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# Task Design and Intervention Model for Integrating Computational Thinking into Primary Mathematics

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**Abstract**. The integration of computational thinking (CT) into mathematics education has attracted increasing attention; however, there is limited methodological clarity about how CT can be systematically embedded in primary mathematics instruction. In particular, empirical research linking CT to multi-step mathematical problem-solving remains scarce. This paper presents the design and implementation of a task-based intervention model developed within the DigiMaths4All project. The model incorporates CT into primary mathematics through a structured framework for task selection and design, combined with implementation in a technology-enhanced learning environment (ViLLE). Mathematical tasks focus on arithmetic fluency and multi-step problem solving, while CT tasks are tailored to operationalize key processes such as decomposition, abstraction, algorithmic thinking, and debugging. The intervention was carried out through a class-based randomized controlled trial in primary education, comparing traditional instruction with technology-supported approaches, including an integrated mathematics CT model. The study uses a mixed-methods approach, incorporating assessments and learning analytics data to examine implementation processes. The main contribution of this paper is methodological. It offers a replicable framework for (1) designing interventions that incorporate CT into mathematics, (2) selecting and constructing aligned task sets, and (3) implementing these tasks within an analytics-driven digital environment. The findings enhance understanding of how CT can be operationalized to support mathematical problem solving in primary education.

**Keywords**: computational thinking; mathematical problem solving; primary education; technology-enhanced learning; task design; learning analytics.

## 1. Introduction

In recent years, concerns about decreasing student achievement in mathematics have grown across many OECD countries (OECD, 2023). Despite ongoing curricular reforms and investments in STEM education, students' mathematical problem-solving skills, especially those involving multi-step reasoning and real-world applications, remain difficult

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to develop (Oliver, 2024; Rio & Protacio, 2025; Gradini et al., 2025). Early intervention in primary education is therefore essential to strengthen foundational skills such as logical reasoning, abstraction, and problem solving, which are vital for both academic success and participation in a digital society (Wing, 2006; Blyznyuk et al., 2025).

At the same time, Computational Thinking (CT) has become a crucial skill for the 21st century and is increasingly integrated into school curricula, including primary education (Aydeniz, 2018; Bilbao et al., 2024; Dagienė et al., 2024; Hsu et al., 2018; Kong, 2016). CT includes a set of cognitive skills, such as decomposition, abstraction, algorithmic thinking, and debugging, that are closely related to those needed for mathematical problem-solving (Lehmann, 2025; Wu & Yang, 2022; Kadijevich et al., 2023). This similarity suggests that adding CT to mathematics instruction could be a promising way to improve students' problem-solving skills. Although CT has been widely supported in education policy and research, its practical use in math classrooms remains underdeveloped.

Existing studies on CT in education mainly focus on programming activities or standalone CT instruction, often using small or exploratory designs (Ye et al., 2023; Sun et al., 2021; Sun & Zhou, 2023). Research systematically examining how CT can be integrated into mathematics learning, especially in primary education and in relation to complex problem-solving, is still limited. Additionally, there is a lack of clear methods for designing tasks that effectively combine mathematical content with CT processes, and for implementing this integration in real classroom settings using robust research methods.

To address these gaps, the DigiMaths4All (2026) project creates and tests an intervention model that integrates CT into primary mathematics through technology-enhanced learning. The project uses a digital learning environment (ViLLE) that offers interactive, gamified exercises and employs learning analytics to support adaptive learning and real-time feedback (Laakso et al., 2018). In this environment, both mathematical and CT tasks are carefully designed and implemented to help develop multi-step problem-solving skills.

This paper emphasizes the methodological contribution of the study. Specifically, it outlines: (1) the design of an intervention model that integrates CT into mathematics instruction, (2) a framework for selecting and designing mathematical and CT tasks, and (3) the implementation of these tasks within a digital learning environment based on learning analytics. By detailing these components, the study aims to offer a replicable method for incorporating CT into primary mathematics education.

To achieve this aim, the study addresses the following research questions:

**RQ1:** How can an intervention model be designed to integrate computational thinking into primary mathematics instruction?

**RQ2:** What principles guide the selection and design of mathematical and computational thinking tasks for supporting multi-step problem solving?

**RQ3:** How can these tasks be implemented effectively within a learning analytics-based digital environment to support classroom interventions?

## 2. Theoretical Background

### *2.1 Mathematical Problem Solving in Primary Education*

Mathematical problem-solving is an essential part of primary education because it enables students to apply their mathematical knowledge in real-world, often complex situations. More than just basic arithmetic, effective problem solving demands multiple thinking skills, such as understanding the problem, selecting appropriate strategies, and verifying solutions.

A particularly important and challenging category is multi-step problems, which include both word problems and symbolic equations (Mandal & Naskar, 2018). Word problems require students to interpret linguistic information, identify relevant quantities and relationships, and translate them into mathematical representations (Verschaffel et al., 2020; Vidlak, 2025). In contrast, symbolic equations demand manipulating abstract structures and understanding underlying mathematical relationships (Susac et al., 2014). Both forms require students to move flexibly between representations and to integrate conceptual and procedural knowledge.

The cognitive demands of multi-step problem solving are substantial. Students must engage in translation processes, converting verbal descriptions into mathematical expressions, in abstraction, focusing on essential information while disregarding irrelevant details. In addition, they must plan and sequence solution steps, monitor their progress, and revise their approach when errors occur (Peng et al., 2025; Xin, 2008). These processes are closely related to higher-order thinking skills and are often sources of difficulty for learners, particularly at the primary level (Gradini et al., 2025).

Given these challenges, there is a need for instructional approaches that explicitly support the development of the cognitive processes underlying problem solving. In particular, approaches that scaffold problem decomposition, structured reasoning, and reflective evaluation may improve students' ability to solve multi-step mathematical tasks effectively.

### *2.2 Computational Thinking as a Framework for Problem Solving*

Computational Thinking (CT) is an educational concept by Seymour Papert (1980), who developed the Logo programming language to support children's learning through exploration and construction. Papert's work emphasized the importance of learners building personal mental models to understand abstract concepts through computational means. The concept of CT was later popularized by Jeannette Wing in her article (2006), where she advocated for CT as a fundamental skill for everyone, not just computer scientists. Wing defined CT as solving problems, designing systems, and understanding human behaviour, by drawing on the concepts fundamental to computer science (Wing, 2006).

CT has been recognized as a fundamental competence for understanding and solving complex problems. It encompasses a set of cognitive processes, including decomposition, abstraction, algorithmic thinking, and debugging, which enable individuals to analyze problems and develop structured solutions (Shute et al., 2017; Denning & Tedre, 2019; Palts & Pedaste, 2020).

These processes closely align with the demands of mathematical problem solving. For example: a) decomposition supports breaking down complex problems into manageable parts; b) abstraction enables focusing on essential information and ignoring irrelevant details; c) algorithmic thinking supports planning solution steps; d) debugging relates to checking and correcting errors.

Despite this conceptual alignment, the integration of CT into mathematics education has often remained implicit or limited to programming-related activities. There is a lack of clear frameworks that operationalize CT within mathematical tasks, particularly in primary education. This creates a need for approaches that explicitly connect CT processes to mathematical problem-solving activities.

### *2.3 Technology-Enhanced Learning and Learning Analytics*

Technology-enhanced learning (TEL) has become increasingly common in mathematics education to boost student engagement, provide immediate feedback, and support personalized learning paths. Digital learning environments provide opportunities to go beyond traditional teaching by using interactive tasks, adaptive support, and ongoing monitoring of learning progress (Clark & Mayer, 2016; Kulik & Fletcher, 2016). In particular, gamification features such as points, levels, and instant feedback have been shown to improve students' motivation, engagement, and persistence in learning activities (Hamari et al., 2014; Rodrigues et al., 2021).

In mathematics education, TEL has shown positive effects, especially in helping students develop and practice basic skills. However, evidence regarding its impact on more complex abilities, such as multi-step problem-solving, remains mixed. While some studies report improvements in learning outcomes, others identify limited or inconsistent effects depending on instructional design, implementation quality, and the integration of pedagogical support (Peng et al., 2025; Rojo et al., 2024; Ye et al., 2023). These inconsistencies highlight the importance of not only adopting digital tools but also creating pedagogically grounded interventions that effectively use their capabilities.

A major advance in TEL is the integration of learning analytics, which allows the collection and analysis of detailed data on students' interactions with digital tasks. Learning analytics can offer insights into learners' progress, strategies, and challenges by tracking data such as response accuracy, time on task, and error patterns. These data can support adaptive learning, inform teaching decisions, and track the implementation of interventions in real time (Ferguson, 2012; Holmes et al., 2019; Matcha et al., 2019). Such approaches are increasingly important in personalized and data-informed mathematics education environments.

The ViLLE learning environment exemplifies this approach by combining interactive, gamified exercises with analytics-driven feedback and recommendations. In this setting, students receive immediate feedback on their performance, while teachers can review detailed data on learners' progress and engagement. This dual functionality supports personalized learning and data-informed teaching methods, making it especially useful for implementing complex interventions that incorporate multiple learning elements (Laakso et al., 2018).

Despite the potential of TEL and learning analytics, a significant limitation in current research is the lack of rigorous experimental designs. Many studies depend on small samples, short intervention periods, or lack control groups, which restricts the generalizability and validity of their findings (Cheung & Slavin, 2013; Räsänen et al., 2019). Specifically, there is a need for studies that systematically compare instructional approaches and examine how specific design elements, such as task structure or CT integration, affect learning outcomes.

To address this gap, the present study uses a class-based randomized controlled trial (RCT) design conducted in real classroom settings. This design enables the comparison of traditional teaching with technology-enhanced interventions, including those that incorporate CT, while accounting for contextual variables. By combining TEL, learning analytics, and rigorous experimental methods, the study seeks to offer a stronger understanding of how digital environments can help develop mathematical problem-solving skills.

### *2.4 Need for Integrated and Methodologically Grounded Approaches*

Although prior research has explored the integration of CT and TEL in mathematics education, several important limitations remain. A substantial proportion of existing studies rely on small-scale or exploratory designs, often conducted in controlled or non-authentic settings, which limits the generalizability of their findings. Moreover, many studies lack control groups or systematic comparisons between instructional approaches, making it difficult to draw robust conclusions about the effectiveness of CT integration in mathematics learning (Cheung & Slavin, 2013; Räsänen et al., 2019).

In addition to methodological limitations, there is a lack of clarity about how CT is used in mathematics education. Although CT is often described as a set of mental processes, few studies offer specific frameworks that turn these processes into real task designs aligned with mathematics content (Weintrop et al., 2016; Shute et al., 2017). As a result, CT is frequently applied either implicitly or through programming activities that are disconnected from the main mathematics learning goals, especially in primary education.

Furthermore, the integration of CT and mathematics has rarely been studied in real classroom environments that reflect the complexity of actual educational settings. Implementing these approaches in classrooms involves multiple interacting factors, including teacher practices, curriculum limitations, student diversity, and different levels of technological readiness. Without considering these contextual factors, it is hard to assess how well integrated methods work in practice or to ensure they can be scaled and transferred (Brown, 1992; Cobb et al., 2003).

Another key gap is the limited use of learning analytics to support and evaluate such interventions. Although digital environments increasingly allow for the collection of detailed data on student interactions, these data are often underused in designing adaptive learning experiences or in monitoring how well interventions are implemented. Incorporating learning analytics into intervention design can help better understand learning processes and provide evidence-based insights into how students engage with both mathematical and CT tasks (Siemens & Baker, 2012; Ferguson, 2012).

Taken together, these limitations highlight the need for integrated, methodologically sound approaches that combine theoretical consistency, systematic task design, and rigorous empirical validation. Specifically, there is a need for:

- Clearly defined intervention models that explicitly incorporate computational thinking into mathematics instruction, rather than treating CT as a separate or loosely connected component;
- Systematic frameworks for designing and selecting tasks that operationalize CT processes (e.g., decomposition, abstraction, algorithmic thinking, debugging) within mathematical content, especially in the context of multi-step problem solving;
- Implementation within digital environments based on learning analytics, which enable adaptive learning, real-time feedback, and detailed monitoring of student interactions;
- Robust research designs, such as randomized controlled trials conducted in authentic classroom settings, that allow for reliable evaluation of intervention effects while considering contextual variables.

Addressing these needs is crucial for advancing research and practice at the intersection of CT and mathematics education. Specifically, developing theoretically sound, methodologically rigorous, and practically feasible approaches can clarify how CT can be successfully integrated into primary mathematics to enhance complex problem-solving skills.

## 3. Design of the Intervention Model

Building on the theoretical link between CT and mathematical problem-solving, as well as the recognized need for integrated, methodologically sound approaches, this study develops a structured intervention model to incorporate CT into primary mathematics. The model aims to operationalize CT processes through deliberate task design and to implement these tasks within a learning analytics-based digital environment.

The intervention model has three connected parts: (1) a teaching approach that combines mathematics and CT, (2) a framework for designing and choosing tasks, and (3) implementation within a technology-supported learning environment enhanced by learning analytics. All these parts together offer a clear structure for designing, implementing, and assessing classroom interventions.

### *3.1 Pedagogical Framework*

The educational framework (Figure 1) is based on the idea that computational thinking can help develop mathematical problem-solving skills by organizing the mental processes involved in solving multi-step problems. Instead of viewing CT as a separate subject, the model incorporates CT processes directly into mathematics learning activities.

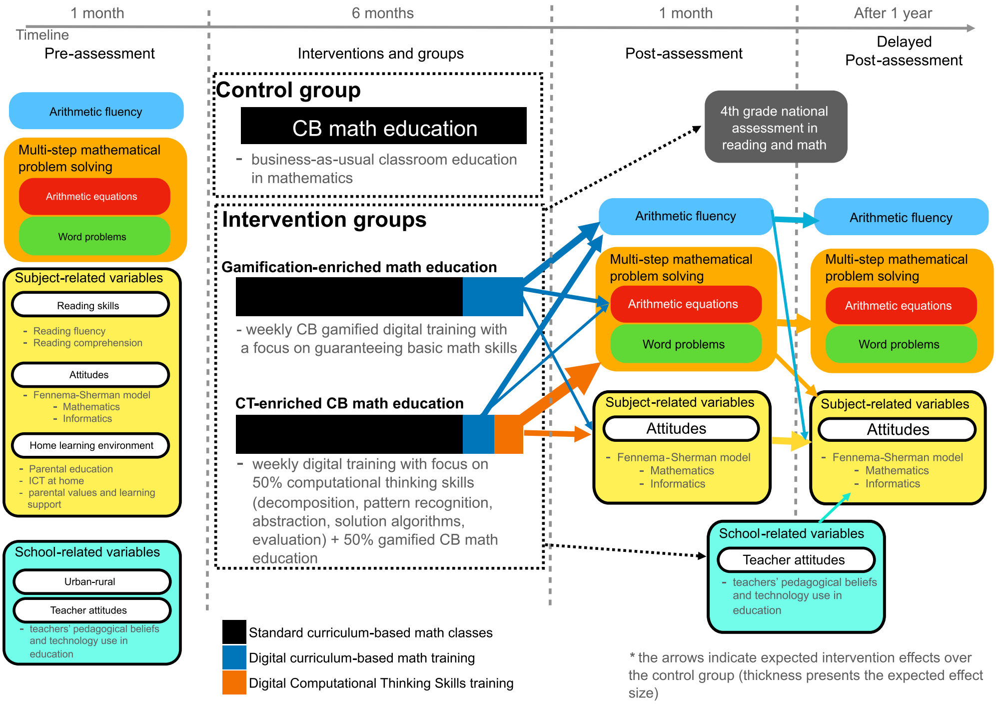


Figure 1. Research design.

The framework focuses on four core CT processes, namely decomposition, abstraction, algorithmic thinking, and debugging, and aligns them with corresponding mathematical problem-solving processes. In this way, CT serves as a cognitive scaffold that supports students in understanding problem structure, planning solution strategies, and evaluating outcomes.

To evaluate the effectiveness of this integration, the model is implemented with three instructional conditions:

- *Control condition:* Traditional mathematics instruction following the national curriculum, without digital tools or explicit CT integration;
- *Intervention condition 1* (mathematics-focused TEL): Use of gamified, curriculum-aligned mathematical tasks within a digital learning environment to support practice and engagement;

- *Intervention condition 2* (integrated mathematics and CT): Combination of mathematical tasks and CT tasks, where CT processes are explicitly involved alongside mathematical problem-solving.

This structure allows for systematic comparison between traditional instruction, technology-enhanced mathematics learning, and integrated mathematics-CT learning.

### *3.2 Task Design and Selection Framework*

A key part of the intervention model is the task design and selection framework, which makes sure that CT processes and mathematical problem-solving requirements are clearly aligned within learning activities. Instead of treating CT and mathematics as separate areas, the framework aims to integrate them through well-structured task types and sequencing.

Within this framework, three complementary task categories are distinguished. Mathematical tasks focus on developing arithmetic fluency and multi-step problem solving, including both word problems and symbolic equations that require translation between representations and sequential reasoning. Meanwhile, CT tasks are designed to operationalize key CT processes, such as decomposition, abstraction, algorithmic thinking, and debugging, by engaging learners in activities that involve identifying patterns, structuring procedures, and detecting and correcting errors. Finally, integrated tasks combine these two domains by embedding CT processes into mathematical problem-solving, either explicitly through prompts that guide students' reasoning or implicitly through task structures that require CT-like strategies.

The design of these tasks is guided by several interconnected principles. First, tasks align with curriculum objectives while going beyond procedural practice to highlight higher-order cognitive processes, including reasoning, representation, and reflection. Second, CT processes are not seen as abstract ideas but are clearly put into use within tasks, enabling learners to work with them in real problem-solving situations. Third, tasks are arranged in a progressive manner, with increasing complexity that gradually helps develop both mathematical understanding and CT skills. Lastly, the order of tasks is planned to complement each other, so that working on CT tasks supports and strengthens the cognitive skills needed for solving mathematical problems, especially in multi-step scenarios.

By structuring task design this way, the framework provides a systematic approach to integrate computational thinking into mathematics learning. It addresses a major gap in earlier research, where CT is often discussed as a concept but not implemented through specific teaching methods. In contrast, the proposed framework clearly shows how CT processes can be put into practice through task design, supporting their integration into primary mathematics education in a clear and meaningful way.

### *3.3 Technology-Enhanced Implementation and Integration Logic*

The intervention model is implemented within a learning analytics-based digital environment (ViLLE), which provides the infrastructure for delivering tasks, supporting adaptive learning, and collecting detailed data on student interactions. Technology-enhanced learning environments have been shown to support engagement, offer immediate feedback, and enable personalized learning pathways, especially when combined with gamification elements (Deterding et al., 2011; Rodrigues et al., 2021). In this study, gamification features, such as immediate feedback, scoring, and progression indicators, are used to boost students' motivation and sustained participation in learning activities.

Furthermore, the environment supports adaptive task delivery, enabling task difficulty and sequencing to be adjusted based on student performance. Such adaptive methods are viewed as essential for addressing individual differences and fostering effective learning in digital settings (Blyznyuk et al., 2025; Schwartz & Schmid, 2012). Simultaneously, learning analytics allow for the collection and analysis of detailed data, including response accuracy, time spent on tasks, and error patterns, offering insights into students' learning processes and strategies (Siemens & Baker, 2012; Ferguson, 2012).

These features support both learners and teachers. Students gain from immediate, personalized feedback and tailored learning paths, while teachers can use analytics to track progress, identify challenges, and make data-driven instructional decisions. Crucially, integrating learning analytics also enables monitoring of intervention fidelity, ensuring that the implementation matches the intended design and enabling a detailed review of how students engage with different types of tasks.

Within this environment, the integration of mathematical and CT tasks follows a structured implementation approach. In the integrated condition, learning sessions are designed to include both mathematical and CT tasks within the same instructional sequence. Mathematical tasks emphasize multi-step problem solving, while CT tasks target the underlying cognitive processes, such as decomposition, abstraction, algorithmic thinking, and debugging, that support these activities. This design aligns with calls to embed CT within subject areas rather than treating it as a separate discipline (Weintrop et al., 2016; Bocconi et al., 2022) and aims to promote transfer across domains by enabling students to apply CT processes directly within mathematical problem-solving.

The model is implemented in real classroom settings, with teachers actively choosing and incorporating tasks into their everyday instruction. This method improves ecological validity and aligns with recommendations for conducting research in real educational environments to better understand the complexity of classroom learning (Brown, 1992; Cobb et al., 2003). By combining a pedagogically grounded task design framework with a learning analytics-based digital platform, the intervention model offers a clear and scalable way to incorporate computational thinking into primary mathematics education.

## 4. Task Design and Selection Framework

The task design and selection framework is the main methodological contribution of this study. It offers a structured method for linking mathematical content with CT processes, making sure both are clearly represented and support each other within learning activities. Unlike approaches that treat CT as an extra element, this framework applies CT directly through task design and sequencing, with a particular focus on aiding multi-step mathematical problem solving in primary education.

### *4.1 Selection of Mathematical Tasks*

The selection of mathematical tasks is guided by the goal of supporting both foundational skills and higher-order problem-solving processes. Tasks are therefore designed to target two complementary areas: arithmetic fluency and multi-step problem solving, including both word problems and symbolic equations.

Arithmetic tasks (Figure 2) focus on developing accuracy and efficiency in basic operations, providing the procedural foundation necessary for more complex reasoning (Raza & Math, 2022). In contrast, multi-step problems require students to interpret problem situations, identify relationships between quantities, and execute sequences of operations (Wang & Lu, 2023).

Word problems (Figure 3) emphasize the translation of linguistic information into mathematical representations, while symbolic equations require reasoning within abstract structures (Duval, 2006). The inclusion of both formats supports flexibility in moving between representations, a key aspect of mathematical competence.

Task selection follows a progressive structure in which difficulty increases along several dimensions. These include the number of required solution steps, the complexity of relationships between quantities, and the linguistic demands of problem statements. In particular, word problems are designed to vary in language complexity, requiring students to extract relevant information, ignore distractors, and construct appropriate mathematical models.


Figure 2. Example of a mathematical task featuring arithmetic fluency.

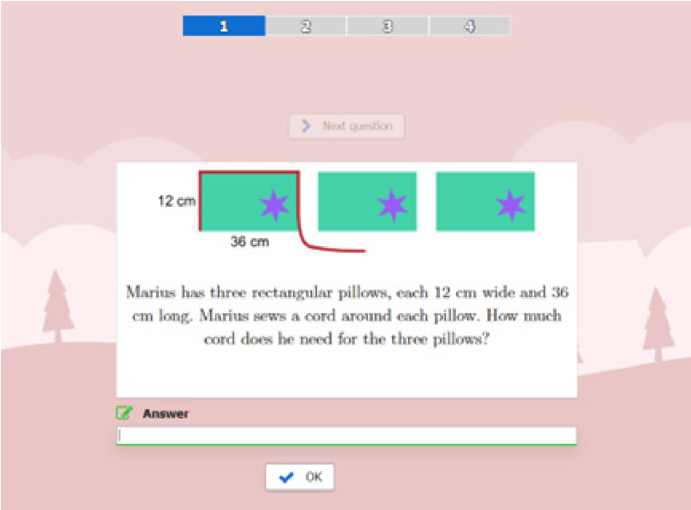


Figure 3. Example of a mathematical task featuring a multi-step word problem (translated into English).

All tasks align with the curriculum objectives for primary mathematics, ensuring relevance to classroom practice while extending beyond routine exercises. Emphasis is placed on tasks that require reasoning, representation, and structured problem solving, rather than isolated procedural execution. This approach enables the development of mathematical understanding that is both conceptually grounded and applicable to complex problem situations.

### 4.2 *Selection and Design of CT Tasks*

Computational thinking tasks (Figure 4) are designed to explicitly operationalize core CT processes: decomposition, pattern recognition, algorithmic thinking, and debugging, within accessible, domain-general contexts (Denning & Tedre, 2019; Lowe & Brophy, 2017; Duckworth & Fraillon, 2024). Instead of presenting CT as an abstract idea, these tasks involve students in tangible activities that simulate the mental processes required for structured problem-solving.

Each CT task type is designed to make specific processes visible and actionable. Decomposition tasks require students to break down complex situations into smaller, manageable parts, often by identifying subgoals or organizing steps logically. Pattern recognition tasks engage learners in identifying regularities, structures, or repeated relationships, supporting generalization and abstraction. Algorithmic thinking tasks involve creating or completing step-by-step procedures, encouraging students to think systematically about solutions. Finally, debugging tasks require students to detect, analyze, and correct errors in given solutions or procedures, fostering reflective thinking and evaluation.

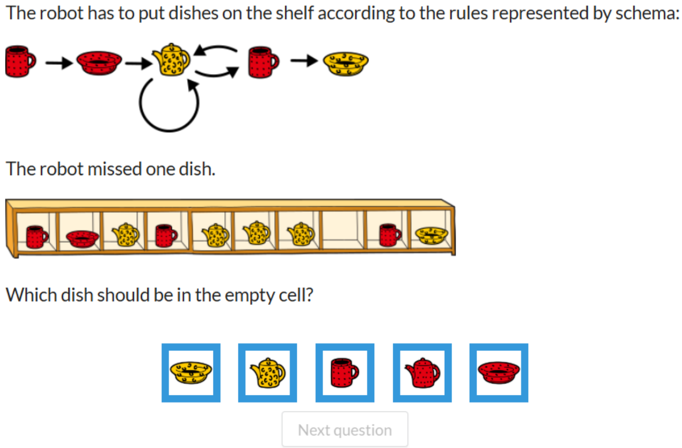


Figure 4. Example of a CT task featuring algorithmic thinking (translated into English).

Importantly, these tasks are not isolated exercises but are designed with transferability in mind. The structure of CT tasks reflects the cognitive demands of mathematical problem-solving, allowing students to practice processes directly relevant to multi-step problems. In this way, CT is implemented not as content to be learned separately, but as a set of processes activated through task engagement.

### *4.3 Integration of Mathematical and CT Tasks*

The integration of mathematics and CT tasks (Figure 5) is a key feature of the intervention model. In the integrated condition, learning activities are designed so that mathematics problem-solving and CT processes develop simultaneously and interactively. According to the intervention plan, instructional time is divided roughly equally between mathematics and CT tasks, enabling students to work on both areas within the same learning sequence.

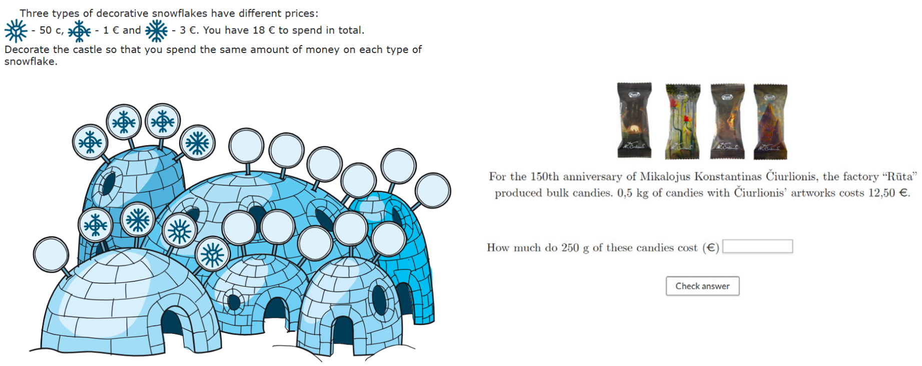


Figure 5. CT task featuring decomposition, followed by a multi-step word problem (translated into English).

The sequencing of tasks follows a deliberate pedagogical logic. CT tasks are designed to highlight and practice essential cognitive processes that are then used in later mathematical tasks. For example, engaging in decomposition tasks can help students organize multi-step word problems, while algorithmic thinking tasks can improve their ability to plan solution procedures. Similarly, debugging tasks prepare students to identify and correct errors in mathematical reasoning.

This design is based on a cognitive transfer hypothesis, which suggests that practicing CT processes in structured settings can support their use in solving mathematical problems. By aligning task structures across different areas, the model aims to promote transfer not just through explicit instruction but through repeated engagement with similar cognitive challenges. As a result, CT becomes integrated into mathematical activities rather than remaining a separate or disconnected skill set.

4.4. Task Implementation in the Learning Environment

All tasks are carried out within a learning analytics-based digital environment (Figure 6) that ensures consistent delivery, offers adaptive support, and collects detailed data. The environment includes gamification elements, such as immediate feedback, scoring, and progress indicators, to maintain engagement and motivate persistence in problem-solving.

The digital environment further enables the collection of detailed data on student interactions, including time spent on tasks, the number of attempts, and types of errors. These data offer insights into students' learning processes and support both research analysis and instructional decision-making. Additionally, they allow for monitoring how different types of tasks, mathematical, CT, and integrated, are engaged with in practice.

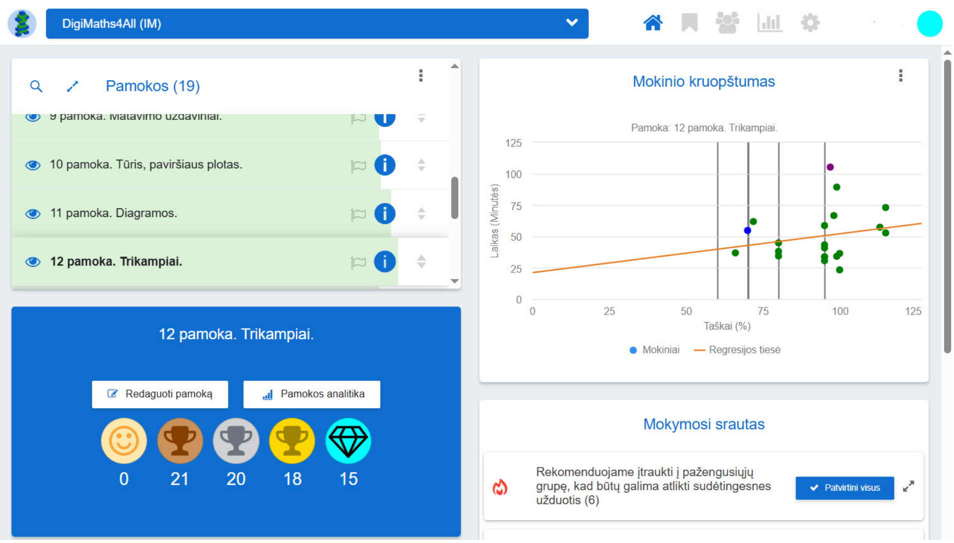


Figure 6. Teacher dashboard in the learning environment (screenshot from the original Lithuanian-language user interface).

A key feature of the implementation is adaptive feedback (Figure 7a and 7b), which gives students tailored information based on their responses. This includes not only correctness feedback but also guidance that encourages reflection and revision, especially in tasks that require multi-step reasoning. Task sequencing can also be modified dynamically, allowing learners to advance at an appropriate difficulty level.

**1 / 2**

Emma needs five necklaces, each with 10 glossy beads. She counts all the available beads, and unfortunately there are not enough. She still needs 5 beads.

How many beads does Emma have? [50]

[Check again]

Be careful.
Sketch a picture to figure out the problem.
In the sketch, o is a bead Emma has, and x is a missing bead.
5·10 beads are needed, and 5 are missing.
ooooo ooooo
ooooo ooooo
ooooo ooooo
ooooo ooooo
ooooo xxxxx
Count all the o:s. You can also write the math expression and solve it.
$5 \cdot 10 - 5 =$

Figure 7. A task (a) and its adaptive feedback (b).

Through this combination of structured task design and technology-enhanced implementation, the framework ensures that computational thinking and mathematical problem solving are not only conceptually aligned but also put into practice through observable learning activities.

## 5. Methodology

This study adopts a mixed-methods approach to examine both the implementation and the methodological characteristics of the proposed intervention model. The research design is intended to capture not only learning outcomes but also the processes through which students engage with mathematical and computational thinking (CT) tasks. By combining quantitative measures, qualitative insights, and learning analytics data, the study provides a comprehensive perspective on how the intervention operates in authentic classroom settings. Particular attention is given to ecological validity, scalability, and alignment with everyday teaching practices.

### *5.1 Research Design*

The study employs a class-based randomized controlled trial (RCT) design to evaluate the implementation of the proposed intervention model in real classroom contexts. RCT designs enable systematic comparison between instructional approaches while controlling for contextual variables that may influence learning outcomes. In educational research, such designs are considered essential for generating robust and generalizable evidence on intervention effectiveness (Cheung & Slavin, 2013; Rojo et al., 2024).

Three instructional conditions were established: (1) a control group receiving traditional mathematics instruction, (2) an intervention group engaging with technology-enhanced mathematical tasks, and (3) an integrated intervention group combining mathematical and CT activities.

This design allows for comparison between conventional teaching, digital mathematics learning, and the proposed integrated mathematics-CT approach.

### *5.2 Participants and Context*

The study was conducted in elementary education settings and involved approximately 2,500–3,500 students aged 10–11 years and over 150 teachers across 51 schools in the country. The participating classes were assigned to one of three instructional conditions at the class level to preserve ecological validity and prevent disruption of regular classroom organization.

Participating schools included both urban and rural schools, ensuring diverse student backgrounds and learning environments. This diversity enhances the external validity of the study and supports the applicability of findings across a range of educational settings.

### *5.3 Procedure*

The intervention followed a structured sequence that included pre-assessment, intervention, post-assessment, and delayed post-assessment phases.

Before the intervention, students completed baseline assessments that measured arithmetic fluency, multi-step problem-solving skills, and attitudes toward mathematics and learning. In addition, background information about the student and school characteristics was gathered.

The intervention was carried out over 16 instructional sessions, usually once a week during regular mathematics lessons. In the control group, students received standard curriculum-based instruction without digital tools. In the mathematics-focused intervention group, students worked on gamified mathematics tasks in a digital environment. In the integrated group, instructional time was split between mathematics and CT tasks, allowing students to work with both during the same learning session.

The intervention content aligned with the primary mathematics curriculum. Based on an analysis of the curriculum, the 16 sessions covered the following topics: (1) multiplication, (2) division, (3) problems involving multiplication and division, (4) area, (5) perimeter, (6) distance and speed, (7) fractions, (8) decimal numbers, (9) measurement tasks, (10) volume and surface area, (11) diagrams, (12) triangles, (13) comparison of numbers, (14) calculations with large numbers, (15) missing number problems, and (16) word problems involving equations and inequalities.

Following the intervention, students completed post-assessments that were structurally equivalent to the pre-assessments. A delayed post-assessment was conducted to examine the persistence of learning effects over time.

### *5.4 Measures*

Multiple measures were used to capture both learning outcomes and contextual variables:

- mathematics performance, including arithmetic fluency and multi-step problem solving (word problems and equations);
- processes related to CT, inferred through performance on CT tasks and interaction patterns;
- student attitudes, such as motivation and perceptions of mathematics and digital learning, and
- background variables, including prior achievement and demographic factors.

Additionally, learning analytics data from the digital environment were collected, including response accuracy, time on task, number of attempts, and error patterns. These data provide detailed insights into students' engagement and learning processes during the intervention.

### *5.5 Data Analysis*

Data analysis combines quantitative and qualitative methods to capture outcomes and the implementation process. Quantitative analyses use statistical techniques, including multilevel linear regression models, to evaluate the impact of instructional conditions on student performance while considering individual and contextual factors.

Group comparisons identify differences between instructional conditions, and additional analyses examine how baseline characteristics relate to learning outcomes. Learning analytics data supplement these analyses by offering process-level insights into how students engage with various tasks.

Qualitative data, such as teacher feedback and classroom observations, support the interpretation of quantitative results and examine how well the intervention is implemented in practice.

### *5.6 Ethical Considerations*

The study was conducted in accordance with established principles of educational research ethics. Participation was voluntary, and informed consent was obtained from all participating students and their guardians. Data were anonymized before analysis to protect confidentiality, and all procedures adhered to institutional and national guidelines for research involving minors.

## 6. Discussion

The aim of this study was not only to implement an intervention but also to develop a methodologically sound approach for incorporating CT into primary mathematics. Therefore, the discussion emphasizes the contribution of the proposed design, along with key insights and challenges encountered during its implementation in real classroom settings.

### *6.1 Methodological Contribution of the Design*

The main contribution of this study is the development of a clear intervention model that incorporates computational thinking into mathematics education through explicit task design and organized implementation. Unlike methods that treat CT as an extra or separate element, the proposed model integrates CT processes directly into mathematics learning activities. This is done by connecting core CT skills, such as decomposition, abstraction, algorithmic thinking, and debugging, to the cognitive demands of multi-step mathematics problem-solving.

A second key contribution is the task design and selection framework, which operationalizes CT within concrete learning activities. The framework goes beyond conceptual definitions of CT by specifying how these processes can be enacted through task structures, sequencing, and variation. By distinguishing between mathematical, CT, and integrated tasks, the framework provides a systematic approach to designing learning experiences in which CT supports mathematical reasoning. This addresses a significant gap in previous research, in which CT is typically discussed theoretically but not translated into explicit instructional design.

A third contribution is integrating the intervention into a learning analytics-based digital environment, which facilitates both implementation and detailed evaluation. Learning analytics not only collect outcome data but also examine learning processes, including how students engage with different task types. Additionally, analytics aid in monitoring implementation fidelity, which is vital in complex classroom-based interventions. Together, these components create a scalable, data-informed model for incorporating CT into mathematics education.

### *6.2 Implementation Insights and Challenges*

Implementing the intervention in real classroom settings provided valuable insights into both its potential and its challenges. A key factor was teacher variability. Although the model was designed to be structured, teachers actively selected and integrated tasks into their lessons. This flexibility increased ecological validity but also led to variation in how the intervention was implemented. Differences in teachers' familiarity with digital tools, confidence in using CT-related tasks, and instructional practices affected the extent to which the intended integration was achieved.

Another challenge involved balancing mathematical and CT tasks. Although the model aimed to divide instructional time evenly between the two in the integrated condition, achieving an effective balance was difficult in practice. If CT tasks were seen as unrelated to mathematical goals, they risked being viewed as extra rather than essential. On the other hand, excessive integration could make it harder to view CT processes as distinct cognitive tools. These issues show the importance of careful task sequencing and clear connections between different task types to ensure meaningful integration.

Despite these challenges, the implementation shows that integrating CT into mathematics is possible within standard classroom practices, as long as teachers receive enough support and the task design clearly connects the two areas.

### *6.3 Implications for Informatics Education*

The findings of this study have several implications for the field of informatics education. First, they support the view that CT can be integrated into subject areas beyond programming, especially mathematics. Instead of viewing CT as a separate discipline, the proposed approach shows how CT can serve as a mental framework that improves domain-specific learning.

Second, the study emphasizes the importance of short, structured tasks, like those inspired by Bebras-type activities, for developing CT skills. These tasks are particularly effective in primary education because they allow students to explore key computational concepts without needing extensive programming knowledge. When incorporated into a broader instructional plan, such tasks can help develop transferable problem-solving skills.

Lastly, integrating CT within a learning analytics-based environment highlights the potential of combining informatics and educational research methods. By connecting task design, digital implementation, and data analysis, the study advances a deeper understanding of how informatics concepts can be put into practice and assessed in educational settings.

## 7. Conclusion

This study set out to develop a methodologically grounded approach for integrating computational thinking (CT) into primary mathematics education. The findings demonstrate that such integration can be achieved through a coherent combination of intervention design, task structuring, and technology-enhanced implementation.

The main contribution of the study is to demonstrate how CT can be put into practice through task design and classroom implementation, rather than remaining at the conceptual level. By providing a structured, repeatable model, the study fills important gaps in previous research and lays a foundation for future work at the crossroads of mathematics and informatics education.

With respect to RQ1, the study shows that an effective intervention model can be designed by aligning CT processes, such as decomposition, abstraction, algorithmic thinking, and debugging, with the cognitive demands of mathematical problem solving. Rather than treating CT as a separate domain, the proposed model embeds these processes directly within mathematics instruction, supported by a structured pedagogical framework and implemented in authentic classroom settings.

Regarding RQ2, the study identifies key principles guiding the selection and design of tasks. Mathematical tasks and CT tasks can be systematically combined by ensuring curriculum alignment, progressive complexity, and explicit operationalization of CT processes within task structures. The introduction of distinct yet complementary task types, mathematical, CT, and integrated, provides a practical framework for designing learning activities that support multi-step problem solving. This approach moves beyond abstract definitions of CT by demonstrating how it can be enacted through concrete instructional design.

In relation to RQ3, the results indicate that effective implementation is supported by the use of a learning analytics-based digital environment, which enables adaptive task delivery, immediate feedback, and detailed monitoring of student interactions. Such environments not only support individualized learning but also provide valuable data to understand learning processes and ensure intervention fidelity. Importantly, integrating tasks into regular classroom practice with active teacher involvement ensures both feasibility and ecological validity.

Taken together, the study contributes a scalable and replicable intervention model that bridges computational thinking and mathematics education. Its reliance on structured task design, alignment between cognitive processes and subject content, and data-informed implementation supports its adaptability across different educational contexts. Furthermore, the design principles underlying the model, such as explicit integration of CT processes, progressive task complexity, and embedding within authentic classroom settings, are transferable and can inform future research and practice in both mathematics and informatics education.

In this way, the study advances the field by demonstrating how computational thinking can be operationalized in primary mathematics through methodologically robust, practically applicable approaches that move beyond conceptual discussion to concrete implementation.

Importantly, the model is designed to be scalable and adaptable to different educational contexts. Its reliance on structured tasks, digital environments, and data-informed implementation supports its potential for broader application. At the same time, the design principles underlying the model, such as explicit alignment between CT processes and mathematical reasoning, progressive task complexity, and integration within authentic classroom settings, are transferable beyond the specific context of this study.

In this way, the study contributes not only to integrating CT into mathematics education but also to developing methodologically solid and practically useful approaches in informatics education research.

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## Declarations

*Generative AI disclosure:* OpenAI's ChatGPT was used to improve manuscript clarity; it was not used for analysis, interpretation, or content generation. The author reviewed and verified all AIassisted edits and takes full responsibility for the content of the manuscript.

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