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Metasystem Transitions in Education: Human-AI Interactions as Catalysts for Computational Thinking

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Abstract: *The paper explores how human–AI interactions, particularly with generative artificial intelligence (Gen-AI), serve as catalysts for developing computational thinking (CT) as a creative meta-competence. Grounded in a theoretical framework that synthesises Vygotsky's mediated learning, Lotman's Semiosphere, and Turchin's Metasystem Transition theory, the study conceptualises education as a process of collaborative meaning-making within human–machine teams. Two case studies conducted in Russian middle schools provide empirical grounding: one involving scaffolded Gen-AI use in project-based learning, and the other involving unstructured Gen-AI use during programming tasks. Results indicate that structured, reflective engagement with Gen-AI enhances students' CT skills and supports self-regulation, while not scaffolded use yields mixed outcomes. The findings suggest that Gen-AI can function as a semiotic and cognitive scaffold when meaningfully integrated into educational activities. The study contributes to the understanding of computational thinking as a form of cultural and cognitive mediation, and positions Gen-AI as a driver of metasystem transitions in education.*

Keywords: *computational thinking; generative artificial intelligence; metasystem transition; semiosphere; mediated learning; scaffolded learning; human–machine teams; creative thinking; educational technology; metacognition.*

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1. Introduction

Over the past fifty years, the evolution of technology has profoundly affected the field of education (Reeves, 2016). Over this period, key innovations—including computers (Kay & Goldberg, 1977; Kay, 1991), the Internet (Bruckman, 1997; Leuf, 2002), digital data processing (Klopfer et al., 2005; Kross et al., 2020), the Internet of Things (Badshah et al., 2023), and, most recently Gen-AI (Dasgupta et al., 2023; Resnick, 2024) have transformed educational processes. Consequently, many previously successful educational approaches and models have lost relevance and gradually disappeared. For example, MediaMOO, the pioneering virtual community created by Bruckman at MIT in 1992, initially attracted over 1,000 members but later declined; its constructionist principles, however, influenced later virtual learning environments (Bruckman & Resnick, 1996; Bruckman & Jensen, 2002; Fiesler & Bruckman, 2019).

A similar trajectory was observed with educational wikis such as Letopisi.org, which flourished in the 2000s but later declined, before re-emerging in modified form to support computational thinking (Patarakin, 2009; Patarakin & Visser, 2010).

We view computational thinking as a key competence for engaging with modern technologies, where individuals must effectively negotiate with digital agents—software entities that, according to the principles of the Media Equation (Reeves & Nass, 2003), are treated by people as social actors. In this context, computational thinking encompasses the abilities to frame problems for algorithmic reasoning, design interactive protocols, and reflect critically on human–agent interactions (Patarakin et al., 2019). This creative dimension highlights how computational thinking goes beyond technical skills, encouraging innovation and imaginative engagement with technology. It also has a creative dimension, enabling learners to generate novel solutions in programming, design, and problem-solving (Israel-Fishelson & Hershkovitz, 2025; Romero et al., 2017). While large language models like ChatGPT may reduce the diversity of creative outputs and often converge on common ideas (Doshi & Hauser, 2024), they can still enhance the quality of creative responses and serve as a useful support for less experienced users during idea generation (Lee & Chung, 2024).

We adopt the perspective of Human–Machine Teams, where humans and AI function as collaborative partners rather than mere tools (Endsley, 2023; Newton et al., 2024). This framework emphasises the complementary strengths of human flexibility and creativity and machine consistency and processing power, with success depending on shared mental models (Chiou et al., 2022; Costa et al., 2022).

The most recent shift is the rise of Gen-AI, based on large language models(LLM). Yet, the idea of learners as active creators has deep roots in Papert and Solomon's (1971) constructionist vision, which emphasised students as designers, programmers, and explorers. Rather than passively receiving information, learners shape processes and direct computational agents, thereby fostering critical thinking, creativity, and technical skills. In this approach, the learner becomes an active creator who governs the executor's behaviour. Modern technologies extend this vision, offering powerful tools for experimentation and creation (Cress & Kimmerle, 2023; Faruqi et al., 2024; Kafai & Morales-Navarro, 2024). Gen-AI represents the latest shift toward hybrid learning teams where students collaborate with intelligent computational agents. The present study investigates how scaffolded and non-scaffolded uses of Gen-AI shape students' computational thinking as a form of creativity and self-regulation in coding tasks.

2. Problem

The rapid evolution of educational technologies has produced recurring cycles of innovation, decline, and reinvention, yet many promising tools fail to sustain meaningful learning without careful pedagogical integration. The recent emergence of Gen-AI introduces new opportunities for human–AI collaboration in education, particularly in supporting computational thinking as a creative and problem-solving competence. However, while Gen-AI is increasingly adopted as a learning aid, its role as a cognitive and semiotic partner in learning remains poorly understood.

Current research rarely addresses how AI functions within human–machine teams to scaffold higher-order thinking, or how such interactions contribute to systemic educational transformation. Specifically, there is a lack of empirical evidence and conceptual clarity about how Gen-AI affects students' development of computational thinking and self-regulation when integrated with or without instructional scaffolding. This study addresses this gap by examining Gen-AI's potential to act as a catalyst for metasystem transitions in learning through the lens of mediated learning, cultural semiotics, and systems theory.

3. Theoretical Aspects

Learning and socio-cognitive development emerge most powerfully within hybrid teams that integrate human learners, educators, and intelligent computational agents. In these mixed human–machine collectives, mediation is not a one-way transfer of tools or information but a co-creative process that reshapes both individual minds and the sociotechnical environments they inhabit. To make sense of this dynamic interplay, the present framework brings together three foundational perspectives — Vygotsky's mediated learning, Lotman's Semiosphere, and Turchin's Metasystem Transition — within the context of Human–Machine Teams. This synthesis will illuminate how scaffolding, shared meaning-making, and evolutionary leaps in organisational complexity converge to support learning in the age of Gen-AI.

Vygotsky's theory of mediated learning posits that learners can achieve higher levels of understanding and skill development through guided interaction with a "more knowledgeable other," who provides contingent support to bridge the gap between the learner's current abilities and potential development (Wood et al., 1976). This scaffolding unfolds through social dialogue, joint problem solving, and the co-construction of meaning, underscoring the fundamentally social and dialogical nature of cognitive growth (Vygotsky, 1978). In this view, cognitive and semiotic processes are mediated not only by human mentors but also by symbolic artefacts and technological systems, which function as active partners in learners' development (Cole & Wertsch, 1995). This type of support can be described as semiotic scaffolding, where signs, symbols, and cultural tools act as mediators that extend learners' cognitive activity and enable higher-order thinking (Vygotsky, 1934/1987; Lotman, 1990).

In computer-mediated environments, Vygotsky's insights have been elaborated and operationalised in multiple ways. Pea and Kurland (Pea & Kurland, 1984) demonstrated how programming activities serve as vehicles for mediated reflection, enabling learners to externalise their reasoning and iteratively negotiate solutions with computer-based feedback. Jonassen (1996) extended the concept of the computer as a more knowledgeable other, showing how software tools can provide dynamic, context-sensitive support aligned with learners' development. Wing's formulation of computational thinking as a fundamental literacy emphasised the importance of constructive scaffolds, such as visual programming environments and collaborative coding platforms, that embody Vygotskian mediation by enabling learners to experiment, receive immediate feedback, and engage in social negotiation of code structures (Wing, 2009). Constructionist environments, pioneered by Harel and Papert (Harel & Papert, 1991), translate Vygotsky's mediated learning into learner-centred software designs, where the act of programming itself becomes a socially situated scaffold for cognitive and metacognitive development.

Lotman's concept of the Semiosphere extends mediated learning to the level of culture and signs, positing that all cognitive and communicative acts take place within a shared semiotic space (Lotman, 2005). This Semiosphere comprises the entire network of sign systems—languages, symbols, images, interfaces—that enable collective meaning-making. Within this symbolic environment, agents of all kinds—human teachers, student peers, software tutors, AI assistants—serve as scaffolds, dynamically generating, transforming, and interpreting signs to support learners' navigation of the cultural space. By acting as semiotic mediators, these agents both shape and are shaped by the Semiosphere: their interventions introduce new pathways for meaning, and in turn the evolving cultural milieu constrains and amplifies subsequent interactions.

Developments in computer-supported learning have applied Lotman's ideas to the digital Semiosphere, demonstrating how scaffolded interactions with wikis, coding platforms, and intelligent tutors foster computational literacy and collaborative skills in richly signified virtual environments (Clark, 2010; Hartley et al., 2020). Lotman's emphasis on the generative and dialogical functions of texts and interfaces thus provides a vital lens for understanding how human and non-human scaffolds co-construct knowledge in digital culture.

Turchin's Metasystem Transition (MST) theory illuminates how existing systems of lower complexity become integrated into higher-order metasystems, catalysing new forms of control, coordination, and creative capacity (Turchin, 1993). Central to this process is the introduction of scaffolding agents — human, technological, or hybrid — whose interventions mediate and elevate interactions among subsystems. These agents support routine functions and routine problem-solving, thereby freeing human participants to engage in genuinely novel, boundary-crossing creativity. A creative act, in Turchin's terms, is any operation performed for the first time that transcends the rules or limits of the prior system; mere repetition or rule-following does not qualify. When scaffolding agents absorb or automate established patterns, handling lower-level coordination, data processing, or repetitive procedures — they enable humans to invent unprecedented solutions. This dynamic interplay of human ingenuity and agent support produces a qualitative leap in systemic organisation: the new metasystem integrates the old, incorporates creative extensions, and establishes a fresh level of control and functionality. Over successive cycles, creative acts once deemed creative become routine as scaffolding agents master and internalise them, raising the threshold for what counts as a creative contribution. In this way, the scaffolding role of agent systems not only accelerates individual innovation but also drives the entire system upward through continuous metasystem transitions, each marked by increasingly sophisticated forms of human-agent collaboration.

The works of Valentin Turchin's colleagues significantly advanced his cybernetic philosophy within the digital semiosphere through the Principia Cybernetica Project. Building on Turchin's foundational concept of metasystem transitions, collaborators like Francis Heylighen and Cliff Joslyn extended his approach by developing a comprehensive, evolutionary worldview implemented as an interactive semantic network on the web (Heylighen et al., 2001; Turchin & Joslyn, 2018). This digital environment enabled collective, computer-supported theory-building that reflected the self-organising, hierarchical nature of complex systems, thus embodying Turchin's vision of creativity and evolution as continuous metasystem transitions. Their contributions not only enriched the theoretical content but also innovated the methodology, making Principia Cybernetica a pioneering platform for collaborative cybernetic philosophy in the information age (Joslyn & Rocha, 2000).

The convergence of Lotman's semiospheric concepts with Turchin's metasystem transition theory suggests that educational transformation involves not merely the accumulation of new information or skills, but the emergence of new forms of semiotic organisation that enable more complex and adaptive forms of learning. This understanding has profound implications for educational practice, suggesting the need for pedagogical approaches that attend to the semiotic dimensions of learning and that create conditions for the emergence of higher-order cognitive and cultural capabilities. Moreover, in this reconceptualised Semiosphere, computational thinking emerges as the indispensable meta-competence that underpins all creative collaboration within human–computer teams. In this study, we interpret this capacity as a form of **creative meta-competence**—the ability to monitor, regulate, and expand one's own creative processes across contexts, combining metacognitive awareness with creative problem-solving (Papert & Solomon, 1971; Romero et al., 2017; Israel-Fishelson & Hershkovitz, 2025). It is through computational thinking that learners acquire the capacity to negotiate with software agents and generative-AI collaborators, treating these non-human actors as semiotic partners in co-construction. Without computational thinking, participants in a hybrid learning team cannot fully engage in the generative cycles of meaning-making that produce new levels of semiotic organisation. Only by mastering the language of code, the logic of digital agents, and the affordances of AI-driven environments can learners and educators jointly transcend the constraints of prior metasystems. In effect, computational thinking acts as both scaffold and gateway, enabling the human mind to collaborate creatively with machine-based agents, drive metasystem transitions, and realise emergent forms of collective intelligence and cultural evolution.

4. Results

To ground the theoretical perspectives discussed above, we now turn to two case studies that illustrate how human–AI collaboration unfolds in educational settings. Both cases focus on computational thinking, understood here not only as a set of technical problem-solving skills but also as a form of creative thinking that enables learners to generate novel solutions and design meaningful interactions. By examining how students engaged with Gen-AI in the form of ChatGPT 4.5 under different conditions, we highlight the ways AI can shape and support the development of computational thinking as a creative competence. The two case studies presented below draw on small-scale interventions conducted in Russian middle schools as part of extracurricular computer science programs. Each study explored students' interactions with Gen-AI tools in project-based or programming tasks, focusing on the development of computational thinking. The first case examined the development of computational thinking through scaffolded, structured use of Gen-AI in project-based learning. The second case focused on students' self-regulation during programming tasks, where Gen-AI was available but not supported by instructional scaffolding. Our analysis combines quantitative measures (e.g., CT skill assessments) and qualitative data (e.g., observations, think-aloud protocols, interviews), offering a comparative perspective on how different types of human–AI interaction may shape creative, computational thinking. In the first study, CT skills were assessed using the Bebras International Challenge as a standardised pre- and post-test covering decomposition, pattern recognition, abstraction, and algorithmic thinking. Additionally, students' CT performance was evaluated through an AI-based analysis of their interactions with the GPT-4.5 chatbot, focusing on how they demonstrated decomposition, abstraction, algorithmic reasoning, and reflection during problem-solving. In the second study, CT was assessed through qualitative indicators embedded in students' project work—by analysing how they demonstrated these CT components in different project stages (problem formulation, coding, debugging, modeling).

<u>Case Study 1. Scaffolded use of Gen-AI</u>

RQ1: To what learning improvements in terms of computational thinking is the scaffolded use of Gen-AI connected ?

<u>Procedure and sample</u>

The aim of this Study 1 was to explore how Gen-AI tools can support the development of computational thinking (CT) skills among students, with a particular focus on how students' prompt formulation evolves during task-based interactions. The experiment was conducted in 2025 at a private secondary school in Russia as part of extracurricular project-based learning in computer science. Participants were students from grades 5 to 9 (n=30), and they were divided evenly into control and experimental groups. All students were involved in interdisciplinary projects (e.g., literature, language, arts), which they worked on weekly during scheduled project hours in the computer science classroom. While all students engaged in similar project-based learning, only the experimental group received structured guidance on using Gen-AI tools to enhance their CT skills. The experimental group was guided to actively engage with Gen-AI tools (such as DeepSeek, Suno, Sora, etc.) throughout the project process. They used Gen-AI in various ways: generating ideas, creating visual/audio outputs, researching, and enhancing presentations. Their interaction with Gen-AI was iterative and scaffolded, with increasing complexity and autonomy over time. Students' prompt history ("digital trace") was used as evidence of how their CT skills evolved during the project. The control group worked without Gen-AI. The examples of students' interaction with Gen-AI under its scaffolded use are shown in Table 1.

Table 1. Examples of scaffolded student–Gen-AI interaction

Student's Prompt	Gen-AI Response
"Can you give me three ideas for the project about recycling materials? They should be suitable for students around 13 years old."	"Here are three suggestions: (1) Build a bird feeder from plastic bottles, (2) Create a pencil holder from old cans, (3) Design a tote bag from old T-shirts."
"I started thinking about doing something with plastic waste, but I don't know what exactly. Maybe something that can be useful at home? Can you help me think of options?"	"Of course! You could try (1) making storage boxes from plastic bottles, (2) creating a small indoor garden using old containers, or (3) building a lamp from recycled plastic parts."

Pre-test

Students were given a task to plan meals for 100 people using a budget of 20,000 rubles (equivalent to 230 USD). They were instructed to solve the task by interacting with a Gen-AI chatbot of their choice. Students had to describe their problem to the chatbot and develop a solution through multiple prompts, without asking the AI to solve the entire task at once. All instructions were delivered orally to ensure that prompt formulation reflected the students' own thinking. The prompts generated by students were evaluated by the GPT-4.5, DeepSeek-R1, and Grok-3 chatbots using a 10-point scale, where 1 indicated the lowest and 10 the highest level of computational thinking. The assessment was based on six computational thinking components: decomposition, abstraction, algorithmisation, iteration, debugging, and generalisation (i.e., identifying patterns). To ensure the reliability of AI-based scoring, three independent language models—GPT-4.5, DeepSeek-R1, and Grok-3—were used as parallel evaluators. Each model assessed the students' prompts using an identical rubric aligned with these six components, and the final score for each prompt represented the average of their ratings. The consistency among the models' evaluations was high (Cronbach's $\alpha = 0.89$), indicating strong inter-rater reliability. In the pre-test, the average CT score in the experimental group was 3.46, while the control group averaged slightly lower at 3.12. Both groups showed relatively low baseline levels across all six CT components. The most challenging areas for students were abstraction and debugging, where many scored between 1 and 3. Only a few students in either group achieved scores above 4 in components like algorithmisation and generalisation. These results indicate a generally low but comparable level of computational thinking skills prior to the intervention.

Analytical strategy

To evaluate the impact of the intervention on students' computational thinking (CT) development, pre- and post-intervention scores were collected for both experimental and control groups. A non-parametric statistical Mann–Whitney U test was applied to compare post-test scores between the experimental and control groups.

Results

The analysis of post-intervention data revealed that scaffolded use of generative AI in project-based learning was associated with significant improvements in students' CT. Specifically, students in the experimental group, who were guided to take an agentive role in their interactions with Gen-AI tools, demonstrated a greater increase in CT scores compared to their peers in the control group. The average CT score in the experimental group rose from 34.3% to 41.2% over the academic year, representing a 6.9 percentage point gain. In contrast, the control group, which used Gen-AI tools without targeted scaffolding, showed a smaller increase from 30.4% to 33.5%, a 3.1-point improvement. (see Figure 1). The Mann–Whitney U test confirmed the statistical significance of these differences (U = 209, p = 0.000542). These findings support the hypothesis that scaffolded, reflective use of Gen-AI — where students position themselves as mentors guiding the AI — enhances their ability to engage with key components of CT such as decomposition, abstraction, iteration, and generalisation.

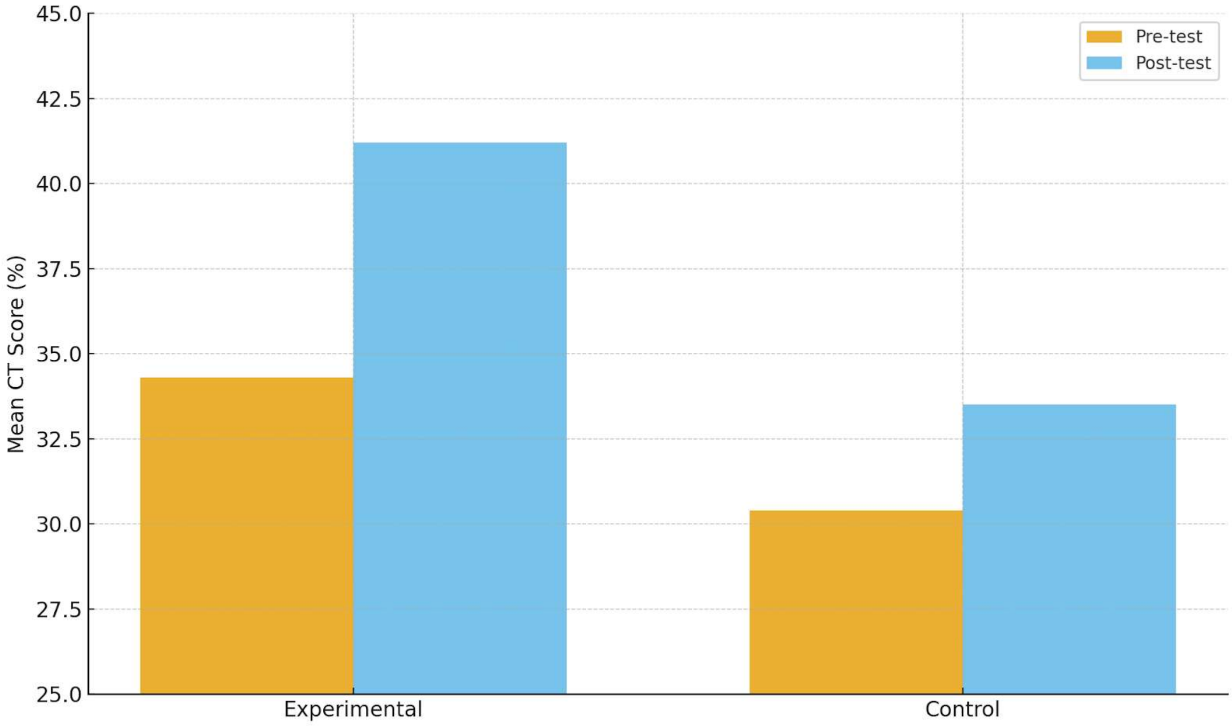

Figure 1. Comparison of pre- and post-test computational thinking (CT) scores between experimental and control groups

Case Study 2 - Not scaffolded use of Gen-AI

To complement the findings of Study 1, which emphasised the value of structured Gen-AI support for developing CT, Study 2 investigates how students self-regulate their learning in programming tasks when Gen-AI is introduced without scaffolding.

RQ2: Does the use of Gen-AI without strategic instructional scaffolding support the development of students' self-regulation skills when solving programming tasks?

Procedure and sample

The study was conducted as part of an extracurricular course on the fundamentals of Python programming. The course took place over a three-month period, with students attending one session per week. A total of nine thematic lessons were held, covering basic Python constructs. During some of the sessions, students used the Black Box AI platform to assist with programming tasks. No strategies for interacting with the Gen-AI were introduced. The instructional approach was intentionally non-intrusive: students were given unrestricted access to Gen-AI and were free to decide when and how to use it. In total, 36 prompt interactions were recorded over the course of the study. Participants were students from the 7th grade of middle school (n=4).

Analytical strategy

Self-regulation was analysed using a qualitative case study approach based on direct observation and think-aloud data. This method enabled close examination of each student's interaction with Gen-AI tools and specific self-regulatory behaviours. Midpoint and final interviews supplemented the observations.

Results

Based on the findings from four student cases, this study identified diverse patterns of self-regulation when students used Gen-AI tools without explicit guidance. For example, student 1 demonstrated a high level of self-regulation, using Gen-AI critically for idea generation and debugging while maintaining independent control over the process; however, a tendency to delegate planning to the AI was observed:

Student's prompt: "I wrote this Python code for a guessing game, but it doesn't run. Can you find the mistake?"

Gen-AI response: "The error is in line 5: you used = instead of = for assignment."

The student framed the problem clearly and then integrated the feedback into their own debugging process, showing ownership of the solution.

Student 2 showed moderate self-regulation, engaging thoughtfully with the AI for clarification and validation, yet struggled with articulating reasoning (self-explanation):

Student's prompt: "I wrote a loop to print numbers from 1 to 10, but it keeps printing 1 forever. Can you explain what I did wrong?"

Gen-AI response: "You used while number == 1: instead of while number <= 10:. Because of that, the condition never changes, so the loop runs endlessly."

Here, the student demonstrated initiative by identifying a problem and asking for clarification. However, rather than debugging step by step, they relied on the AI to point out the mistake directly. This reflects a **moderate self-regulation profile**: the student used AI productively for validation but did not fully explain the error or attempt independent reasoning before turning to the tool.

Student 3 almost entirely avoided Gen-AI but still exhibited strong self-regulatory skills, emphasising that AI avoidance may reflect autonomous and mature learning behaviour rather than disengagement. In contrast, Student 4 showed low self-regulation, using Gen-AI superficially for quick answers without reflection or understanding.

Student's prompt: "Write the code for a guessing game in Python for me"

Gen-AI response: "Here is a complete version of the guessing game…"

The student bypassed problem-solving altogether, delegating the task entirely to the AI and accepting its solution without verification.

Across all cases, the quality of interaction with Gen-AI—not merely its use—emerged as the key factor connected with self-regulation. Productive use occurred when students treated the AI as a partner for thinking and understanding, while passive use risked undermining deeper learning processes.

These cases illustrate how students' interactions can be systematically aligned with the three self-regulation profiles used in this study. **High self-regulation** (e.g., Student 1) was characterised by clear problem formulation, selective use of Gen-AI for support, and integration of feedback into independent reasoning. **Moderate self-regulation** (e.g., Student 2) involved partial reliance on AI for clarification and validation, but with limited evidence of self-explanation or independent debugging. **Low self-regulation** (e.g., Student 4) was marked by direct delegation of tasks to AI with little or no reflection, while **AI avoidance with self-regulation** (e.g., Student 3) highlighted that autonomy can also manifest through minimal AI use, provided the student demonstrates independent planning and problem-solving.

A summary of students' self-regulation profiles is provided in Table 2.

Table 2. Summary of students' Gen-AI interaction types and self-regulation levels

Student	*AI Interaction Type*	*Self-Regulation Level*	*Behavioural Indicators*
Student 1	Debugging with Gen-AI as a thinking partner	High	Clearly formulated problem; integrated AI feedback into own reasoning; revised code independently after receiving hints.
Student 2	Clarification and validation with AI	Moderate	Asked AI for explanations and corrections; relied on AI to identify mistakes; limited self-explanation or step-by-step debugging.
Student 3	Minimal AI use (self-directed work)	High (autonomous)	Chose to solve tasks independently; planned and debugged code manually; demonstrated strong self-monitoring without AI support.
Student 4	Task delegation to AI	Low	Requested complete solutions from AI; accepted output without verification; showed low reflection and minimal problem-solving effort.

Summary

To complement the qualitative analyses, Figure 2 illustrates the estimated distribution of self-regulation profiles across the two case studies. In the scaffolded condition (Case Study 1), the majority of students were aligned with the moderate self-regulation profile, supported by structured prompts that encouraged productive but not entirely independent use of Gen-AI. A smaller proportion demonstrated high self-regulation, showing more autonomous integration of AI feedback, while only a few fell into the low self-regulation category.In contrast, in the non-scaffolded condition (Case Study 2), the distribution shifted markedly. A larger number of students were classified as low self-regulation, reflecting a tendency to delegate tasks directly to the AI. Fewer students reached the moderate or high categories, though some (like Student 3) demonstrated strong self-regulation through limited or cautious AI use. This comparison underscores the importance of scaffolding in shaping how students regulate their engagement with Gen-AI.

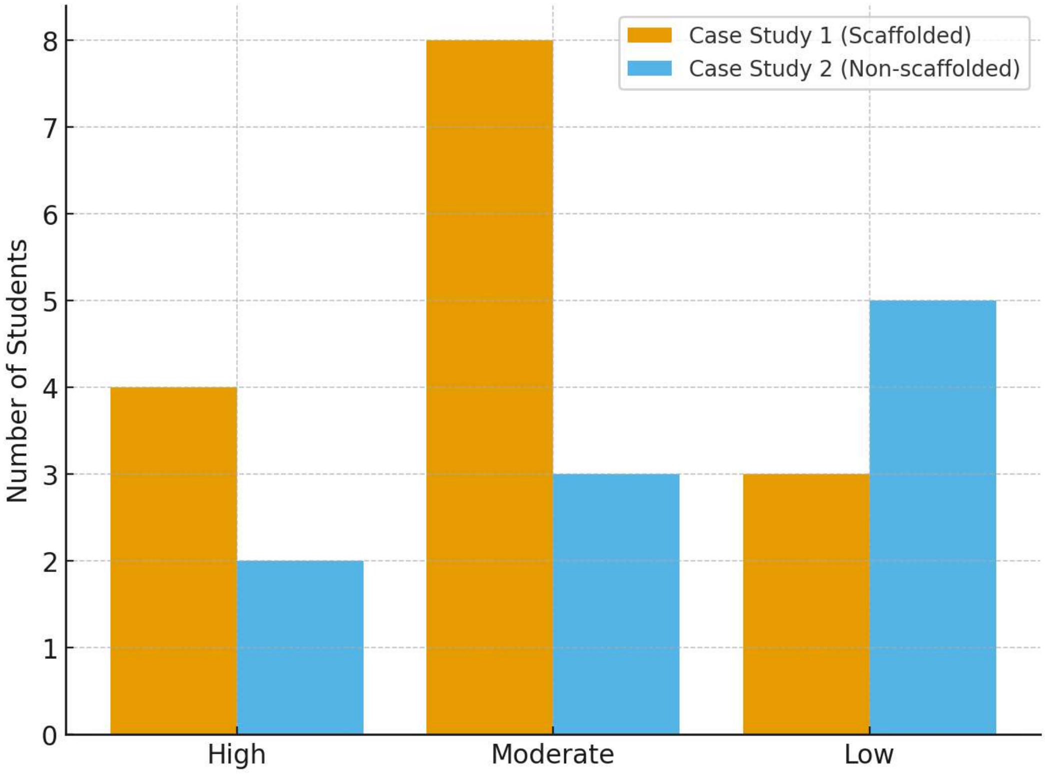

Figure 2. Distribution of self-regulation profiles across Case Study 1 (scaffolded use of Gen-AI) and Case Study 2 (non-scaffolded use)

5. Discussion

The two case studies offer contrasting perspectives on how Gen-AI can affect the development of computational thinking (CT) as a form of creative thinking. When interpreted through the theoretical lenses of Vygotsky's mediated learning (Vygotsky, 1978; Wood et al., 1976), Lotman's Semiosphere (Lotman, 2005), and Turchin's Metasystem Transition theory (Turchin, 1993), several insights emerge about the conditions under which human–AI interaction supports meaningful and creative learning.

From a Vygotskian perspective, the scaffolded use of Gen-AI in Study 1 demonstrates how AI systems can act as "more knowledgeable others" when deliberately structured to guide students through their zone of proximal development (Wood et al., 1976). The iterative process of refining prompts and engaging in purposeful interactions with Gen-AI mirrors the kind of social scaffolding essential for mediated cognitive growth (Vygotsky, 1978). This process nurtured not only technical problem-solving but also creative exploration — aligning with earlier claims that computational thinking encompasses the ability to generate novel, purposeful solutions in design and programming contexts (Israel-Fishelson & Hershkovitz, 2025; Romero et al., 2017). The learners did not simply solve problems; they imagined, iterated, and designed — behaviours at the heart of both computational and creative thinking. In contrast, Study 2, which removed scaffolding, revealed fragmented and inconsistent engagement with Gen-AI. While one student used the tool strategically, others avoided or misused it. Without shared norms for using Gen-AI as a learning partner, students struggled to develop reflective or creative learning behaviours. This illustrates the risk of "under-mediated" learning — a situation where powerful tools are introduced without meaningful integration into the social learning process. As Vygotsky (1978) argued, tools alone do not teach; their value depends on how they are embedded in joint activity and supported by guided interaction.

Through the lens of Lotman's Semiosphere, we can understand computational thinking as a symbolic practice situated in a shared cultural and semiotic space. In Study 1, scaffolded interaction with Gen-AI allowed students to engage in semiotic co-construction — using prompts, visual outputs, and code as sign systems for expressing and negotiating meaning. AI here functioned as a semiotic agent, not just an assistant, enabling learners to explore and reshape the symbolic environment (Lotman, 2005). In contrast, the unstructured context of Study 2 left students without cultural framing for their engagement, which limited the generative potential of the AI. Without scaffolded access to the semiosphere of digital meaning-making, students either fell back on habitual strategies or disengaged entirely.

Turchin's (1993) Metasystem Transition theory provides a final layer of interpretation. In Study 1, Gen-AI supported the automation of lower-level tasks — such as decomposition and basic information retrieval — thus freeing students to engage in creative, boundary-crossing acts. This shift aligns with Turchin's idea that higher-order systems emerge when scaffolding agents allow human actors to transcend routine processes and engage in novel, systemic coordination. The statistically significant CT gains in Study 1 point to the emergence of such a hybrid human–AI learning system, in which learners and generative agents collaboratively produce solutions neither could generate alone (Endsley, 2023; Schelble et al., 2022). In contrast, Study 2 lacked the scaffolding needed to catalyse such a transition — resulting in fragmented or regressive uses of Gen-AI that did not elevate students' creative or computational capabilities.

These findings confirm that computational thinking is more than a technical skill — it is a creative meta-competence that empowers learners to think algorithmically, design iteratively, and collaborate with intelligent systems. When scaffolded effectively, Gen-AI can amplify this creative potential, helping students explore ideas, test possibilities, and express their thinking in novel ways (Romero et al., 2017). However, as the second case illustrates, this potential is not automatic. Gen-AI must be socially and semiotically embedded — positioned as a partner in meaning-making, not just a shortcut or passive tool.

To support the development of computational thinking (CT) skills through scaffolded use of generative AI, educators should design structured activities that gradually build students' ability to formulate effective prompts. Such scaffolding helps develop decomposition, abstraction, and debugging—core components of CT that demonstrated significant growth during the intervention. A range of targeted task types can be incorporated to reinforce these skills in practical and engaging ways. For example, prompt debugging tasks require students to analyse flawed prompts and propose improvements, fostering critical thinking and abstraction. Minimal prompt challenges encourage students to produce high-quality outputs using the shortest and most concise inputs possible, sharpening synthesis and precision. Activities like the "prompt telephone game," where students iteratively revise and pass on prompts and outputs, highlight the importance of clarity and specificity. Collaborative storytelling tasks using Gen-AI-generated visuals support group-based planning and logical sequencing while promoting iteration. Educators are also encouraged to integrate cross-disciplinary prompt-based activities that connect AI use with literature, languages, history, and art, cultivating a STEAM-oriented approach to CT. In addition to instructional tasks, teachers should track students' prompt histories (digital traces) as formative assessment tools to capture the evolution of students' CT over time. Analysing these interactions offers insights into how students refine their thinking and engage with iterative problem-solving. The use of multiple Gen-AI tools (e.g., DeepSeek, Sora, Suno) is also recommended, as it promotes reflection on the differences between platforms and deepens understanding of how AI systems operate. To further strengthen analytical thinking and hypothesis testing, students can compare outputs generated by different models or prompt variations. For more advanced learners, integrating prompt-based tasks with coding—such as writing Python scripts to automate AI input/output cycles—can help students connect computational thinking with real-world programming practices.

Based on the results of Study 2, educators are encouraged to design explicit instructional strategies that guide students in using Gen-AI tools as study partners rather than shortcuts. Students who demonstrated higher levels of self-regulation used Gen-AI selectively—for clarifying concepts, testing hypotheses, and reflecting on understanding—while maintaining control over planning, monitoring, and debugging. Therefore, teachers should foster metacognitive awareness by encouraging students to explain their reasoning, evaluate AI outputs critically, and identify when and why they choose to consult the AI. Reflection prompts, guided questioning, and discussions about AI limitations can help prevent over-reliance and promote mindful use. Additionally, it is important to support students with lower self-regulatory skills by scaffolding their interactions with AI—for example, through structured tasks that require planning before prompting and justification after receiving AI assistance. Integrating Gen-AI into programming tasks with an emphasis on thoughtful interaction can enhance students' self-regulated learning and long-term problem-solving abilities.

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