Journal of Information Technology Education: Innovations in Practice

An Official Publication of the Informing Science Institute
InformingScience.org

JITEiip.org

Volume 24, 2025

PERSONALIZED DIGITAL LEARNING ENVIRONMENT WITH DIFFERENTIATED INSTRUCTION TO FOSTER COMPUTATIONAL THINKING IN ROBOTICS EDUCATION

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ABSTRACT

Aim/Purpose	This study aims to implement and evaluate a personalized digital learning environment (PDLE) that delivers differentiated instruction for enhancing computational thinking competencies through robotics education.
Background	The background emphasizes the growing demand for computational thinking skills in the modern workforce and the need for flexible learning approaches that accommodate diverse student needs.
Methodology	A mixed-methods research approach was employed, utilizing a pre-experimental design with One-Group Pretest-Posttest assessments to evaluate students' computational thinking development, complemented by classroom observations and instructor feedback to provide deeper insights into the learning process within the PDLE system.
Contribution	The key contribution of this study is the integration of PDLE with DI to provide personalized learning pathways that promote deeper engagement and skill development in computational thinking.
Findings	Findings suggest that the PDLE significantly enhances students' computational thinking abilities, particularly in problem-solving and algorithmic thinking, while also improving abstraction, pattern recognition, and fostering greater student independence through self-regulated learning.

Accepting Editor Fariza Khalid | Received: September 23, 2024 | Revised: November 27, December 11, December 16, 2024 | Accepted: December 31, 2024.
Cite as: Kurniawan, W., Anwar, K., Jufrida, J., Kamid, K., & Riantoni, C. (2025). Personalized digital learning environment with differentiated instruction to foster computational thinking in robotics education. *Journal of Information Technology Education: Innovations in Practice, 24,* Article 4. https://doi.org/10.28945/5427

Recommendations for Practitioners	Recommendations for practitioners include adopting personalized and differentiated learning environments to accommodate diverse learners.
Recommendations for Researchers	Recommendations for researchers suggest further exploration of adaptive learning technologies in robotics education.
Impact on Society	The impact on society lies in equipping students with essential computational skills that are crucial for success in the digital economy.
Future Research	Should explore the scalability of PDLE in other STEM disciplines and investigate long-term impacts on students' cognitive and career development.
Keywords	personalized digital learning environment, differentiated instruction, computational thinking, robotics education, mathematics education

INTRODUCTION

The development of digital technology has brought significant changes in various aspects of life, including in the world of education. In the context of higher education, the integration of digital technology in the learning process has become essential to address the challenge of 21st-century learning. One of the relevant approaches to facing this challenge is the development of a personalized digital learning environment (PDLE). PDLEs are digital platforms designed to adjust teaching materials, methods, and resources according to the unique needs, preferences, and abilities of each student, enabling more effective and meaningful learning experiences (Maier & Klotz, 2022; Murray & Pérez, 2015; H. P. Singh & Alshammari, 2021). Within this context, differentiation-based learning, a pedagogical approach that tailors teaching to accommodate individual needs, interests, and learning styles, plays a crucial role. Differentiated instruction (DI) is a specific strategy under this umbrella, aimed at modifying the content, process, and environment of learning to better suit diverse learners, ensuring that each student has access to the most suitable learning experience.

The rapid advancement of digital technology and its integration into various sectors has necessitated the development of computational thinking (CT) skills among students (Wing, 2006). CT, encompassing algorithmic thinking, problem-solving, and logical reasoning, has been identified as a fundamental skill for students to thrive in the digital era (Grover & Pea, 2013). As a subset of STEM education, robotics education has emerged as a powerful medium to promote CT by engaging students in hands-on, practical learning experiences (Eguchi, 2014). However, traditional instructional methods often fail to accommodate the diverse learning needs and styles of students, leading to unequal outcomes in CT skill development (Hsu et al., 2018). In this context, the implementation of PDLE, combined with DI, has been proposed as a solution to provide tailored learning experiences that cater to individual differences and optimize CT development (Hwang et al., 2020).

Personalized learning is a broader approach where the educational experience is customized to meet the specific preferences, abilities, and prior knowledge of each learner (Chai & Kong, 2017). Research suggests that DI can enhance student engagement and learning outcomes by adjusting the content, process, and learning environment to match individual student needs (Subban, 2006). In the context of robotics education, where students encounter complex problem-solving tasks, personalizing the learning experience through digital platforms can provide the scaffolding necessary for CT skill acquisition (Le et al., 2018). Furthermore, personalized learning environments, empowered by adaptive technologies, offer opportunities for continuous feedback and real-time adjustments, making the learning process more dynamic and responsive (Nouri, 2016). Given the increasing reliance on CT skills in various professional fields, this study addresses an urgent need to explore how PDLE with DI can be used effectively in robotics education to better prepare students for the demands of the future workforce (Curto & Moreno, 2016).

Despite the growing body of literature emphasizing the importance of CT in STEM education, few studies have explored how PDLE can be effectively combined with DI to address the varying abilities of students in the field of robotics education (Chithrra Raghuram et al., 2022). Most prior research on PDLE focuses on the technical aspects of personalized learning platforms but lacks comprehensive integration with DI strategies that address pedagogical needs (Fang, 2024; Xue & Zeng, 2020; Zhang, 2022). Moreover, while the efficacy of PDLE and DI has been studied independently, there is limited empirical evidence on their combined effect on enhancing CT in a robotics education context. This gap highlights the need for a more robust exploration of the intersection between personalized learning and differentiated instructional approaches in fostering CT (Lye & Koh, 2014).

This study aims to examine effectiveness by implementing a PDLE embedded with DI strategies to enhance CT among students engaged in robotics education. Specifically, the study seeks to evaluate the effectiveness of the PDLE in improving CT skills, including algorithmic thinking and problem-solving. The findings from this study will contribute to the ongoing discourse on adaptive learning technologies by presenting a framework for integrating DI into PDLE, particularly in the context of robotics education. This study will also provide empirical data on how personalized learning environments can support the development of key CT skills, offering insights for educators and instructional designers aiming to implement differentiated learning approaches in STEM disciplines (Hwang et al., 2020). Additionally, this research will fill the gap in the literature concerning the combined use of PDLE and DI to promote CT, contributing to both educational theory and practice.

LITERATURE REVIEW

The integration of robotics in education has gained significant attention in recent years due to its potential to enhance students' computational thinking (CT) skills. Robotics education provides an active learning environment that encourages problem-solving, logical reasoning, and creativity, all of which are key components of CT (Amri et al., 2019; Latip et al., 2020; Wing, 2006). Research has demonstrated that embedding robotics in the classroom, particularly through project-based learning, promotes the development of CT skills by allowing students to engage in hands-on, interactive tasks (Bers et al., 2014; Tramonti & Dochshanov, 2018; Y. Wang, 2023). These activities require students to decompose problems, test solutions, and iterate on their designs, which mirrors the cognitive processes used in programming and algorithm development (Sullivan & Heffernan, 2016).

Personalized digital learning environments (PDLE) have been identified as a critical tool in differentiating instruction, allowing for tailored learning experiences that meet the diverse needs of students (Bakker et al., 2020; Pane et al., 2015). Differentiated instruction (DI) involves modifying teaching methods, materials, and assessments to cater to the varying levels of readiness, interests, and learning preferences within a classroom (Tomlinson, 2014a). In robotics education, DI enables educators to scaffold learning experiences for students with different levels of prior knowledge, providing appropriate challenges to facilitate optimal learning outcomes (Graham et al., 2014; Hasselbring et al., 2005). Studies show that when students work within their zone of proximal development, supported by technology, they experience more meaningful engagement and higher achievement (Zakaria & Zualkernan, 2015).

Recent advancements in educational technology have enhanced the potential of PDLE to support differentiated instruction in robotics education. These environments utilize data-driven insights to adapt content and pacing in real-time, ensuring that each learner can progress at their own rate while still engaging with the curriculum (Munshi & Biswas, 2019; Shute & Ventura, 2013). Tools such as Makeblock, LEGO Mindstorms, and VEX Robotics provide platforms for students to explore robotics concepts while receiving personalized feedback, which supports the development of CT skills (Erwin et al., 2016; Mataric et al., 2007). This personalized approach not only addresses cognitive differences among students but also fosters a more inclusive learning environment (Steinkuehler et al., 2012)

Moreover, research suggests that PDLE in robotics education enhances students' intrinsic motivation and self-regulation, which are essential for the cultivation of CT (Pintrich, 2004; Zimmerman & Schunk, 2011). Self-regulated learning in PDLE allows students to set goals, monitor their progress, and reflect on their learning strategies, which aligns with the iterative nature of CT tasks (Gaudioso et al., 2012). The feedback loops provided by these environments offer opportunities for formative assessment, allowing students to adjust their thinking processes and problem-solving strategies in real time (Black & Wiliam, 2009).

The intersection of robotics education, PDLE, and DI also highlights the importance of developing 21st-century skills such as collaboration, communication, and creativity (Voogt & Roblin, 2012). Robotics projects often involve group work, which fosters peer-to-peer learning and the co-construction of knowledge (Barron & Darling-Hammond, 2008; Bransford et al., 2001). Through collaboration, students not only develop CT skills but also gain exposure to diverse problem-solving strategies, which enriches their learning experience (Nyoman et al., 2024; Ung et al., 2022).

In conclusion, personalized digital learning environments, when integrated with differentiated instruction in robotics education, provide an effective framework for enhancing students' computational thinking. This approach addresses the diverse needs of learners by offering tailored instructional support while fostering key 21st-century skills. The combination of hands-on robotics projects and data-driven personalization enhances student engagement and achievement, positioning robotics education as a critical component in developing future-ready learners (Grover & Pea, 2013; Xia & Zhong, 2018).

THEORETICAL FRAMEWORKS

The theoretical foundations of this study are rooted in several established educational frameworks that collectively inform the design and implementation of PDLE in robotics education. These frameworks include constructivism, the zone of proximal development (ZPD), differentiated instruction (DI), self-regulated learning (SRL), computational thinking (CT), and 21st-century learning skills. Each of these theories plays a crucial role in shaping how students engage with robotics tasks, developing computational thinking skills, and achieving differentiated learning outcomes. The interaction between these frameworks creates a comprehensive model that supports individualized, active learning experiences tailored to diverse student needs, ultimately fostering essential problem-solving and collaborative abilities. Table 1 outlines the key concepts and applications of these theoretical frameworks within the context of this study.

Table 1. Theoretical frameworks

Theoretical framework	Key concepts	Application to study
Constructivism (McLeod, 2019; Piaget, 1970; Ugwuozor, 2020)	Learners construct knowledge through active engagement with their environment	Robotics education encourages hands-on, inquiry-based learning where students build their own understanding through exploration.
Zone of Proximal Development (ZPD) (Eun, 2019; Margolis, 2020; Vygotsky, 1978)	The difference between what a learner can do independently and what they can do with guidance	PDLE and differentiated instruction provide scaffolding, helping students progress through personalized guidance.
Differentiated Instruction (Tomlinson, 2014a)	Tailoring instruction to meet individual student's needs in readiness, interest, and learning profile	PDLE allows teachers to offer differentiated tasks, content, and assessments based on individual CT skill levels.
Self-Regulated Learning (Gambo & Shakir, 2021; Khiat & Vogel, 2022)	The process by which learners actively control their own learning through goal setting, monitoring, and reflection	PDLE promotes self-regulation by allowing students to set goals and receive personalized feedback in robotics education.

Theoretical framework	Key concepts	Application to study
Computational Thinking Framework (Isharyadi & Juandi, 2023; Wing, 2006)	CT involves problem decomposition, pattern recognition, abstraction, and algorithm design	Robotics education develops CT skills as students engage in problem-solving tasks that reflect core CT processes.
21st Century Learning Skills (Battelle for Kids, 2019; Hussin et al., 2019; Voogt & Roblin, 2012)	Skills like collaboration, communication, and creativity are essential for future workforce readiness	Robotics projects in PDLE encourage teamwork and problem-solving, fostering key 21st-century skills alongside CT.

The development of a PDLE to build CT is grounded in the integration of several interconnected learning theoretical frameworks. The fundamental foundation begins with Constructivism theory (McLeod, 2019; Piaget, 1970), which emphasizes that learning occurs through students' active engagement in constructing their understanding, particularly in the context of CT skill development. This theory is reinforced by Vygotsky's (1978) concept of the Zone of Proximal Development (ZPD), which explains how scaffolding can help students achieve higher learning potential in understanding complex CT concepts. In its implementation, Differentiated Instruction (Tomlinson, 2014b) provides a framework for learning personalization, enabling the adjustment of CT content and tasks according to individual student needs. This approach synergizes with the concept of Self-Regulated Learning (Gambo & Shakir, 2021; Khiat & Vogel, 2022), which encourages students to actively control their learning process through goal setting, progress monitoring, and reflection in developing CT skills.

The Computational Thinking Framework (Isharyadi & Juandi, 2023; Wing, 2006) becomes the core of PDLE application development, where students learn about problem decomposition, pattern recognition, abstraction, and algorithm design. This framework effectively integrates with the development of 21st-century skills (Battelle for Kids, 2019; Hussin et al., 2019), encompassing collaboration, communication, and creativity, which are crucial in modern learning contexts. The interaction between these theories creates a comprehensive learning environment where students can develop CT skills through personal and meaningful learning experiences. Constructivism and ZPD provide the theoretical foundation for how learning occurs, while differentiated instruction and self-regulated learning provide practical frameworks for implementation. The Computational Thinking Framework provides learning content structure, while 21st-century skills ensure relevance to future demands. All are integrated into PDLE to create an adaptive, personal, and effective learning ecosystem in building CT competencies.

The significance of integrating these theories lies in their ability to create a learning environment that not only facilitates CT skill development but also supports students' holistic development as independent and competent learners. As explained by Voogt and Roblin (2012), this integrated approach is crucial in preparing students to face challenges in the digital era. Through PDLE, students not only learn about CT but also develop 21st-century skills essential for their future success.

METHODOLOGY

RESEARCH TYPE AND DESIGN

This study employed a mixed-methods research approach to comprehensively evaluate the implementation of a personalized digital learning environment (PDLE) with differentiated instruction (DI) in fostering computational thinking through robotics education. The integration of quantitative and qualitative methodologies provided a robust framework for understanding both the measurable outcomes and the underlying processes of learning within the PDLE system. The research design utilized a pre-experimental approach with a one-group pretest-posttest design, which was selected to systematically examine the intervention's effectiveness. While this design did not include a control group, it enabled the measurement of changes in students' computational thinking skills through pre-

tests and post-tests. The quantitative component focused on analyzing these test results, while the qualitative aspect enriched the study through classroom observations and instructor feedback, providing detailed insights into the learning process.

This mixed-methods framework allowed for a more comprehensive understanding of how the PDLE with DI impacts students' computational thinking development in robotics education, combining statistical analysis with rich, descriptive data from the learning environment. The research design incorporated concurrent data collection strategies, where quantitative and qualitative data were gathered simultaneously during the 4-week implementation period. Quantitative data collection focuses on measuring four key computational thinking indicators: algorithmic thinking, problem-solving, abstraction, and pattern recognition. These measurements were obtained through pre-tests and post-tests, student performance analytics, and structured surveys assessing student engagement and perception. Simultaneously, qualitative data were collected through systematic classroom observations, instructor feedback forms, and documentation of student interactions within the PDLE.

Table 2. Instructional design for experimental classes in robotics education study

No	Aspect	Experimental class (PDLE + DI)
1	Objective	Enhance computational thinking skills through a personalized and differentiated approach in robotics education.
2	Learning approach	Personalized Digital Learning Environment (PDLE) integrated with Differentiated Instruction (DI)
3	Instructional strategy	Differentiated tasks tailored to individual, abilities concept under, and prior knowledge
4	Content delivery	Digital platform with adaptive learning resources and real-time feedback
5	Groupings	Flexible grouping based on skill level and learning needs
6	Instructional materials	Interactive simulations, digital resources, robotics kits with varied levels
7	Assessment	Formative assessments with adaptive feedback, pre-test and post-tests
8	Duration	4 weeks
9	Instructor's role	Facilitator and guide, adjusting instructional content and approaching per student needs
10	Feedback mechanism	Real-time adaptive feedback provided through PDLE platform
11	Computational thinking focus	Emphasis on individualized problem-solving, logical reasoning, and algorithmic thinking
12	Expected outcomes	Improved computational thinking skills tailored to individual learning profiles

RESEARCH INSTRUMENT

To assess the effectiveness of the PDLE integrated with DI strategies in fostering computational thinking among students in robotics education, several research instruments were developed.

Pre-test and post-test on Computational Thinking (CT) skills

This instrument (Table 3) aims to measure the improvement in students' CT skills before and after the intervention. The test is based on established frameworks for CT and includes tasks that assess key CT components such as algorithmic thinking, problem-solving, abstraction, and pattern recognition. Each task was evaluated using a rubric that considers the accuracy, complexity, and efficiency of the students' solutions.

Table 3. Structure of pre-test and post-test for computational thinking skills

No	Indicator	Aspect assessed	Scoring criteria	Item no.
1	Algorithmic Thinking	Ability to create and follow algorithms	Accuracy, Efficiency, Complexity	1, 2
2	Problem-Solving	Ability to solve computational problems	Solution Correctness, Strategy Used	3, 4
3	Abstraction	Ability to identify patterns and simplify tasks	Identification of Key Information, Clarity	5, 6
4	Pattern Recognition	Ability to recognize recurring structures	Pattern Identification, Consistency	7, 8

To ensure the accuracy and consistency of the test used in this study, both validity and reliability analyses were conducted. Table 4 summarizes the results of these analyses, including the types of validity and reliability tested, the methods employed, and the interpretations of the findings.

Table 4. Validity and reliability results of the computational thinking skills test

No	Aspect	Type of validity/reliability	Method	Result	Interpretation
1	Content Validity	Expert Judgment	Reviewed by three experts in computational thinking and robotics education	90% agreement on item relevance	High content validity
2	Construct Validity	Factor Analysis	Exploratory Factor Analysis (EFA)	Items loaded on four distinct factors aligned with indicators	Valid construct structure
3	Internal Consistency	Cronbach's Alpha	Calculated for total test items	$\alpha = 0.82$	Acceptable internal consistency
4	Inter-rater Reliability	Inter-rater Agreement	Scored by two independent raters on essay items	85% agreement	High inter-rater reliability
5	Test-retest Reliability	Correlation between two test administrations	Pearson Correlation on pilot group	$r = 0.78$	Reliable over time

Student perception survey

The perception survey (Table 5) was designed to gather students' feedback on the PDLE and DI strategies used. The survey includes 20 items measured on a 5-point Likert scale, covering key aspects such as the usability of the PDLE, the effectiveness of personalized learning pathways, student engagement, and overall satisfaction with the DI strategies applied. Additionally, open-ended questions allow students to provide qualitative feedback about their learning experience.

Table 5. Student perception survey outline

No	Variable	Indicator	Item No
1	Usability	Ease of use of PDLE	1, 2, 3
2	Personalized Learning Pathways	Appropriateness of learning pathways	4, 5, 6
3	Engagement	Level of engagement with PDLE activities	7, 8, 9
4	Motivation	Student interest and effort in completing tasks	10, 11, 12
5	Feedback on DI	Student perception of DI's application	13, 14, 15

Classroom observation protocol

In this research methodology, a classroom observation protocol (Table 6) was developed to measure the effectiveness of personalized digital learning environments with differentiated instruction in robotics education. The observation protocol comprises four main indicators designed to evaluate various aspects of learning.

The first indicator focuses on Student Engagement, measured through items 1 and 2, which assesses students' active participation in learning tasks. The assessment utilizes a three-level scale: high, medium, and low engagement, providing a clear metric for evaluating student involvement in the learning process. The second indicator evaluates Peer Collaboration through items 3 and 4, which observe the quality of interaction and teamwork among students. The assessment is based on the quality of interaction and contributions made by each student within their groups, reflecting the collaborative aspects of robotics education. Teacher's Differentiation serves as the third indicator, assessed through items 5 and 6, focusing on the implementation of Differentiated Instruction strategies in content delivery. The scoring criteria encompass the teacher's ability to adapt to student needs and demonstrate flexibility in instruction, ensuring personalized learning experiences.

The final indicator examines problem-solving behaviors through items 7 and 8, which evaluate students' approaches to solving robotics problems. Assessment is conducted based on problem-solving strategies employed and the level of independence demonstrated by students in addressing challenges.

Table 6. Classroom observation protocol overview

No	Indicator	Item no.	Aspect assessed	Scoring criteria
1	Student Engagement	1, 2	Active participation in learning tasks	High, Medium, Low Engagement
2	Peer Collaboration	3, 4	Interaction and teamwork among students	Quality of Interaction, Contribution
3	Teacher's Differentiation	5, 6	Use of DI strategies in delivering instruction	Adaptation to Student Needs, Flexibility
4	Problem-Solving Behavior	7, 8	Students' approach to solving robotics problems	Problem-Solving Strategy, Independence

Instructor feedback form

Instructors participating (Table 7) in the study were asked to complete a feedback form to evaluate the PDLE's effectiveness in facilitating DI and enhancing students' CT. The form includes Likert-scale items and open-ended questions that address the ease of implementing DI, the system's adaptability to various student needs, and the challenges encountered during the instruction process.

Table 7. Instructor feedback form layout

No	Indicator	Item no.	Aspect assessed
1	Ease of Implementation	1, 2	Ease of implementing PDLE with DI
2	Effectiveness of DI	3, 4	How well DI addressed student needs
3	PDLE Usability	5, 6	Ease of navigating and using the PDLE platform
4	Challenges Encountered	7, 8	Difficulties faced during the teaching process

Student performance analytics

The PDLE system was equipped with built-in analytics to collect real-time data on student progress. This includes metrics such as time spent on tasks, task completion rates, number of help requests, and success rates in solving CT-related problems. The analytics provided (Table 8) insights into individual learning trajectories and helped assess the impact of personalized learning on student outcomes.

Table 8. Student performance analytics framework

No	Indicator	Item no.	Aspect assessed	Scoring criteria
1	Time on Task	1	Time spent on solving each task	Time taken (minutes)
2	Task Completion Rate	2	Number of tasks completed successfully	Number of completed tasks
3	Help Requests	3	Number of help requests during task completion	Number of help requests
4	Problem-Solving Success Rate	4	Success rate in solving tasks	Percentage of correct solutions

Population and Sample

The population for this study consists of students enrolled in the mathematics education program at Universitas Jambi, Indonesia, during the academic year 2023/2024 in the even (second) semester. From this population, a sample of 120 students was selected using a purposive sampling technique. The students were chosen based on their enrollment in robotics-related courses and their familiarity with digital learning environments. The sample includes a diverse range of students in terms of academic performance (level of concept understanding) and prior experience with computational thinking tasks. These selection criteria were applied to ensure that participants had a sufficient foundational understanding of technology and computational thinking concepts, allowing them to effectively engage with the intervention.

Data Analysis Techniques

The data analysis in this study employs both quantitative and qualitative techniques to assess the effectiveness of the Personalized Digital Learning Environment integrated with Differentiated Instruction in fostering Computational Thinking. Quantitative data from the pre-test and post-tests are analyzed using paired sample t-tests (H0: $\mu = 0$, H1: $\mu \neq 0$, where μ represents the mean difference between pre-test and post-test scores) to measure the improvement in CT skills, while the Student Perception Survey is examined through descriptive statistics and Pearson correlation analysis (H0: $\rho = 0$, H1: $\rho \neq 0$, where ρ represents the population correlation coefficient) to explore relationships between usability, engagement, and personalized learning pathways. Additionally, student performance analytics, such as time on task and task completion rates, are analyzed with regression analysis to identify factors influencing CT development. For qualitative data, classroom observations are analyzed thematically to capture patterns in student engagement and differentiated instruction, while instructor feedback is examined through content analysis to uncover key insights regarding the instructional design's effectiveness. The integration of both data types ensures a comprehensive and reliable understanding of the research outcomes.

RESULTS

The following section presents the results of the study, which evaluates the effectiveness of the Personalized Digital Learning Environment integrated with Differentiated Instruction in enhancing students' Computational Thinking skills. The results are divided into quantitative and qualitative findings. Quantitative results are based on pre-tests and post-tests, student perception surveys, and performance analytics data, which are summarized in tables, followed by a descriptive statistical analysis and interpretations. Qualitative data from classroom observations and instructor feedback complement the quantitative findings.

QUANTITATIVE RESULTS

The quantitative data analysis focuses on the comparison of pre-test and post-test results across four key indicators of computational thinking: Algorithmic Thinking, Problem-Solving, Abstraction, and Pattern Recognition. Table 9 presents the means, standard deviations, and maximum values for both pre-test and post-test scores, along with the corresponding *t-test* values and *p-values*, indicating the significance of observed improvements.

Table 9. Pre-test and post-test results for computational thinking

Indicator	Pre-test			Post-test			t-value	p-value
	Mean	Std dev	Max	Mean	Std dev	Max		
Algorithmic Thinking	60.5	7.5	72	75.0	6.0	85	5.47	0.001
Problem-Solving	63.0	6.8	75	78.5	5.9	88	5.61	0.001
Abstraction	68.0	7.2	80	82.0	6.5	90	5.12	0.001
Pattern Recognition	69.5	7.0	78	80.0	6.2	87	4.35	0.002

As shown in Table 9, there is a substantial improvement in the post-test scores across all four indicators compared to the pre-test results. Algorithmic Thinking increased from a mean score of 60.5 in the pre-test to 75.0 in the post-test ($t = 5.47$, $p = 0.001$). Problem-Solving exhibited a similar improvement, rising from 63.0 to 78.5 ($t = 5.61$, $p = 0.001$). Abstraction scores increased from a pre-test mean of 68.0 to 82.0 in the post-test ($t = 5.12$, $p = 0.001$). Finally, Pattern Recognition demonstrated a rise from 69.5 to 80.0 ($t = 4.35$, $p = 0.002$). These results demonstrate that the intervention had a statistically significant positive impact on students' computational thinking skills, as indicated by the significant *p-values* (all $p < 0.005$), supporting the hypothesis of improvement post-intervention.

Figure 1 presents the distribution of responses across five key indicators in terms of Feedback on Differentiated Instruction, Motivation, Engagement, Personalized Learning Pathways, and Usability. The responses are categorized into three levels: High, Moderate, and Low. As observed, most responses across all indicators fall into the *High* category (green), with a notable portion of responses in the *Moderate* category (yellow) and a small percentage in the *Low* category (red). Specifically, indicators such as *Motivation* and *Engagement* demonstrate a strong tendency towards the high response category, reflecting positive feedback. Meanwhile, *Feedback on Differentiated Instruction* and *Usability* also shows similar trends, though with slightly more moderate responses compared to other indicators. This distribution highlights overall positive perceptions of the evaluated aspects of the learning environment, indicating its effectiveness in engaging students and providing personalized support. The balanced yet predominantly high ratings across indicators suggest that the instructional design and personalized pathways were successful in meeting diverse student needs.

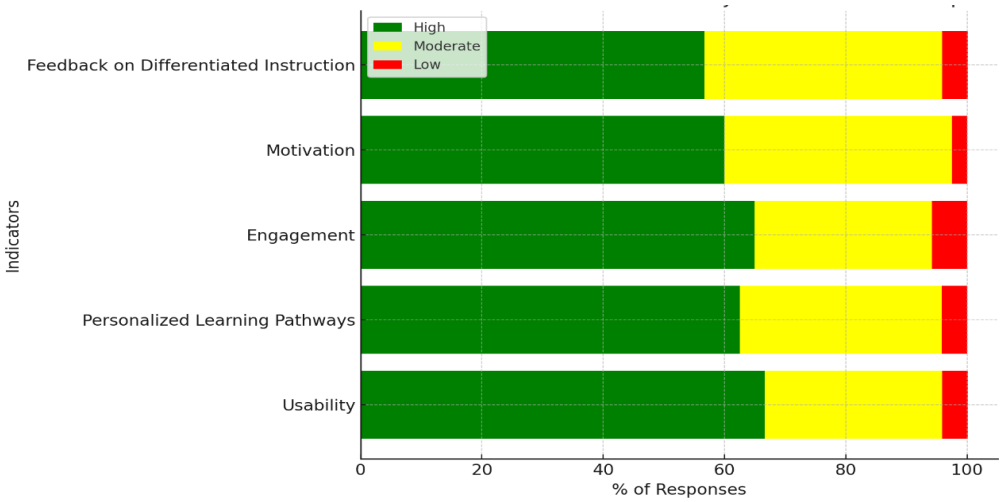

Figure 1. Distribution of responses uses of PDLE

Figure 2 presents four-line charts depicting key performance metrics over a four-week period: Time on Task, Task Completion Rate, Help Requests, and Problem-Solving Success Rate. These metrics were tracked to evaluate the progression of students' task engagement and problem-solving efficiency over time.

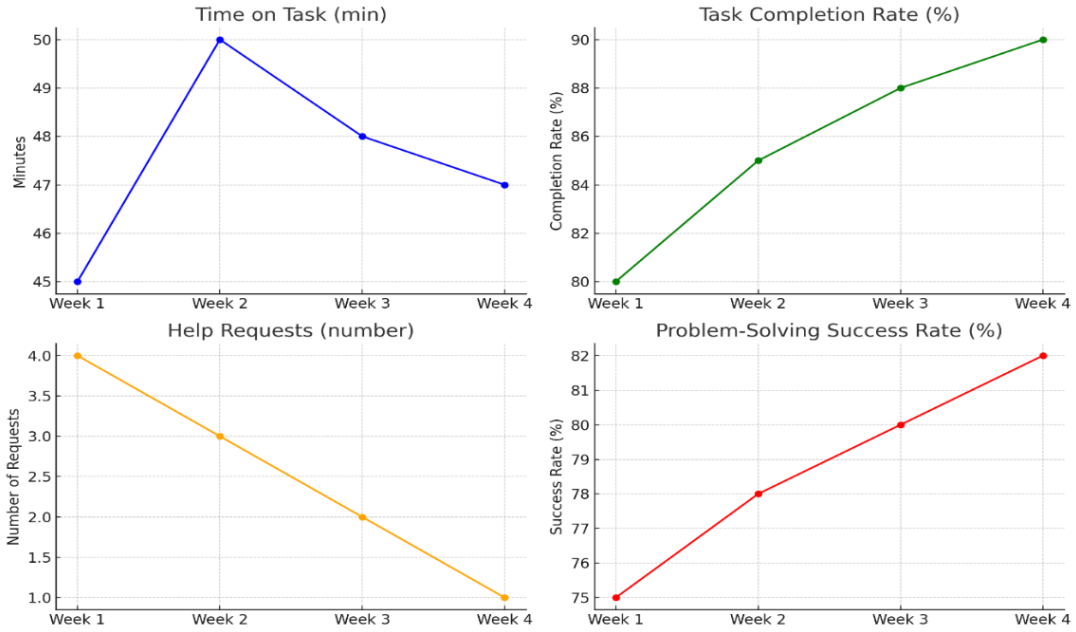

Figure 2. Student performance analytics

The data in Figure 2 reveals a clear trajectory of student improvement over the four-week period, characterized by enhanced task efficiency, problem-solving abilities, and reduced reliance on help. Initially, students spent more time on tasks, peaking at 50 minutes in Week 2, before gradually decreasing their time on tasks, indicating growing familiarity and proficiency. This trend aligns with the steadily increasing Task Completion Rate, rising from 80% in Week 1 to 88% in Week 4, reflecting improved competence in task management. Simultaneously, Help Requests saw a significant reduction, dropping from 4 to 1 over the same period, suggesting growing independence as students required less external assistance. The Problem-Solving Success Rate also consistently increased, moving from 75% to 82%, further supporting the conclusion that students not only became faster but also

more accurate in their problem-solving efforts. These patterns demonstrate a marked improvement in student performance, where increased efficiency, accuracy, and independence indicate the effectiveness of the instructional intervention in fostering both cognitive growth and self-reliance in completing tasks.

QUALITATIVE RESULTS

Table 6 presents the results of classroom observation focusing on four key indicators: *Student Engagement, Peer Collaboration, Teacher Differentiation,* and *Problem-Solving Behavior*. The observation shows that 20 students actively participated in learning tasks, categorized as high engagement. Interaction among students was deemed good, with 15 students actively collaborating, indicating a positive quality of interaction in collaborative learning. Additionally, the teacher successfully adapted differentiated instruction strategies tailored to different students' concept abilities, which was rated as high flexibility. This demonstrates the teacher's ability to customize teaching methods to individual needs, enhancing learning effectiveness. Finally, 12 students demonstrated independent problem-solving skills in robotics-related tasks, which were categorized as medium independence. While some students displayed sufficient independence, there remains room to foster greater self-reliance in problem-solving across the class through additional support. These findings suggest that the applied teaching methods were effective in promoting student engagement and collaborative interaction, though there is an opportunity for improvement in developing students' independent problem-solving skills

Table 10. Classroom observation result

No	Indicator	Aspect assessed	Observation result	Scoring criteria
1	Student Engagement	Active participation in learning tasks	20 students actively participated	High Engagement
2	Peer Collaboration	Interaction and teamwork among students	Good interaction: 15 students collaborated actively	Quality of Interaction: Good
3	Teacher's Differentiation	Use of DI strategies in delivering instruction	Teacher adapted materials for different students' concept ability	Flexibility: High
4	Problem-Solving Behavior	Students' approach to solving robotics problems	12 students demonstrated independent problem-solving	Independence: Medium

The data in Table 11 summarizes instructor feedback on the implementation of the *Personalized Digital Learning Environment* (PDLE) system. Instructors found the system easy to integrate into their teaching practices and appreciated its straightforward application for differentiated instruction. They highlighted the effectiveness of the PDLE in providing personalized content to students with varying abilities, allowing real-time adaptation of tasks based on individual progress. The platform's usability was praised for being user-friendly and intuitive for both instructors and students, with easy navigation that facilitated lesson planning. However, instructors encountered challenges, including difficulties managing students' diverse needs and technical issues that disrupted lesson implementation. While the PDLE system was generally well-received, these challenges indicate areas where further improvements are necessary.

Table 11. Instructor's feedback

No	Indicator	Statement
1	Ease of Implementation	"The PDLE system was easy to integrate into my teaching practices."
		"I found it straightforward to apply differentiated instructions using the PDLE."
3	Effectiveness of Differentiated Instruction	"The PDLE effectively helped me provide differentiated content to students with varying abilities."
		"The PDLE allowed me to adapt tasks based on individual student progress in real-time."
5	Usability of PDLE System	"The PDLE platform was user-friendly and intuitive for both instructors and students."
		"Navigating the various functions of the PDLE was simple and effective for lesson planning."
7	Challenges Encountered	"I experienced difficulties in managing students' diverse needs through the PDLE system."
		"There were technical issues when using the PDLE that hindered the smooth implementation of lessons."

Figure 3 illustrates the results from an initial diagnostic, formative test designed to map students' levels of conceptual understanding within the Personalized Digital Learning Environment**.** This formative test serves as a crucial diagnostic tool to assess the initial understanding of students and allows educators to identify areas where students hold misconceptions or incomplete knowledge. The insights gained from this test provide a foundation for implementing differentiated instruction and targeted interventions to enhance students' conceptual mastery in subsequent learning phases.

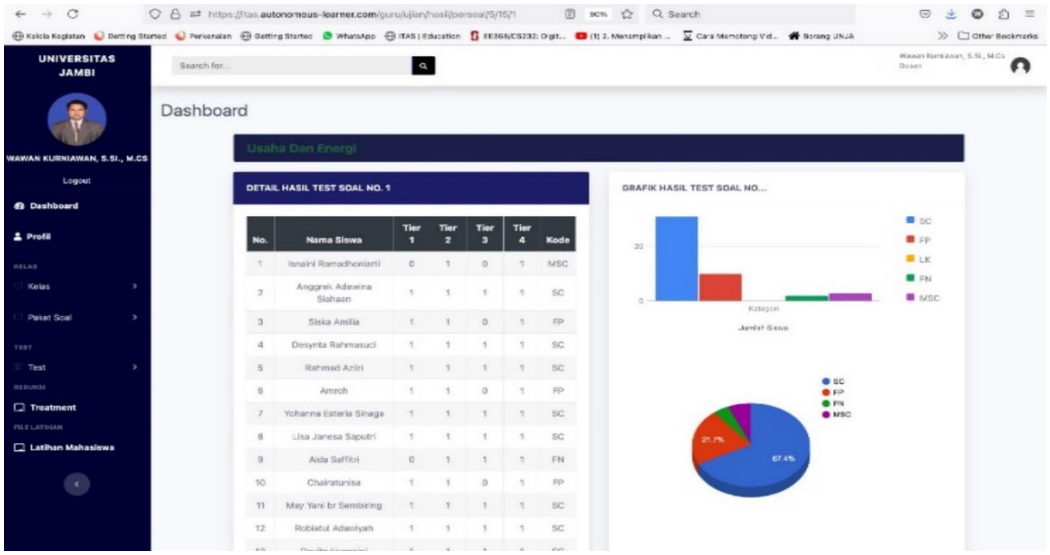

Figure 3. Dashboard display of diagnostic formative test results for conceptual understanding

This treatment (Figure 4) is an example tailored specifically for students at the basic conceptual understanding level (Level 1). It is a follow-up form of differentiation instruction learning approach (content and process) that provides them with structured, step-by-step tasks to reinforce their foundational knowledge. The activity is designed to help students grasp essential physics and mathematics concepts, encouraging them to interact with visual aids and practical problems that align with their

current cognitive level. The use of simple, real-world applications, such as robot movement, helps bridge the gap between abstract theory and tangible learning experiences. Through such differentiated treatments, educators can target students' specific learning needs and gradually scaffold their understanding to higher levels of conceptual mastery.

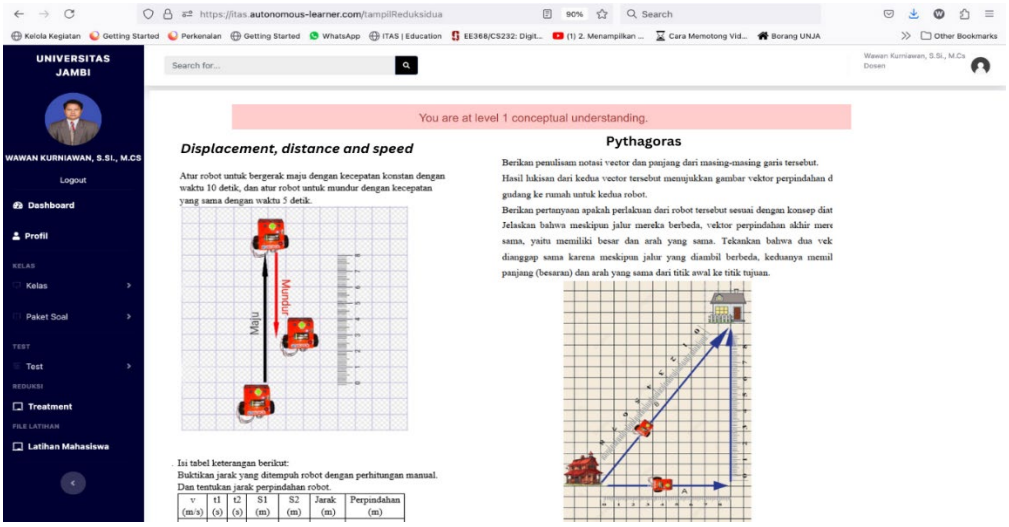

Figure 4. Treatment activity for displacement, distance, and speed using Pythagoras' theorem

Figure 5 presents a visual programming interface used to simulate robot movement as part of an educational activity within a PDLE. The workspace on the right side of the interface features a block-based programming tool where students can command a virtual robot to perform specific tasks using predefined logic blocks.

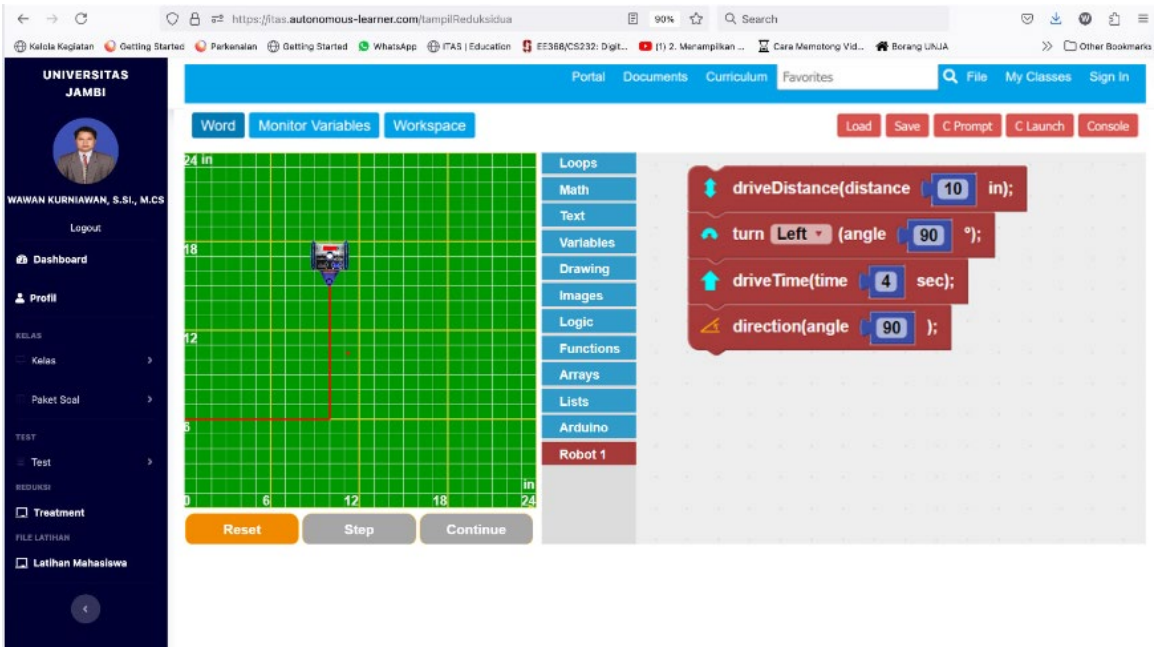

Figure 5. Visual programming interface for robot movement simulation

This interface serves as a powerful educational tool for reinforcing students' understanding of robotics, programming, and basic mathematical principles in a visually engaging manner. It also supports differentiated learning by allowing students at various conceptual levels to explore programming concepts at their own pace, promoting a deeper understanding of how logical instructions translate into real-world actions.

DISCUSSION

This study examined the effectiveness of the Personalized Digital Learning Environment (PDLE) integrated with Differentiated Instruction (DI) in improving students' Computational Thinking (CT) skills. The findings demonstrate a significant improvement in all four indicators of computational thinking: algorithmic thinking, problem-solving, abstraction, and pattern recognition. Students' post-test results showed substantial gains compared to their pre-test scores, particularly in algorithmic thinking and problem-solving, where improvements were most pronounced (Tondeur et al., 2021). These results are consistent with previous research emphasizing the role of personalized learning environments in enhancing computational thinking (Filipcik & Bielikova, 2014) and critical problem-solving skills (L. Wang & Duh, 2021).

Algorithmic thinking, which improved significantly, is fundamental to CT and has been supported by several studies showing that individualized and differentiated instruction enhances students' ability to decompose and sequence steps in problem-solving (Mulder, 2014; Siburian et al., 2022). Similarly, problem-solving skills, which also showed substantial gains, highlight the effectiveness of DI in providing tailored support that aligns with students' individual progress. This finding resonates with prior work by Magableh and Abdullah (2020), who found that differentiated instruction has a direct impact on improving students' problem-solving capacity, especially when combined with technology-enabled personalized environments.

Abstraction and pattern recognition, though also significantly improved, exhibited slightly lower rates of progress compared to algorithmic thinking and problem-solving. These findings suggest that while PDLE is effective across all CT indicators, certain higher-order thinking skills may require additional instructional scaffolding to foster deeper understanding. Future interventions could benefit from incorporating more structured activities focusing on abstraction, which would allow students to better generalize and apply concepts in diverse contexts (Anggoro et al., 2024; Krishan & Al-Rsa'I, 2023).

Qualitative feedback from instructors and students revealed strong engagement and motivation throughout the course of the study. Instructors reported that PDLE facilitated the ability to offer differentiated instruction in real-time, which enabled them to adapt to each student's learning pace and needs. This real-time adaptability aligns with findings by Sheromova et al. (2020), S. Singh and Alshammari (2021), and Villegas-Ch et al. (2020). They emphasized the critical role of technology in enabling immediate instructional adjustments based on student performance. Moreover, students demonstrated increased self-regulated learning, which was evident from fewer help requests and higher task completion rates. This finding supports Kinshuk's (2016) research, which suggests that PDLE can foster student independence by allowing them to take more control over their learning pathways.

Despite the positive outcomes, the study encountered technical limitations that impacted its overall effectiveness. Teachers experienced challenges with the technological infrastructure, particularly with system malfunctions that hindered the seamless delivery of instruction. These findings are consistent with Gretter and Yadav (2016) and Lydia et al. (2023) observation that technology integration, while promising, often faces practical implementation barriers. This technological challenge suggests the need for more robust, reliable systems to ensure that PDLE can function as intended without interruptions.

In terms of pedagogical implications, this study confirms the value of combining PDLE with DI to address diverse student needs and foster critical 21st-century skills such as problem-solving, abstraction, and independent learning (Redding, 2016). The study highlights the importance of personalized learning environments in encouraging not only cognitive development but also student agency as students take ownership of their learning (Tomlinson, 2017). Furthermore, the PDLE's ability to adapt in real-time is crucial for ensuring that students are challenged appropriately without becoming frustrated, a balance that Mötteli et al. (2023) identified as vital for student success.

Looking forward, the limitations of the study, including its relatively small sample size and the duration of the intervention, suggest that future research should aim for larger, more diverse samples and longer study periods to verify the generalizability of the findings (M. Wang & Chen, 2020). Technological improvements to the PDLE platform are also necessary to mitigate the challenges identified in this study. These improvements would allow for smoother implementation and ensure that teachers can fully leverage the potential of PDLE without technological disruptions (Hammond et al., 2012).

Recommendations for future research include exploring how PDLE can be further tailored to specific student populations, such as students with learning disabilities or those in under-resourced educational settings. Additionally, more attention should be given to longitudinal studies that track the sustained impact of PDLE on CT skills development over time. These studies could provide deeper insights into how PDLE supports students' long-term academic growth and prepares them for future challenges. In conclusion, this study has demonstrated that PDLE combined with DI is highly effective in enhancing students' CT skills, especially in algorithmic thinking and problem-solving, while also fostering greater independence in learning. The overall findings underscore the potential of personalized learning environments to meet the diverse needs of learners and improve essential 21st-century competencies.

CONCLUSION

This study confirms that the integration of Personalized Digital Learning Environment (PDLE) with Differentiated Instruction (DI) significantly improves students' Computational Thinking (CT) skills. Notable gains were observed in algorithmic thinking, problem-solving, abstraction, and pattern recognition, with the most substantial improvements in algorithmic thinking and problem-solving. These results underscore the effectiveness of personalized and differentiated learning in fostering key 21st-century skills. Additionally, the real-time adaptability of PDLE systems was found to enhance student engagement and self-regulated learning, allowing students to take more ownership of their learning process while teachers could adjust instructional strategies based on individual progress. However, the study also revealed challenges, particularly with technological infrastructure, which sometimes limited the effectiveness of the PDLE. These limitations highlight the need for improvements in technology to fully leverage the potential of PDLE. Future research should focus on long-term, large-scale studies to explore the sustained impact of PDLE on students' CT skills and other cognitive abilities. Overall, PDLE combined with DI offers a promising approach to enhancing computational thinking and preparing students for the demands of the digital era, provided that technological and practical barriers are addressed.

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