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"The Effects of Educational Robotics and Unplugged Coding on Preschoolers' Cognitive and Coding Skills: A Pilot Study"

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Introduction

Technology has been developing rapidly for the past twenty-five years. Today, most jobs and activities, including education, the healthcare system, and even communication, rely on technological devices. People start engaging with them from an early age onward. However, making the most efficient use of them is not straightforward. In particular, effective use of computing devices requires computer-like thinking on the part of the user. This issue gave rise to the concept of "computational thinking", which has become part of school curricula in the past couple of years. It drew the attention of scientists who would like to explore the benefits of computational thinking and how to teach it from an early age. Adequate tests have been designed to teach it and to explore its potential impacts on cognitive abilities. Numerous studies indicate that computational thinking training improves academic achievement (Oliveira et al., 2014) by supporting the development of problem-solving skills and thinking processes (Lockwood & Mooney, 2017).

Training computational thinking via coding activities is a method commonly used by many researchers (Polat & Yilmaz, 2022; Arfé et al., 2020; Kalelioğlu, 2015). Coding activities also appear to affect mental abilities, such as executive functions and visuo-spatial abilities (Brainin et al., 2022). Therefore, the impact of computational thinking training via coding activities on mental abilities has also become a popular research topic (Montuori et al., 2023; Bers, 2020). Although there are many studies on computational thinking training and its benefits, most focus on primary school children (Li et al., 2023; Özcan et al., 2021) rather than preschoolers (Montuori et al., 2023; Somuncu et al., 2022). A reason may be that they have tested complex cognitive abilities, such as problem solving (Arfé et al., 2019), and used different teaching methods for coding such as Robotic Education, Unplugged Coding, and Virtual Coding

(Choi et al., 2024; Brackmann et al., 2017; Weigend et al., 2019). Consequently, it remains unclear which teaching method is most beneficial for preschoolers.

The present thesis was a pilot investigation within a broader research project. The study implemented a computational thinking intervention in a preschool classroom, delivered through two instructional approaches (educational robotics and unplugged coding), to examine potential differences in coding learning outcomes. Moreover, the study aims to assess the effectiveness of these CT training programs across different cognitive abilities (i.e., inhibitory control and visuo-spatial abilities).

Chapter 1: Theoretical background

1.1 Computational thinking

Computational thinking has become a highly popular topic among researchers in recent years. Although numerous studies have addressed this concept (Hsu et al., 2018; Wing, 2011; Aranda et al., 2018), no single, definitive, and widely agreed-upon definition has been reached yet, as the understanding of computational thinking continues to evolve with ongoing research. To understand the concept of computational thinking, it is first necessary to examine the term *computation*, which is as old as computer science itself. Denning (2010) provides insight into the historical development of this concept. In the 1930s, the term computation referred to the mechanical steps to be followed in evaluating mathematical expressions, as described by early computer science pioneers and mathematicians (Post, 1936; Turing, 1936). Later, in the ACM Curriculum 1968 (Atchison et al.,1968), the first curriculum recommendation in computer science, computation was defined as information processes generated by algorithms. In the late 1980s, computation was described as a new way of doing science (Denning and Freeman, 2009). From this perspective, computation was no longer considered an activity performed solely by computers but rather a way of thinking. In the 1990s, natural scientists also started to adopt this approach and claimed that computation exists within the deep structures of natural phenomena (Denning, 2007). As a result of these conceptual shifts, computation came to be understood not only as an artificial process but also as a natural one.

Wing et al. (2011) describe computational thinking (CT) as a mental activity that involves formulating problems and their possible solutions to identify the most effective one. They argue that solving complex problems requires multiple forms of thinking, such as logical and systems thinking, which include algorithmic reasoning and overlap with computational thinking. These cognitive processes also engage other modes of thought, including pattern recognition and procedural thinking. Because solving complex problems typically involves multiple steps, computational thinking frequently overlaps with other types of thinking.

For example, design thinking emphasizes problem-solving by focusing on product specifications and requirements. Although computational thinking and design thinking share similarities, design thinking is often constrained by physical limitations (Razzouk & Shute, 2012). Another related concept is systems thinking, which refers to the investigation of the relationships among various elements within an environment (Shute, Masduki, & Donmez, 2012). While both systems thinking and computational thinking involve modeling systems to develop effective solutions, computational thinking places additional emphasis on understanding how a system operates as a whole to identify the most efficient solution.

Wing (2006) argued that computational thinking (CT) involves engagement with five different types of cognitive processes aimed at solving problems in the most efficient way: problem *reformulation*, defined as reframing a problem in a familiar and solvable form; *recursion*, which designates the iterative generation of a solution via incorporation of information acquired at earlier steps; *problem decomposition*, i.e. division of a complex problem into more manageable parts; *abstraction*, which focuses on identifying the essential aspects of a problem while ignoring irrelevant details; and *systematic testing*, which refers to the planning and execution of appropriate actions to derive a solution. Building on Wing's framework, Atmatzidou and Demetriadis (2016) proposed a descriptive model of computational thinking comprising five core facets. Their model retains abstraction and decomposition, reinterprets problem reformulation as a form of generalization, introduces algorithms as ordered instructions for executing solutions, and incorporates modularity, defined as the automation of problem-solving strategies. In addition, Shute et al. (2017) identified *debugging* as another important facet of computational thinking, referring to the identification and correction of errors when solutions fail to function as intended.

The term *computational thinking* (CT) and the proposal to introduce it to children from an early age onward were first advanced by Papert (1980), who emphasized the value of computer literacy in primary and secondary education for enabling children to solve complex problems in an algorithmic and efficient manner. Expanding this perspective, Wing (2006) argued that CT should be considered a fundamental analytical skill for all individuals—alongside reading, writing, and arithmetic—rather than a competence reserved exclusively for computer scientists. More recently, the importance of CT education in preschool settings has been highlighted by McCormick and Hall (2022), particularly for its potential to foster young children's understanding of cause-and-effect relationships and sequencing. Furthermore, the relevance of CT education extends beyond the growing role of technology in everyday life.

In their systematic literature review, Lockwood & Mooney (2017) expressed their opinion in favor of the benefits of CT training in the school context and referred to CT as part of the problem-solving and thinking process, the enhancement of which would be to the advantage of students in school and in many fields of life in general. Citing Oliveira et al. (2014) they highlight the potential benefits of CT training for primary school students' academic achievements. The aim of their study was to determine whether a quantitative correlation exists between students' "ability to compute" (i.e., their ability to think computationally) and their academic achievement. Toward this end, they developed a seven-question test, of which five were designed to measure students' ability to think abstractly and perform calculations using a version of the Turing Machine appropriate for primary schoolers. The last two questions aimed to assess the students' ability to read, to design and write, and to understand. Data gathered from 81 students showed a significant and positive correlation between the test scores and academic scores. In their literature review, Lockwood & Mooney (2017) summarize the conclusions on the integration of CT training into the school curricula as follows: (i) CT scores correlate strongly with academic scores, and (ii) CT training activities improve the students' analytical skills and provides an understanding of programming as something that potentially improves problem-solving skills, thus, (iii) CT training introduces also other improvements beyond coding skills alone.

1.2 The basic tool for CT training

Research on computational thinking (CT) in early childhood education typically distinguishes among four instructional methods: *unplugged coding activities*, *educational robotics* (plugged-in approaches), *mixed interventions* combining both formats, and *virtual coding activities*. Although these approaches differ in implementation, they share the goal of fostering algorithmic reasoning, sequencing, problem-solving, and executive function (EF) development.

1.2.1 CT training via Unplugged Coding

Unplugged coding activities are among the earliest and most widely used approaches to teaching computational thinking (CT) in early education. These activities do not rely on digital devices; instead, they involve physical interaction, object manipulation, role-play, or board games (Aranda et al., 2018). This type of setup was designed in the 1990s, when computers were available only in a limited number of schools. Furthermore, compared with their present-day counterparts, the available computers were much slower and therefore unsuitable for children's activities (Munasinghe et al., 2023). According to Caeli & Yadav (2020), learners need to understand the basic concepts and perception of coding to learn it, starting with an unplugged coding approach.

The survey by Weigend et al. suggests that unplugged coding activities can promote interdisciplinary learning and help children recognize connections across subject areas (Weigend et al., 2019). Game-based unplugged coding interventions are particularly common. For example, Apostolellis et al. (2014) developed *RaBit EscAPE*, a collaborative board game designed to cultivate CT skills such as sequencing, algorithmic reasoning, and problem-solving, where children are expected to construct a predefined path using magnetic pieces and evaluate alternative solutions collaboratively. Results of this study demonstrate that structured scaffolding supports cooperative problem-solving and increases motivation through collaborative engagement.

Similarly, Tsarava et al. (2017) implemented game-based unplugged coding activities grounded in embodied learning, which emphasizes physical interaction as a means of developing abstract reasoning. Using life-sized board games, children practiced strategic thinking and were introduced to CT concepts such as loops through repeated movement sequences. Although the intervention aimed to enhance both CT and numerical abilities, no significant improvement in numerical performance was observed. The authors suggest that understanding iterative concepts such as loops may require pre-existing numerical competencies, including counting.

In contrast, Brackmann et al. (2017) report significant improvements in CT skills following an unplugged coding intervention using diverse instructional materials. Although the unplugged coding approach yields good results for computational thinking in most studies, findings may differ when researchers examine specific abilities, suggesting it may not have a significant impact on all the abilities that schools require.

Overall, unplugged coding interventions appear effective in introducing foundational CT concepts in a developmentally appropriate and collaborative manner. Chen et al. (2023) concluded in their meta-analysis that unplugged pedagogy is a promising, cost-effective solution that makes CT training accessible and is a highly effective instructional strategy for promoting CT skills. However, evidence regarding their broader cognitive impact remains mixed, suggesting that their effectiveness may depend on the specific competencies assessed and the children's prior knowledge. This variability highlights the importance of examining not only whether unplugged coding approaches enhance CT but also which cognitive domains benefit most from such interventions.

1.2.2 CT training via Educational Robotics

With the widespread adoption of technological devices in education, studies on computational thinking (CT) have increasingly focused on plugged-in activities. These primarily include educational robotics (e.g. Bee-Bot) and digital coding platforms (e.g. Code.org). Unlike unplugged coding activities, plugged-in methods integrate programmable tools that allow children to directly interact with technological devices and receive immediate feedback.

Bee-Bot, a small programmable robot controlled through directional buttons (forward, backward, left, right), is widely used in early childhood settings. Hristova & Topalska (2025) proposed that robotic education tools are seen as a great way to learn abstract concepts through concrete action, which eventually leads to learning those concepts with a minimum cognitive load and by making mistakes that can be easily seen and corrected. Bee-Bot has been described as an educational toy that promotes pattern recognition and sequencing skills, making it particularly suitable for children in Piaget's preoperational stage (ages 2–7), where symbolic thought has already emerged but logical reasoning is still under development (Saxena et al., 2020).

Empirical evidence supports the instructional potential of robotics-based CT interventions. For example, Choi et al. (2024) implemented a seven-week Bee-Bot program using a pretest-posttest design. Children first completed a baseline CT assessment and a motivation questionnaire, then proceeded to progressively structured sequencing activities of increasing complexity. Their results indicate significant improvements in both sequencing skills and learning motivation, suggesting that robotics-based activities may enhance CT development, while simultaneously increasing engagement.

Beyond cognitive outcomes, robotics education has also been applied to interdisciplinary domains, including environmental education. Laut et al. (2014) and Phamduy et al. (2015) demonstrated how interactive robotic exhibits—such as a remotely controlled robotic fish presented at informal science events—can attract children's attention and evoke interest in environmental issues. Although these projects did not directly assess CT development, findings demonstrate that interactive robotics significantly increases children's motivation to engage with complex topics, such as marine pollution and climate change.

Similarly, Kanaki et al. (2025) combined Bee-Bot activities with environmental education on water conservation in a sample of first-grade students. The intervention first introduced sequencing practice and later integrated algorithmic thinking into lessons about the water cycle and water preservation. Students demonstrated high motivation, collaborative engagement, and evidence of debugging through trial-and-error strategies. While the study primarily relied on qualitative measures, the findings suggest that robotics-based CT instruction may support both algorithmic reasoning and broader interdisciplinary learning.

1.2.3 CT Training via Virtual Coding

Another widely used plugged-in tool for teaching coding is a platform offered by Code.org, a non-profit organization that provides free computer science and artificial intelligence curricula for children aged five and above. The platform uses block-based, drag-and-drop programming activities embedded in game-like environments, allowing children to practice sequencing, debugging, and problem-solving through structured levels of increasing complexity.

Research findings regarding the cognitive and motivational impact of engagement with Code.org are mixed. Kalelioğlu (2015) examined the effects of a five-week Code.org engagement on fourth-grade pupils' reflective problem-solving skills. Although no significant improvements were observed in reflective thinking scores, pupils developed more positive attitudes and greater motivation toward learning coding. Arfé et al. (2020) suggested that the absence of cognitive effects in this study may have been due to the complexity and sensitivity of the assessment instrument rather than to the intervention itself.

In contrast, Arfé et al. (2020) conducted a pretest–posttest study with younger children (ages 5–6) to examine the impact of short-term Code.org practice on executive functions (EFs), specifically planning and inhibition. Using standardized EF measures, they found significant improvements in planning skills and overall coding performance following the intervention. However, inhibitory control, as measured by the Stroop task, led to a slight decrease in accuracy rather than an improvement. The researchers suggest that the specific design of the coding activities—requiring children to switch between sequencing, debugging, and other CT components—prevents them from automating the problem-solving procedure and encourages them to think and search for new solutions across different kinds of tasks. These findings indicate that digital coding platforms may support certain executive processes, particularly planning, but their effects on inhibition appear less consistent.

1.2.4 Comparative research

Comparative studies examining unplugged coding and plugged-in approaches further highlight the difficulty of determining the most effective method among these approaches. Polat & Yılmaz (2022) compared the impact of unplugged coding and plugged-in activities on 6th graders and found that both groups exhibit very similar and significant CT skill development. However, the students in the unplugged coding group scored higher on basic programming. Similarly, Wohl et al. (2015) compared unplugged coding, tangible (robotics-based) computing, and screen-based computing activities among children aged 5–7 years. While unplugged coding activities generated the strongest conceptual understanding of algorithmic thinking and debugging, tangible computing was found to be the most engaging and to support error correction through physical interaction. Screen-based computing was perceived as more challenging, but also curiosity-stimulating. These findings suggest that different methods may target distinct aspects of learning, such as conceptual understanding, engagement, or persistence.

Lin et al. (2024) extended this line of research by examining the role of cooperative learning in unplugged coding and robotics-based activities. Their findings indicate that cooperative structures enhance engagement and learning outcomes, particularly when children can manipulate tangible tools. Importantly, the quality of collaboration was strongly influenced by teacher guidance, underscoring the role of instructional scaffolding in maximizing the effectiveness of CT interventions.

Overall, research in the literature suggests that digital platforms such as Code.org can enhance planning skills and motivation, although evidence regarding inhibition and broader cognitive transfer remains inconsistent. Comparative studies indicate that unplugged coding, tangible computing, and screen-based methods each offer distinct advantages: unplugged coding approaches may strengthen conceptual understanding, educational robotics may increase engagement and debugging skills, and screen-based methods may stimulate curiosity and exposure to more complex tasks. However, few studies directly compare these approaches within the same developmental stage using standardized executive function measures. Consequently, it remains unclear which method is most effective for promoting CT and executive development, particularly in early childhood.

1.3 The relationship between CT and various cognitive abilities

CT activities also support the development of broader cognitive abilities, including executive functions, which are critical for children's adaptation to school and, more broadly, to life (Masten et al., 2012). This connection is especially significant given that executive functions undergo rapid development between the ages of 3 and 5 (Gopnik & Rosati, 2001; Kloo & Perner, 2005). During this period, improvements in executive functioning help children organize their behavior and thoughts across different contexts, reduce reactivity to external stimuli, and regulate emotions and behavior (Garon et al., 2008). These capacities are also foundational for later academic achievement and development of self-regulation skills (Peng & Kievit, 2020). Arfé et al. (2019) investigated whether training computational thinking (CT) skills through Code.org could enhance executive functions, particularly planning and inhibition, in early elementary school children. In Study 1, 76 first-grade students completed a pretest–posttest design using standardized measures of planning (Elithorn Maze Test; Tower of London) and inhibition (NEPSY-II; Numerical Stroop). The experimental group received coding training and showed significantly greater improvements in planning and inhibition than the control group. Study 2 replicated these findings in a longitudinal sample of 19 students followed from first to second grade and compared with a matched control group. After one month of coding intervention, the experimental group demonstrated higher coding performance and planning accuracy, along with increased planning time, indicating improved strategic control. Overall, the results suggest that coding training can enhance executive functions beyond typical cognitive development associated with regular schooling.

Pellas (2025) synthesized findings by various researchers, including Bers (2020), about the effectiveness of tangible programming tools, such as robotic education or unplugged coding activities, on enhancing CT skills, and eventually, the skills in early childhood that could be enhanced via those activities. Overall results support that tangible programming tools help learners to visualize the steps and understand logic flow by manipulating physical objects. For example, placing physical obstacles on the trajectory of the robot during a robotic education activity promotes the learner's problem solving and logical thinking performance. Placing obstacles also enhances spatial reasoning skills, which include the mental manipulation of objects and understanding of spatial relationships, as well as the executive function skills. It is proposed that learners are engaged in hands-on problem solving by physically arranging and rearranging the objects, and training their planning skills, all of which are core components of executive functions. Physically arranging and rearranging programming elements requires sustained attention and strategic planning, directly engaging core components of executive functioning. Thus, the findings summarized by Pellas (2025) align with the broader literature on executive functions by illustrating how structured, tangible learning environments can simultaneously foster computational thinking and strengthen foundational cognitive processes in early childhood.

1.3.1 CT training at preschool level

Although numerous studies have examined unplugged coding, plugged-in, and mixed computational thinking (CT) interventions, most have focused on primary school children rather than preschoolers (e.g., Li et al., 2023; Thompson & Childers, 2021). Research specifically targeting preschool populations remains comparatively limited, despite the rapid development of executive functions (EFs) during this stage. One of the few studies addressing this gap is the one by Montuori et al. (2023), who investigated the effects of mixed interventions of educational robotics (ER) and unplugged coding on five-year-old preschoolers' CT and EF skills. Using a pretest–posttest design with a waiting-list control group, they assessed coding performance, planning (Tower of London), inhibition (NEPSY-II), and visuospatial abilities. Results indicate that children who receive the intervention between T1 and T2 show significant improvements in visuospatial skills. However, it remains unclear whether these gains resulted specifically from the mixed nature of the intervention or whether a single instructional method was primarily responsible for the observed improvement.

Similarly, Somuncu et al. (2022) investigated whether coding activities could enhance the mathematical reasoning skills of preschool-aged children. The study included 29 children from a public kindergarten who were randomly assigned to experimental and control groups. Pretest results revealed no significant difference between the groups; however, posttest results showed that children in the experimental group demonstrated significantly greater improvements in mathematical reasoning skills than those in the control group.

The broader evidence base has been synthesized in a recent meta-analysis by Montuori et al. (2024), who examined CT interventions across ages 4 to 16. The analysis investigated which EF components were most affected by CT instruction, whether effects varied by age, and which instructional methods were most effective. Although preschool-focused studies are relatively few, those included in the investigation generally suggest positive effects of robotics-based interventions on problem-solving and planning-related skills. For example, Çakır et al. (2021) report significant improvements in problem-solving and creative thinking among five-year-olds following a four-week robotics program. Likewise, Nam et al. (2019) found that kindergarteners receiving robotics-based sequencing instruction demonstrate higher sequencing and mathematical problem-solving performance than peers engaged in traditional activities. These findings collectively suggest that robotics interventions may support planning-related processes and structured reasoning in early childhood. However, the predominance of short-term pretest-posttest designs limits conclusions about long-term developmental impact.

1.3.2 CT Training at the primary school level

Evidence at the primary school level is more extensive and methodologically diverse. For example, Özcan et al. (2021) compared three 10-week programs—coding, mathematics, and reading—in a sample of fourth-grade students. While fluid intelligence improved across all groups, only the coding group showed significant gains in computational thinking. No improvements were observed in spatial orientation. These findings suggest evidence of near transfer (improvements in skills directly related to the trained domain) but limited support for far transfer to broader cognitive abilities.

Taken together, research across preschool and primary school populations indicates that CT interventions—particularly robotics-based and structured coding programs—can enhance computational thinking and certain executive processes, especially planning and sequencing. However, several limitations persist. First, preschool studies remain underrepresented relative to primary-level research. Second, many studies rely on short-term interventions without longitudinal follow-up. Third, evidence for far transfer to broader cognitive domains (e.g. fluid intelligence or spatial reasoning) remains inconsistent. These gaps highlight the need for systematic research to determine which CT training method (educational robotics, unplugged coding activities, or a combination of both) yields the greatest improvements in executive functions and visuo-spatial abilities.

1.4 Different CT-related cognitive abilities

1.4.1 Executive Functions

Executive functions (EFs) are essential for effective functioning in both everyday life and educational contexts. They can be described as a set of higher-order neurocognitive processes supported by distributed neural networks, particularly involving the prefrontal cortex, which continues to mature into early adulthood. Core components of EFs include goal-directed problem-solving, cognitive shifting, working memory use, and inhibitory control (Carlson et al., 2013). In daily life, these processes enable reasoning, planning, and adaptive behavior (Blair, 2017).

The structure and development of EFs have been extensively investigated, particularly regarding whether they constitute a unitary construct or a set of separable but related components (Miyake et al., 2000; Miyake et al., 2012; Doebel, 2020). Early research suggested that EFs demonstrate both unity and diversity (Tauber et al., 1972). Subsequent studies asserted that executive functions comprise distinct but interrelated components that share common underlying mechanisms (Miyake et al., 2000; Miyake et al., 2012). Blair (2017) further argues that EFs are supported by interconnected neural regions, including the prefrontal cortex, cingulate cortex, parietal cortex, and subcortical structures, which function as an integrated network to support complex problem solving.

Diamond (2013) defines the EFs as a set of top-down mental processes required in order to concentrate on a task, make decisions, and maintain attention. He refers to three core functions, namely *cognitive flexibility*, *inhibition*, and *working memory*, which construct higher-order EFs: reasoning, problem-solving, and planning.

Inhibition consists of several components. *Self-control* (response inhibition) is the component that enables restraint of impulsive behaviors, as well as delayed gratification, which is strongly related to the ability to resist impulsivity and temptation (Mischel et al., 1970). *Interference control* can be further divided into two categories: *Selective/focused attention*, which is the ability to maintain focus on the chosen stimuli while suppressing the disruptive external or internal stimuli, and *Cognitive inhibition*, which refers to the ability to suppress unwanted thoughts or memories (therefore, also called “intentional forgetting”) and often supports the working memory. Diamond also notes that inhibition improves during the developmental course. For younger children, it is harder not to respond to every stimulus, while it becomes easier during adolescence.

Working memory (WM) is the capacity to hold information in mind and manipulate it to guide behavior. It is essential for tasks such as mental arithmetic, reasoning, and evaluating alternative solutions. Reasoning requires a strong WM to understand connections between seemingly unrelated things and to disassemble and recombine the elements in new ways. WM differs from short-term memory: while short-term memory involves the temporary storage of information, WM entails both storage and active manipulation. Working memory and inhibitory control frequently operate together. WM maintains task goals and relevant information, guiding appropriate behavioral responses, while inhibitory control suppresses irrelevant thoughts and impulses, thereby protecting WM's limited capacity and ensuring efficient task execution.

Cognitive flexibility, also referred to as shifting or mental flexibility, represents the third core executive function. It involves the ability to adjust perspectives or strategies in response to changing demands. This may include the ability to change perspectives spatially (e.g. imagining how an object appears from a different angle) or interpersonal perspective-taking, which relates to metacognitive awareness. Successful shifting typically requires inhibition of a prior perspective and activation of the working memory to implement a new one. Thus, cognitive flexibility builds upon inhibitory control and working memory. It enables task switching, adaptation to new circumstances, and creative recombination of information. Developmentally, cognitive flexibility tends to mature later than inhibitory control and working memory (Davidson et al., 2006).

These three core functions are related to very important mental abilities. Fluid intelligence, which is defined by Ferrer et al. (2009) as a set of abilities, includes simultaneous activation of problem solving, pattern recognition, reasoning, and recognizing the relationship among items. It is considered completely synonymous to the higher-order EFs. Another very important mental ability is self-regulation. This ability maintains the optimal cognitive arousal, as well as emotional and motivational level to execute a task (Liew, 2012). It overlaps with the inhibitory control. Overall, executive functions constitute a multidimensional yet integrated system of cognitive processes that support goal-directed behavior, adaptive functioning, and complex reasoning throughout the developmental process.

Building on the conceptual framework outlined above, empirical investigations have attempted to elucidate the structure of executive functions and how they contribute to complex cognition. A seminal study by Miyake et al. (2000) aimed to develop a theory about the organization of the EFs and their roles in complex cognition. The researchers focused on three executive functions frequently identified in the literature: (i) mental shifting, (ii) updating and monitoring of information in working memory, and (iii) inhibition of prepotent responses.

In doing so, they addressed methodological limitations associated with traditional factor-analytic approaches (Rabbitt, 1997), particularly the “task impurity problem” (Baggetta et al., 2016). This problem refers to the fact that performance on any single executive task reflects not only executive processes but also the variance that can be attributed to non-executive components, such as language comprehension or visuospatial abilities. To more accurately capture individual differences in executive functioning, researchers employed a latent variable approach using Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM). Latent variables are not directly observable; rather, they are inferred from shared variance across multiple tasks designed to tap the same underlying construct. This approach enhances construct validity in psychological assessment (DiStefano et al., 2005) and allows for the modelling of complex relationships among cognitive processes (Hair et al., 2021). The study included 137 native English-speaking college students. For each executive function, the researchers selected several relatively simple tasks to minimize task impurity while maximizing construct representation. To assess shifting, they used the plus–minus task (Jersild, 1972), the number–letter task, and the global–local task, all of which require moving back and forth between multiple tasks or mental sets.

Updating was measured using three paradigms. In the Keep Track Task (Yntema, 1963), participants monitor a sequence of items from different categories and must recall the most recent item from each category at the end of the trial. The letter memory task (Morris & Jones, 1990) shows to the participants a continuous sequence of letters of unknown length, and the participants are expected to recall the last n letters presented. The task requires constant updating, and emphasizes executive control rather than rehearsal. In the tone-monitoring task, participants are asked to listen to a continuous sequence of tones and must monitor the stream for specific target tones. When a target tone is detected, they must press the button. It is used for measuring selective attention, sustained attention, and monitoring ability, which require constant updating.

In (Miyake et al., 2000), inhibition was assessed using three well-established tasks. The first task they have used is the Stroop task (Stroop, 1953), where the participants have to inhibit the name of the color they read, and say the name of the color that the word is written in. The second one is the antisaccade task by Hallet (1978), where the participants must suppress a reflexive saccade towards a visual stimulus and generate a voluntary saccade in the opposite direction. Finally, the stop-signal task (Logan, 1997) is based on a race model between a "go" process that initiates a response and a "stop" process that attempts to inhibit it; the response of the participant depends on which process is finished first. This task assesses the speed and efficiency of response inhibition.

The CFA results found in (Miyake et al., 2000) indicate that shifting, updating, and inhibition were clearly separable, yet moderately correlated constructs. These findings provide empirical support for the "unity and diversity" framework: executive functions are distinct components but share a common underlying variance. SEM analyses further demonstrate that each executive function contributes differentially to performance on complex cognitive tasks. Thus, EFs cannot be considered either fully unitary or entirely independent; rather, they represent interrelated processes that jointly support higher-order cognition.

Executive functions (EFs) develop gradually and do not reach full maturity until early adulthood, spanning nearly two decades of development (Hodel, 2018). During the first year, infants begin to maintain and update representations of hidden objects, and exhibit the first signs of working memory and inhibitory control in their gaze; intentionality and goal-directed behavior are observed between the 8-12 months (Piaget's sensorimotor stage) (Aguiar & Baillargeon, 1998; Huntley-Fenner et al., 2002; Káldy & Leslie, 2003; Piaget, 2013). Diamond (2020) defines the period between 2-5 years as preschool years. This period is characterized by a transition from cognitive rigidity to significant improvements in cognitive flexibility and self-regulation. In this period, children exhibit rigidity and reactive inhibitory control (responding to the moment), while lacking proactive control (planning ahead). They typically stick to an initial perspective of ambiguous figures and fail to see second perspective. Between the ages of 3-5, they show drastic changes in inhibitory control and cognitive flexibility (Gopnik & Rosati, 2001; Kloo & Perner, 2005). The relevance of this structural framework becomes particularly evident in educational settings. As discussed in the previous section, executive functions underpin reasoning, planning, and adaptive behavior (Diamond, 2013). In the classroom, these skills enable students to resist distractions (response inhibition), retain and integrate instructional information (working memory), and adapt to changing task demands (cognitive flexibility). Inhibitory control, for example, supports the selection of task-relevant information and the suppression of competing stimuli—such as refraining from checking a mobile phone during a lesson (Serpell et al., 2016).

In their review, Jacob & Parkinson (2015) collected the studies about the impact of EF on academic achievement. Gathercole et al. (2004) found a strong association between working memory task scores and performance in mathematics and science in school. Andersson (2008) aimed to pinpoint the contribution of central executive functions to children's written arithmetic performance. Results show that working memory contributes to arithmetic skills. Although these studies give insights into the relationship between EFs and academic achievement, it remains unclear whether EFs other than working memory contribute to achievement. Furthermore, several studies suggest that the development of EFs is associated with the socio-economic status and educational level of the children's families (Ardila, Rosselli, Matute, & Guajardo, 2005; Li-Grining, 2007). In their review, Jacob & Parkinson (2015) aimed to clarify (i) whether there is an unconditional association between EFs and school achievement; (ii) whether the unconditional association varies by outcome (math) under the aspect of EF in the study, or of the age of the child; and (iii) whether there is evidence of a causal relationship between EFs and academic achievement. Results suggest that, while children with high EF skills generally perform better in school, improvement of EFs alone may not lead to academic gains. Additionally, no compelling evidence was found indicating that EFs causally improve academic achievement.

Stucke & Doebel (2024) aimed to fill the gap in the literature about the relationship between EFs and domains beyond academics. In their meta-analysis, where they report the studies done on children between the ages of 3-5, they set out to answer three main questions: 1) Does performance on standard EF tasks in preschool predict children's social skills (emotion understanding, peer acceptance, prosocial behavior, etc.) concurrently or longitudinally?; 2) Do behavioral measurements of EFs in preschool predict behavioral adjustment (adaptive classroom behavior, inattention/hyperactivity etc.) concurrently or longitudinally? and 3) Do early EF skills relate to early health indicators (body mass index, physical fitness etc.) concurrently or longitudinally? While EFs and health didn't show any correlation, key findings of social outcomes showed that EFs are positively associated with emotion understanding, emotion regulation, prosocial skills, lying skills, and peer acceptance. Concurrent and longitudinal assessments of behavioral outcomes of higher EF predicted greater peer acceptance, adaptive classroom behavior, and social competence, while predicting lower hyperactivity and inattention symptoms.

Taken together, the structural evidence from latent variable modelling and the findings from intervention studies reinforce the view presented earlier: executive functions constitute a multifaceted but integrated system. Their unity and diversity not only characterize their cognitive architecture but also the shape of their developmental trajectory, their practical relevance, and responsiveness to training.

1.4.2 Visuo-spatial abilities

The concept of "visuospatial" was defined by Halpern & Collaer (2005) as information that is visual in nature, has spatial properties (such as relationships between objects within that space), and can be retrieved from memory or sensed directly. In addition, the authors indicate that the ability to mentally transform visuospatial information is crucial, particularly for professionals in fields such as design, chemistry, and engineering. Spatial abilities are essential for gaining independence and becoming autonomous in life (Fernandez-Baizan et al., 2021). Furthermore, it has been solidified that spatial abilities significantly predict achievement in STEM (science, technology, engineering, and mathematics) (Wai, Lubinski, & Benbow, 2009).

Scientific literature offers definitions for several subcomponents of spatial abilities. For example, Castro-Alonso & Atit (2019) define the following subcomponents: *spatial visualization* – mental manipulation of spatial information with multiple steps; *spatial working memory* – temporary storage of visuo-spatial information under attentional control, supporting navigation and problem-solving; *visual working memory* – short-term maintenance of visual information (color, shape etc.) independently from location; and *field independence* – the tendency to segregate the object from its surrounding context, facilitating accurate spatial judgments. Together, these components form an integrated visuo-spatial system that is distinct from, but can interact with, cognitive domains (Castro-Alonso & Atit, 2019; Bar-Hen-Schwaiger & Henik, 2024). Additionally, Linn and Peterson (1985) describe *mental rotation,* as the ability to mentally rotate a 2D and/or 3D figure rapidly and accurately.

In their meta-analysis, Uttal and Newcombe (2013) investigated whether and to what extent spatial skills can be improved by training and experience. Their results show that spatial skills are significantly malleable. Training effects are durable over time, with no significant differences in performance between participants tested immediately after training and those tested after a period. Transferability was observed as well. Training of one type of spatial task (e.g. mental rotation) improves performance on another type of spatial task (e.g. spatial orientation). Researchers identify key moderators of the success of spatial abilities training, one of them being sex differences. The results of a prior study by Linn and Peterson (1985) showed large and consistent sex differences, favoring males in the mental rotation test scores, and a moderate difference in spatial perception test scores. However, Uttal and Newcombe (2013) observed that both genders improve equally with training. Another moderator of success is age. It was observed that spatial skills are malleable across the entire lifespan. Also, children showed numerically higher gains compared to adolescents and adults. However, the differences were not statistically significant due to high variability between studies. Individuals who initially perform poorly on spatial tests benefit significantly more than those who start with higher scores. Additionally, it was confirmed that all types of spatial ability training, such as video games, semester-long courses, and laboratory-based task training, provide statistically similar improvements. Furthermore, the conclusions of their meta-analysis support the idea that spatial abilities significantly predict STEM achievement.

The study of Linn and Peterson (1985) not only examined the strength of spatial abilities based on sex differences, but also gave insight into the emergence of different spatial abilities during the lifespan based on specific performance patterns. The results of the meta-analysis support the idea that spatial perception, which involves determining spatial relationships such as horizontal and vertical, and spatial visualization skills, can be observed at age 4. Mental rotation skills were found to develop later than the previous two skills, emerging at age 10.

For effective assessment of individuals' spatial abilities, it is crucial to know which tests are reliable and consistent. Toward this end, Morawietz et al. (2024) investigated these issues across different age groups. Their research included five different spatial ability tests: *Paper Folding Test* (Ekstrom & Harman, 1976) – Evaluates spatial visualization by requiring participants to mentally unfold a folded, hole-punched sheet of paper; *Mental Rotation Test* (Vandenberg & Kuse, 1978) – Examines the ability to mentally rotate and manipulate 3D block figures; *Water Level Task* (Inhelder, 1967) – Determines spatial perception by having participants draw a horizontal water line in tilted jars; *Corsi Block Test* (Corsi, 1972) – A computer-based task that measures visuospatial short-term and working memory; and *Numbered Cones Run* (Hirtz & Ludwig, 2010) – A real-world motor task requiring the participants to run to numbered cones in a semicircle to assess spatial orientation. Results showed excellent relative reliability, indicating that the tests produce highly reproducible results across children, adolescents, and adults. Additionally, they had a low margin of error and were precise. Taken together, the authors conclude that this set of five tests is a reliable and feasible instrument for evaluating a spectrum of spatial abilities.

Although spatial abilities are strong predictors of success in STEM (Uttal & Newcombe, 2013; Wai, Lubinski, & Benbow, 2009), Brainin, Shamir, and Eden (2021) argued that studies of spatial abilities in young children have not clarified which educational tool would be appropriate to foster their spatial abilities. In their study, they aimed to investigate the impact of robot-based intervention on the spatial abilities of kindergarten children. They specifically focused on three components: spatial relation, mental rotation, and visual memory. Children were divided into 3 groups: programmable-robot intervention group, which used Bee-Bot during the activities; traditional intervention group, which used cars or dolls; and control group, which continued with their regular school activities. After 10 weeks of intervention, the programmable-robot intervention group showed significantly higher improvement in spatial relations and mental rotation, while not having a significant difference in visual memory compared to the other two groups. According to the researchers, the success of robot-based programs can be attributed to its unique qualities, such as giving children immediate feedback, and encouraging them to imagine the robot's actions, which directly exercises mental rotation and spatial planning skills.

As it has been mentioned before, Montuori et al. (2023) investigated the effectiveness of a combined intervention of unplugged coding and educational robotics programs in improving

CT and cognitive abilities, such as executive functions and spatial abilities, in kindergarten children. They aimed to observe improvement in coding skills as the near transfer effect, and in complex cognitive skills, such as spatial skills, as the far transfer effect by teaching to code via a combined intervention. The testing tool they used for spatial abilities was the Primary Mental Ability (PMA) subtest, which is standardized for children aged 5-7. This test is used to assess spatial relations and mental rotation skills of the children. The results of the 7-week program, which consisted of 14 sessions, demonstrated that learning to code in a tangible environment has a significant impact on complex mental abilities. The researchers observed statistically significant improvements in the visuo-spatial accuracy of the experimental group, compared to the control group. Overall, this study provides evidence for far transfer effects, successfully transferred to other tasks that require mental rotation and spatial reasoning. This supports the idea that coding education in early ages could improve complex cognitive abilities beyond solely technical digital literacy.

Preschool years (between the ages of 2 and 5) constitute a particularly sensitive developmental period during which significant advances in cognitive abilities can be observed (Diamond, 2020). Previous research has demonstrated that unplugged coding activities foster embodied learning, effectively support the acquisition of fundamental coding concepts, and provide a cost-effective approach to computational thinking (CT) education (Apostolellis et al., 2014; Tsarava et al., 2017; Chen et al., 2023). However, the majority of studies reporting these benefits have been conducted with elementary school children. Addressing this gap, Saygıner and Tüzün (2025) examined the effects of unplugged coding activities on preschool children's motivation, problem-solving skills, and CT skills. The findings revealed that participants in the experimental group demonstrated greater improvements across most sub-dimensions of the motivation scale compared to those in the control group. Furthermore, CT skills increased significantly among children in the experimental group. Although problem-solving skills improved in both groups, the magnitude of improvement was greater for the experimental group than for the control group.

On the other hand, studies on educational robotics have highlighted its potential benefits for teaching computational thinking and early programming concepts. Educational robotics appears to support the development of sequencing and algorithmic thinking skills, while also providing immediate feedback and enhancing learners' motivation (Hristova & Topalska, 2025; Kanaki et al., 2025). However, similar to research on unplugged coding activities, most studies on educational robotics have been conducted with children older than the preschool age group. To address this issue, Sullivan and Bers (2016) investigated the learning outcomes of educational robotics coding activities among pre-kindergarten, kindergarten, first-grade, and second-grade children. Their findings indicated that kindergarten children were able to master at least one of the targeted programming concepts—namely sequencing, repeat loops with numerical and sensor parameters, and the *wait-for-it* command—at a level comparable to that of older children. These findings suggest that educational robotics can effectively support the development of programming skills even among young learners. Although robotics-based interventions show promising results, further research is needed to clarify the mechanisms underlying their cognitive benefits and to compare their effectiveness with alternative instructional methods.

To fill the gap in literature on the relative benefits and drawbacks of unplugged coding versus educational robotic applications in enhancing the EFs of preschoolers and providing them with CT skills, Zhang et al. (2024) have conducted a comparative study. The researchers observed that the educational robotics group outperformed the unplugged coding group in inhibition, working memory, and cognitive flexibility. They explained these results by referring to the relative advantages of educational robotics over unplugged coding activities. The advantages include the debugging opportunity offered by immediate feedback and the enhancement of engagement and reinforcement enabled by physical interaction with tangible objects, which helps the preschoolers to turn abstract concepts into concrete operations. Nevertheless, this study has not addressed the effects of the two methods compared on visuo-spatial abilities.

Zurnacı et al. (2024) conducted a similar study and concluded that, while both methods are valuable, educational robotics is more effective than unplugged coding in teaching CT skills to preschoolers. Their results also show higher scores in cognitive flexibility for both groups during post-test. However, as with Zhang et al., they have excluded the assessment of visuo-spatial abilities. Taken all, the potential results of a similar study in a different sample, for example, children in Italy, and the benefits that both methods might provide to visuo-spatial abilities, which are highly related to CT, remain unknown.

Although the results obtained by Montuori et al. (2023) demonstrated significant improvement in the visuo-spatial reasoning of the experimental group, as well as in their planning accuracy and CT skills, it is not specified whether these achievements are the result of one of the activities between Educational Robotics and Unplugged Coding, or their combination.

Overall, the effectiveness of CT training methods on cognitive abilities and their near-transfer effect on coding skills give mixed results.

Chapter 2: The present study

2.1 Aim of this thesis

The aim of the present thesis is to contribute to existing literature by exploring the effects of unplugged coding and educational robotics activities on preschoolers' computational thinking skills, visuo-spatial abilities, and inhibitory control. In this context, the study seeks to address the following research questions:

1) To what extent are tangible coding interventions associated with near-transfer effects on coding abilities, and which instructional approach appears to be more effective?

2) To what extent are these interventions associated with far-transfer effects on cognitive abilities (e.g., inhibition and visuo-spatial skills), and which instructional approach appears to be more effective?

2.2 Methodology

2.2.1 Experimental design

The study was designed as a cluster-randomized control trial. Children were randomly divided into four groups: Educational Robotics (EDRO), Unplugged coding (UNPL), Combined (COMB), and Waiting List. Experimental groups (EDR, UNPL, and COMB) had standard pre-test (T1) – intervention – post-test (T2) assessments, while the control group had pre-test (T1) – standard school activities – post-test (T2) assessments. The children from three classes in preschool were randomly assigned to the experimental groups, and participated in coding activities once a week for one hour for 6 weeks. To benefit from the potential cognitive improvements, the waiting list group children received interventions after the post-tests as well.

The schedule and organization of the interventions were discussed with the teachers of the preschool. Children's attendance was recorded in the logbook in order to keep track of those who missed interventions, and, if necessary, eventually organize recovery interventions to guarantee that all children receive intervention for the same amount of time. Before the interventions, all the children were asked to do the tests of T1, which include PMA, NEPSY-II, and CoThi programming tests. The data of PMA were recorded by the researchers, while the data of NEPSY-II and CoThi programming were coded by CoThi application. Activities of the interventions were designed with a gradual approach: the first intervention was an introduction of fundamental concepts of CT (e.g., algorithms and sequences) via unplugged coding activities for both groups. Unplugged Coding group continued to play the games specifically designed to teach unplugged coding, for the next five interventions, while the Educational Robotics group was introduced to robotics activities with Bee-Bot from the second intervention onward. The difficulty of the tasks increased gradually throughout the interventions. The procedure is explained step by step in **Table 2.**

2.2.2 Information about consent forms

Parents of the participants were asked to sign the consent form prior to the study. All collected data will be conserved in the archive of the University of Padova, and the names of the participants will be anonymized. The data will be used exclusively for this study and will not be accessible to anyone but the researchers and data collectors.

2.2.3 Participants

This study was conducted with 22 children between the ages of 4.5-6, who are attending a kindergarten in North of Italy. None of the children have been exposed to coding activities before this project. They were divided into groups randomly, and all the groups contain between 4-7 children.

The ages of children varied between 61-69 months in the Educational Robotics group, 60-67 months in the Unplugged Coding group, 64-66 months in the Combined Coding group, and 58-67 months in the Control group. Mean and Standard Deviation of the ages of children in each group are given in **Table 1**.

Table 1.

Descriptive statistics of the ages of the children in months

GROUP	**MEAN**	**SD**
Educational Robotics	64.29	2.87
Unplugged Coding	62.5	3.32
Combined Coding	64.8	1.1
Waiting List	61.67	2.94

Parents were asked to fill out a questionnaire to assess the socio-economic status of the family (SES) and the familiarity of the children with technological devices in the beginning of the study when they signed the consent forms. The occupation of both parents and their education levels were asked in the questionnaire. Information about education level was coded in three levels, between 1 (elementary school/middle school) and 3 (university), while the information about occupation was categorized in 5 levels. A composite index was then calculated as the sum of the highest education score and the highest occupational score obtained by one of the parents, with maximum 8 points. The mean of SES point was M= 4.7, with SD=1.75.

The questions about children's familiarity with technology (FamTech) aimed to gather information about their use of technological devices (smartphones, tablets, and computers) in everyday life. Parents were asked to answer "Yes" to the technological devices that the child uses, and "No" to the ones they do not usually use. The questionnaire also included questions about the type of computer that they use, and the purpose of their usage (e.g. for playing videogames), although these pieces of information were excluded from the scoring in this study. The intensity of technological device usage of the children was expressed in terms of a measure between 0 and 3 points, obtained by giving 1 point to every "Yes", and 0 to every "No". The mean score of FamTech of this sample is M= 1.2, with SD= 0.75.

2.2.4 Procedure and materials

2.2.4.1 Pre-test and post-test assessment

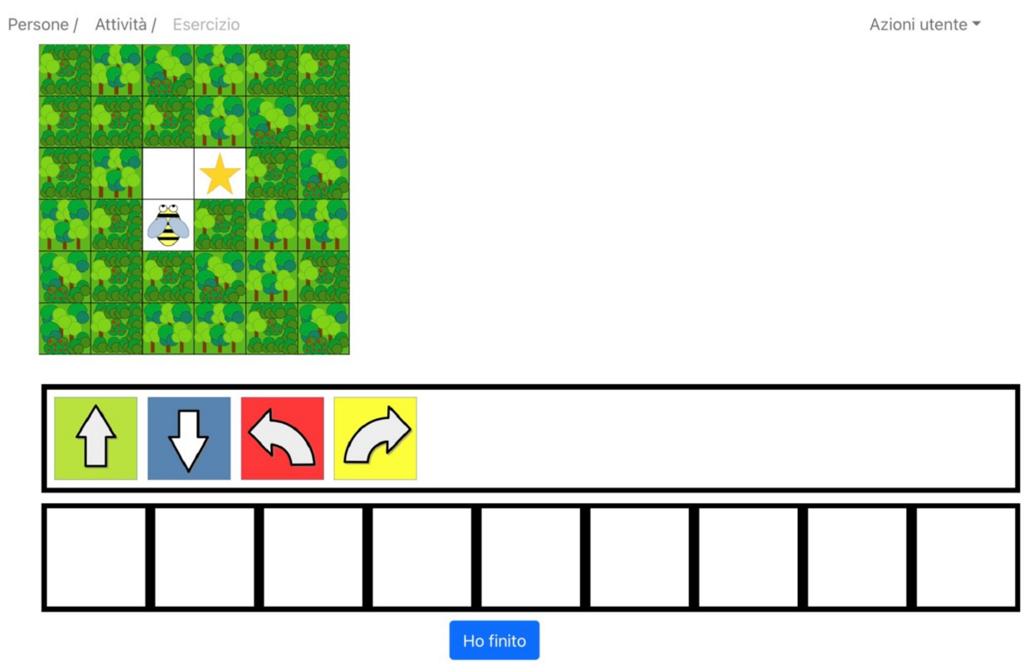
This project was designed to measure two dependent variables during T1 and T2: accuracy and speed. At the pretest and posttest, children individually performed 4 coding problems (they were given tablets to solve these tests on a digital platform called "CoThi") and two standardized neurocognitive tests to assess response inhibition and visuo-spatial skills. The assessment was conducted by researchers in the classrooms of the kindergarten during school hours. Children were asked to take the tests under the supervision of the researchers, who conducted them one by one in a corner of their classroom. Researchers were responsible for explaining to children the rules of the tests, which were presented to them as games, and encouraged them to answer the questions.

Coding skills

The coding game was developed to assess children's coding skills in a virtual environment using a tablet-based platform. The assessment consisted of four different games, each presenting a path that a bee had to follow in order to reach a star (see the example in **Figure 1)**. Below the path, a series of empty boxes was provided for constructing a sequence of commands. Children were required to select the appropriate directional arrows and place them in the correct order to create the code that would guide the bee along the designated path. The tasks were designed with increasing levels of difficulty, with each subsequent game involving more complex path configurations and requiring more advanced sequencing skills.

Figure 1

The first coding game implemented within the CoThi platform



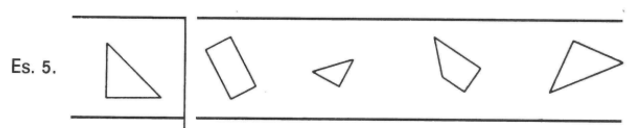
Visuo-Spatial Skills: Mental Rotation

The Primary Mental Abilities subtest (PMA) was used to assess visuo-spatial skills (see **Figure 2)**. The PMA test examines the capacity of pre-school and elementary school children to think of two-dimensional objects as three-dimensional, to rotate and manipulate them in their minds. To complete the task, children are asked to choose one of four given options as the missing piece that would complete the figure. Child's visuo-spatial skills were scored for:

• Visuo-spatial accuracy: one point was awarded for each trial correctly solved in 6 min; 0 otherwise

Figure 2

An example of the visuospatial abilities test



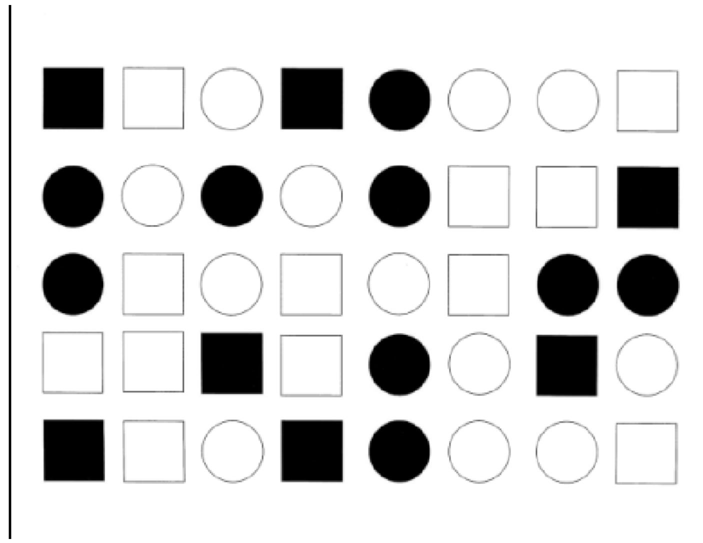
<u>Inhibitory control</u>

The NEPSY inhibition (squares/circles) subtest of NEPSY-II was used to assess children's response inhibition skills (see **Figure 3)**. The test consists of 40 items, including circles and squares presented in a randomized order. During administration, children are required to identify each shape sequentially from left to right; however, instead of naming the presented shape, they must provide the name of the opposite shape (i.e., saying "square" when a circle is shown and "circle" when a square is shown). Throughout the assessment, the researcher records both the time taken to complete all items and the number of errors made by the child. The scoring procedure is based on these performance measures and is calculated as follows:

- Response inhibition errors: one point was awarded for each correct item; 0 otherwise

Figure 3

NEPSY-II inhibition task



2.2.5 Instructional design

During the first fifteen minutes of the first two interventions, all experimental groups were involved in an activity to learn the meaning of the arrows in the activities. First, they were asked to stay in a line, side by side, facing the researchers, who explained them the meaning of the arrows. A green arrow means one step forward; a red arrow means turning to the left; and a yellow arrow means turning to the right. Researchers showed the arrows in a mixed order to train the children. If needed, the same explanations were repeated also during the interventions. After these first fifteen minutes and the following interventions, the participants were asked to play the games as explained below.

<u>*EDRO (Educational Robotics)*</u>

The group of participants assigned to educational robotics engaged in the same set of exercises during all sessions. For these activities, a set of small printed paper arrows was prepared representing the commands *move forward*, *turn left*, and *turn right*. Participants were escorted from their classroom to another room, where they sat on the floor around a checkered grid map (see **Figure 4)**. The researchers selected one square on the grid as the starting point and placed a LEGO piece on another square to represent the target location, progressively creating more complex paths. The Bee-Bot robot was positioned on the starting square. Participants were then asked, one at a time, to arrange the arrow cards on the floor in the correct sequence to represent the steps the Bee-Bot needed to follow in order to reach the target location. After arranging the arrow cards, participants entered the corresponding sequence by pressing the buttons on the robot in the exact order of the constructed code. They were then asked to observe the robot's movement and compare the executed path with their planned sequence. If discrepancies or errors occurred, participants were encouraged to identify and correct the mistakes by modifying their code.

Figure 4

Materials for Educational Robotics coding activities

(a)

(b)

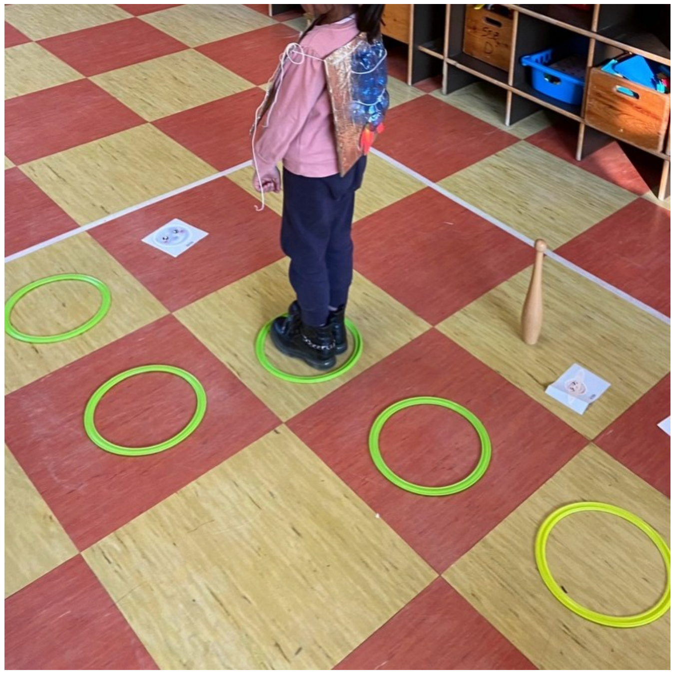
Note. Figure ***(a)*** presents examples of two different types of grid maps, whereas Figure ***(b)*** shows the Bee-Bot robot used during the activities.

<u>*UNPL (Unplugged coding)*</u>

Participants in the unplugged coding group completed the same set of exercises during all sessions. Prior to each session, data collectors prepared a large checkered grid on the floor using paper tape and randomly placed pictures of planets within the grid squares (see **Figure 5**). Participants were escorted from their classroom to another room where the activity took place. At the beginning of each round, data collectors placed a LEGO piece on one of the squares to indicate the target planet and identify the starting square. For each round, three participants volunteered to take on different roles: one acted as the "robot", another one arranged the arrow cards on the floor in the correct sequence to represent the code, and a third one read the code aloud and verbally instructed the robot to execute the commands. These roles rotated in each round, with the aim of ensuring that every participant experienced all three roles during the activity.

Figure 5

Unplugged Coding activity



Note. This photograph was taken during the Unplugged Coding intervention. The circles placed on the floor represented a pathway that had been arranged according to the code created by the children.

Table 2

Procedure of the experiment

Stage	groups			
	EDRO	**UNPL**	**COMB**	**Waiting List**
Initial Stage	Consent forms collected	Consent forms collected	Consent forms collected	Consent forms collected
Pre-test	Participants conduct PMA, NEPSY-II and the Coding game.	Participants conduct PMA, NEPSY-II and the Coding game.	Participants conduct PMA, NEPSY-II and the Coding game.	Participants conduct PMA, NEPSY-II and the Coding game.
First three interventions	Participants perform the Educational Robotics training activities.	Participants perform Unplugged coding training activities.	Participants perform Unplugged coding training activities.	Participants perform their usual classwork.
Last three interventions	Participants perform the Educational Robotics training activities.	Participants perform Unplugged coding training activities.	Participants perform Educational Robotics training activities.	Participants perform their usual classwork.
Post-test	PMA, NEPSY-II, Coding game	PMA, NEPSY-II, Coding game	PMA, NEPSY-II, Coding game	PMA, NEPSY-II, Coding game

Note. The experiment proceeds to the next stage only after the previous one is completed. A period of one week is dedicated to each intervention during the intervention stages (First three interventions and Last three interventions).

Chapter 3: Results

3.1 Preliminary analysis

The data gathered in this study have been analyzed using IBM SPSS (*Statistical Package for the Social Sciences*). Preliminary analyses indicated that the data were not normally distributed; therefore, non-parametric statistical methods were employed for group comparisons.

To assess baseline group equivalence in terms of socioeconomic status (SES), familiarity with technology, and age, these variables were examined using the Kruskal–Wallis test, which is appropriate for comparing three or more groups under conditions of small sample size and non-normal distribution. No statistically significant differences were found for any of these variables, indicating group equivalence:

- age of children: $H(3)= 5.18$, $p = 0.16$
- SES: $H(3)= 7.20$, $p = 0.066$
- familiarity with the technology: $H(3)= 3.24$, $p = 0.36$.

The Kruskal-Wallis test was used again to determine the differences at the pre-test (T1) between groups. As children's scores were not normally distributed, we used non-parametric tests in the data analysis. Between-group differences at the pre-test (T1) were preliminarily explored by a Kruskal-Wallis test, which confirmed that the groups did not differ significantly in any dependent measure:

- coding accuracy: $H(3)= 0.50$, $p= 0.92$
- coding planning time: $H(3)= 2.02$, $p= 0.57$
- response inhibition errors: $H(3)= 3.70$, $p= 0.30$
- response inhibition time: $H(3)= 1.81$, $p= 0.61$
- visuo-spatial accuracy: $H(3)= 2.46$, $p= 0.48$

No statistically significant differences were found among the four groups in pre-test scores, indicating baseline equivalence across groups. Participants did not differ significantly prior to the intervention and can be considered comparable at pre-test.

The descriptive statistics of T1 and T2 are summarized in **Table 3** and **Table 4**, respectively. The Kruskal-Wallis test has not been applied to T2 because in this case only the change score is informative about the efficiencies of different methods.

Table 3

Descriptive statistics of T1 tests results

Dependent Variable	Group	Mean	SD
Coding	Educational Robotics	0.57	0.90
	Unplugged Coding	0.50	1.0
accuracy	Combined Activities	0.60	0.89
	Waiting List	0.33	0.82
Coding	Educational Robotics	13.92	7.83
	Unplugged	10.33	9.74
planning time	Combined Activities	9.93	3.9
	Waiting List	8.62	5.31
NEPSY-II	Educational Robotics	3.43	1.90
	Unplugged Coding	5.50	1.92
response inhibition errors	Combined Activities	4.20	2.69
	Waiting List	0.79	1.94
NEPSY-II	Educational Robotics	75.60	21.28
	Unplugged Coding	81.89	11.84
inhibition time	Combined Activities	78.99	15.50
	Waiting List	77.11	23.19
PMA	Educational Robotics	8.57	4.60
accuracy	Unplugged Coding	11.50	3.12
	Combined Activities	9.20	2.85
	Waiting List	6.67	6.15

Table 4

Descriptive statistics of T2 test results

Tests	Group	Mean	SD
Coding accuracy	Educational Robotics	1.57	2.07
	Unplugged Coding	3.25	2.75
	Combined Activities	3.80	2.50
	Waiting List	0.67	1.03
Coding planning time	Educational Robotics	11.60	4.17
	Unplugged	5.67	0.84
	Combined Activities	16.08	9.46
	Waiting List	5.89	1.10
NEPSY-II response inhibition errors	Educational Robotics	4.14	2.85
	Unplugged Coding	2.75	1.26
	Combined Activities	1.60	0.90
	Waiting List	2.0	1.67
NEPSY-II inhibition time	Educational Robotics	70.6	16.45
	Unplugged Coding	48.79	3.81
	Combined Activities	56.64	16.70
	Waiting List	59.53	12.39
PMA accuracy	Educational Robotics	11.14	3.70
	Unplugged Coding	16.0	1.41
	Combined Activities	15.20	2.85
	Waiting List	7.33	3.72

3.2 Analysis of the effects of interventions

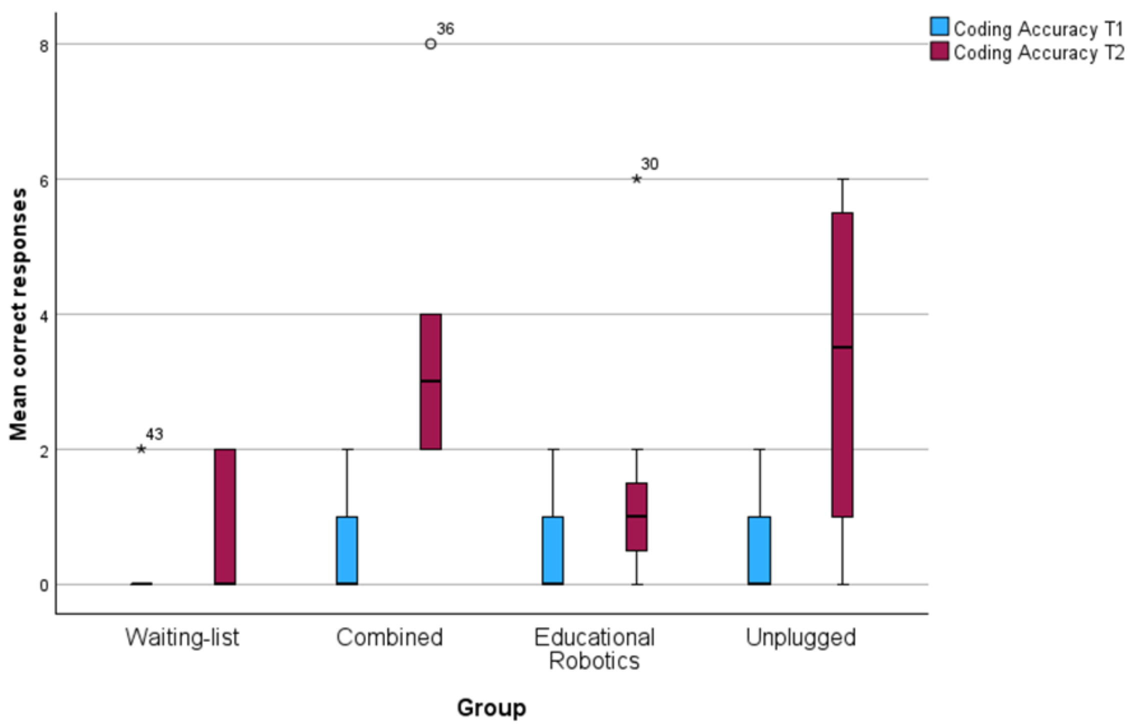
To examine the effects of the different instructional approaches, Kruskal–Wallis tests were conducted on change scores computed as the difference between T1 and T2.

Coding skills

No statistically significant difference was observed among the groups for *coding accuracy* [H(3)= 6.63, *p*= 0.085]. However, pairwise comparison revealed a significant difference between the combined coding group and the control group, with higher coding accuracy in the combined condition [H(3)= -8.30, *p*= 0.028]. No statistically significant difference was observed among the groups for coding planning time [H(3)= 4.22, *p*= 0.24], as can be observed from **Figure 6**.

Figure 6

Groups' accuracy on coding tasks at the pretest (T1)and posttest (T2)



Visuo-Spatial skills

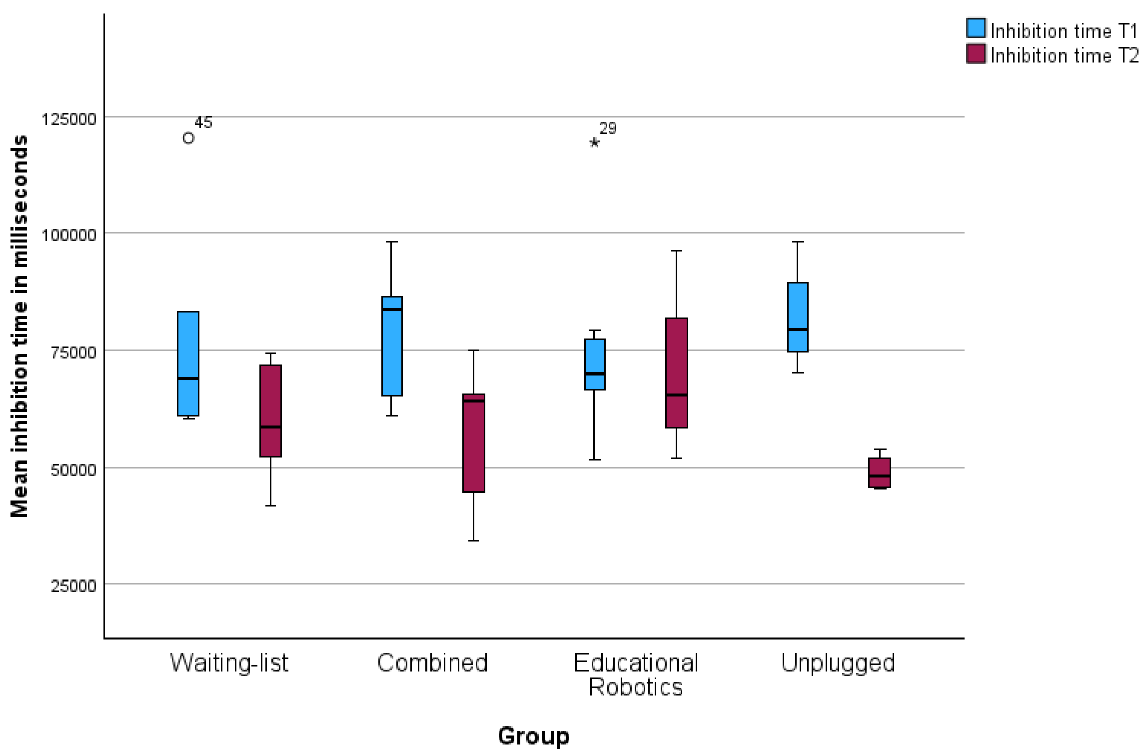
No statistically significant differences were found among groups [H(3)= 3.15, p= 0.37]. Visuospatial abilities did not show any improvement in this study.

Response inhibition

No statistically significant differences were found among the groups in the change scores for the total number of inhibition errors [H(3)= 4.12, p= 0.25]. No statistically significant differences were found among the groups in the change scores for the inhibition time [H(3)= 5.42, p= 0.14]. However, exploratory pairwise comparisons suggested a significant difference between the Unplugged Coding group and the Educational Robotics group, indicating greater improvement in processing speed for the Unplugged Coding condition [H(3)= 8.86, p= 0.03]. These results are shown in **Figure 7**.

Figure 7

Groups' errors on inhibition task at the pretest (T1) and posttest (T2)



Chapter 4: Discussion and conclusion

4.1 Discussion

This study is a cluster randomized trial to investigate the effects of different intervention methods on young children's CT skills, visuospatial abilities, and executive functions (especially inhibition). Previous studies have indicated that CT training activities can provide a far transfer effect (e.g., Arfé et al., 2019; Di Lieto et al., 2020; Montuori et al., 2024; Scherer & Sánchez Viveros, 2019; Scherer & Viveros, 2020) by helping children connect different subjects and enhance their abstract thinking (Weigend et al., 2019; Tsarava et al., 2017). Training CT skills was found to be effective in enhancing executive functions and visuospatial abilities (Arfé et al., 2019, 2020; Montuori et al., 2023), which help children perform better in the classroom and predict success in STEM (Serpell et al., 2016; Uttal & Newcombe, 2013).

The interventions in this study were designed to teach the children the coding game, aiming to observe near transfer for the same game on screen and far transfer to cognitive abilities. The main goal of this thesis was to determine which of the two teaching methods, such as Educational Robotics and Unplugged Coding, offers greater development on them.

<u>*Coding skills*</u>

This game was created to promote children's computational thinking through a coding game. Change scores for coding have not shown significant development in the Educational Robotics and Unplugged coding groups, compared with each other and the control group. The only significant change score is from the pairwise comparison between the Combined Activities group and the control group, indicating that neither the Educational Robotics nor the Unplugged Coding interventions were sufficient to develop CT skills when children received only one of those methods. A near transfer effect was observed only in the Combined Activities group. This can be explained in terms of the fact that the combination of two methods combines the relative advantages and compensates for the weaknesses of the individual methods. Unplugged coding offers the opportunity to directly experience the robot's perspective and movements, while its major drawback is the lack of immediate feedback. Furthermore, debugging is challenging in unplugged coding because it involves multiple sources of potential error: the participant who writes the code by placing the arrows, the participant who follows the instructions, and possibly the participant who reads the code to the instruction follower. Educational Robotics activities, on the other hand, are known for providing immediate feedback that accelerates debugging. But because participants observe the robot only from their own perspective and do not experience changes in perspective during motion, Educational Robotics activities lack embodied learning. The results of the present pilot study are not consistent with the findings of Zurnacı et al. (2024), who reported that educational robotics activities were more effective than unplugged coding activities in enhancing computational thinking skills. On the other hand, the improvement observed in coding skills is in line with the results reported by Montuori et al. (2023).

Inhibitory control

The accuracy and inhibition time of the inhibition task were tested. This skill has been identified as an important predictor of later academic achievement (Peng & Kievit, 2020) and has shown improvements across numerous studies (Arfé et al., 2020, Montuori et al., 2023). Therefore, one of the primary aims of the present study was to examine whether it could be enhanced through Educational Robotics and Unplugged Coding interventions.However, the results revealed no significant differences across the groups. The reason may be that in this task, children were required to name two figures (a circle and a square) while inhibiting the prepotent response and providing the opposite label. Considering the participants' family backgrounds, language may have represented an additional challenge, as Italian was not the native language of most of the children. Consequently, some participants may have had difficulty retrieving the appropriate words, which could have affected their performance regardless of their inhibitory abilities. This issue is particularly relevant, given that inhibitory control is already highly demanding at this developmental stage and has been identified as one of the executive functions most resistant to improvement through training (Kassai et al., 2019).

On the other hand, the Unplugged Coding group completed the inhibition test significantly faster than Educational Robotics group.. However, this finding is not consistent with the results reported by Zhang et al. (2025), who found significant improvements in inhibitory control following computational thinking training through coding activities. Specifically, their results indicated enhanced inhibitory control, as reflected by a lower number of errors on the inhibition task. One possible explanation for this discrepancy is the difference in sample size between Zhang et al. (2025) and the present study. Zhang et al. (2025) included 198 participants, substantially more than the present study, which may have increased the reliability and statistical power of their findings. In addition, their intervention lasted 12 weeks, whereas the present study implemented a 6-week program. It is possible that the longer duration of the intervention allowed the benefits associated with Educational Robotics activities to emerge more fully over time. A longer intervention period may also have enabled the advantages of the different intervention methods to become more evident. However, no significant improvement in inhibitory control was observed in the present study, as indicated by the change score comparisons between groups.

Visuo-spatial abilities

In this study, PMA was used to test mental rotation skills. The previous study of Montuori et al. (2023) indicates that combined activities improve visuo-spatial reasoning. However, the current results do not align with the earlier results. The meta-analysis conducted by Uttal and Newcombe (2013) highlighted the potential for visuospatial abilities to improve through training and experience. However, no significant improvement in visuospatial abilities was observed in the present study. One possible explanation for this finding is the intervention's shorter duration. While Montuori et al. (2023) implemented a 14-session program, the present study provided only 6 weeks of intervention. Therefore, it is possible that participants did not have sufficient exposure to the activities for measurable improvements in visuospatial abilities to emerge.

Another important difference between the participants in the present study and those included in Montuori et al. (2023) concerns their socioeconomic status (SES). While the participants in Montuori et al. (2023) predominantly came from medium- to high-SES families, the participants in the present study were primarily from low-SES backgrounds. This difference may have contributed to the contrasting findings regarding visuospatial abilities. In support of this interpretation, Johnson et al. (2022) examined the relationship between SES and children's spatial and mathematical skills and found that socioeconomic status significantly influenced performance. Specifically, children from higher-SES families outperformed their peers from lower-SES families on measures of spatial abilities. Therefore, the lower SES of the participants in the present study may have limited the extent to which improvements in visuospatial abilities could be observed following the intervention.

4.2 Limitations

There are several limitations that appeared during the execution of the project that might have an influence on the results. Most of the participants were coming from immigrant families, where they speak other languages with their families than Italian. Some of them were not speaking Italian at all. The present study was characterized by a relatively small sample size, and most participants came from low-SES backgrounds. These characteristics can be considered both a strength and a limitation. The study aimed to contribute to the literature by providing preliminary evidence regarding the effects of Educational Robotics and Unplugged Coding interventions in a preschool population that is often underrepresented in research. On the other hand, the limited sample size and the specific socioeconomic characteristics of the participants restrict the generalizability of the findings. Therefore, the results should be interpreted with caution and cannot be considered representative of the broader population of Italian preschool children. Another limitation was the organization of the classrooms. The researchers were not allowed to take children outside their classroom to conduct the pre- and post-test. Conversely, in the other participating schools, researchers were permitted to assess children individually in a quiet, dedicated classroom, thereby ensuring a distraction-free environment. In our case, the distraction in the classroom caused a challenge for children to concentrate on the games in some cases. The tests of T1 and T2 were the same, and the researchers were responsible for encouraging children to do the tests without telling them the right answers. This situation creates a risk for children to give the same answers, especially for the PMA test, although eight weeks passed between T1 and T2. The experimental groups were selected randomly, however, since there are 22 children and four groups, some of the classmates were in the same experimental groups. The dynamics between children created challenges during the interventions. Although the difficulty of the tasks of the interventions were gradually enhancing, the repetition of the game and concentrating to them became less engaging for the children of that age time to time.

4.3 Conclusion

The results of this study indicate that, although the advantages of Educational Robotics and Unplugged Coding activities are not significantly effective by themselves, they give significant results when the interventions are designed to use those methods together, so the sum of their advantages is offering a significant development of CT skills that coding games offer to develop. The two methods do not have near transfer effect for the coding game. On the other hand, the impact of the activities on cognitive abilities, which means the far transfer effect, is bigger. The unplugged coding group outperformed the robotics education group on the inhibitory control task, not in accuracy but in speed. One benefit observed during the intervention was that both Educational Robotics and Unplugged Coding activities fostered collaboration among children. During the training sessions, several children from different classrooms who had not previously interacted were observed working together, sharing ideas, and explaining task-related details to one another. Furthermore, all participants had the opportunity to take on different roles within the activities, allowing them to approach the tasks from multiple perspectives. Although the sample size is relatively small, the significant results are encouraging for conducting studies with larger groups and using different tests to explore other possible benefits of the activities.

These findings suggest that such activities could be implemented with larger groups of children to further promote collaboration and peer learning. Although the present study aimed to improve visuospatial abilities, it did not assess whether children's orientation skills were enhanced as a result of the intervention. Future studies and educational practices could incorporate orientation-based games organized in teams to encourage collaboration while also examining the potential effects of Educational Robotics and Unplugged Coding on orientation abilities.

Bibliography

Aguiar, A., & Baillargeon, R. (1998). Eight-and-a-half-month-old infants' reasoning about containment events. *Child Development*, *69*(3), 636–653.

Andersson, U. (2008). Working memory as a predictor of written arithmetical skills in children: The importance of central executive functions. *British Journal of Educational Psychology*, *78*(2), 181–203.

Apostolellis, P., Stewart, M., Frisina, C., & Kafura, D. (2014). RaBit EscAPE: A board game for computational thinking. *Proceedings of the 2014 Conference on Interaction Design and Children*, 349–352.

Aranda, G., & Ferguson, J. P. (2018). Unplugged Programming: The future of teaching computational thinking? *Pedagogika*, *68*(3).

Ardila, A., Rosselli, M., Matute, E., & Guajardo, S. (2005). The influence of the parents' educational level on the development of executive functions. *Developmental Neuropsychology*, *28*(1), 539–560.

Arfé, B., Vardanega, T., & Ronconi, L. (2020). The effects of coding on children's planning and inhibition skills. *Computers & Education*, *148*, Article 103807.

Arfé, B., Vardanega, T., Montuori, C., & Lavanga, M. (2019). Coding in primary grades boosts children’s executive functions. *Frontiers in Psychology*, *10*, Article 2713.

Atchison, W F., Conte, S. D., Hamblen, J. W., Hull, T. E., Keenan, T. A., Kehl, W. B., McCluskey, E. J., Navarro, S. O., Rheinboldt, W. C., Schweppe, E. J., & others. (1968). Curriculum 68:

Recommendations for academic programs in computer science: A report of the ACM curriculum committee on computer science. *Communications of the ACM*, *11*(3), 151–197.

Atmatzidou, S., & Demetriadis, S. (2016). Advancing students' computational thinking skills through educational robotics: A study on age and gender relevant differences. *Robotics and Autonomous Systems*, *75*, 661–670.

Baggetta, P., & Alexander, P. A. (2016). Conceptualization and operationalization of executive function. *Mind, Brain, and Education*, *10*(1), 10–33.

Bar-Hen-Schweiger, M., & Henik, A. (2024). Looking beyond seeing: Components of visual-spatial ability as an overarching process. *Acta Psychologica*, *251*, Article 104577.

Bers, M. U. (2020). *Coding as a playground: Programming and computational thinking in the early childhood classroom*. Routledge.

Blair, C. (2017). Educating executive function. *Wiley Interdisciplinary Reviews: Cognitive Science*, *8*(1-2), Article e1403.

Brackmann, C. P., Román-González, M., Robles, G., Moreno-León, J., Casali, A., & Barone, D. (2017). Development of computational thinking skills through unplugged activities in primary school. *Proceedings of the 12th Workshop on Primary and Secondary Computing Education*, 65–72.

Brainin, E., Shamir, A., & Eden, S. (2022). Robot programming intervention for promoting spatial relations, mental rotation and visual memory of kindergarten children. *Journal of Research on Technology in Education*, *54*(3), 345–358.

Caeli, E. N., & Yadav, A. (2020). Unplugged approaches to computational thinking: A historical perspective. *TechTrends*, *64*(1), 29–36.

Çakır, R., Korkmaz, Ö., İdil, Ö., & Erdoğmuş, F. U. (2021). The effect of robotic coding education on preschoolers' problem solving and creative thinking skills. *Thinking Skills and Creativity*, *40*, Article 100812.

Carlson, Stephanie M., Zelazo, P. D., & Faja, S. (2013). Executive function.

Castro-Alonso, J. C., & Atit, K. (2019). Different abilities controlled by visuospatial processing. In *Visuospatial processing for education in health and natural sciences* (pp. 23–51). Springer.

Chen, P., Yang, D., Metwally, A. H. S., Lavonen, J., & Wang, X. (2023). Fostering computational thinking through unplugged activities: A systematic literature review and meta-analysis. *International Journal of STEM Education*, *10*(1), Article 47.

Choi, W. C., Choi, I. C., Lam, C. T., & Mendes, A. J. (2024). Learning sequencing with Bee-Bot: A study on improving computational thinking and motivation for young learners in programming education. *2024 IEEE Frontiers in Education Conference (FIE)*, 1–8.

Corsi, P. M. (1972). *Human memory and the medial temporal region of the brain* (Doctoral dissertation). McGill University.

Davidson, M. C., Amso, D., Anderson, L. C., & Diamond, A. (2006). Development of cognitive control and executive functions from 4 to 13 years: Evidence from manipulations of memory, inhibition, and task switching. *Neuropsychologia*, *44*(11), 2037–2078.

Denning, P. J. (2007). Computing is a natural science. *Communications of the ACM*, *50*(7), 13–18.

Denning, P. J. (2010). What is computation. *Ubiquity*, 2–11.

Denning, P. J., & Freeman, P. A. (2009). The profession of IT computing's paradigm. *Communications of the ACM*, *52*(12), 28–30.

Diamond, A. (2013). Executive functions. *Annual Review of Psychology*, *64*(1), 135–168.

Diamond, A. (2020). Executive functions. *Handbook of Clinical Neurology*, *173*, 225–240.

DiStefano, C., & Hess, B. (2005). Using confirmatory factor analysis for construct validation: An empirical review. *Journal of Psychoeducational Assessment*, *23*(3), 225–241.

Doebel, S. (2020). Rethinking executive function and its development. *Perspectives on Psychological Science*, *15*(4), 942–956.

Ekstrom, R. B., & Harman, H. H. (1976). *Manual for kit of factor-referenced cognitive tests, 1976*. Educational Testing Service.

Fernandez-Baizan, C., Arias, J. L., & Mendez, M. (2021). Spatial orientation assessment in preschool children: Egocentric and allocentric frameworks. *Applied Neuropsychology: Child*, *10*(2), 171–193.

Ferrer, E., O'Hare, E. D., & Bunge, S. A. (2009). Fluid reasoning and the developing brain. *Frontiers in Neuroscience*, *3*, Article 481.

Garon, N., Bryson, Susan E., & Smith, Isabel M. (2008). Executive function in preschoolers: A review using an integrative framework. *Psychological Bulletin*, *134*(1), Article 31.

Gathercole, S. E., Pickering, S. J., Knight, C., & Stegmann, Z. (2004). Working memory skills and educational attainment: Evidence from national curriculum assessments at 7 and 14 years of age. *Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition*, *18*(1), 1–16.

Gopnik, A., & Rosati, A. (2001). Duck or rabbit? Reversing ambiguous figures and understanding ambiguous representations. *Developmental Science*, *4*(2), 175–183.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). An introduction to structural equation modeling. In *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook* (pp. 1–29). Springer.

Hallett, P. E. (1978). Primary and secondary saccades to goals defined by instructions. *Vision Research*, *18*(10), 1279–1296.

Halpern, D. F., & Collaer, M. L. (2005). Sex differences in visuospatial abilities. *The Cambridge Handbook of Visuospatial Thinking*, 170–212.

Hirtz, P., Hotz, A., & Ludwig, G. (2010). Orientierung [Orientation]. *Hofmann-Verlag: Schorndorf*.

Hristova, H., & Topalska, R. (2025). Application of Bee-Bot in first grade math lesson. *KNOWLEDGE-International Journal*, *70*(2), 249–254.

Hsu, T. C., Chang, S. C., & Hung, Y. T. (2018). How to learn and how to teach computational thinking: Suggestions based on a review of the literature. *Computers & Education*, *126*, 296–310.

Huntley-Fenner, G., Carey, S., & Solimando, A. (2002). Objects are individuals but stuff doesn't count: Perceived rigidity and cohesiveness influence infants' representations of small groups of discrete entities. *Cognition*, *85*(3), 203–221.

Inhelder, B., & Piaget, J. (1967). *The child's conception of space*. Routledge & K. Paul.

Jacob, R., & Parkinson, J. (2015). The potential for school-based interventions that target executive function to improve academic achievement: A review. *Review of Educational Research*, *85*(4), 512–552.

Jersild, A. T. (1927). *Mental set and shift* (No. 89). Columbia University.

Johnson, T., Burgoyne, A. P., Mix, K. S., Young, C. J., & Levine, S. C. (2022). Spatial and mathematics skills: Similarities and differences related to age, SES, and gender. *Cognition*, *218*, 104918.

Káldy, Z., & Leslie, A. M. (2003). Identification of objects in 9-month-old infants: Integrating 'what' and 'where' information. *Developmental Science*, *6*(3), 360–373.

Kalelioğlu, F. (2015). A new way of teaching programming skills to K-12 students: Code.org. *Computers in Human Behavior*, *52*, 200–210.

Kanaki, K., Chatzakis, S., & Kalogiannakis, M. (2025). Fostering algorithmic thinking and environmental awareness via bee-bot activities in early childhood education. *Sustainability*, *17*(9), Article 4208.

Kloo, D., & Perner, J. (2005). Disentangling dimensions in the dimensional change card-sorting task. *Developmental Science*, *8*(1), 44–56.

Kassai, R., Futo, J., Demetrovics, Z., & Takacs, Z. K. (2019). A meta-analysis of the experimental evidence on the near-and far-transfer effects among children's executive function skills. *Psychological bulletin*, *145*(2), 165.

Laut, J., Wright, S. N., Nov, O., & Porfiri, M. (2014). Gowanus voyage: Where mechatronics, public art, community members, and environmental science meet [Focus on Education]. *IEEE Control Systems Magazine*, *34*(1), 60–64.

Li, Q., Jiang, Q., Liang, J. C., Xiong, W., Liang, Y., & Zhao, W. (2023). Effects of interactive unplugged programming activities on computational thinking skills and student engagement in elementary education. *Education and Information Technologies*, *28*(9), 12293–12318.

Li-Grining, C. P. (2007). Effortful control among low-income preschoolers in three cities: Stability, change, and individual differences. *Developmental Psychology*, *43*(1), Article 208.

Liew, J. (2012). Effortful control, executive functions, and education: Bringing self-regulatory and social-emotional competencies to the table. *Child Development Perspectives*, *6*(2), 105–111.

Lin, Y., Liao, H., Weng, S., & Dong, W. (2024). Comparing the effects of plugged-in and unplugged activities on computational thinking development in young children. *Education and Information Technologies*, *29*(8), 9541–9574.

Lockwood, J., & Mooney, A. (2017). Computational thinking in education: Where does it fit? A systematic literary review. *arXiv preprint arXiv:1703.07659*.

Logan, G. D., Schachar, R. J., & Tannock, R. (1997). Impulsivity and inhibitory control. *Psychological Science*, *8*(1), 60–64.

Masten, A. S., Herbers, Janette E., Desjardins, C. D., Cutuli, J., McCormick, C. M., Sapienza, J. K., Long, J. D., & Zelazo, P. D. (2012). Executive function skills and school success in young children experiencing homelessness. *Educational Researcher*, *41*(9), 375–384.

McCormick, K. I., & Hall, Jacob A. (2022). Computational thinking learning experiences, outcomes, and research in preschool settings: A scoping review of literature. *Education and Information Technologies*, *27*(3), 3777–3812.

Mischel, W., & Ebbesen, E. B. (1970). Attention in delay of gratification. *Journal of Personality and Social Psychology*, *16*(2), Article 329.

Miyake, A., & Friedman, N. P. (2012). The nature and organization of individual differences in executive functions: Four general conclusions. *Current Directions in Psychological Science*, *21*(1), 8–14.

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex “frontal lobe” tasks: A latent variable analysis. *Cognitive Psychology*, *41*(1), 49–100.

Montuori, C., Gambarota, F., Altoé, G., & Arfé, B. (2024). The cognitive effects of computational thinking: A systematic review and meta-analytic study. *Computers & Education*, *210*, Article 104961.

Montuori, C., Pozzan, G., Padova, C., Ronconi, L., Vardanega, T., & Arfé, B. (2023). Combined unplugged and educational robotics training to promote computational thinking and cognitive abilities in preschoolers. *Education Sciences*, *13*(9), Article 858.

Morawietz, C., Dumalski, N., Wissmann, A. M., Wecking, J., & Muehlbauer, T. (2024). Consistency of spatial ability performance in children, adolescents, and young adults. *Frontiers in Psychology*, *15*, Article 1365941.

Morris, N., & Jones, D. M. (1990). Memory updating in working memory: The role of the central executive. *British Journal of Psychology*, *81*(2), 111–121.

Munasinghe, B., Bell, T., & Robins, A. (2023). Unplugged activities as a catalyst when teaching introductory programming. *Journal of Pedagogical Research*, *7*(2), 56–71.

Nam, K. W., Kim, H. J., & Lee, S. (2019). Connecting plans to action: The effects of a card-coded robotics curriculum and activities on Korean kindergartners. *The Asia-Pacific Education Researcher*, *28*(5), 387–397.

Oliveira, O. L., Nicoletti, Maria C., & del Val Cura, L. M. (2014). Quantitative correlation between ability to compute and student performance in a primary school. *Proceedings of the 45th ACM Technical Symposium on Computer Science Education*, 505–510.

Özcan, M. Ş., Çetinkaya, E., Göksun, T., & Kisbu-Sakarya, Y. (2021). Does learning to code influence cognitive skills of elementary school children? Findings from a randomized experiment. *British Journal of Educational Psychology*, *91*(4), 1434–1455.

Papert, S. A. (2020). *Mindstorms: Children, computers, and powerful ideas*. Basic Books.

Pellas, N. (2025). Enhancing computational thinking, Spatial reasoning, and executive function skills: The impact of tangible programming tools in early childhood and across different learner stages. *Journal of Educational Computing Research*, *63*(1), 3–32.

Peng, P., & Kievit, R. A. (2020). The development of academic achievement and cognitive abilities: A bidirectional perspective. *Child Development Perspectives*, *14*(1), 15–20.

Phamduy, P., Milne, C., Leou, M., & Porfiri, M. (2015). Interactive robotic fish: A tool for informal science learning and environmental awareness. *IEEE Robotics & Automation Magazine*, *22*(4), 90–95.

Piaget, J. (2013). *The construction of reality in the child*. Routledge.

Polat, E., & Yilmaz, R. M. (2022). Unplugged versus plugged-in: Examining basic programming achievement and computational thinking of 6th-grade students. *Education and Information Technologies*, *27*(7), 9145–9179.

Post, E. L. (1936). Finite combinatory processes—Formulation1. *The Journal of Symbolic Logic*, *1*(3), 103–105.

Rabbitt, P. (1997). *Methodology of frontal and executive function*. Psychology Press.

Razzouk, R., & Shute, V. (2012). What is design thinking and why is it important?. *Review of Educational Research*, *82*(3), 330–348.

Saygıner, Ş., & Tüzün, H. (2025). Investigation of the effects of unplugged coding activities developed for preschool on motivation, computational thinking and problem-solving skills. *Education and Information Technologies*, *30*(18), 26569–26597.

Scherer, R., Siddiq, F., & Sánchez Viveros, B. (2019). The cognitive benefits of learning computer programming: A meta-analysis of transfer effects. *Journal of Educational Psychology*, *111*(5), 764.

Scherer, R., Siddiq, F., & Viveros, B. S. (2020). A meta-analysis of teaching and learning computer programming: Effective instructional approaches and conditions. *Computers in Human Behavior*, *109*, 106349.

Serpell, Z. N., & Esposito, A. G. (2016). Development of executive functions: Implications for educational policy and practice. *Policy Insights from the Behavioral and Brain Sciences*, *3*(2), 203–210.

Shute, V. J., Masduki, I., & Donmez, O. (2010). Conceptual framework for modeling, assessing and supporting competencies within game environments. *Technology, Instruction, Cognition & Learning*, *8*(2).

Shute, V. J., Sun, C., & Asbell-Clarke, J. (2017). Demystifying computational thinking. *Educational Research Review*, *22*, 142–158.

Somuncu, B., & Aslan, D. (2022). Effect of coding activities on preschool children's mathematical reasoning skills. *Education and Information Technologies*, *27*(1), 877–890.

Stroop, J. R. (1935). Studies of interference in serial verbal reactions. *Journal of Experimental Psychology*, *18*(6), Article 643.

Stucke, N. J., & Doebel, S. (2024). Early childhood executive function predicts concurrent and later social and behavioral outcomes: A review and meta-analysis. *Psychological Bulletin*, *150*(10), Article 1178.

Thompson, J., & Childers, G. (2021). The impact of learning to code on elementary students' writing skills. *Computers & Education*, *175Trace*, Article 104336.

Tsarava, K., Moeller, Korbinian., Pinkwart, N., Butz, M., Trautwein, U., & Ninaus, M. (2017). Training computational thinking: Game-based unplugged and plugged-in activities in primary school. *European Conference on Games Based Learning*, 687–695.

Turing, A. M., & others. (1936). On computable numbers, with an application to the Entscheidungsproblem. *J. of Math*, *58*(345-363), 5.

Uttal, D. H., Meadow, N. G., Tipton, E., Hand, L. L., Alden, A. R., Warren, C., & Newcombe, N. S. (2013). The malleability of spatial skills: A meta-analysis of training studies. *Psychological Bulletin*, *139*(2), Article 352.

Vandenberg, S. G., & Kuse, A. R. (1978). Mental rotations, a group test of three-dimensional spatial visualization. *Perceptual and Motor Skills*, *47*(2), 599–604.

Wai, J., Lubinski, D., & Benbow, C. P. (2009). Spatial ability for STEM domains: Aligning over 50 years of cumulative psychological knowledge solidifies its importance. *Journal of Educational Psychology*, *101*(4), Article 817.

Weigend, M., Vaníček, J., Pluhár, Z., & Pesek, I. (2019). Computational thinking education through creative unplugged activities. *Olympiads in Informatics*, *13*, 171–192.

Wing, J. (2011). Research notebook: Computational thinking—What and why. *The Link Magazine*, *6*(1), 20–23.

Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, *49*(3), 33–35.

Wohl, B., Porter, B., & Clinch, S. (2015). Teaching Computer Science to 5-7 year-olds: An initial study with Scratch, Cubelets and unplugged computing. *Proceedings of the Workshop in Primary and Secondary Computing Education*, 55–60.

Yntema, D. B. (1963). Keeping track of several things at once. *Human Factors*, *5*(1), 7–17.

Zurnacı, B., & Turan, Z. (2024). Educational robotics or unplugged coding activities in kindergartens?: Comparison of the effects on pre-school children's computational thinking and executive function skills. *Thinking Skills and Creativity*, *53*, Article 101576.

Zhang, X., Chen, Y., Hu, L., Hwang, G. J., & Tu, Y. F. (2025). Developing preschool children's computational thinking and executive functions: Unplugged vs. robot programming activities. *International Journal of STEM Education*, *12*(1), Article 10.