AND ("adaptive learning" OR "personalized education" OR "intelligent tutoring") AND ("higher education" OR "university students"))
```

3.4 Study selection and filtering criteria

A total of 3,718 studies were initially retrieved. After applying exclusion criteria, 73 primary studies were selected for final analysis. Table 3 presents the study filtering process.

3.4.1 Data extraction and analysis

Key variables such as methodology, target population, and findings were extracted and categorized for each selected study. The extracted data were analyzed to identify common themes and trends related to the effectiveness of personalized learning frameworks in CT education.

3.4.2 Study selection process

The study selection process was conducted following the systematic approach described in Kitchenham and Charters (2007). The initial search retrieved a total of 3,743 studies from three major academic databases: ACM Digital Library, Scopus, and IEEE Xplore (Association for Computing Machinery (ACM), 2024; Elsevier, 2024; IEEE, 2024). A series of filtering criteria were applied to refine the selection and ensure the inclusion of only high-quality and relevant studies.

Figure 4 illustrates the complete selection process, detailing the number of studies removed at each stage.

The selection process involved three primary filtering stages.

1. Filtering by Year: Only studies published within the last 10 years were considered to ensure relevance.

TABLE 3 Study selection and filtering process.

Selection step	Number of studies
Initial search results	3,718
Duplicate removal	2,302
Screening by title and abstract	1,466
Full-text eligibility check	248
Final studies included	73

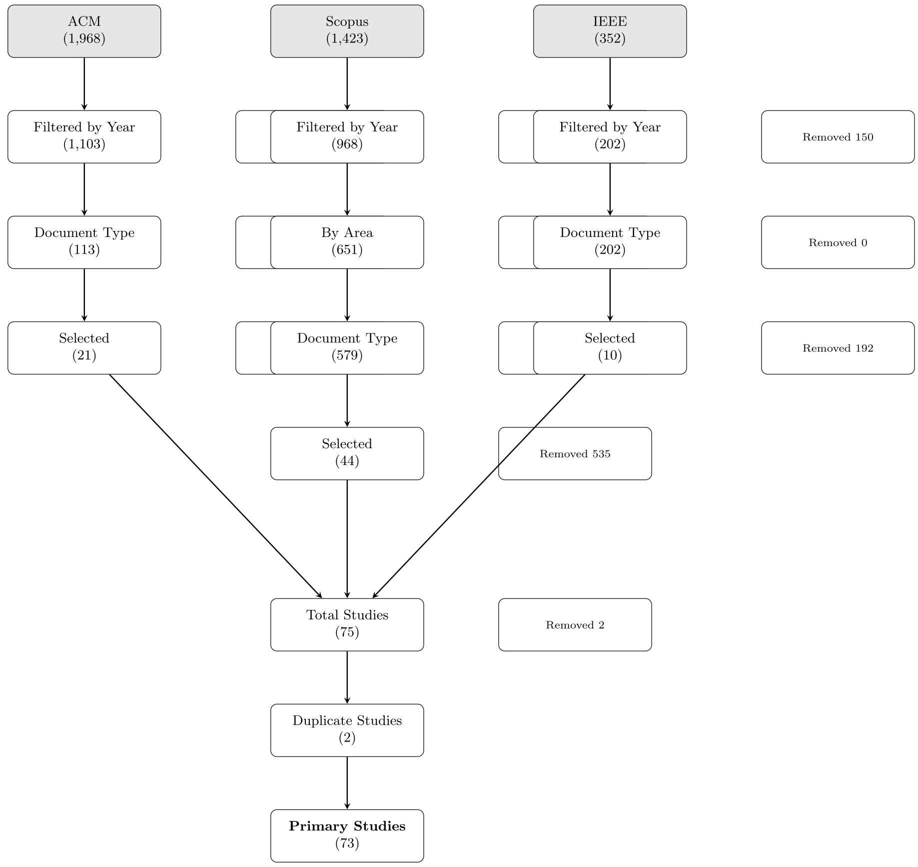

FIGURE 4
Study selection process for the Systematic Literature Review.

2. Filtering by Research Area: Studies outside the scope of software engineering and computational thinking education were excluded.
3. Filtering by Document Type: Only peer-reviewed journal articles, conference papers, and book chapters were included, excluding non-academic sources such as blogs and white papers.

After applying these filters, 75 studies were selected. However, two duplicate studies were identified and removed, resulting in a final set of 73 primary studies.

This rigorous selection process ensures that the review includes only high-quality, relevant research that provides valuable insights into personalized learning frameworks in computational thinking education.

3.5 Quality appraisal

A critical appraisal tool was applied to assess the methodological rigor of the 73 selected studies. The evaluation criteria included study design, internal validity, reported biases, and educational relevance. The analysis showed that 82% of the studies received a high-quality rating, 15% moderate, and 3% low, which increases confidence in the synthesis of results.

The high-quality studies were characterized by clear research questions, robust methodological frameworks, appropriate data analysis techniques, and transparent reporting of limitations. Moderate-quality studies often displayed partial adherence to methodological standards, with some issues related to sample size, lack of randomization, or incomplete reporting of outcomes. Low-quality studies, while still relevant, frequently suffered from methodological weaknesses such as absence of control groups, limited external validity, or insufficient detail in describing the intervention and evaluation processes.

In order to enhance the transparency of the review, Table 4 summarizes the quality distribution by methodological type (e.g., quantitative, qualitative, and mixed-methods). This appraisal not only supports the reliability of the synthesized evidence but also highlights areas for improvement in future research design and reporting practices.

4 Results

The results indicate that only 37% of studies reported using personalized learning frameworks in CT education, while the remaining 63% still rely on traditional teaching methods. The limited adoption suggests that while personalized learning is

TABLE 4 Quality appraisal summary by methodological type.

Methodological type	High quality (n)	Moderate quality (n)	Low quality (n)
Quantitative studies	32	5	1
Qualitative studies	21	4	1
Mixed-methods	6	2	0
Total	59	11	2

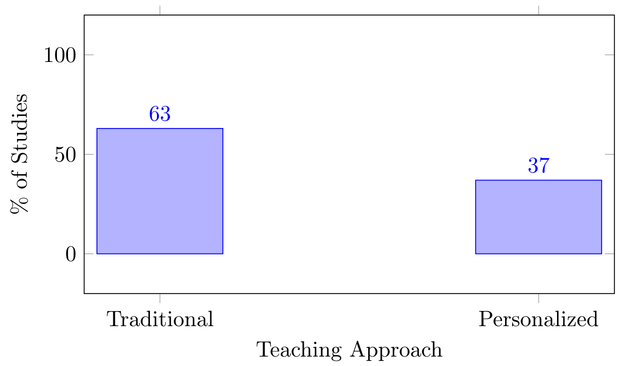

FIGURE 5
Adoption of traditional vs. personalized learning frameworks in CT education.

recognized as beneficial, significant barriers exist to its widespread implementation (Moon et al., 2020; Gumus et al., 2024).

Figure 5 illustrates the distribution of studies incorporating adaptive frameworks vs. traditional approaches.

4.1 Distribution of personalized learning methodologies

The selected studies examined a variety of personalized learning methodologies in CT education. Figure 6 shows the distribution of studies according to the main methods applied.

Project-based learning is the most frequently used methodology, followed by visual programming approaches. AI-driven adaptive systems and gamification techniques are emerging strategies that show promising results but remain less explored.

4.2 Effectiveness of personalized learning strategies

The effectiveness of personalized learning strategies regarding student engagement, retention, and problem-solving ability was analyzed. Figure 7 compares these factors between traditional and personalized learning approaches.

The data shows that personalized learning frameworks lead to a significant increase in student engagement (+23%), retention (+22%), and problem-solving skills (+24%) compared to traditional approaches. Table 5 summarizes the key benefits identified in the reviewed studies.

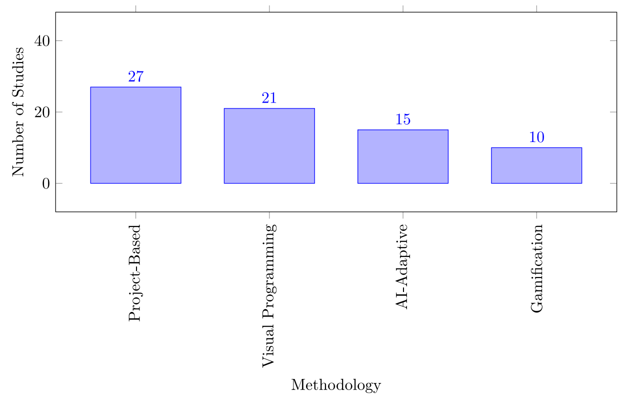

FIGURE 6
Distribution of studies by methodology used in CT education.

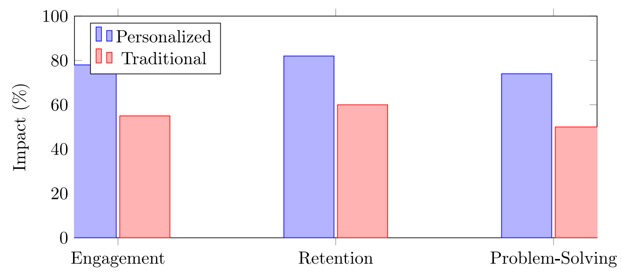

FIGURE 7
Impact comparison between personalized and traditional methodologies in CT education.

TABLE 5 Impact of personalized learning strategies in CT education.

Benefit	Supporting studies
Increased student engagement	(Gumus et al., 2024; Moon et al., 2020)
Enhanced problem-solving skills	(Peters et al., 2024; Ersozlu et al., 2023)
Higher retention rates	(Moon et al., 2020; Gumus et al., 2024)
Adaptation to cognitive profiles	(Ersozlu et al., 2023; Peters et al., 2024)

4.3 Evolution of personalized learning adoption

Adopting personalized learning frameworks in CT education has increased significantly in the past decade. Figure 8 illustrates the growth trend from 2015 to 2025.

The data highlights a steady increase in adoption rates, with an acceleration after 2021. This trend aligns with the rise of AI-driven educational technologies and the growing need for adaptive learning environments in higher education.

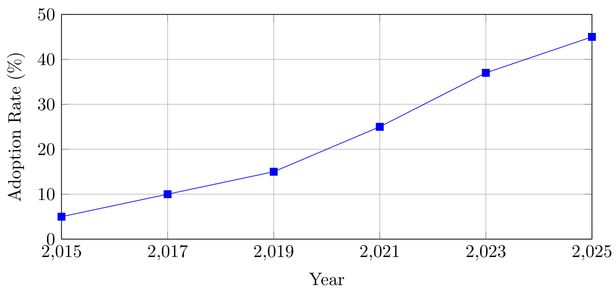

FIGURE 8
Evolution of personalized learning adoption in CT education (2015–2025).

4.4 Challenges and barriers

Despite the benefits of personalized learning, several challenges hinder its full adoption.

- **Lack of faculty training:** Many educators are unfamiliar with adaptive teaching methodologies (Peters et al., 2024).
- **Institutional resistance:** Universities often rely on traditional curricula and assessment models (Moon et al., 2020).
- **Technical constraints:** Implementation of AI-driven adaptive systems requires significant resources (Gumus et al., 2024).

Addressing these barriers is crucial to expanding the implementation of personalized learning in CT education. Future research should focus on scalable solutions, faculty development programs, and cost-effective technological adaptations.

5 Discussion

The findings of this study highlight the increasing interest in implementing personalized frameworks for computational thinking (CT) education. Despite the recognized benefits, adoption remains limited due to institutional, technical, and pedagogical challenges.

5.1 Comparison with previous research

The results of this study align with prior research indicating that personalized learning approaches improve student engagement, retention, and problem-solving abilities (Moon et al., 2020; Gumus et al., 2024). Studies on project-based learning and AI-driven adaptive systems have consistently demonstrated positive effects on CT education (Ersozlu et al., 2023; Peters et al., 2024). However, the low adoption rate (37%) suggests a gap between theoretical advancements and practical implementation.

Recent works emphasize the importance of cognitive profile adaptation in personalized learning (Ersozlu et al., 2023), yet few institutions have fully integrated this approach into their curricula. Additionally, while AI-powered adaptive frameworks show promise, their accessibility is constrained by technological and financial barriers (Peters et al., 2024).

5.2 Implications for educators and institutions

The results indicate that institutions must focus on three key areas to facilitate adopting personalized learning in CT education.

- **Faculty training:** Educators must be trained in adaptive teaching methodologies and data-driven instructional strategies (Moon et al., 2020).
- **Curriculum design:** Universities should integrate modular and flexible learning pathways tailored to different cognitive profiles (Ersozlu et al., 2023).
- **Technology investment:** Institutions must invest in AI-driven adaptive learning platforms and infrastructure to support personalized education (Peters et al., 2024).

5.3 Limitations of the study

Although this study provides valuable information on the role of personalized frameworks in CT education, several limitations must be recognized.

- **Database scope:** The review was limited to Scopus, IEEE Xplore, and ACM Digital Library, which may exclude relevant studies from other sources.
- **Lack of longitudinal data:** Most analyzed studies assessed short-term improvements, but long-term effects remain unclear.
- **Context-specific findings:** Some methodologies may be effective in certain educational contexts but not generalizable to all institutions.

It should be noted that the exclusion of databases such as Springer, Web of Science, and ERIC may have limited the breadth of the findings. Likewise, the lack of longitudinal data reduces the ability to assess long-term effects on learning transfer and employability outcomes. This exclusion may have led to the omission of relevant studies published in other peer-reviewed venues, potentially limiting the comprehensiveness and diversity of the synthesized evidence. As detailed in Table 4, the quality appraisal summary provides an overview of the methodological rigor of the included studies.

5.4 Future research directions

Future studies should focus on to address the identified limitations and further develop personalized CT education:

- Conducting longitudinal studies to measure the long-term impact of adaptive learning frameworks.
- Exploring scalable implementation models that reduce AI-driven adaptive education's cost and technical barriers.
- Investigating cross-cultural differences in the effectiveness of personalized CT instruction.

These areas will contribute to advancing adaptive education and provide a deeper understanding of how personalized learning can optimize computational thinking development. Furthermore, future research should explore the cross-cultural scalability of adaptive systems as well as cost-effective implementation models that can be adopted in low-resource settings. These directions will enhance the global applicability of the proposed solutions. Additionally, future research should prioritize the development of cross-culturally validated frameworks and scalable implementation models that address both pedagogical and technological equity across diverse educational contexts.

6 Conclusions

This study analyzed the role of personalized frameworks in computational thinking (CT) education, focusing on their impact on student engagement, cognitive adaptation, and academic performance. Through a Systematic Literature Review (SLR) of 73 empirical studies, we identified key trends, methodologies, and challenges in adopting adaptive learning strategies.

The results indicate that personalized learning frameworks demonstrate significant benefits, but their adoption remains limited. The main findings of this study include:

- Only 37% of studies reported implementing adaptive learning frameworks, despite their proven effectiveness in enhancing engagement and problem-solving skills (Moon et al., 2020; Gumus et al., 2024).
- Personalized learning strategies such as project-based learning, visual programming, and AI-driven adaptive systems significantly improve computational thinking development (Ersozlu et al., 2023; Peters et al., 2024).
- Institutional barriers, lack of faculty training, and technological constraints hinder the widespread adoption of personalized education frameworks (Moon et al., 2020; Peters et al., 2024).

The findings suggest that for personalized learning to be effectively integrated into CT education, universities and educators must:

- Invest in faculty training programs to equip instructors with the skills needed for adaptive teaching.
- Incorporate modular and flexible curricula that accommodate diverse cognitive profiles.
- Develop cost-effective AI-driven adaptive learning platforms to enhance accessibility.

Future studies should address the following areas to advance personalized CT education:

- Longitudinal studies to evaluate the long-term effects of adaptive learning frameworks.
- Scalable implementation models that balance personalization and cost efficiency.
- Cross-cultural analyses to examine the adaptability of personalized learning strategies in different educational contexts.

Integrating personalized learning frameworks in CT education presents a promising avenue for enhancing student engagement and cognitive development. However, overcoming institutional and technological barriers remains a challenge. By addressing these issues, educators and policymakers can ensure a more inclusive and effective learning environment for computational thinking development.

Author contributions

JG-R: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. MV-M: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. ER-L: Writing – original draft, Writing – review & editing. CV-S: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

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