

Research Article

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The Relationship Between Computational and Creative Thinking in Preschool Children: An Application Through Gamification and Artificial Intelligence-Supported Constructivist Personalized Learning Environment

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Abstract

Background/purpose. In response to the increasing need to foster future-ready competencies, this study investigates the relationship between computational thinking (CT) and creative thinking (CrT) in early childhood. Traditional early education often overlooks the integration of these higher-order cognitive skills. This research aims to examine how a constructivist personalized learning Environment—integrating gamification and artificial intelligence—can simultaneously develop CT and CrT among preschool learners.

Materials/methods. A mixed-methods design was employed, involving 30 preschool children in Kindergarten Year 2 at a university demonstration school. Participants engaged in adaptive learning tasks delivered through a constructivist, gamified platform enhanced by AI. Quantitative data were collected using validated CT and CrT assessment tools, while qualitative data were derived from protocol-based interviews and performance observations.

Results. The findings indicated high proficiency in both CT (mean = 33.36/40; 83.4%) and CrT (mean = 28.47/40; 71.18%). Strong correlations were observed between CT and CrT total scores ($r = .74$, $p < .01$), especially between Pattern Recognition and Fluency ($r = .66$) and Decomposition and Originality ($r = .57$). Qualitative data supported these outcomes, revealing that children applied structured problem-solving and imaginative strategies concurrently in open-ended tasks.

Conclusion. CT and CrT are mutually reinforcing cognitive domains that can be effectively developed through constructivist, personalized, and technology-enhanced learning environments. The integration of gamification and AI in early education facilitates engagement, differentiation, and cognitive growth, offering a promising model for cultivating foundational 21st-century thinking skills.

1. Introduction

In an era marked by rapid technological advancements and complex global challenges, cultivating foundational thinking skills in early childhood education has become increasingly essential. Among the most crucial of these skills are computational thinking (CT) and creative thinking (CrT)—core competencies that underpin problem-solving, adaptability, and innovation in the 21st century (Wing, 2006; Bocconi et al., 2022). Both CT and CrT are recognized by leading educational frameworks, including those of the OECD and UNESCO, as essential for preparing future-ready learners in a digital society (OECD, 2021).

Computational thinking equips learners with the cognitive tools to approach problems methodically, drawing on skills such as decomposition, pattern recognition, abstraction, and algorithmic thinking (Bers et al., 2022; Kalelioglu et al., 2016). These abilities enable children not only to understand how systems work but also to design and construct solutions—a mindset increasingly valuable in fields beyond computer science, including science, language, and everyday decision-making (Papadakis, 2023). On the other hand, creative thinking is the capacity to imagine, generate, and elaborate on novel ideas. It nurtures flexibility, fluency, and originality—characteristics essential for innovation, emotional expression, and effective collaboration (Torrance, 1974; Phungching & Laddaklom, 2020).

Early childhood is considered a critical window for nurturing these abilities. Neuroscientific and developmental studies emphasize that children's brains develop most rapidly during the early years, making this stage an optimal period for fostering higher-order thinking skills (Shonkoff & Phillips, 2000). However, in many traditional preschool classrooms, teaching often emphasizes rote memorization, limiting opportunities for inquiry-based or exploratory learning. The intentional integration of CT and CrT in preschool curricula can bridge this gap by enabling children to explore, experiment, and express their thinking in diverse and meaningful ways (Hwang & Chien, 2022; Romero et al., 2023).

Developing CT and CrT from the preschool level is especially significant in light of global educational trends and future labor market projections. As automation, robotics, and artificial intelligence redefine job structures, human-centric skills such as creativity, critical thinking, and computational logic are becoming indispensable (World Economic Forum, 2020). Teaching these skills early promotes long-term cognitive flexibility, confidence in using digital tools, and the ability to face novel problems with both logic and imagination.

Importantly, recent interdisciplinary research highlights a strong connection between computational and creative thinking. While CT provides structured, logical approaches to problem analysis, CrT introduces openness, originality, and ideation into the process (Kong et al., 2022). The two modes of thinking are not opposites but mutually reinforcing—successful problem-solving often requires both systematic strategies and creative insight (Romero et al., 2023). For example, when children design a solution to help a character cross a river in a story-based coding activity, they must apply both algorithmic logic and imaginative reasoning. These synergies become most evident in learning environments that are hands-on, personalized, and constructivist in nature.

Early childhood represents a critical period for the development of foundational cognitive and socio-emotional capacities (Shonkoff & Phillips, 2000; OECD, 2021). The heightened neuroplasticity during this stage enables young learners to form new neural connections rapidly, making it an optimal window for cultivating higher-order thinking skills such as computational thinking (CT) and creative thinking (CrT) (Goswami, 2006; Center on the Developing Child, Harvard University, 2016). Neuroscience research suggests that early experiences shape the brain's architecture, influencing its lifelong learning potential (Shonkoff et al., 2012). The preschool period represents a uniquely opportune window for developing complex cognitive skills, including computational and creative

thinking. According to Piaget's (1952) stages of cognitive development, children between the ages of 2 and 7 enter the preoperational stage, characterized by symbolic thinking, rapid language development, and the emergence of intuitive reasoning. While children at this stage are not yet capable of fully operational logical thought, they exhibit a remarkable capacity for imaginative play, narrative construction, and exploratory problem-solving—abilities that are foundational for both computational and creative thinking (Piaget, 1952; Berk, 2013).

Moreover, young children naturally engage in exploratory play and imaginative thinking, which align closely with the cognitive processes involved in CT and CrT (Bers, 2018; Papadakis et al., 2023). Introducing CT and CrT during this period capitalizes on children's intrinsic curiosity and capacity for divergent thinking (Guilford, 1950; Vygotsky, 1978), thereby fostering cognitive flexibility, problem-solving skills, and creative confidence from an early age (Romero et al., 2023).

Importantly, early exposure to these skills has been shown to promote long-term academic achievement and adaptability (Resnick, 2017; Wing, 2006). As global educational goals increasingly emphasize future-ready competencies (UNESCO, 2022), embedding CT and CrT within early childhood curricula becomes essential for preparing learners to thrive in a rapidly evolving digital society (World Economic Forum, 2020).

The integration of gamification and artificial intelligence (AI) into early childhood learning environments is grounded in robust theoretical and empirical foundations. Gamification leverages principles from self-determination theory (Ryan & Deci, 2000), which posits that intrinsic motivation arises when learners experience autonomy, competence, and relatedness. Game elements such as challenges, feedback, and rewards have been shown to enhance engagement, persistence, and cognitive investment in learning tasks (Hamari et al., 2014; Saenboonsong & Poonsawad, 2024). This is particularly relevant for young children, who are naturally drawn to play-based and interactive experiences (Zainuddin, 2018). Artificial intelligence, when embedded within personalized learning environments, offers dynamic adaptation of content and pacing based on individual learner profiles (Holmes et al., 2019; Krath et al., 2023). This supports differentiated instruction and scaffolding aligned with Vygotsky's (1978) zone of proximal development (ZPD), enabling each child to progress at an optimal challenge level. Research indicates that AI-driven personalization enhances both learning outcomes and learner autonomy (Ouyang & Jiao, 2021).

Furthermore, the combined use of gamification and AI aligns with constructivist pedagogical principles (Piaget, 1954; Papert, 1980), fostering active engagement, experimentation, and self-directed learning. Such environments not only support the development of CT and CrT but also cultivate essential 21st-century skills such as digital literacy, adaptability, and creative problem-solving (OECD, 2021; Papadakis et al., 2023).

In response to this educational need, the present study aims to explore the relationship between computational thinking and creative thinking among preschool children using a Constructivist Personalized Learning Environment Model that integrates gamification and artificial intelligence (AI). Constructivist theory emphasizes the importance of learning through active engagement and personal relevance. When combined with personalization through AI and motivational game-based elements, such an environment can dynamically respond to individual learners' needs while maintaining interest and cognitive challenge (Papadakis et al., 2023; Hwang & Chien, 2022).

The learning model proposed in this study provides young learners with adaptive tasks that balance cognitive structure (through CT tasks) with freedom of expression and play (through CrT tasks). Gamification mechanisms—such as rewards, missions, and challenges—enhance motivation and engagement, while AI algorithms offer real-time feedback, scaffolding, and differentiated instruction. This holistic approach aligns with the developmental nature of preschool children who learn best through play, exploration, and social interaction.

This study is significant in two primary ways. First, it addresses a research gap in understanding how dual cognitive abilities (CT and CrT) interact and develop among preschoolers within a technologically enriched, constructivist learning setting. Second, it contributes practical insights for designing early childhood curricula that are both engaging and cognitively stimulating, supporting global goals for inclusive, future-focused education (UNESCO, 2022).

In conclusion, by investigating the interrelationship between computational thinking and creative thinking within a personalized, gamified, AI-supported learning environment, this study seeks to provide empirical evidence and pedagogical guidance for educators, curriculum designers, and policymakers aiming to prepare preschool learners for the cognitive demands of the 21st century.

2. Literature Review

2.1. The Use of Artificial Intelligence-Based Learning Environments in Early Childhood

Artificial intelligence (AI) has emerged as a transformative technology in education, enabling highly personalized, adaptive, and data-driven learning experiences (Holmes et al., 2019; Krath et al., 2023). In early childhood education (ECE), AI can support differentiated instruction by dynamically adjusting content, difficulty level, and feedback based on individual learner profiles (Ouyang & Jiao, 2021). Such personalization aligns closely with Vygotsky's (1978) zone of proximal development, ensuring that learning tasks remain optimally challenging and supportive.

Research indicates that AI-driven learning environments enhance young children's engagement, cognitive development, and self-directed learning (Papadakis et al., 2023; Romero et al., 2023). For example, AI-based educational games and storytelling applications can adapt in real time to children's responses, promoting deeper cognitive engagement (Krath et al., 2023). Moreover, AI facilitates formative assessment and learning analytics, providing educators with actionable insights to tailor instruction further (Holmes et al., 2019).

Integrating AI in ECE must be approached thoughtfully, considering ethical and developmental appropriateness (Zawacki-Richter et al., 2019). However, when well-designed and grounded in constructivist principles, AI-based learning environments can effectively support the development of both computational and creative thinking in young learners (Ouyang & Jiao, 2021; Papadakis et al., 2023).

2.2. Supporting Creative Thinking with Gamification

Gamification—the incorporation of game elements into non-game contexts—has proven to be a powerful approach for enhancing motivation, engagement, and learning outcomes in early childhood education (Hamari et al., 2014; Saenboonsong & Poonsawad, 2024). Drawing on self-determination theory (Ryan & Deci, 2000), gamification fosters intrinsic motivation by supporting learners' needs for autonomy, competence, and relatedness.

In the context of creative thinking, gamification has been shown to stimulate divergent thinking, risk-taking, and sustained engagement in open-ended tasks (Zainuddin, 2018). Studies indicate that game elements such as challenges, rewards, and feedback loops encourage children to explore multiple solutions and think flexibly (Romero et al., 2023).

Furthermore, gamified environments often incorporate narrative, role-play, and problem-solving scenarios that naturally foster creativity (Papadakis et al., 2023). By creating playful and immersive learning experiences, gamification aligns with the developmental needs of preschoolers, supporting the cultivation of fluency, originality, and elaboration in their creative thinking (Torrance, 1974; Wojciechowski & Ernst, 2018).

2.3. Personalized Learning and Computational Thinking Development

Computational thinking (CT), as a foundational approach to problem-solving, encompasses decomposition, pattern recognition, abstraction, and algorithmic design—skills that can be nurtured through playful, creative, and interdisciplinary learning experiences from early childhood (Wing, 2006; Bers et al., 2022). Activities such as storytelling, tangible programming, and block-based coding have proven effective in fostering young children’s logical reasoning and structured thinking (Bers et al., 2022; Zhang & Nouri, 2019). Furthermore, engaging children in cross-disciplinary contexts—bridging domains such as science, art, and mathematics—enhances their collaborative and communicative competencies while deepening their CT abilities (Tikva & Tambouris, 2021).

However, young learners exhibit diverse developmental profiles, learning paces, and cognitive strengths. A one-size-fits-all approach to CT instruction may not adequately address these individual differences (Grant & Basye, 2014). Personalized learning frameworks are therefore essential for ensuring that each child engages with CT tasks that are optimally aligned with their abilities, interests, and readiness (Brennan & Resnick, 2012; Holmes et al., 2019).

AI-driven personalization technologies can dynamically adapt CT tasks—such as coding challenges, pattern recognition games, and algorithm design activities—based on real-time analysis of learners’ performance and progress (Ouyang & Jiao, 2021). For instance, a child demonstrating proficiency in pattern recognition may be provided with more complex design and abstraction tasks. At the same time, another requiring support in decomposition can receive targeted scaffolding and guided practice (Holmes et al., 2019). Such differentiation ensures that children remain within their zone of proximal development (Vygotsky, 1978), fostering sustained engagement and deeper learning.

Moreover, personalized learning environments can integrate formative feedback and adaptive scaffolding to enhance CT skill acquisition in developmentally appropriate ways (Papadakis et al., 2023). By tailoring task complexity, sequencing, and instructional strategies to individual learner profiles, personalized learning not only amplifies the efficacy of CT instruction but also reinforces essential interdisciplinary competencies—creativity, collaboration, and communication—that are cultivated through CT-rich activities (Tikva & Tambouris, 2021; Junruang, Kanjug, & Samat, 2021).

Ultimately, the synergy of personalized learning and constructivist pedagogy provides a powerful framework for fostering CT development in early childhood education. It enables young learners to explore computational concepts through meaningful, differentiated, and engaging experiences, thereby building cognitive flexibility and digital literacy essential for navigating future educational and societal challenges (OECD, 2021; World Economic Forum, 2020)

Personalized Constructivist Learning Environment Model Integrating Gamification and Artificial Intelligence to Foster Creativity and Computational Thinking in Early Childhood Learners This model refers to the design of a learning environment based on model development research (Richey & Klein, 2007), synthesizing key principles from Instructional Design (ID) theory to form the core components of the personalized learning environment. The model involves analyzing individual learner differences to enable the adaptive personalization of learning tasks through artificial intelligence (Holmes, Bialik, & Fadel, 2019), with gamification elements adjusted according to learners’ competencies (Hamari, Koivisto, & Sarsa, 2014). The theoretical foundation of the model is drawn from seven key domains: 1) Learning Psychology Foundations, encompassing Constructivist Theory (Piaget, 1954; Vygotsky, 1978) and Cognitive Theory (Anderson, 1980); 2) Instructional Science Foundations, emphasizing experiential learning and meaning-making (Jonassen, 1999); 3) Computational Thinking Foundations (Wing, 2006; Brennan & Resnick, 2012); 4) Creative Thinking Foundations (Guilford, 1950; Runco,

2004); 5) Personalized Learning Foundations (Grant & Basye, 2014; Zheng, Lin, & Kwon, 2022); 6) Media and Technology Foundations, particularly the use of digital media to support creative learning and the development of 21st-century skills (Jonassen, Carr, & Yueh, 1998) Gamification—the use of game elements in non-game contexts—has been increasingly used to enhance motivation and engagement in early childhood education. Studies have confirmed that gamification strategies support children's active participation, collaboration, and cognitive development, particularly in problem-solving and creative tasks (Saenboonsong & Poonsawad, 2024). Artificial Intelligence (AI), when embedded in personalized learning environments, offers dynamic content adaptation, real-time feedback, and learner analytics that enhance learner engagement and individualized instruction (Krath et al., 2023). Research by Ouyang and Jiao (2021) showed that AI tools can be aligned with constructivist principles to personalize learning experiences and support knowledge construction. These tools help identify learning needs and adjust difficulty levels in real time, thus supporting differentiated learning paths; and 7) Contextual Foundations, which stress the importance of linking learning to the learners' real-world contexts (Brown, Collins, & Duguid, 1989).

These theoretical principles are operationalized through the design and development of the personalized constructivist learning environment, which functions as a learning medium. It emphasizes learner autonomy and hands-on engagement, allowing learners to explore and construct knowledge in ways that align with their individual learning styles (Tam, 2000). Simultaneously, gamification mechanisms are employed to enhance learner motivation (Zainuddin, 2018). The learning media are categorized into two types: Network-Based Multidimensional Learning Media, which includes seven components: (1) Problem-Based Situations (2) Knowledge Resources (3) Related Cases (4) Cognitive Tools (5) Collaborative Problem-Solving (6) Scaffolding Bases (7) Coaching Centers Learning Kits, which consist of printed and physical materials, including: (1) Thinking Centers Figure 1 shows the components and their interrelations are illustrated.



Figure 1. Illustrates the Personalized Constructivist Learning Environment Model integrating Gamification and Artificial Intelligence into Foster Creativity and Computational Thinking in Early Childhood Learners

3. Methodology

3.1. Research Design

This study employed a mixed-methods design combining quantitative and qualitative approaches to investigate the relationship between computational thinking (CT) and creative thinking (CrT) among preschool learners. The research aimed to evaluate the effects of a Constructivist

Personalized Learning Environment integrating Gamification and Artificial Intelligence on students' thinking skills. The study followed a model validation phase (Phase II) within an intervention-based design research framework (Richey & Klein, 2007), using both performance-based assessments and protocol analysis to ensure robust evaluation.

3.2. Participants

The participants consisted of 30 preschool learners (16 girls and 14 boys), aged 5–6 years ($M = 5.6$, $SD = 0.42$), enrolled in Kindergarten Year 2 at the Demonstration School of Khon Kaen University, Early Childhood Division, during the first semester of the 2024 academic year. The school is a public university-affiliated demonstration school serving a diverse population of students from middle to upper-middle socioeconomic backgrounds. The children were selected using a purposive sampling technique based on their enrollment in the experimental program, with informed consent obtained from parents and school authorities, as shown in Table 1.

Table 1. Participant Demographics

Variable	Category	n
Gender	Female	16
	Male	14
Age	5 years	12
	6 years	18
School type	University Demonstration School	30

3.3. Instruments

To collect reliable data regarding students' cognitive development, the research utilized two main instruments:

- A Computational Thinking Assessment
- A Creative Thinking Assessment

Each tool was designed and validated based on theoretical frameworks and empirical studies relevant to the target age group.

3.3.1. Computational Thinking Assessment Tool

The development of the CT assessment was based on the framework proposed by Wing (2006) and later refined for early childhood by Bers et al. (2022). The instrument focused on the following four constructs:

- Decomposition
- Pattern Recognition
- Abstraction
- Algorithm Design

Each dimension was measured through performance-based tasks and situational problems aligned with the developmental abilities of preschool children. The test comprised 10 items per domain, with a total of 40 points, and included the following features:

- Visual prompts (e.g., animal parts for Decomposition)
- Pattern-matching games (for Pattern Recognition)

- Classification activities (e.g., identifying animals based on features for Abstraction)
- Path-planning games (e.g., navigating a bird to its nest for the Algorithm)

The tool was subjected to expert validation, and content validity was verified using the Index of Item-Objective Congruence (IOC), with all items receiving IOC scores ≥ 0.67 . Internal consistency was calculated using Cronbach's alpha, yielding a reliability coefficient of $\alpha = .87$.

Additionally, a semi-structured interview protocol was designed to capture students' verbalized thought processes. This protocol was based on the protocol analysis method, enabling the qualitative exploration of cognitive reasoning in each domain of CT

3.3.2. Creative Thinking Assessment Tool

The CrT assessment was constructed based on the creative thinking model by Guilford (1967) and adapted using criteria from Jarunee Samat (2009) for the Thai early childhood context. It included four key domains:

- Fluency
- Flexibility
- Originality
- Elaboration

Students were given tasks such as building a city using various classroom materials, imagining animals that do not exist, or solving creative problems like cooling a hot classroom using unconventional tools. Each domain was assessed through a combination of:

- Performance Tasks (e.g., using materials to create new structures)
- Product Evaluation Rubrics (scored on a 10-point scale per domain)
- Creative Behavior Interviews: 10 students were randomly selected for protocol-based interviews to analyze verbal explanations and ideation processes in depth. Result: Creative thinking.

Reliability of the CrT instrument was assessed via inter-rater agreement, and Cronbach's alpha yielded $\alpha = .84$. Content validity was verified by a panel of three experts in early childhood creative development.

3.4. Duration and Experimental Procedures

The experimental phase was conducted over a 6-week period (12 instructional sessions, two sessions per week), with each session lasting approximately 45 minutes.

Learning Environment Design:

- Gamification elements: The environment incorporated the following game-based mechanisms:
 - o Score systems for tracking performance across tasks.
 - o Badges awarded for specific milestones (e.g., completing a complex algorithm design task).
 - o Task-based challenges designed to encourage exploration and problem-solving in both CT and CrT domains.
- AI integration: Artificial Intelligence was employed to support personalized learning pathways through:
 - o Adaptive content delivery: Adjusting task complexity and sequencing in real time based on learners' performance data.

- o Dynamic pacing: Modifying the speed of content presentation to align with individual learning speeds.
- o Real-time feedback: Providing personalized prompts and scaffolding tailored to each learner's progress and cognitive profile.

3.5. Data Collection and Procedures

1. Pre-Activity Preparation: Students participated in a learning environment designed based on constructivist principles, supported by gamified challenges and personalized AI recommendations.
2. Task Administration: CT and CrT tasks were conducted in a 1-on-1 format with child-friendly visuals and verbal instructions. Responses were video-recorded and transcribed for later analysis.
3. Data Recording: Quantitative scores were recorded on structured scoring sheets. Qualitative data from interviews were analyzed using protocol analysis and categorized under respective domains.
4. Validation Phase: This study represents the second phase (model validation) of a broader intervention-based design research framework. The scores and protocol data served to assess the validity and effectiveness of the integrated model.

3.6. Data Analysis

- Quantitative data were analyzed using descriptive statistics (mean, standard deviation, percentage) to report performance in each CT and CrT dimension.
- Qualitative data from interviews and protocol analysis were coded thematically and triangulated with performance scores for interpretation.

Ethical Considerations: This study was conducted in full compliance with ethical standards for research involving young children. Approval was obtained from the Institutional Review Board (IRB) of Khon Kaen University (Research Ethics Committee, Approval No. HE673136). All participants were recruited through an open invitation to families enrolled in the experimental program. Written informed consent was obtained from parents or legal guardians of all participating children. In addition, age-appropriate assent procedures were implemented: the study purpose and procedures were explained to the children using developmentally suitable language and visual aids, and their voluntary participation was reaffirmed before each research session.

Participation was entirely voluntary, and families were informed that they could withdraw from the study at any time without any adverse consequences for the child's educational experience. The confidentiality and anonymity of all participants were strictly maintained throughout the research process. All data were stored securely and used solely for research purposes.

4. Results

This section presents the findings from the investigation into the relationship between computational thinking (CT) and creative thinking (CrT) among preschoolers who engaged in a constructivist personalized learning environment incorporating gamification and artificial intelligence. The results are organized into two main sections in accordance with the mixed-methods design: (1) Quantitative Findings and (2) Qualitative Findings.

4.1. Quantitative Findings

4.1.1. Computational Thinking Performance

The quantitative results from the CT assessment showed that students exhibited high levels of competence across the four CT domains:

Table 2. The quantitative results from the CT assessment

CT Domain	Mean ($\bar{X}$)	SD	Percentage (%)
Decomposition	8.53	1.22	85.33%
Pattern Recognition	8.43	1.25	84.33%
Abstraction	8.10	1.17	81.00%
Algorithm Design	8.30	1.18	83.00%
Total	33.36	2.41	83.40%

These results indicate that the constructivist personalized learning model effectively supported the development of CT in early learners across multiple dimensions.

4.1.2. Creative Thinking Performance

The CrT assessment revealed the following average scores across the four dimensions:

Table 3. The quantitative results from the CrT assessment

CrT Domain	Mean ($\bar{X}$)	SD	Percentage (%)
Fluency	8.67	1.11	86.67%
Flexibility	7.17	1.63	71.67%
Originality	7.47	1.50	74.67%
Elaboration	5.17	1.83	51.67%
Total	28.47	2.65	71.18%

The highest performance was observed in Fluency, reflecting students' ability to generate multiple ideas rapidly. The lowest scores appeared in Elaboration, indicating potential areas for further instructional support.

4.1.3. Correlational Analysis between CT and CrT

To examine the relationship between computational and creative thinking, Pearson's correlation coefficient was calculated using total scores and sub-dimensions of both constructs. The results are summarized below:

Table 4. The correlational Analysis between CT and CrT

CT Domain	Fluency	Flexibility	Originality	Elaboration	CrT Total
Decomposition	.62**	.51*	.57**	.33	.64**
Pattern Recognition	.66**	.58**	.55**	.36	.68**
Abstraction	.53**	.50*	.61**	.39	.63**
Algorithm Design	.58**	.49*	.59**	.42*	.67**
CT Total	.71	.62	.68	.45	.74

(* $p < .01$, $p < .05$)

(* $p < .05$, ** $p < .01$)

Effect sizes (r^2) indicated that CT Total explained approximately 54.8% of the variance in CrT Total scores ($r^2 = .74^2 = .548$), suggesting a substantial positive relationship.

The quantitative findings reveal a statistically significant and meaningful relationship between CT and CrT, with particularly strong associations observed between Pattern Recognition and Fluency, as well as between Decomposition and Originality. These results suggest that computational processes, such as identifying patterns and decomposing problems, contribute directly to the generation of divergent and original thought in young children.

4.2. Qualitative Findings

4.2.1 Thematic Analysis of Protocol Data and Interviews

Qualitative data from protocol analysis and student interviews were analyzed using thematic analysis (Braun & Clarke, 2006). Three key themes emerged, illustrating how CT and CrT processes interacted during learning tasks.

Theme 1: CT Facilitating Creative Problem Structuring

Children who demonstrated strong decomposition skills were more adept at structuring creative solutions. For example:

"I put the big blocks first to make the bridge strong. Then I used string so the toy can go across safely."
(Participant 12, age 6)

This reflects how breaking down problems supported the planning and design of original solutions.

Theme 2: Adaptive Flexibility through Iterative Design

Several children exhibited flexibility by modifying their initial designs during problem-solving:

"First, I wanted to build a house, but then I thought—what if it's a tunnel for the toy car? So, I changed it." (Participant 5, age 5)

This indicates a dynamic interplay between CT processes (algorithmic planning) and CrT (flexibility and originality).

Theme 3: Abstraction Supporting Conceptual Creativity

In abstraction tasks, children demonstrated the ability to generalize and reimagine concepts:

"These round things can be wheels, but also eyes for my robot!" (Participant 17, age 6)

Such examples show how abstraction can fuel imaginative reinterpretation and originality.

The qualitative findings reinforce the quantitative results, illustrating that computational and creative thinking are not separate processes but mutually supportive cognitive modes in young children. The constructivist, gamified, and AI-personalized learning environment provided rich opportunities for these synergies to emerge.

4.2.2. Interpretive Synthesis and Qualitative Insights

Qualitative findings from protocol analysis and student interviews further clarified how the two domains interacted in actual problem-solving scenarios. For example:

In a task where children designed a bridge without standard materials, students who were able to decompose the task (identify purpose, structure, and support) were also more likely to generate original or flexible solutions using materials such as string, paper rolls, or folded cardboard (CT → CrT transfer).

In abstraction activities, students who could generalize categories or visualize functions were also the ones who displayed elaborative design abilities, although elaboration remained the weakest area overall.

Several students demonstrated adaptive flexibility by modifying their initial ideas mid-task—such as converting a box into a tunnel rather than a house—illustrating dynamic use of both CT and CrT simultaneously.

These findings confirm that when provided with open-ended, gamified tasks in a personalized environment, young learners actively draw upon and strengthen both computational and creative capacities.

Students exhibited high proficiency in both CT and CrT, with especially strong scores in fluency and decomposition.

There was a statistically significant positive relationship between computational thinking and creative thinking ($r = .74$).

Certain sub-domains (e.g., pattern recognition and fluency) appear particularly interdependent.

Constructivist, gamified, AI-driven learning models fostered simultaneous development of both skills.

4.2.3. In-depth Interpretation of CT–CrT Correlation

The correlation matrix and heatmap visualization reveal a consistent and meaningful relationship between domains of Computational Thinking (CT) and Creative Thinking (CrT) in preschool learners who engaged with a constructivist personalized learning environment enhanced by gamification and artificial intelligence.

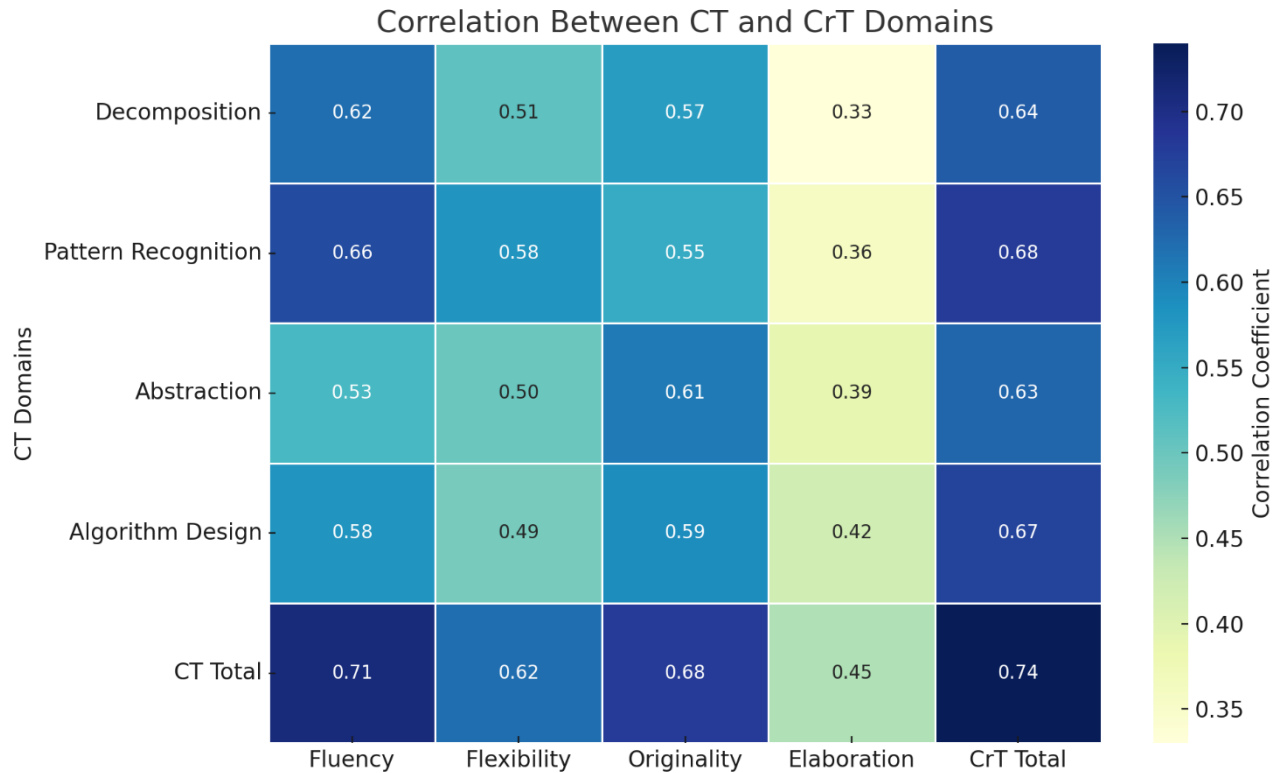


Figure 2. Correlation Between CT And CrT Domains

4.2.4. CT Total vs CrT Total (r = .74)

The overall computational thinking ability demonstrated a strong positive correlation with total creative thinking performance. This result implies that children who scored higher in CT tasks also tended to perform better in CrT assessments. This reinforces the emerging theory that CT and CrT are mutually reinforcing cognitive domains rather than separate constructs. It reflects the effectiveness of the integrated model in cultivating both analytical and imaginative thinking simultaneously.

4.2.5. Strongest Domain Correlations

Table 5. The correlational Analysis between CT and CrT

CT Domain	Highest CrT Correlation	Interpretation
Pattern Recognition	Fluency (r = .66)	Children who can identify and predict patterns more easily also generate a higher volume of ideas. This supports the idea that recognition of repeated elements enhances ideational fluency.
Decomposition	Originality (r = .57)	Breaking complex problems into parts enables learners to generate more novel and original solutions. This suggests that structured thinking can lead to more divergent thinking.
Algorithm Design	Originality (r = .59), Elaboration (r = .42)	Designing procedures or steps is linked to creating unique solutions and refining them with detail. This shows that algorithmic reasoning enhances structured creativity.
Abstraction	Originality (r = .61)	The ability to generalize or simplify concepts correlates with imaginative reconstruction, showing that abstract thought fuels idea generation.

4.2.6. Relatively Lower Correlation with Elaboration (r = .33–.45)

Although still positive, the correlations between CT domains and Elaboration (the ability to refine and detail an idea) were consistently lower than other CrT dimensions. This may suggest that while CT enhances idea generation and transformation (fluency, flexibility, originality), it does not inherently encourage in-depth detailing unless explicitly supported by tasks requiring elaboration. Therefore, further scaffolding or reflection-based tasks may be needed to foster elaboration in tandem with computational tasks.

5. Discussion

The results of this study demonstrated a statistically significant and meaningful relationship between computational thinking (CT) and creative thinking (CrT) among preschool learners engaged in a Constructivist Personalized Learning Environment integrating gamification and artificial intelligence. The overall correlation between CT and CrT (r = .74, p < .01) supports the central hypothesis of this study—that computational and creative thinking are not separate cognitive domains but mutually reinforcing capacities that can and should be fostered simultaneously from early childhood.

This finding aligns with the results of Kong et al. (2022), who demonstrated that the co-development of CT and CrT promotes deeper cognitive engagement and enhances problem-solving skills. Similarly, Romero et al. (2023) reported that when CT and CrT tasks are integrated within

technology-supported learning environments, young learners exhibit improved flexibility and originality in their cognitive responses.

The strong associations observed between specific sub-dimensions—such as Pattern Recognition and Fluency ($r = .66$), and Decomposition and Originality ($r = .57$)—further affirm that structured cognitive processes support generative ideation. These results align with the work of Jalinus et al. (2019), who found that blending systematic reasoning with exploratory play in early learning contexts enhances holistic cognitive development.

In contrast, the relatively lower correlations between CT dimensions and Elaboration suggest that while computational approaches foster divergent ideation, they may not inherently promote the depth of idea refinement unless explicitly scaffolded. This observation aligns with findings by Hwang and Chien (2022), who emphasized the importance of guided reflection and cognitive prompting in fostering elaboration within game-based learning environments.

The study also highlights the effectiveness of gamification and artificial intelligence in enabling differentiated and responsive learning. This finding aligns with the results reported by Yildiz Durak and Saritepeci (2020), who found that adaptive digital platforms enhanced learner engagement and cognitive development.

In this study, students responded positively to motivational game elements, and AI-driven personalization allowed for dynamic task adaptation and real-time feedback, which in turn supported learner autonomy.

The model developed in this study is further supported by Vygotsky's social constructivism, particularly through its emphasis on scaffolded support and operation within the zone of proximal development (ZPD). As learners engaged with game-based, open-ended tasks supported by AI and peer interaction, they consistently performed beyond their initial developmental level—a dynamic also observed in enhanced CrT and CT scores. In a broader educational context, these results contribute to the growing body of evidence advocating for early childhood education that integrates higher-order cognitive skills within playful and technology-enhanced frameworks (UNESCO, 2022; Papadakis et al., 2023). The study responds to calls for ECE curricula that move beyond basic literacy and numeracy to include skills critical for the 21st century.

6. Conclusion

This study provides compelling empirical evidence that computational thinking (CT) and creative thinking (CrT) are interrelated and mutually reinforcing cognitive domains in early childhood education. The observed correlation ($r = .74$, $p < .01$) substantiates the central hypothesis that these thinking skills can develop synergistically when appropriately scaffolded within a constructivist, gamified, and AI-supported learning environment. This finding aligns with the work of Kong et al. (2022), who demonstrated that the co-integration of CT and CrT enhances young learners' cognitive flexibility and problem-solving abilities. Furthermore, the strong domain-level correlations—particularly between decomposition and originality, and pattern recognition and fluency—align with prior findings by Romero et al. (2023), underscoring the capacity of structured problem-solving tasks to foster divergent ideation and creative fluency.

From a practical perspective, this study provides a validated instructional framework for early childhood educators and curriculum designers who seek to integrate high-order thinking skills into playful and developmentally appropriate learning experiences. The model emphasizes the value of leveraging gamification and AI-driven personalization to adapt learning pathways to individual learner profiles, thereby enhancing engagement and cognitive growth. This contributes directly to the global movement toward innovative, technology-supported pedagogy in early childhood education (UNESCO, 2022).

From a theoretical perspective, the study advances understanding of the cognitive interplay between CT and CrT in young children, a relationship that has often been assumed but insufficiently evidenced in prior literature. By demonstrating how specific CT sub-skills support distinct dimensions of creative thinking, the study contributes to a more nuanced conceptualization of how these domains interact within constructivist learning contexts.

The originality of this study lies in its integrated methodological approach, combining AI-based adaptive learning, gamification, and constructivist pedagogy to promote the simultaneous development of CT and CrT in preschool learners. This contribution addresses a notable gap in existing literature, which has traditionally examined these domains in isolation, and provides a scalable model for their co-development in early learning settings.

Future research could explore longitudinal outcomes of this integrated instructional model and investigate its applicability across diverse cultural and educational contexts. Additionally, further work is needed to refine strategies for supporting elaboration and depth of creative thinking within AI-personalized learning environments.

6.1. Implications

The findings of this study have several important implications for early childhood education, educational technology, and curriculum design. First, the strong positive correlation between computational thinking and creative thinking suggests that these competencies should be developed not in isolation but as interconnected domains. Educators should be encouraged to integrate both types of thinking in early learning experiences, especially through open-ended, exploratory activities that allow children to apply logic and imagination simultaneously.

Second, the effectiveness of a constructivist personalized learning environment that incorporates gamification and artificial intelligence underscores the value of using technology-enhanced, learner-centered pedagogies. Such environments support differentiated instruction, motivation, and real-time scaffolding, particularly for young learners with diverse developmental needs. This aligns with the global emphasis on innovation and equity in early childhood education.

Third, the study provides a replicable model for designing educational interventions that balance cognitive structure (CT) with creative freedom (CrT). This has practical implications for curriculum developers, teacher educators, and policymakers working to enhance the quality and relevance of early education in the digital age.

6.2. Limitations and Future Research

While this study provides valuable insights into the relationship between computational thinking (CT) and creative thinking (CrT) in early childhood education, several limitations must be acknowledged.

First, the sample consisted of 30 preschool children from a single university-affiliated demonstration school serving primarily middle to upper-middle socioeconomic families. This sample may not fully represent the broader population of preschool learners, particularly those from diverse socioeconomic, cultural, or linguistic backgrounds. Future research should aim to replicate and extend these findings across more heterogeneous samples and varied educational contexts to enhance generalizability.

Second, the duration of the experimental implementation was relatively short (six weeks). As such, the results primarily reflect short-term impacts of the integrated instructional model. Longitudinal studies are needed to examine whether the observed gains in CT and CrT are sustained over time and how they influence subsequent academic trajectories and creative development throughout the primary years and beyond.

Third, the artificial intelligence (AI) integration in this study was limited to certain instructional modules, specifically those related to adaptive task sequencing and real-time feedback. Other potential AI applications—such as natural language processing for creative dialogue support or advanced learning analytics—were not explored. Future research could expand the scope of AI integration to examine its broader impact on young learners' cognitive and creative growth.

Fourth, qualitative data interpretation involved researcher-driven thematic analysis, which inherently carries the risk of subjective bias. Although steps were taken to enhance trustworthiness—such as triangulating data sources and conducting inter-rater reliability checks—complete objectivity cannot be guaranteed. Future studies could employ additional methods, such as peer debriefing or participatory analysis involving educators, to further mitigate potential researcher subjectivity.

Finally, as AI technologies continue to evolve rapidly, it is critical to explore their ethical and developmental implications in early childhood contexts. Issues such as data privacy, screen time balance, and maintaining learner agency warrant careful consideration. Future research should address these dimensions to ensure that AI-enhanced learning environments remain developmentally appropriate and ethically sound for young children.

7. Suggestion

The findings from this study underscore the need for early childhood educators to design learning experiences that intentionally integrate computational and creative thinking. Rather than treating these as separate skill domains, the results suggest that they are most effectively nurtured in tandem through open-ended, exploratory tasks that combine structured reasoning with imaginative expression. Therefore, it is recommended that early childhood curricula be re-envisioned to include activities such as digital storytelling, coding through tangible tools, and project-based learning that allows children to engage both cognitively and creatively.

In implementing such curricula, schools should consider adopting constructivist, technology-supported learning environments that personalize instruction through artificial intelligence and enhance engagement through gamified design. These environments not only support differentiated learning but also provide real-time feedback and scaffolded support, which are essential for young learners with varying developmental needs. In doing so, educators will be able to move beyond rote learning and foster deeper, more meaningful learning experiences that prepare children for the challenges of the digital world.

Equally important is the professional development of teachers. Training programs should emphasize constructivist pedagogy, digital literacy, and the integration of high-order thinking into early learning contexts. Educators must be equipped not only to use technology effectively but to design learning environments that promote inquiry, reflection, and innovation. Furthermore, play-based learning should be recognized as a legitimate and powerful context for developing complex cognitive skills. Carefully designed play scenarios can promote computational logic while simultaneously encouraging originality, flexibility, and elaboration.

Finally, the use of artificial intelligence and gamification in early childhood education must be implemented with careful ethical consideration. Systems should be developmentally appropriate, protect learner privacy, and ensure that children's agencies are preserved. Tools must be accessible and inclusive to serve the diverse needs of learners, especially those from underserved backgrounds. By aligning pedagogical goals with technological possibilities, educators and policymakers can build early education systems that truly support the development of 21st-century learners.

Declarations

Author Contributions. All authors have read and approved the published on the final version of the article.

Ethical Approval. This study was conducted in full compliance with the ethical guidelines as approved by the Khon Kaen University Research Ethics Committee, No. HE673136.

Data Availability Statement. The datasets generated and analyzed during the current study are not publicly available due to ethical restrictions related to the privacy of child participants but are available from the corresponding author on reasonable request. Data include assessment scores, interview transcripts, and protocol analysis documents collected from preschool participants within a controlled educational setting. Requests for data access should be directed to the corresponding author via institutional email.

References

- Anderson, J. R. (1980). *Cognitive psychology and its implications*. W.H. Freeman.
- Bers, M. U. (2018). *Coding as a playground: Programming and computational thinking in the early childhood classroom*. Routledge. <https://doi.org/10.4324/9781315398945>
- Bocconi, S., Chiocciariello, A., Dettori, G., Ferrari, A., Engelhardt, K., Kampylis, P., & Punie, Y. (2016). *Developing computational thinking in compulsory education*. Publications Office of the European Union. Retrieved from <https://publications.jrc.ec.europa.eu/repository/handle/JRC104188>
- Brennan, K., & Resnick, M. (2012). New frameworks for studying and assessing the development of computational thinking. In *Proceedings of the 2012 Annual Meeting of the American Educational Research Association*. Retrieved from <http://scratched.gse.harvard.edu/ct/files/AERA2012.pdf>
- Brown, J. S., Collins, A., & Duguid, P. (1989). Situated cognition and the culture of learning. *Educational Researcher*, 18(1), 32–42. <https://doi.org/10.3102/0013189X018001032>
- Center on the Developing Child at Harvard University. (2016). *From best practices to breakthrough impacts*. Retrieved from <https://developingchild.harvard.edu/resources/from-best-practices-to-breakthrough-impacts/>
- Goswami, U. (2006). Neuroscience and education: From research to practice? *Nature Reviews Neuroscience*, 7(5), 406–413. <https://doi.org/10.1038/nrn1907>
- Grant, P., & Basye, D. (2014). *Personalized learning: A guide for engaging students with technology*. ISTE.
- Guilford, J. P. (1950). Creativity. *American Psychologist*, 5(9), 444–454. <https://doi.org/10.1037/h0063487>
- Hamari, J., Koivisto, J., & Sarsa, H. (2014). Does gamification work? – A literature review of empirical studies on gamification. In *Proceedings of the 47th Hawaii International Conference on System Sciences*. <https://doi.org/10.1109/HICSS.2014.377>
- Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign. Retrieved from https://curriculumredesign.org/wp-content/uploads/AI-in-Education-Promises-and-Implications_CCR-2019.pdf

- Hwang, G. J., & Chien, T. C. (2022). A review of artificial intelligence applications in early childhood education: Learning, assessment, and challenges. *Computers & Education*, 182, 104463. <https://doi.org/10.1016/j.compedu.2022.104463>
- Jalinus, N., Nabawi, R. A., & Putra, A. S. (2019). The seven components of project-based learning to enhance productive competencies of vocational students. *Journal of Technical Education and Training*, 11(1), 34–43. <https://doi.org/10.30880/jtet.2019.11.01.005>
- Jonassen, D. H. (1999). Designing constructivist learning environments. In C. M. Reigeluth (Ed.), *Instructional-design theories and models: A new paradigm of instructional theory* (Vol. II, pp. 215–252). Lawrence Erlbaum Associates.
- Jonassen, D. H., Carr, C., & Yueh, H. P. (1998). Computers as mindtools for engaging learners in critical thinking. *TechTrends*, 43(2), 24–32. <https://doi.org/10.1007/BF02818172>
- Junruang, C., Kanjug, I., Samat, C. (2021). The Development of a Computational Thinking Learning Package that Integrates a Learning Experience Design for Grade K. In: Huang, YM., Lai, CF., Rocha, T. (eds) Innovative Technologies and Learning. ICITL 2021. *Lecture Notes in Computer Science*, vol 13117. Springer, Cham. https://doi.org/10.1007/978-3-030-91540-7_16
- Kalelioglu, F., Gülbahar, Y., & Kukul, V. (2016). A framework for computational thinking based on a systematic research review. *Baltic Journal of Modern Computing*, 4(3), 583–596.
- Kong, S. C., Lai, M., & Sun, D. (2022). Developing computational and creative thinking through the integration of coding activities and maker education. *British Journal of Educational Technology*, 53(1), 96–113. <https://doi.org/10.1111/bjet.13171>
- Krath, J., Günther, S., & Süß, H. M. (2023). Adaptive learning with AI in education: Benefits and challenges. *Computers & Education*, 184, 104545. <https://doi.org/10.1016/j.compedu.2022.104545>
- OECD. (2021). *OECD future of education and skills 2030*. <https://doi.org/10.1787/bf31d04a-en>
- Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: Opportunities and challenges for personalized learning. *Educational Technology Research and Development*, 69(4), 2109–2133. <https://doi.org/10.1007/s11423-021-09985-4>
- Papadakis, S., & Kalogiannakis, M. (2023). Editorial: The Impact of Smart Screen Technologies and Accompanied Apps on Young Children's Learning and Developmental Outcomes, Volume 2. *Frontiers in Education*, 8, Article ID: 1249116. <https://doi.org/10.3389/educ.2023.1249116>
- Papert, S. (1980). *Mindstorms: Children, computers, and powerful ideas*. Basic Books.
- Phungching, S., & Laddaklom, T. (2020). Developing creative thinking through nature-integrated art-based learning in early childhood. *Journal of Early Childhood Education Research*, 9(2), 321–336.
- Piaget, J. (1954). *The construction of reality in the child*. Basic Books.
- Resnick, M. (2017). *Lifelong kindergarten: Cultivating creativity through projects, passion, peers, and play*. MIT Press.
- Romero, M., Lille, B., & Vernay, C. (2023). Supporting creative thinking through computational thinking activities in early childhood. *British Journal of Educational Technology*, 54(1), 145–165. <https://doi.org/10.1111/bjet.13210>
- Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation. *American Psychologist*, 55(1), 68–78. <https://doi.org/10.1037/0003-066X.55.1.68>

- Saenboonsong, W., & Poonsawad, P. (2024). Gamification for enhancing creative thinking skills in early childhood education. *Early Child Development and Care*.
- Shonkoff, J. P., & Phillips, D. A. (2000). *From neurons to neighborhoods: The science of early child development*. National Academies Press. <https://doi.org/10.17226/9824>
- Shonkoff, J. P., et al. (2012). The lifelong effects of early childhood adversity and toxic stress. *Pediatrics*, 129(1), e232–e246. <https://doi.org/10.1542/peds.2011-2663>
- Tikva, C., & Tambouris, E. (2021). Fostering computational thinking through interdisciplinary teaching in early childhood. *Computers & Education*, 164, 104112. <https://doi.org/10.1016/j.compedu.2020.104112>
- Torrance, E. P. (1974). *Torrance tests of creative thinking*. Scholastic Testing Service.
- UNESCO. (2022). *Reimagining our futures together: A new social contract for education*. UNESCO Publishing. <https://unesdoc.unesco.org/ark:/48223/pf0000379707>
- Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.
- Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, 49(3), 33–35. <https://doi.org/10.1145/1118178.1118215>
- World Economic Forum. (2020). *The future of jobs report 2020*. Retrieved from <https://www.weforum.org/reports/the-future-of-jobs-report-2020>
- Yildiz Durak, H., & Saritepeci, M. (2020). The effect of adaptive digital learning environment on student engagement and achievement. *Interactive Learning Environments*, 28(6), 713–727. <https://doi.org/10.1080/10494820.2018.1552873>
- Zainuddin, Z. (2018). Students' learning performance and perceived motivation in gamified flipped-class instruction. *Computers & Education*, 126, 75–88. <https://doi.org/10.1016/j.compedu.2018.07.003>

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