Enhancing Computational Thinking through a metacognitive–collaborative instructional sequence (NEXUS) in STEM Education

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ABSTRACT

In this quasi-experimental pre-test/post-test design study, 145 students participated to examine the effectiveness of a metacognitive–collaborative instructional sequence, NEXUS, using analog tasks to foster computational thinking (CT) in a flipped STEM classroom. A GroupxTime mixed ANOVA revealed that NEXUS had greater post-test gains than the control across the three CT dimensions, with the highest gain in CT-Practices. Significant post-task differences were found in extraneous load, germane load, and metacognitive regulation (specifically metacognitive monitoring) in favor of NEXUS, while no differences emerged in intrinsic load. A hierarchical regression analysis revealed that students' readiness for collaborative learning was a significant predictor of their post-test CT scores; however, it was not a significant moderator for the effect of NEXUS.

KEYWORDS

Computational thinking, cognitive load, metacognition, collaborative learning, STEM education

RÉSUMÉ

Dans cette étude quasi-expérimentale avec pré-test et post-test, 145 étudiants ont participé afin d'examiner l'efficacité d'une séquence pédagogique métacognitive *et collaborative, NEXUS, utilisant des tâches analogiques pour favoriser la pensée informatique (PI) dans une classe inversée en STIM. Une ANOVA mixte (Groupe x Temps) a révélé que le groupe NEXUS a enregistré des gains au post-test supérieurs à ceux du groupe témoin dans les trois dimensions de la PI, le gain le plus élevé concernant les pratiques de la PI. Des différences significatives post-tâche ont été observées au niveau de la charge extrinsèque, de la charge germane et de la régulation métacognitive (spécifiquement la surveillance métacognitive) en faveur de NEXUS, tandis qu'aucune différence n'est apparue concernant la charge intrinsèque. Une analyse de régression hiérarchique a révélé que la disposition des étudiants à l'apprentissage collaboratif était un prédicteur significatif de leurs scores de PI au post-test ; cependant, elle ne constituait pas un modérateur significatif de l'effet de NEXUS.*

MOTS CLÉS

Pensée computationnelle, charge cognitive, métacognition, apprentissage collaboratif, enseignement STEM

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INTRODUCTION

Computational thinking (CT) has been recognized as a fundamental skill in Science, Technology, Engineering, and Mathematics (STEM) education in the 21st century. It is not limited to the field of computer science. Several recent educational policy documents and meta-analysis studies have argued that CT is an essential competency for tackling problems involving AI, big data, and the 4th industrial revolution (Mills et al., 2025; Tariq et al., 2025; Weng et al., 2024). CT is a set of practices used in STEM to develop models, model systems, reason with a systems perspective, and develop algorithmic problem-solving plans that will function within contextual constraints.

Computational thinking (CT) refers to a set of problem-solving practices that encompass a cluster of skills (abstraction, decomposition, generalization, pattern recognition, and algorithmic thinking) used to understand problems, judge solutions, and modify problem-solving approaches for use in different situations (Acosta et al., 2024; Fadillah & Usmeldi, 2025; Wu et al., 2024). We posit that the emphasis on programming masks the component skills of CT and the ability to make one's reasoning about those skills explicit as a significant learning challenge. Producing the correct answer is not the only hurdle for students, particularly in introductory STEM classes. Students need to make their CT skills explicit, testable, and portable.

However, it is not easy to successfully support the development of CT in STEM education. The empirical research still identifies issues such as STEM problems being too complex and resulting in cognitive load, designing learning activities that are separated from real-world problems, and depending too much on programming tools that could distract from CT by focusing on programming syntax and tool usage (Fang et al., 2025; Romero et al., 2025; Yun & Crippen, 2025). Furthermore, STEM activities often involve multiple representations and mathematical reasoning, demand simultaneous conceptual and procedural knowledge, and require students to manage their problem-solving process (Asyhari et al., 2023; Fang et al., 2025). Such situations can lead to superficial engagement and may have low transfer to new situations.

The literature on instructional design offers several explanations for these potential barriers. Cognitive Load Theory (CLT) argues that intrinsic and extraneous loads should be reduced and germane load increased to promote schema construction (Sweller, 2020). More specifically, Collaborative Cognitive Load Theory (CCLT) claims that appropriate collaborative learning will share the cognitive load among learners and facilitate learning. On the contrary, inappropriate collaborative learning will generate coordination costs and unequal participation (Janssen & Kirschner, 2020). Additionally, empirical evidence from metacognitive regulation research has indicated that the metacognitive strategies, such as planning, monitoring, and evaluating cognitive processes, are beneficial for improving problem-solving skills and conceptual understanding when metacognitive activity is practiced and scaffolded in the collaborative learning context (Järvelä et al., 2021; Saadati et al., 2023).

However, a missing piece of the puzzle is a theoretically grounded, empirically validated, and mechanism-oriented learning trajectory that integrates CT with appropriate cognitive load, scripted collaborative learning, and metacognitive regulation in a STEM learning context. A large majority of the current CT programs are designed without load-oriented learning tasks, scripted scaffolds for group learning processes to overcome coordination failures, and metacognitive guidance to facilitate routine strategy selection and reflection. Hence, their effects on CT may not yield to the acquisition of long-term transferable reasoning.

This research helps fill the current void by examining the impact of NEXUS, a metacognitive–collaborative learning sequence that introduces and supports the use of CT in STEM classes. NEXUS makes CT accessible, tangible, and transferable by presenting it as analog (non-code-based) CT problems that use representational tools to manifest the step, conditional, and error-checking aspects of programming. The NEXUS sequence is administered in a flipped classroom setting that involves students' pre-class homework activities designed to leverage prior knowledge and pre-activity cognitive preparation, and in-class activities that involve teams of students engaged in structured collaborative activity (e.g., role-playing and peer explanation protocols) with built-in metacognitive questions to facilitate shared reasoning and regulation. The learning sequence concludes with a transfer activity in which students apply the CT problem-solving tools learned to a new or science-integrated problem.

Based on the design outlined above, the study investigates to what extent NEXUS fosters learners' CT performance and whether these benefits are accompanied by more favorable patterns of cognitive load and better metacognitive strategy use during problem-solving. Moreover, the study explores whether the mechanisms underlying the sequence work equally well for learners with varying degrees of readiness to collaborate, if learners' attributes may influence how the mechanisms of the interventions are used in group work. Combining quantitative and qualitative data on learners' perceptions and enactment, the present study should shed light not only on whether NEXUS is beneficial but also on the mechanisms that foster CT in STEM education.

THEORETICAL FRAMEWORK

The NEXUS instructional sequence is designed to strengthen computational thinking (CT) in STEM disciplines that addresses five interrelated design elements: (a) making CT transparent (providing learners with processes to transform instead of facts to remember), (b) creating solutions to control for the innate overtness of the task, (c) promoting shared, social learning experiences, (d) embedding metacognitive tools to support planning, monitoring, and evaluating, and (e) grounding symbolic representations with physical models. Instead of being disconnected add-ins, theories are used in NEXUS to provide mechanistic explanations for the design of tasks, the orchestration of roles, the incorporation of scaffolds, and the strategic development of generalizability across STEM disciplines.

CT can be described as a multilayered thinking process that includes abstraction, decomposition, pattern identification, generalization, and algorithmic problem-solving, as well as problem representation, procedure development, and effectiveness evaluation under certain conditions (Belmar, 2022; Voon et al., 2022). In the context of STEM, CT is used to achieve modeling, sequential programming, data structure, and systematic thinking (Wang et al., 2022). Thus, NEXUS focuses more on non-coding (analogical) activities, with greater emphasis on thinking methods such as sequence, conditional statements, decision-making, iteration, testing, and transferable CT skills rather than tool-specific skills (Chen et al., 2023).

Due to the inherent difficulty of many CT tasks, representational design plays a key role. According to the Cognitive Theory of Multimedia Learning (CTML), it is essential to select, organize, and integrate multimedia information in ways that acknowledge the constraints of working memory and avoid unnecessary processing (Mayer, 2024; Mayer & Moreno, 1998). In NEXUS, CTML serves as a design heuristic: tasks are broken down, and scaffolding in the form of visual-verbal signals (flow/step representations, rule prompts) is provided to decrease split attention and highlight decision points.

Finally, collaboration can enhance CT if it externalizes one's thought process, provides the opportunity to receive feedback from others, and facilitates collective error resolution. Drawing on collaborative learning frameworks (Adams & Hamm, 2019), NEXUS employs collaboration as a cognition-enhancing strategy rather than merely engagement in groupwork. Given that unrestricted collaboration can lead to coordination losses and effort differentials, NEXUS incorporates role-specific routines, norms of peer explanation, and collaborative materials to facilitate shared agency and maintain classroom discourse about computational thinking.

Students may carry out the steps of a solution without considering their correctness, relevance, or adherence to the problem's constraints. Students can plan, monitor, and evaluate their solutions to identify impasses, repair flawed reasoning, and verify their quality (Zimmerman, 1995). Co-regulation may occur in a collaborative setting where students negotiate the shared meaning of their mental models of a problem through questions and explanations (Ataş & Yıldırım, 2025; Clark et al., 2025; Lobczowski et al., 2021). In NEXUS, strategy evaluation is instantiated by asking, 'Why this rule?', 'What evidence?', 'Where could the logic go wrong?', throughout the solution, rather than being treated as a feature of NEXUS to be tacked on every so often.

Second, embodiment theory provides a further basis for CT's effectiveness. Given that the abstract behaviors of the logic are represented in physical space, performing the logic as an embodied action can help solidify the ideas for students and reduce the load on their working memory (Black et al., 2012; Zou et al., 2025). Similarly, in STEM subjects, the use of physical modeling can reduce the representational gap between abstract processes and concrete phenomena (Zeng et al., 2025). NEXUS students use sequencing cards, physical representations of flow, and personification to model the logic in the physical space and "execute" it. Students can thus easily check one another's answers and refine their arguments through successive refinement.

In total, these warrants merge into a mechanism-based chain—NEXUS (Navigate, Engage, Xcel, Understand, Step)—such that each stage is designed for cognitive preparation, construction of a shared mental model, collaborative problem-solving, metacognitive integration, and application. Tables 1 and 2 summarize the connections between theoretical warrants and design mechanisms and then between the design mechanisms and NEXUS stages and CT outcomes.

TABLE 1

Theoretical warrants as design requirements and mechanisms in NEXUS

Theoretical warrant	Design requirement	Target mechanism	Concrete implication in NEXUS
CT theory	Make CT processes explicit beyond coding	Clarifies abstraction/decomposition/algorithmic design	Stepwise representations (rules, sequences, decision points) require logical explanations
CTML / cognitive architecture	Keep tasks manageable under WM limits	Reduces extraneous processing; supports integration	Segmented tasks; visual-verbal supports; signaling; minimized split attention
Collaborative learning	Use interaction as a cognitive mechanism	Transactive reasoning; shared error detection	Role rotation, peer explanation routines, and shared artifacts focused on logic
Metacognitive regulation	Monitor the validity/efficiency of strategies	Increases plan–monitor–evaluate (self/co-regulation)	Embedded prompts; checkpoints; “why/what-if” questioning within task flow
Embodied cognition	Externalize abstract computation tangibly	Offloads WM; anchors abstract logic	Hands-on simulations; physical representations of steps and decision points

TABLE 2

NEXUS phases: goals, mechanisms, and expected CT outcomes

Phase	Primary goal	Dominant mechanism(s)	Typical enactment	Expected CT outcome
Navigate	Stabilize readiness	Load management; schema activation	Individual pre-task, signaling; rule rehearsal	Baseline CT readiness
Engage	Align representations	Collaborative sense-making	Co-construct flow/ step maps; peer explanation	Shared problem representation
Xcel	Distributed problem-solving	Role-structured cognition; co-regulation	Role rotation; joint execution + verification	Decomposition, algorithmic reasoning, testing
Understand	Consolidate + justify	Monitoring/evaluation; reflective abstraction	Error analysis; strategy comparison; synthesis	Stronger metacognitive control + explainability
Step	Promote transfer	Generalization; germane processing	Novel constraints/ context; justify adaptations	Flexible application across STEM contexts

Although there are theoretical reasons to believe that cognitive load–sensitive design, structured collaboration, metacognitive scaffolding, and concrete representations will be helpful, the literature has not yet provided much insight into whether they lead to reliable CT gains when used in combination as a scripted sequence of instructional activities in a STEM domain. Most studies to date have focused on some, but not all, of these aspects, and it is not clear whether they are associated with similar CT gains and/or concurrent positive effects on reported levels of cognitive load and the quality of metacognitive processing during problem solving. In addition, the effectiveness of collaborative approaches depends on participants' coordination and participation levels; accordingly, it is not known whether similar benefits are provided to students with differing collaborative abilities. To begin filling these voids, the current study will investigate the effectiveness of the NEXUS intervention. It will assess the effects on CT performance, cognitive load, and metacognitive regulation. It will be supported by a qualitative analysis that provides insights into participants' perceptions and behaviors regarding the targeted aspects.

Research Questions

RQ1. To what extent does NEXUS improve students' CT performance in a flipped STEM context, compared with conventional instruction?

RQ2. How does NEXUS shape cognitive load (intrinsic, extraneous, germane) and metacognitive regulation during collaborative problem-solving?

RQ3. Do NEXUS effects on CT performance differ as a function of students' initial collaborative readiness?

METHODOLOGY

Research design

This study employed a quasi-experimental pre-test/post-test control-group design with a nested qualitative design to assess the impact of the NEXUS metacognitive–collaborative instructional sequence on students' CT in a flipped STEM setting and to describe the enactment of the proposed mechanisms during problem-solving. We could not randomize at the individual level because class sections clustered the students, and individual randomization would interfere with their original class schedules and management. Instead, we randomly assigned class sections (clusters) to the experimental group (NEXUS) or the control group (direct instruction with guided practice). Although we could not establish baseline equivalence, we measured the CT pre-test scores and baseline readiness for collaboration and controlled for them in the analyses to strengthen the internal validity for causal claims under the practical constraints of a real classroom environment. This design is consistent with recent quasi-experimental intervention studies on CT in STEM education (e.g., Musaeus & Musaeus, 2024; Zhang et al., 2024). For the nested qualitative design, we used a post-intervention semi-structured focus group interview protocol to gather students' descriptions of their experiences of (a) embodied abstraction, (b) balance between cognitive and collaborative efforts, and (c) reflective transfer to enrich the interpretation of the quantitative results.

Setting and participants

A total of 145 STEM students who registered in an introductory STEM course at UIN Raden Intan Lampung, Indonesia, participated in this study. The purposive sampling technique was employed to capture the diversity of students' prior experiences with CT-related knowledge and their readiness for collaboration. Then, the section of classes was assigned to the experimental and control groups. We also collected demographic data (including age, sex, study program/major, and whether they had learned about CT-related concepts) from students to better understand the sample's characteristics and to test the homogeneity of the experimental and control groups before the treatment. Moreover, the readiness for collaboration was measured before the treatment and used as a covariate and/or conditioning variable for RQ3.

Instructional intervention

The two conditions were taught the same STEM content, posed the same problems, and were given the same amount of time to isolate the effect of the treatments. The treatments focused on a subset of computational thinking skills that are generalizable to STEM disciplines, including (1) algorithmic thinking and conditional rule use (in sorting and traffic examples), (2) constraint reasoning (in traffic and lab examples), and (3) planning and testing (in lab example). In all examples, students were asked to define choice points, explain their solutions, and test for errors.

Experimental condition: NEXUS instructional sequence

The treatment group received an intervention based on NEXUS (Navigate, Engage, Xcel, Understand, Step), a set of mechanism-driven lesson plans that combine (a) task representations designed to manage the level of cognitive load, (b) collaborative activity with scripted participant roles, and (c) designed metacognitive support. We implemented CT tasks in a non-programming environment that leveraged physical objects (e.g., numbered cards, flow diagrams, condition cards) to represent computational thinking and thereby reduce the required domain knowledge. Student participation was also encouraged by defining and rotating among student roles in collaborative groups (e.g., manager, skeptic, explainer, scribe) and providing a rubric to guide planning, monitoring, and reflection within their group work.

Control condition: direct instruction with guided practice

The control condition involved teacher-led presentations with practice using the same scenarios as the treatment group. Teachers taught through examples, and students practiced individually or in small groups. Social interactions were limited to unstructured interactions (e.g., chatting) during the practice activity, and the control condition did not include the three phases of NEXUS, the explicit role shifts, or metacognitive prompts embedded in the procedure.

Table 3 provides a structured comparison of instructional elements across conditions.

TABLE 3

Comparison of instructional design in the experimental and control conditions

Instructional aspect	Experimental: NEXUS instructional sequence	Control: Direct instruction with guided practice
Pre-class preparation	**Navigate**: brief analog preparatory tasks to activate prior knowledge and reduce extraneous processing	Reading/worked example review to activate prior knowledge
Initial engagement	**Engage**: teams co-construct problem representations using shared artifacts to externalize reasoning	Teacher-led representation + Q&A; learners receive representations largely completed
Core problem-solving	**Xcel**: structured collaboration with role rotation and shared checking routines to distribute cognitive work	Guided practice individually or in small groups; no formal roles or structured coordination routine
Reflection & consolidation	**Understand**: explicit metacognitive prompts (plan–monitor–evaluate) and peer feedback on strategy quality	Teacher-led summary discussion; optional/general reflection prompts
Transfer application	**Step**: transfer tasks requiring adaptation of CT strategies to new constraints/contexts	Practice tasks similar in surface structure; transfer prompts not systematically embedded

Instruments

We used four instruments to assess the target variables, including CT performance, cognitive load, metacognitive regulation, and collaboration attitude. The items for each instrument were adapted from existing instruments and then validated by at least 2 relevant content experts to ensure they were contextually relevant to our study. Table

4 lists the construct, subconstruct, item type, and validation. The instruments, item descriptions, scoring rubrics, and item-construct alignment are publicly accessible via OSF: https://osf.io/3ghk5.

Table 4

Summary of research instruments

Instrument	Construct measured	Source/ adaptation	Dimensions	Format & scoring	Notes on quality assurance
Computational Thinking Skills Test (CTS-T)	Computational thinking performance	Adapted from Yağcı (2019); Zakwandi et al. (2024)	Concepts, Practices, Perspectives	Mixed-format test (MC + short-answer)	α = 0.85; content validity via expert review.
Cognitive Load Questionnaire	Intrinsic, Extraneous, and Germane load	Adapted from Krieglstein et al. (2023	IL, EL, GL	9-point rating scale	Construct validity via factor analysis; α > 0.80.
Metacognitive Regulation Scale (MRS)	Metacognitive regulation	Adapted from Kirbulut et al. (2016)	Planning, Monitoring, Evaluation	9-point rating scale	α = 0.87; expert-reviewed for collaborative CT context.
Collaborative Skills Inventory (CSI)	Collaborative readiness	Adapted from Hinyard et al. (2019)	Communication, Coordination, Conflict Management	Baseline 5-point Likert scale	α = 0.83; validated in prior STEM studies.

Data collection procedure

The study ran for eight weeks. In Week 1, students completed the CTS-T pretest, baseline CSI, and demographics, followed by an orientation to the flipped workflow and task expectations. Weeks 2–6 comprised the intervention (NEXUS vs control). In Week 7, students completed the CTS-T post-test and, immediately after the learning tasks, the MRS and cognitive load questionnaire. In Week 8, semi-structured focus groups were conducted to capture students' experiences of the learning process and the mechanisms targeted by NEXUS (e.g., externalization of reasoning, role-based coordination, metacognitive monitoring). Table 5 provides the timeline overview.

TABLE 5

Data collection timeline and activities

Week	Activity	Instruments/data	Target group
1	Pretest & orientation	CTS-T (pre), CSI (baseline), demographics	Experimental & Control
2–6	Intervention	NEXUS vs control instruction using the same STEM scenarios	Experimental & Control
7	Posttest	CTS-T (post), MRS, Cognitive Load Questionnaire	Experimental & Control
8	Focus groups	Semi-structured interviews	Experimental & Control

Data analysis

Quantitative data analysis was performed using IBM SPSS Statistics 29, and thematic analysis was facilitated with NVivo 14. Data were checked for missingness, outliers, and violations of assumptions (normality, homogeneity) before the primary analysis, and when violations were detected, effect sizes and sensitivity analyses were emphasized for interpretation. For RQ1, to compare pre- and post-test CT scores between NEXUS and the control group, 2 (Group: NEXUS vs control) X 2 (Time: pre- vs post-CT scores) mixed ANOVA was conducted, and simple effects analysis was conducted as necessary. ANOVA effect sizes were interpreted based on partial eta-squared (ηp^2). For RQ2, as learners responded to cognitive load and metacognitive regulation items after completing the task, independent-samples t-tests were conducted to examine differences between the control and NEXUS groups. For both outcomes, Cohen's d was calculated with a 95% CI. For cognitive load, subscales (intrinsic, extrinsic, germane) were compared separately between groups. For metacognitive regulation, subscales (planning, monitoring, evaluation) were compared separately between groups. For RQ3, to examine whether collaborative readiness moderated CT pre- and post-test scores, a series of hierarchical multiple regression analyses was conducted. The dependent variable was CT post-test scores, and the independent variables were Group (0 = control, 1 = NEXUS), learners' mean-centered collaborative readiness, and the interaction between Group and readiness (i.e., Group X readiness). The covariate was CT pre-test scores (and possibly other covariates if needed). If the interaction was significant, conditional effects were further probed using simple slopes at ±1 SD and/or the Johnson–Neyman technique. Finally, thematic analysis (Creswell & Creswell, 2023) was employed to analyze focus group transcripts to explore how learners perceived and practiced the designed mechanisms (e.g., externalization of representations, role-based coordination, and metacognitive monitoring) during the task. Qualitative findings were expected to provide explanatory power for the quantitative results.

RESULTS

The results are organized according to the three research questions, comparing the effects of the NEXUS metacognitive–collaborative instructional sequence and the control condition (direct instruction with guided practice) on (a) computational thinking (CT) performance from pre-test to post-test, (b) post-intervention cognitive load and metacognitive regulation, and (c) the role of baseline collaborative readiness in shaping CT post-test performance. CT outcomes collected at two time points were evaluated using a Group X Time mixed ANOVA, while post-intervention outcomes (cognitive load and metacognitive regulation) were compared using between-group tests. For RQ3, hierarchical regression with an interaction term (Group X collaborative readiness) was conducted to test whether NEXUS effects differed by baseline collaborative readiness.

RQ1. To what extent does the NEXUS instructional sequence improve computational thinking performance?

Descriptive gains across CT dimensions

To summarize improvement transparently, Table 6 reports mean gain scores (post-test/pre-test) for each CT dimension (Concepts, Practices, Perspectives). Across all dimensions, the NEXUS group exhibited larger gains than the control group. The most substantial advantage appeared in CT–Practices, indicating that NEXUS particularly supported procedural and strategy-oriented aspects of CT (e.g., decomposition routines, iterative checking, and systematic execution of solution steps).

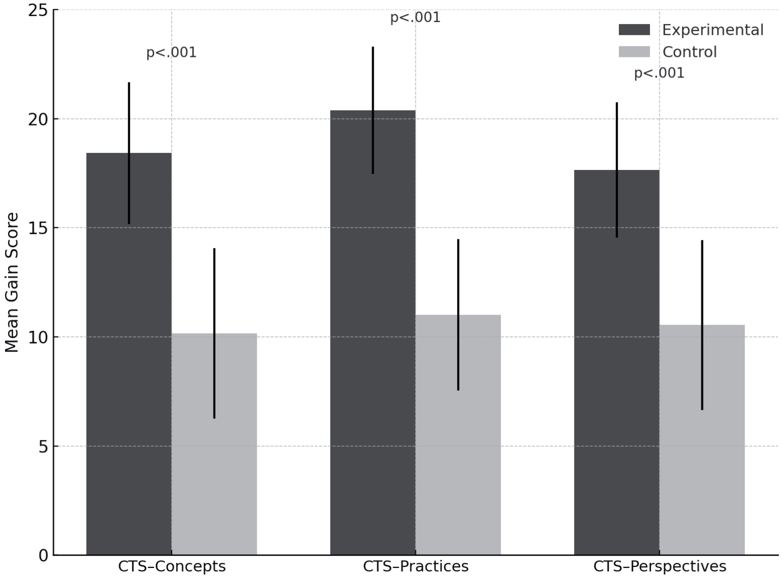
TABLE 6

Mean gain scores in CT dimensions (post/pre)

CT dimension	Group	Gain M	SD	TimeXGroup F(1, 143)	p	ηp²
CTS–Concepts	NEXUS	18.42	3.25	46.79	< .001	0.247
	Control	10.16	3.91			
CTS–Practices	NEXUS	20.38	2.91	66.42	< .001	0.317
	Control	11.02	3.47			
CTS–Perspectives	NEXUS	17.64	3.10	35.64	< .001	0.200
	Control	10.54	3.89			

Figure 1 visualizes these patterns, showing a consistent gain advantage for the NEXUS group, with the steepest improvement in CT Practices.

FIGURE 1

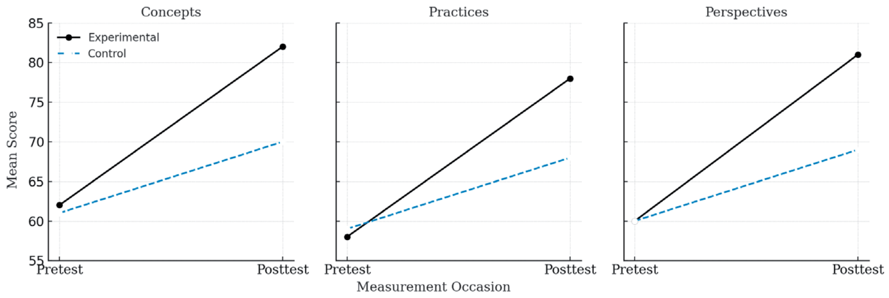


Gain scores in CTS dimensions

Mixed ANOVA: differential improvement over time

A mixed ANOVA indicated statistically significant Group X Time interaction effects across CT dimensions (p<.001), demonstrating that improvements from pre-test to post-test were contingent on instructional condition. In each CT dimension, the NEXUS group showed a markedly steeper increase than the control group. Figure 2 illustrates these interaction patterns, with the most pronounced divergence observed for CT–Practices, consistent with the NEXUS emphasis on (a) externalizing computational logic through shared representations, (b) role-structured collaboration, and (c) metacognitive monitoring and consolidation during problem-solving.

FIGURE 2



Interaction plots (pre-test/post-test)

RQ2. How does the NEXUS sequence influence cognitive load and metacognitive regulation during collaborative problem-solving?

Cognitive load profiles (post-intervention)

Post-intervention cognitive load component scores are presented in Table 7. Intrinsic load did not differ significantly between groups, suggesting that students in both conditions perceived comparable inherent task complexity. In contrast, the NEXUS group reported significantly lower extraneous load and significantly higher germane load than the control group. This pattern indicates that NEXUS reduced avoidable cognitive burdens (e.g., disorganized coordination, representational confusion, or unnecessary processing) while increasing productive cognitive investment aligned with deeper processing and schema construction.

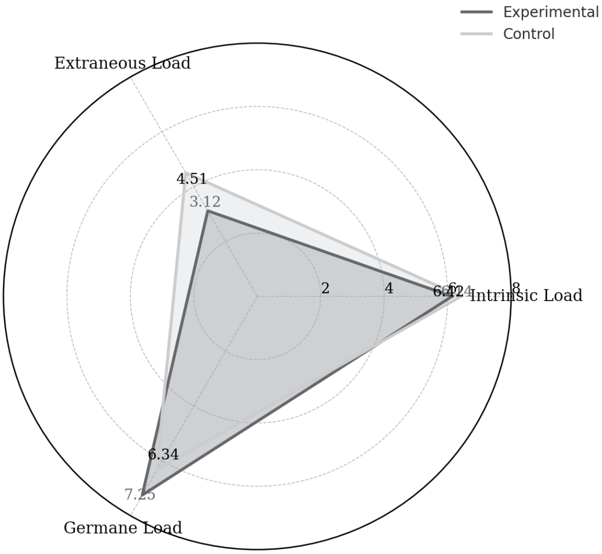
TABLE 7

Cognitive load means (post-test)

Load component	Group	Mean	SD	t(143)	p	Cohen's d [95% CI]
Intrinsic load	NEXUS	6.14	1.01	-1.25	.213	-0.21 [-0.54, 0.12]
	Control	6.42	1.14			
Extraneous load	NEXUS	3.12	0.89	-5.37	< .001	-0.90 [-1.24, -0.56]
	Control	4.51	1.07			
Germane load	NEXUS	7.25	0.82	4.89	< .001	0.82 [0.48, 1.16]
	Control	6.34	0.94			

Figure 3 reinforces these differences, showing reduced extraneous load alongside elevated germane load in the NEXUS condition.

FIGURE 3



Cognitive load profiles

Metacognitive regulation (post-intervention)

Metacognitive regulation component scores are summarized in Table 8. The NEXUS group scored significantly higher on planning, monitoring, and evaluation than the control group, indicating stronger self- and co-regulatory engagement during collaborative problem-solving. The largest between-group difference emerged in monitoring, suggesting that NEXUS learners engaged more consistently in checking, verifying, and adjusting their reasoning as they executed problem-solving steps—consistent with the sequence's embedded plan–monitor–evaluate prompts and structured debriefing routines.

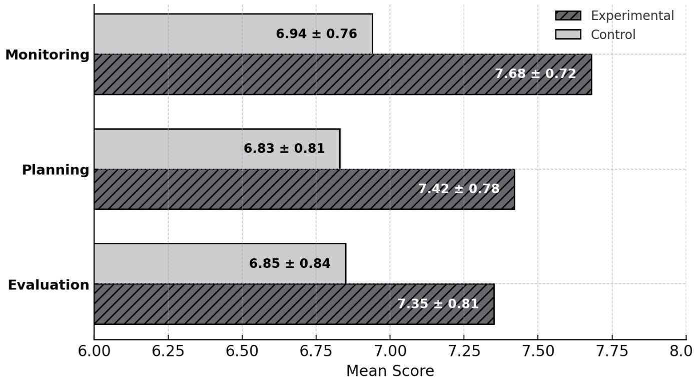
TABLE 8

Metacognitive regulation component scores (post-test)

Metacognitive component	Group	Mean	SD	t(143)	p	Cohen's d [95% CI]
Planning	NEXUS	7.42	0.78	4.21	< .001	0.70 [0.37, 1.04]
	Control	6.83	0.81			
Monitoring	NEXUS	7.68	0.72	5.02	< .001	0.84 [0.50, 1.18]
	Control	6.94	0.76			
Evaluation	NEXUS	7.35	0.81	3.89	< .001	0.65 [0.32, 0.98]
	Control	6.85	0.84			

Figure 4 visualizes these differences across components.

FIGURE 4



Metacognitive regulation scores

RQ3. Do the effects of NEXUS on CT post-test performance differ by baseline collaborative readiness?

Moderation analysis indicated that baseline collaborative readiness did not significantly moderate the effect of the NEXUS sequence on CT post-test performance (Group X CR, B=0.22, SE=0.17, β=0.04, p=0.198). The interaction accounted for a small, non-significant increase in variance ($\Delta R^2=0.004$; $\Delta F(1, 140)=1.67$, $p=0.198$). However, both collaborative readiness (p<0.001) and participation in the NEXUS condition (p<0.001) independently predicted higher CT post-test performance after controlling for CT pre-test.

Interpretation of RQ3

Moderation analysis indicated that collaborative readiness did not significantly moderate the effect of the NEXUS sequence on CT post-test performance (Group X CR, B=0.22, SE=0.17, β=0.04, p=0.198), and the interaction explained negligible incremental variance ($\Delta R^2=0.004$, $\Delta F(1, 140)=1.67$, $p=0.198$). However, both baseline collaborative readiness ($p<0.001$) and participation in the NEXUS condition ($p<0.001$) independently predicted higher CT post-test scores after controlling for CT pre-test.

TABLE 9

Moderation analysis predicting computational thinking posttest performance (hierarchical regression with interaction)

Predictors	**Model 1: Main effects**				**Model 2: + Interaction**			
	B	SE	β	p	B	SE	β	p
CT pretest	0.68	0.04	0.61	< .001	0.67	0.04	0.60	< .001
Collaborative readiness (CR)	1.05	0.18	0.19	< .001	1.02	0.18	0.18	< .001
Group (0 = Control, 1 = NEXUS)	8.90	0.62	0.36	< .001	8.85	0.63	0.36	< .001
Group X CR	—	—	—	—	0.22	0.17	0.04	.198
Constant	15.80	2.10	—	< .001	15.90	2.11	—	< .001

Model fit (corrected for N = 145)
Model 1: $R^2 = 0.640$, Adjusted $R^2 = 0.632$, $F(3, 141) = 83.56$, $p < .001$
Model 2: $R^2 = 0.644$, Adjusted $R^2 = 0.634$, $F(4, 140) = 63.38$, $p < .001$
ΔR^2 (Model 2 − Model 1) = 0.004; $\Delta F(1, 140) = 1.67$, $p = .198$
Optional 95% CI for Model 2 (B): CT pretest [0.591, 0.749]; CR [0.664, 1.376]; Group [7.604, 10.096]; GroupXCR [−0.116, 0.556]; Constant [11.728, 20.072].

DV=CT posttest (composite score); N=145
Group: 0=Control, 1=NEXUS; CR=collaborative readiness (mean-centered)
Note. Group dummy-coded (0=control, 1=NEXUS). CR mean-centered prior to computing the interaction term. CT pretest included as baseline covariate. B=unstandardized coefficient; B=standardized coefficient; p values two-tailed.

Qualitative findings: explanatory evidence for the observed patterns

Focus group interviews provided convergent evidence on how learners experienced and enacted the key mechanisms emphasized in the NEXUS sequence. Table 10 presents three themes: Embodied Abstraction, Cognitive–Collaborative Balance, and Reflective Transfer. Students described how tangible representations made computational processes visible and easier to reason about, how role-structured collaboration reduced overwhelm and strengthened peer checking, and how guided questioning supported adaptation of strategies across scenarios. These accounts converge with the quantitative results by explaining why the NEXUS condition was associated with lower extraneous load and higher germane load (Table 7) and stronger metacognitive monitoring (Table 8).

TABLE 10

Qualitative findings from focus group analysis

Theme	Elaborative Description	Subthemes	Contextual Evidence
Embodied Abstraction	Unplugged activities acted as tangible mediators for understanding abstract computational concepts. By manipulating physical objects, arranging role-based steps, and enacting algorithms in real space, learners bridged the gap between concrete experiences and abstract reasoning.	- Pattern Recognition - Algorithmic Thinking - Decomposition through Physical Simulation	*"When we arranged the cards in sequence to simulate the sorting process, I could 'see' the algorithm in action". (Participant E3)* *"Using physical objects helped me remember the sequence better than just writing it down". (Participant E6)* *"It felt like playing a game, but I realized later that we were actually practicing decomposition". (Participant E10)*
Cognitive–Collaborative Balance	Structured role rotation ensured equitable distribution of cognitive tasks, preventing overload for any single participant. Collaborative scaffolds (e.g., peer prompts, shared diagrams) enabled group members to validate one another's reasoning, thereby enhancing collective efficiency.	- Role Rotation for Load Management - Peer Validation and Cross-Checking - Shared Problem Representation	*"When I was the 'Verifier', I only focused on checking the group's reasoning, so I didn't feel overwhelmed".* (Participant E7) *"Switching roles made me understand the problem from different angles".* (Participant E2) *"Having someone double-check my work helped me catch mistakes before we finished".* (Participant E4)
Reflective Transfer	Guided metacognitive questioning during the "Understand" phase encouraged participants to connect strategies learned during activities with real-world STEM problem-solving consciously. This reflection promoted adaptability and transferability.	- Linking Past Tasks to New Scenarios - Metacognitive Questioning for Self-Correction - Strategy Adaptation in Novel Contexts	*"During the reflection, I realized the steps we used to solve the traffic flow problem could also work for planning lab experiments."* (Participant E5) *"It made me think about how to adjust strategies if the problem changes".* (Participant E1) *"The questions forced me to explain why we chose each step, and that helped me remember it better".* (Participant E9)

Integrated summary of findings

Across quantitative and qualitative strands, the results present a coherent pattern. First, NEXUS produced substantially greater gains in CT performance than the control condition, especially in practice-oriented CT operations (RQ1). Second, NEXUS was associated with a more favorable cognitive load profile, lower extraneous load and higher germane load, and stronger metacognitive regulation during collaborative problem-solving (RQ2). Third, while baseline collaborative readiness independently predicted CT post-test performance, it did not significantly moderate the effect of NEXUS, suggesting that the sequence's benefits were broadly observed across readiness levels (RQ3).

DISCUSSION

This work demonstrates that the NEXUS metacognitive–collaborative teaching sequence, when used in a flipped STEM classroom and complemented with non-coding CT tasks, brings about significant gains on the Concepts, Practices, and Perspectives aspects of computational thinking, similar to the average to high impact on general learning and low impact on transfer learning as reported in systematic reviews of CT and STEM projects. Interestingly, the largest learning gain was observed on the Practices aspect, which is understandable since most of the improvement in the Practices aspect of computational thinking requires continuous cycles of creating, testing, and refining representations, which are all enhanced with the structured collaborative problem-solving activity (Lee et al., 2024; Yin et al., 2024).

The second major finding of the study is that it provided some evidence for the view that NEXUS was also associated with a better cognitive load profile, in the sense that extraneous load was lower, and germane load was higher and intrinsic load was equivalent, compared to the control group. This is in line with the major claims of Cognitive Load Theory and Cognitive Theory of Multimedia Learning, which state that instructional designs should avoid unnecessary processing and should represent information in ways that harmonize with working memory so as to allow working-memory resources to be devoted to learning-relevant processing (Castro-Alonso et al., 2021; Skulmowski & Xu, 2022). Specifically, the tangible artifacts and coordinated small-group work of NEXUS might have removed some of the representational inconsistencies and coordination difficulties that are known sources of extraneous load in collaborative activities and might also have encouraged more learning-relevant processing that is characteristic of germane load. The pattern is also consistent with results in the STEM education literature indicating that certain types of scaffolding (such as the kinds of scripted reasoning supported tools in this study) lead to better CT outcomes as well as reduced cognitive load during complex tasks (Faulconer et al., 2023). The interview results provided further support for this explanation: students emphasized the idea that, because of role-switching and peer-checking, "it was much clearer what we had to do," and that, because of role-switching and peer-checking, "we didn't get stuck anymore".

The NEXUS condition also had significantly higher average metacognitive regulation scores, with the greatest contrast appearing for monitoring. This is in line with recent formulations of self- and co-regulated learning which identify monitoring as the central control mechanism in ill-defined problem solving where knowledge deficiencies can be identified, strategies shifted, and goals modified (Higgins et al., 2021; Sobocinski et al., 2024; Winne & Azevedo, 2022). The result is also in line with research indicating that metacognitive prompts built into intelligent learning environments facilitate gains in CT and associated cognitive outcomes, especially when the scaffolds are located at knowledge gaps and triggered during task execution (Tang et al., 2023; Wang et al., 2024; Wiest & Crawford-Ferre, 2023). In NEXUS, monitoring gains are plausibly explained by the plan–monitor–evaluate prompts and the structured debriefing routine, which made checking and justification a normative part of group work rather than an optional afterthought.

The qualitative themes, Embodied Abstraction, Cognitive–Collaborative Balance, and Reflective Transfer, provide explanatory depth for the quantitative results. Students' descriptions of manipulating physical artifacts to "see" algorithms reflect embodied cognition perspectives linking sensorimotor engagement with conceptual learning, especially when abstract processes are externalized into tangible representations (Zeng et al., 2025). In addition, reports of playful, hands-on engagement are consistent with evidence that analog CT learning can increase engagement and support metacognitive awareness, particularly when learners are guided to articulate their reasoning rather than merely complete procedures (Chen et al., 2023; Li et al., 2022). The "Reflective Transfer" theme further suggests that NEXUS helped learners build transportable strategy language (e.g., explaining why a step is chosen, when a rule fails, and how a strategy adapts), which is compatible with meta-analytic conclusions that CT–STEM interventions can support both near- and far-transfer, albeit with transfer effects typically smaller than immediate cognitive gains (Lee et al., 2024; Yin et al., 2024).

With respect to RQ3, for the between-subject variable, we found a significant main effect for collaborative readiness on post-CT, controlling for pre-CT, meaning that students who came into the course with more collaborative readiness profited in absolute terms from the course more than those with less readiness. We did not find a significant Group X collaborative readiness interaction, however, meaning that the CT advantage of the NEXUS group appears generally robust, not limited to students with high readiness. This boundary condition suggests that the NEXUS group appears to be a generally effective treatment. Meanwhile, collaborative readiness appears to be an additive resource for learners but not a reliable multiplier of the treatment effect for this sample.

Together, we believe that these findings support NEXUS as a connected set of mechanisms for STEM-focused CT instruction. The NEXUS curriculum integrates research on CT interventions, CL, metacognitive interventions, embodied learning and transfer, to form a connected sequence that can be taught with little to no computer-based tools. In situations with differential access to computers or if a teacher wants to emphasize CT procedures prior to teaching computer code, NEXUS provides a viable option that may reduce ECL and promote SM, while promoting gains in CT.

In summary, NEXUS tackles the three CT learning issues—cognitive overload, atomized thinking, and feeble metacognitive monitoring—via a multi-staged process that makes thinking transparent, fosters collaborative interactions, and incorporates regular review in a socially normative environment. The overall findings suggest that these design aspects not only produce better outcomes but also fundamentally alter the environment in which students engage in difficult, open-ended STEM problem solving.

Study limitations and perspectives

Even in the context of the current quasi-experimental design and mixed evidence approach, we acknowledge the following limitations: (a) although utilizing intact class-sections enhanced the ecological validity of the study, the possibility remains that uncontrolled class-section-level confounding variables impacted the post-intervention differences between the two groups, in spite of our control for pre-intervention scores and covariates; (b) the current study was conducted at one university site, which may not be generalizable to another university site or a different type of institution with a different curriculum, student demographics, and classroom culture; (c) the 8-week intervention does not lend itself to delayed post-intervention tests, and thus the maintenance and transfer of the NEXUS-facilitated gains in CT over time could not be assessed. In response to these limitations, further research could: (a) utilize a multi-site design, and if at all possible, employ a randomized controlled design; (b) employ a longitudinal design that would enable the assessment of the maintenance and far transfer of the NEXUS-facilitated gains in CT; (c) collect additional process measures (e.g., learning analytics, log data, real-time measures of collaboration) and other psycho-physiological measures (e.g., eye movement and EEG) to gain a better understanding of the changes in cognitive load and metacognitive awareness that take place during collaborative problem solving; (d) implement NEXUS in different STEM domains and at different educational levels to better understand its boundary conditions and practical implementation requirements.

CONCLUSION

The results of this study indicate that the NEXUS metacognitive–collaborative instructional sequence, applied in a flipped STEM setting with analog (non-programming) CT tasks, resulted in significantly higher learning gains for CT Concepts, Practices, and Perspectives compared to conventional instruction with guided practice (RQI), with the largest difference in CT Practices, as expected due to NEXUS's scripted, recursive problem-solving and checking scripts. NEXUS further generated a more positive learning-process pattern (RQ2), in terms of lower extraneous load, higher germane load, and more positive metacognitive regulation (particularly monitoring). By contrast, intrinsic load was similar, suggesting a more favorable ecology for productive reasoning under complexity. Concerning RQ3, students' initial level of collaborative readiness did not exert a significant influence on the effectiveness of the NEXUS condition with respect to CT post-test scores. However, initial readiness did predict CT post-test scores, whereas NEXUS remained a significant predictor of CT post-test after controlling for CT pre-test. Taken together, these results suggest that NEXUS may be a theoretically informed and practically feasible instructional sequence that externalizes computational logic with concrete artifacts, structures collaboration through scripted role-taking, and incorporates metacognitive supports into the activity structure in order to facilitate the mass-scale development of transferrable computational reasoning in STEM.

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