Playing with robots to understand computational thinking in children's cognitive development

Anaclara Gerosa

Maestría en Ciencias Cognitivas
Facultad de Ciencias, Facultad de Ingeniería, Facultad de Psicología
Universidad de la República

Montevideo – Uruguay
Febrero de 2021

Playing with robots to understand computational thinking in children's cognitive development

Anaclara Gerosa

Tesis de Maestría presentada al Programa de Posgrado en Ciencias Cognitivas, Facultad de Ciencias de la Universidad de la República, como parte de los requisitos necesarios para la obtención del título de Magíster en Ciencias Cognitivas.

Director:
Prof. Agda. Dra. Alejandra Carboni

Codirector:
Prof. Agdo. Dr. Leonel Gomez-Sena

Director académico:
Prof. Agda. Dra. Alejandra Carboni

Montevideo – Uruguay
Febrero de 2021

Gerosa, Anaclara

Playing with robots to understand computational thinking in children's cognitive development / Anaclara Gerosa. - Montevideo: Universidad de la República, Facultad de Ciencias, Facultad de Ingeniería, Facultad de Psicología, 2021.

XIII, 81 p.: il.; 29, 7cm.

Director:

Alejandra Carboni

Codirector:

Leonel Gomez-Sena

Director académico:

Alejandra Carboni

Tesis de Maestría – Universidad de la República, Programa en Ciencias Cognitivas, 2021.

Referencias bibliográficas: p. 44 – 63.

1. pensamiento computacional, 2. infancia, 3. robotica educativa, 4. desarrollo cognitivo. I. Carboni, Alejandra, *et al.* II. Universidad de la República, Programa de Posgrado en Ciencias Cognitivas. III. Título.

INTEGRANTES DEL TRIBUNAL DE DEFENSA DE TESIS

Ph.D. Prof. Juan Pablo Hourcade

Ph.D. Prof. Elena Pérez

Ph.D. Prof. Juan Carlos Valle Lisboa

Montevideo – Uruguay
Febrero de 2021

ABSTRACT

The term computational thinking (CT) has been used as an umbrella term in order to describe the processes underlying the learning and application of computer science concepts as strategies for problems solving. Despite a growing body of academic literature on the subject, an increasingly established positioning within educational policies and the development of a grand variety of tools designed to enhance computational thinking abilities, the relations between CT and other cognitive abilities in young children have been scarcely explored. In order to contribute to bridging this gap, we compared a previously reported computational thinking assessment with a battery of cognitive tests which included fluid intelligence, working memory, planning, sequencing, mental rotation, vocabulary and early math precursors such as numerical transcoding and symbolic magnitude comparison. Mixed linear regressions were implemented with CT as a dependent variable in order to explore the associations between our variables. Results suggest temporal sequencing ability and symbolic magnitude comparison are significant predictors of CT in preschoolers. Additionally, using a pre-test post-test experimental design with an active control group, we tested the efficacy of an educational robotics intervention with *RoboTito*, a robot designed for children which is programmable through the disposition of tangible objects in its environment. An eleven session intervention program using this robot was designed with the objective of creating playful learning instances were children would practice abilities associated with computational thinking. Data related to children's engagement and participation throughout the intervention was gathered from filmed material from each session. Results suggests children with high engagement levels achieved better CT scores after the intervention.

Keywords:
computational thinking, early childhood, educational robotics, cognitive development.

RESUMEN

El término pensamiento computacional (PC) ha sido utilizado para denominar los procesos que subyacen al aprendizaje y la aplicación de conceptos de las ciencias de la computación para la resolución de problemas. A pesar de una creciente producción de literatura académica y la adopción del término en el marco de políticas educativas tanto a nivel nacional como global, así como la extensa producción de dispositivos tecnológicos y juegos destinados a proveer esta habilidad, las asociaciones entre lo que se define como PC y otras habilidades cognitivas en niños pequeños ha sido escasamente explorada. Con el objetivo de disminuír esta brecha en la literatura, comparamos el desempeño de niños de 5 años de edad en un cuestionario de PC previamente utilizado en la literatura y una batería de tests de habilidades cognitivas que incluyó inteligencia fluída, memoria de trabajo, planificación, secuenciación, rotación mental, vocabulario y precusores de habilidades matemáticas tales como comparación de magnitudes simbólicas y transcodificación. Se utilizaron regresiones lineales con efectos mixtos donde se estableció PC como variable dependiente para explorar estas asociaciones. Los resultados sugieren que la habilidad de secuenciación temporal y comparación de magnitudes simbólicas son predictores significativos del desempeño en PC de los niños en edad preescolar. Adicionalmente, utilizamos un diseño de investigación experimental con medidas pre-test y post-test y grupo control activo para evaluar la eficacia de una intervención en robótica educativa con la herramienta *RoboTito*, un robot diseñado para niños pequeños programable a través de la disposición en el entorno de objetos tangibles. Se diseñó un programa de intervención de 11 sesiones en el cual los niños trabajaron con esta herramienta en formato lúdico a través de resolución de problemas estructurados y semi-estructurados. Se tomaron muestras de datos de los niveles de involucramiento y participación de los niños en el grupo experimental a través de la observación estructurada de material audiovisual de las sesiones. Estos resultados indican un aumento del desempeño en el cuestionario de PC de los niños que participaron del grupo

experimental con altos niveles de involucramiento.

Palabras claves:
pensamiento computacional, infancia, robotica educativa, desarrollo cognitivo.

List of Figures

List of Tables

Contents

Chapter 1

Introduction

Jeanette Wing's 2006 work on computational thinking (Wing, 2006)has been identified by several authors (Grover and Pea, 2013; Voogt et al., 2015; Zhong et al., 2016) as a crucial article in sparking scholars' interest in the construct of computational thinking (CT) within the educational setting. Fundamentally, Wing contributed to the conceptualization of CT as a universal skill therefore broadening the scope of the CT construct into classrooms everywhere. Wing's original definition of CT as a skill that involves "solving problems, designing systems, and understanding human behaviour, by drawing on the concepts fundamental to computer science" (Wing, 2006) and later as the "thought processes involved in formulating problems and their solutions so that the solutions are represented in a form that can be effectively carried out by an information-processing agent" (Cuny et al., 2010) have been highly effective in promoting CT as a useful and attractive idea for education. CT has been embraced in educational settings to describe the thought processes behind computer science and programming, gaining space within state curricula in several countries (Bocconi et al., 2016), the reasoning behind this being that the inclusion of these ideas within school curricula might increase children's problem solving skills and foster their interest in the computer sciences and STEM fields in general (Bocconi et al., 2016) Despite much interest, and even though CT's roots within early childhood education go back to the influential work of Papert (1980) under constructivist paradigms, CT remains an evolving concept (Shute et al., 2017). In a systematic literature review analyzing publication trends regarding the CT concept, Haseski et al. (2018) found a spike in academic publications during the last two decades. However, their findings suggest that while overall publications increased, the concept is still too broad in order to make significant contributions. Other authors have also expressed concern regarding the need for clear, operationalized definitions for research purposes (Grover and Pea, 2013; Zhong et al., 2016), referring to the state of the field as a "definitional confusion". The International Society for Technology in Education (ISTE) and the Computer Science Teacher Association (CSTA) proposed an operational definition which describes CT as a problem solving process that spans characteristics such as formulating problems algorithmically, logically organizing data, achieving representation through abstraction, automatization, procuring time and resource efficiency, and generalization. However, this definition specifically proposes that while CT includes the characteristics mentioned above, it is not limited to this process, therefore leaving the concept open-ended. (ISTE and CSTA, 2011).

Lowe and Brophy (2017) identified up to twenty five different constructs while reviewing computational thinking definitions. The authors ultimately reduce their findings to nine processes, including abstraction, decomposition, pattern recognition and generalization, algorithms, data, parallels, iteration, simulation and debugging, while other authors have aimed to simplify the concept by reducing it to one or a few of its most important elements. Such is the case of Aho (2012), who defines it as problem solving ability and using algorithms to represent its solutions, or Grover and Pea (2013), who prioritizes the process of abstraction as foundational to CT. Brennan and Resnick (2012) created a CT framework which is based around three main components: computational concepts (such as sequencing, loops or conditionals), computational practices (such as debugging or problem solving) and computational perspectives, which describe aspects such as cooperation and communication. Assessment and evaluation has been pointed out as one of the biggest challenges for research (Román-González et al., 2017; Shute et al., 2017). Sondakh (2018) reviewed studies on CT performed at university level and found that 60% of them did not implement any kind of evaluation of CT. Furthermore, for those who did evaluate CT, the methods implemented were highly heterogeneous and tended to put emphasis on different CT-related abilities.

Chapter 2

Theoretical background

2.1 Cognitive development in early childhood

Early childhood has been identified as a window of opportunity for both cognitive and socioemotional development (Britto et al., 2017). Environmental factors such as access to quality childcare and early childhood education during the first 5 years of life have shown to have positive long-term impacts on both an individual (Belsky, 2007; Vandell et al., 2010, 2016) and societal level (Heckman and Masterov, 2007; Magnuson and Duncan, 2016; Richter et al., 2017). During this stage in their development children experience an exponential improvement in their executive function (EF) skills supported structurally by the prefrontal cortex (Perone et al., 2018). EF refers to several top-down neurocognitive processes needed for regulating thoughts, emotions and goal-oriented behaviour (Blair, 2016; Diamond, 2013; Zelazo et al., 2016). Inhibitory control, working memory and cognitive flexibility are the three basic neurocognitive processes identified by Miyake et al. (2000) via factor analysis of adult performance as executive functions. Inhibitory control refers to the ability to effortfully control automatic responses and inhibit distracting stimuli in order to direct our attention. Working memory is defined as our capacity to maintain information "on-line" for the purpose of manipulation, while cognitive flexibility refers to our ability to shift attention between tasks, attributes or strategies (Miyake et al., 2000; Zelazo et al., 2016) and allows us to adjust our responses in the face of change. These basic executive functions (cognitive flexibility developing a bit later than the former two) have been proposed by Diamond (2016) as the basis for other complex cognitive skills such as planning, problem solving and reasoning. Reasoning has been defined as the process of drawing conclusions from premises, principles or evidence, using previous information to infer or deduct a new conclusion (Andrews, 2019). Meanwhile, problem solving is a broad term referring to the steps that allow moving from a given state to a desired outcome (Barbey and Barsalou, 2009). While both concepts certainly overlap, problem solving can be considered the practical goal-oriented counterpart to reasoning's abstraction. Both problem solving and reasoning have been equated with the concept of fluid intelligence (Diamond, 2013) as was theorized by Cattell (1963). The concept of intelligence has been a point of discussion in psychology throughout its history, however most classical definitions point out to some sort of problem solving capacity. Binet and Simon (1905) defined it as: "Judgment, otherwise called "good sense", "practical sense", "initiative", the faculty of adapting one's self to circumstances" while Wechsler (1944) conceptualized it as "the aggregate or global capacity of the individual to act purposefully, to think rationally, and to deal effectively with his environment". Piaget pointed out the adaptive nature of intelligence by arguing that "Intelligence is an adaptation... To say that intelligence is a particular instance of biological adaptation is thus to suppose that it is essentially an organization and that its function is to structure the universe just as the organism structures its immediate environment" (Piaget, 1963). Problem solving literature is often characterized based on the presented task (van de Vijver and Willemsen, 1993). Formal problem solving deals with closed deterministic environments which are context independent, while referring to informal problem solving has been equated to open probabilistic problems that are context dependent, thus having a higher ecological validity. Problem solving often requires planning, that is, the process of establishing a step-by-step guideline toward goal oriented action (Cohen et al., 1995). The act of planning puts emphasis on the fact that our problem solving methodology must not only be effective, but also resource-efficient and often requires keeping and manipulating online information (aka working memory).

2.2 Computing and computational thinking

What is computing? Some identify the earliest use of the word "computer" dating back to the 1600's (Oxford, 2007). The term originally referred to a person that performed calculations, only sometimes with the aid of machines. During the nineteen hundreds, the meaning of the word computer shifted from the person to the devices used to compute: the machines themselves. The human need to simplify tedious calculating processes (computational processes) derived in the invention of many machines used for specific computations. Mechanical aids for computing are, of course, much older than the term itself: artifacts such as the abacus have been used since antiquity (Ceruzzi et al., 2003). However, it wasn't until the nineteenth and twentieth century that we saw the exponential development of computing technology. Charles Babbage's "Analytical Engine", (considered the first general-purpose mechanical computer) certainly is a long way from today's electronic and digital computers, however their initial purpose of solving complex mathematical problems remains, as tasks such as storing and retrieving data, processing text, manipulating images and so on are accomplished through their translation to mathematical language. More specifically, english mathematician George Boole's theoretical contributions in what we know now as Boolean algebra would find applications in the field of electrical engineering through Claude Shannon's thesis: "A symbolic analysis and relay of switching circuits" (Shannon, 1938) in which he proved how switching circuits worked as a physical manifestation of the TRUE and FALSE variable values in Boolean logic (Nahin, 2017). But perhaps the most notable and most well-known contributions are those of Alan Turing, whose Turing Machine (Turing, 1936), an abstract device capable of simulating any given algorithm's logic in order to perform any kind of computation would create a blueprint for modern computers. Turing's ideas would prove essential to the cognitive revolution during the 1950's and 60's, with Cognitive Science emerging as an interdisciplinary field of study that drew on ideas from psychology, neuroscience, linguistics, philosophy, anthropology and computer science for the study of the mind (Bermúdez, 2014). The notion that computer science's approaches would be useful for other disciplines increased as CS curriculums became more prominent at the university level. Pfeiffer (1962) proposed the idea that computers were aids to thinking and allowed users to think about problems in a different way. Seymour Papert's foundational work on LOGO first introduced the idea that children might benefit from programming and computer science (Papert, 1980). Papert had famously worked with developmental psychologist Jean Piaget at the University of Geneva and extended his constructivist theory to what he called constructionism, holding that learning is increased by the child's engagement in constructing an entity (Papert and

Harel, 1991). Namely he called "computational thinking" the idea of computing as an intellectual tool for children that would grant them autonomy to manipulate and extend their applied knowledge. Jeanette Wing's 2006 work on CT marked the beginning of a renewed interest in CT within educational settings by stressing that CT could be a powerful problem-solving tool for everyone, not just computer scientists (Wing, 2006). Wing's article substantially moved forward the idea of integrating computer science and specifically computational thinking into the core curriculum. According to Wing: (CT) "will be a fundamental skill used by everyone in the world by the middle of the 21st century. By fundamental, I mean as fundamental as reading, writing and arithmetic" (Wing, 2017).

2.3 Components of computational thinking

Computational thinking, as conceptualized by Wing (2017, 2006) is a domain-general concept. Arguably, CT is an umbrella term for a variety of skills (Weintrop et al., 2014). Even though most authors agree on the links between CT and problem solving (Lowe and Brophy, 2017), several processes have been included under the term "computational thinking". In order to understand what this meant specifically within the context of early childhood education, we conducted a systematic search of empirical studies which assessed CT in children aged 3-6. We excluded editorials and reviews of literature. We opted to include conference proceedings papers given the amount of thematically relevant publications within that category. The search was performed with the terms "computational thinking", "early childhood"(and synonyms) and "assessment" (and synonyms) and restricting for the appropriate age range. Supplementary information regarding this systematic search can be found in appendix 1. Scopus, ScienceDirect and IEEE were the explored databases. Table 2.1 shows a summary of the components present in the most cited CT definitions from the reviewed publications.

Table 2.1: CT components in the most cited definitions on the reviewed publication

Barr and Stephenson (2011)	Brennan and Resnick (2012)	Grover and Pea (2013)	Dasgupta et al. (2017)	ISTE and CSTA (2011)	Shute et al. (2017)
Abstraction	Abstracting and modularising	Abstraction	Abstraction		Abstraction
Algorithms and procedures	Sequences	Algorithmic notions of flow control	Algorithms and procedures	Algorithmic thinking	Algorithms
Data collection, analysis and representation	Data	Symbol systems and representations	Data collection, analysis and representation	Data	
Problem decomposition		Structured problem decomposition	Problem Decomposition		Decomposition
Parallelisation	Parallelism	Iterative, recursive and parallel thinking	Parallelisation		
Testing and verification	Testing and debugging	Debugging and systematic error detection	Debugging/Troubleshooting		Debugging
Control structures	Conditionals and loops	Conditional logic			
Automation			Automation	Automation	
					Iteration
Simulation			Simulation		
	Events				
		Efficiency and performance constraint		Efficiency and effectiveness	
				Generalisation	Generalisation
			Pattern recognition		

2.3.1 Abstraction

Abstraction has been identified as CT's core element (Shute et al., 2017; Wing, 2008) and refers to the process of extracting general rules from specific cases, by creating or identifying categories. Furthermore, it allows us to use different representations to establish relations between said categories. Abstraction in computer science is undeniably linked to mathematical abstraction, which focuses on removing real world dependent elements in order to create general-application algorithms. Coolidge et al. (2012) proposed that the human ability to detect numerosity lies at the base of abstraction and overall symbolic thinking by arguing that number appreciation happens despite the stimuli's characteristics. Furthermore, this ability is present from early on (Ansari et al., 2005; Cantlon et al., 2006), with evidence from infants as young as 3 days old suggests they're able to perceive abstract numbers (Feigenson et al., 2004; Izard et al., 2009). Wing highlights abstraction as the essence of CT (Wing, 2008): "In working with layers of abstraction, we necessarily keep in mind the relationship between each pair of layers, be it defined via an abstraction function, a simulation relation, a transformation or a more general kind of mapping. We use these mappings in showing the observable equivalence between an abstract state machine and one of its possible refinements, in proving the correctness of an implementation with respect to a specification and in compiling a program written in a high-level language to more efficient machine code. And so the nuts and bolts in computational thinking are defining abstractions, working with multiple layers of abstraction and understanding the relationships among the different layers. Abstractions are the 'mental' tools of computing"

2.3.2 Decomposition

A recent review by Rich and collaborators (2018) on the learning trajectories of decomposition within CT shed light into the relevance of this component. Decomposition was framed as the ability to break down complex systems into simpler parts, and was identified by Selby Woolard (2013) as one of the terms with the highest levels of consensus within CT literature. Sternberg (1998) pointed out problem decomposition as one of the fundamental tools used towards problem solving, stating that problem decomposition could result in finding solution not only through simplification but also by allowing to analyze its parts thoroughly and systematically.

2.3.3 Sequencing

Sequencing involves putting objects or actions into a logical order (Zelazo et al., 1997). Piget (1969) found children below six years of age were unable to complete a story sequencing task, however, this has been challenged by literature showing evidence that children as young as two years old can understand short sequences of up to 3 elements (O'Connell and Gerard, 1985). Moreover, kindergarteners were found to be able to construct sequences but having a hard time discussing internal logic and cause-effects related to them (Brown and French, 1976). Children have also been found to be better at concrete sequencing for events they are familiar with, linking this ability to episodic memory (McColgan and McCormack, 2008). There is evidence that children's ability to process numerical order is related to maths achievement (Attout and Majerus, 2018; Attout et al., 2014; Lyons and Ansari, 2015; Lyons et al., 2014; Sasanguie and Vos, 2018), suggesting that these skills may play an important role in the development of numerical abilities. Kaufmann et al. (2009) found that the processing of both numerical and non-numerical order was supported by activation in the intraparietal sulcus (IPS) in FMRI studies, an area which has been consistently cited as being involved in numerical magnitude processing (Ansari et al., 2006a,b; Holloway and Ansari, 2010). In regards to non-numeric order-processing, previous research shows children are introduced to sequences of temporal events before formal education. Thus, it is argued that even very young children acquire mental representations of repeated sequences of events over multiple time scales during the early years (Fivush and Hamond, 1990). Friedman (1991; 2005) found that young children can judge which daily event comes next in a sequence, judging backwards from different reference points, which further supports the early acquisition of image based representations of familiar daily events, suggesting that even young children are able to spatially code the order of daily events in long-term memory, allowing them to construct spatialized mental models of daily event sequences (O'Connor, 2019).

2.3.4 Generalisation

Generalisation refers to the ability to transfer obtained solutions to similar situations, allowing for broader applicability (at School Working Group et al., 2012; Selby et al., 2014). The term generalisation is often grouped with abstraction, as both processes deal with reducing complexity. However, Angeli and Valanides (2020) emphasise the difference between both processes by stating that “while abstraction reduces complexity by hiding irrelevant detail, generalization reduces complexity by replacing multiple entities that perform similar functions with a single construct" (Thalheim, 1999). Meanwhile, Atmatzidou and Demetriadis (2016) suggest that while abstraction refers to the recognition of existing patterns, generalisation refers to the application process of those abstractions in different situations.

2.3.5 Evaluation and systematic testing

Evaluation has been proposed as the final step of computational thinking (Anderson, 2016). Evaluation and testing are necessary not only to ensure our system is accomplishing the required goals, but also to assess its efficiency (i.e reducing time or allow for a better use of the existing resources). This term is often grouped with the similar term “debugging” which is more specific to the context of programming and entails detecting and solving errors. Its origin notoriously dates to the 1940s in the use of electro-mechanical computers, when actual bugs would often be a problem and interfere with the machine's internal mechanics. Nowadays, a bug is defined as a program error causing inconsistencies between its behaviour and the programmer's expectations (Xu and Rajlich, 2004). Papert (1980) said about debugging that *"The question to ask about the program is not whether it is right or wrong, but if it is fixable"*. Evaluation is the process of detecting said errors in order to create systems which allow us to accomplish a desired outcome. Recent evidence using eye-tracking technology points to the level of systematicity when debugging being an indicator of individual performance while programming: Lin and collaborators 2015 showed that low performance students tended to debug aimlessly while high performance ones applied a logical structure to their debugging behavior, suggesting planning might be an important factor mediating this process. Moreover, debugging skills can be explicitly taught using flowcharts and exercises with erroneous programs (McCauley et al., 2008). In a study with elementary school children, (Wong and Jiang, 2018) showed debugging skills could be improved after applying a CT curriculum based on Scratch programming. Authors presented children with code which contained pre-set errors in order to ensure sufficient practice of this skill. Rich et al. (2019)

performed a systematic literature review on debugging skills learning studies in which participants were children from kindergarten through 8th grade (5 to 14 years of age) in order to determine learning trajectories for these skills. The authors extract five debugging strategies of incremental difficulty from the literature: iterative refinement by trial and error, using intermediate results, observing step-by-step execution, reproducing errors, and addressing compile errors in order. Evidence from young children suggests kindergarteners are able to implement the first of these strategies and often rely on trial and error to work towards their solutions (Fessakis et al., 2013; Flannery and Bers, 2013). However, the authors indicate these stages are not meant to be prescriptive, as evidence suggests with proper scaffolding children are able to improve their debugging strategies. Some authors have argued that the timing in teaching interventions might play an important role in children's learning. A recent case study analysis of robot programming in a preschool classroom showed the debugging process occurred both through teacher and children's initiatives, but teacher interventions should not occur too soon to provide enough time for children to reach a solution (Heikkilä and Mannila, 2018).

2.4 Computational thinking in education

2.4.1 CT in educational policy

Throughout the last decade, initiatives all over the world have been made in order to integrate CT in compulsory education. By 2021, computational thinking will be incorporated into the mathematical module of the standardized PISA assessment (Lorenceau et al., 2019). Two trends in rationales for this change were identified in a review on educational policies in Europe made by Bocconi et al. (2016): firstly, the addition of CT as a general problem-solving skill which will be beneficial to individuals in their transit through a world increasingly shaped by technology and media; secondly, the possibility for economic growth which stems from motivating children and adolescents into STEM or ICT related careers. In this study, England, Denmark, Finland, France, Italy, Croatia, Poland, Portugal and Turkey were identified as countries which went through a curriculum renewal to incorporate CT. Meanwhile, a recent study by So et al. (2020) focusing on CT curricula in the Asia-Pacific region pointed out Korea, Taiwan, Hong Kong and China as countries introducing curricular reforms towards the inclusion of computational thinking. In Latin America, Argentina passed in 2018 resolution CFE N°343/18, which established the prioritary thematic subjects for digital education, programming and robotics (CFE, 2018). Programming, computational thinking, algorithmic thinking and computer science were all included as fundamental competencies. Furthermore, the Ministry of Science, Technology and Innovation and the Sadosky Foundation carry out *Program.ar*, a program with the aim of supporting computer science in schools through professional development courses for teachers, science popularization, and the creation of pedagogical content to support classroom practices (Dapozo et al., 2017). In Mexico, the office of public education published in 2018 the framework for computational thinking in compulsory education (Cardenas Peralta, 2018) with the aim of creating a pedagogical guideline for teachers to introduce CT into classrooms. Similarly, Chile's Ministry of Education launched the national plan for digital languages in alliance with private institutions in order to provide teachers and educators with professional development opportunities in computational thinking and programming (Uscanga et al., 2019). Uruguay's computational thinking program started in 2017 through *Plan Ceibal* in coordination with the national administration of public education (ANEP) and as of 2019 has reached about 30.000 children attending 4th to 6th grade of primary school. In Ceibal's CT program, classroom teachers work collaboratively with remote teachers who support the lessons. Currently, most of the remote teachers belong to the Sadosky Foundation in Argentina. Additionally, Ceibal offers teachers from lower grades (kindergarten through 3rd) CT material elaborated by their technical team, which they may later adapt into their class plan. In 2019, 1300 teachers signed up for these instances. Furthermore, 49 schools take part in *Ceilab*, a program looking to introduce computational thinking through hands on manipulation of technology, sometimes referred to as the *maker movement.* (CEIBAL, 2019) In 2018, ANEP established an inter-institutional comission on CT, in which representatives from both public and private organizations currently working on CT for education come together to coordinate their efforts. In 2019, this comission carried out a national survey in order to assess the current state of CT practices in education in Uruguay (García, 2020).

2.4.2 CT activities for early childhood

2.4.2.1 Programming

Evidence suggests programming is the most frequent practice to introduce individuals to CT (Hsu et al., 2018). Several applications and graphical interfaces have been created in order to scaffold young children's learning of programming. Most of the existing tools aimed at young children use block-based programming, narratives and animations in order to help young children learn basic programming principles. For example, Code.org is a website lead by a non-profit organization with the aim of proving young learners (age 4 and older) with programming courses. Evidence from 4th grade children (Kalelioğlu, 2015) suggests teaching programming with the platform motivated students and fostered positive attitutes towards programming. Similarly, Kodable is a platform and curriculum for children in kindergarten through 5th grade and provides lesson plans aimed both for teachers and parents. Pila et al. (2019) tested both Kodable and a similar app, namely Daisy the Dinosaur, and found that 5 year old children could learn commands and improve their in-game sequencing skills. Similar apps are Lightbot Jr., a programming app with the aim to introduce children to sequencing, recursive loops, conditionals and other principles of computer programming and CT through a gameified environment; or Cargobot, a gameified puzzle-based app for elementary school children. Perhaps the most notorious block-based programming tool has been Scratch. In young learners, Scratch Jr. was designed for children aged 5 to 7 years old (Bers and Resnick, 2015; Flannery et al., 2013; Strawhacker et al., 2015) and has been successful in building a large community of users (Bers, 2018). Evidence from studies on kindergarten teachers suggests Scratch Jr. has positive effects on their self efficacy in programming as well as their understanding of computational constructs (Kalogiannakis and Papadakis, 2017). In children, studies showed Scratch Jr. was a motivating tool that was successful in allowing them to learn basic programming (Papadakis et al., 2016) as well as fostering perseverance and debugging skills (Sullivan and Bers, 2019). In a comprehensive review, Ching et al. (2018) point out that most apps and websites for early childhood function under the premise of sequencing movement of a given character through code elements signaling directions (forward, backward and turns) and most frequently address sequencing and looping.

2.4.2.2 Unplugged activities

Some authors have argued that CT could be taught independently from technology use, thus proposing learning computational thinking through unplugged activities. Mainly, Zapata-Ros (2019) argues that for young learners, beginning their introduction to CT concepts through unplugged methods facilitates children's association of the new concepts to their previous experiences. With these objectives in mind, the initiative CSUnplugged contains proposals for computer science and computational thinking activities that do not require technology use. These activities are targeted to children and adolescents ranging from 5 to 14 years of age and were developed by the University of Canterbury and supported by Google and Microsoft. Parallel efforts have been made in order to create CT boardgames capable of fostering these skills (Tsarava et al., 2018). So far, few comparative studies have been made on the impact of unplugged activities on children's computational thinking in early childhood. Recent studies performed in older children suggest not only is it possible to teach children CT concepts through unplugged activities (Brackmann et al., 2017) but that introducing unplugged activities before introducing technology might results in gains on students' motivation (del Olmo-Muñoz et al., 2020).

2.4.2.3 Robotics

Programmable robots have been proposed as a developmentally appropriate tool to introduce young children to CT. As physical objects, robots could allow preschool children to learn in a non-restrictive embodied way, supporting gross motor development (Bers, 2020). Moreover, budding evidence shows promising results as to their capabilities for promoting young children's CT and cognitive skills. Kazakoff et al. (2013) showed a 1 week robotics intervention could improve kindergarten children's sequencing scores, while Bers et al. (2019) concluded that children as young as 3 years old could grasp CT concepts via robotics. Studies with slightly older children (González and Muñoz-Repiso, 2018; Jung and Won, 2018; Papadakis et al., 2016) have reached similar conclusions. However, despite a wide variety of commercial and non-commercial robots and kits being available (Sapounidis and Demetriadis, 2016; Yu and Roque, 2019) only a handful of them have been used for research purposes in an applied setting. BeeBot (Stoeckelmayr et al., 2011) has been used in educational robotics interventios by several researchers (Angeli and Valanides, 2020;

Di Lieto et al., 2020; García-Valcárcel-Muñoz-Repiso and Caballero-González, 2019; González and Muñoz-Repiso, 2018), as well as LEGO (Bers et al., 2014; Cho and Lee, 2017; Kazakoff et al., 2013; Sullivan and Bers, 2013) and KIBO (Bers et al., 2019; Sullivan et al., 2017).

2.4.3 Assessment

In order to account for changes in a certain variable we need valid and reliable assessment methods that are tailored to its target population's developmental characteristics. Several authors (Grover and Pea, 2013; Román-González et al., 2017) have pointed out the lack of appropriate instruments for CT assessment, with diversity in CT definitions and the variability in the assessed constructs as one of its main challenges. Despite these, a number of attempts have been made in the last decade to operationalize and measure CT. Since 2018, CT was incorporated as an optional assessment module in the *International Computer and Information Literacy Study* (ICILS), a standardized test conducted by the International Association for the Evaluation of Educational Achievement (IEA), which targets children aged thirteen (between 8th and 9th grade of schooling). ICILS assesses CT through a digital platform which presents participants with a set of problems which are solved through conceptualizing and operationalizing solutions (Eickelmann, 2019; Fraillon et al., 2018). In a recent systematic review of CT evaluations, Tang et al. (2020) identified two broad categories in CT assessments: those which assessed direct cognitive manifestations (first-order), thus using assessments that are independent from implementation, and those which did require CT integration to perform a specific action (second-order), such as coding skills. Examples of first-order assessments of CT include the Bebras Tasks items (Chiazzese et al., 2019; Dagienė and Futschek, 2008; Lockwood and Mooney, 2018), the *Computational Thinking Test (CTt)* (González, 2015; Román-González et al., 2017) or Yune Tran's (2018) computational thinking assessment. Second-order assessments include data mining assessments such as Dr. Scratch (Moreno-León et al., 2015) or performance scores during robotics' tasks (Bers et al., 2014). Additionally, the authors further categorized the existing assessments into those tapping cognitive or non-cognitive processes in order to include testing which examined individual's perceptions on self efficacy or factors related to motivation or enjoyment. Similarly, Román-González et al. (2019) also created a classification of CT assessment tools. We provide a summary of its most significant categories below:

- **Diagnostic**: focus on cognitive skills, do not require previous knowledge in order to be applied
- **Summative**: focus on learning processes and thus depend on previous instruction
- **Iterative**: provide feedback on user's skills in order to enhance performance
- **Data mining**: automatically analyse code or user products in order to extrapolate performance (for a comprehensive review of these tools, see Alves et al. (2019))
- **Self-perception**: focus on socio-emotional components such as perception of sef efficacy, self-confidence and motivation

In their study, the authors performed correlation analyses on different types of assessments, namely, the Computational Thinking Test (González, 2015), a set of three Bebras Tasks (Chiazzese et al., 2019) and Dr. Scratch (Moreno-León et al., 2015) in two different samples (n=179 and n=71, respectively) of middle school students. Their results showed partial convergence of the assessment through significant, positive and moderate correlations. Thus, they argued for using multiple assessment in order to obtain a holistic measure of individual's CT based on Brennan and Resnick's (2012) framework: concepts (better assessed through diagnostic or summative tools), practices (iterative and data-mining tools) and perspectives (self-perception tools). If we focus especially on assessments used in early childhood interventions, new testing challenges arise that stem from the nature of the target population we are working with. Several authors working in the field of early childhood have argued for the creation of developmentally appropriate assessment tools that are capable of accurately and reliably evaluate CT in this age span (Relkin and Bers, 2019; Zapata-Cáceres et al., 2020). Despite budding research in this field, most of the evaluation performed in educational interventions for computational thinking in early childhood shows a widespread use of ad-hoc tools (Angeli and Valanides, 2020; Bers et al., 2019; González and Muñoz-Repiso, 2018; Saxena et al., 2020), which hinder the possibility of comparison across studies (Ioannou and Makridou, 2018).

2.4.4 CT and cognitive development

During the 1980's, there was a surge in research exploring the cognitive underpinnings of programming abilities as well as transfer opportunities within domains. In a study involving high school students (15-18 years old), Kurland et al. (1986) found positive correlations between programming skills and reasoning and math abilities, while Pea et al. (1987) linked debugging to metacognitive skills and executive functioning, which was supported by findings by Clements and collaborators (1986; 1984) in regards to young children programming with LOGO. Recently, a meta-analysis of 105 studies performed by Scherer et al. (2019) found evidence for moderate overall transfer effect and strong near transfer effects of programming skills to situations that require creative thinking, mathematics ability and meta-cognitive skills. Studies by Di Lieto et al. (2020) in kindergarteners found improvements on executive function, specifically working memory and inhibition, after an intensive educational robotics intervention with a randomized control trial study design. However, as mentioned in previous sections, recent literature has conceptualized CT as a skill which surpasses programming and refers to a general problem-solving ability (Grover and Pea, 2013; Shute et al., 2017; Voogt et al., 2015; Wing, 2006, 2008), and thus, particularly in the last decade researchers have focused on this concept. Given its widespread use in educational settings, there is a need to better comprehend this concept through exploring its associations with cognitive, socio-emotional and context-related variables. In regards to the former, CT has been previously linked with measures of general intelligence (Ambrosio et al., 2014; Boom et al., 2018), reasoning ability (Boucinha et al., 2019; Guggemos, 2020; Román-González et al., 2017; Tsarava et al., 2019) including mental rotation (Vandenberg and Kuse, 1978) as well as math skills (Guggemos, 2020; Román-González et al., 2017; Tsarava et al., 2019) and executive functions (Gioia et al., 2015). Table 2.2 presents a summary of the total number and age of the studies' participants, assessment methods, target variables and general findings in the empirical studies which have specifically focused on exploring the existence of associations between CT and other cognitive abilities.

Table 2.2: Empirical studies presenting associations between CT and other cognitive skills

Study	N	Target age	CT assessment	Other cognitive assessments	Findings
Città et al. (2019)	92	6-10	Ad-hoc pencil and paper test based on chess problems	Mental rotation test (Vandenberg and Kuse, 1978)	Moderate positive correlations between mental rotation scores and CT scores for younger children aged 6-7 (0.33, p=0.035) and marginal for older children aged 8-10 (0.27, p=0.058).
Tsarava et al. (2019)	31	7-10	CTt (Román-González et al., 2017)	Arithmetic (Haffner, 2005) Visuospatial reasoning (Weiß, 2006) Verbal reasoning (Heller and Perleth, 2000)	Moderate correlations with arithmetic abilities, specifically multiplication (r= 0.42; p=0.02) and problem completion (r= 0.40; p=0.03).
Román-González et al. (2017)	56	10-16	CTt (Román-González et al., 2017)	Spatial, verbal, reasoning and numerical factors (TEA, 1997) Problem solving (Seisdedos, 2002)	Positive correlations between CT and problem solving (r=0.67; p<0.01), as well as the verbal (r=0.27; p<0.01), spatial (r=0.43; p<0.01) and reasoning subscales (r=0.44; p<0.01) of the PMA battery. Linear regression showed only spatial and reasoning subscales significantly predicted CT outcomes (Models' adj. R^2=0.27).
Robertson et al. (2020)	25	11-12	Dr Scratch (Moreno-León et al., 2015) in two ad-hoc programming tasks	Executive functions (Gioia et al., 2015)	Lower BRIEF scores (better executive function) moderately correlate with higher scores in both creative programming (r=-0.6) and debugging (r=-0.4)
Boucinha et al. (2019)	50	12-15	CTt (Román-González et al., 2017)	Reasoning (Lemos et al., 2006)	Positive correlation between CT and reasoning (r=0.69)
Guggemos (2020)	202	17-18	CTt (Román-González et al., 2017)	Reasoning (Heydasch et al., 2013) Math skills Language skills (self-reported last grades)	Both reasoning (β =0.30, p<0.001) and math skills (β =0.13, p<0.001) were significant predictors of baseline CT, while language skills resulted non-significant
Ambrosio et al. (2014)	11	18-29	Final exam results and final grade in programming course	General intelligence (Pichot, 1949) Spatial reasoning (Almeida et al., 1997) Aptitude test (Hunter, 1983)	Larger effect sizes for CT correlations with spatial reasoning and general intelligence
Boom et al. (2018)	71	23 (mean)	Bebras tasks	Fluid intelligence (Brown et al., 1997)	Positive correlation between TONI-3 scores and Bebras tasks' scores (r=0.53; p<0.01)

Examining results from table 2.2 leads to two relevant conclusions: firstly, that empirical studies which specifically target the concept of CT from the perspective of cognitive development are still scarce; and secondly, that so far no study of this kind has been conducted in young children.

2.5 Research questions

Taking the former into account, the present study was undertaken with the following research questions:

- RQ1: Which cognitive abilities are associated with CT assessment outcomes in early childhood?
- RQ2: Could an educational robotics intervention affect children´s performance on CT?

Chapter 3

Methodology

3.1 Participants

102 Uruguayan children (male=52; overall mean age=68 months, standard deviation=5.08) attending level 5 (kindergarten) at a public school in Montevideo were invited to participate in the study. Convenience sampling was implemented. Sociocultural levels for our sample were characterized as Q5 (highest SES classification) by ANEP. Inclusion criteria consisted of children aged 4-6 years with typical development. 1 child was excluded from our sample due to having a diagnosed developmental disorder. Parents were asked to complete a brief questionnaire reporting their perceptions on technology and their children's use of technology at home. A total of 83 parents (male=22) agreed to complete this questionnaire (84% of our sample).

3.2 Ethical considerations

All of the procedures involved followed the ethical principles for human research established by Uruguayan national decree CM/515 and adhere to the United Nations conventions for the rights of the child (Assembly, 1989). Collected data is anonymous and confidential. Parents of children who were invited to take part in the present study received a letter with information regarding the study's objectives and procedures, as well as data treatment and the required steps taken to ensure confidentiality. Parents were fully able to rescind consent to the present study if they chose to without having to provide explanations. Oral assent from children was requested before each testing session.

3.3 Research design

A correlational cross-sectional approach was used to answer RQ1. We assessed children with a battery of cognitive development tasks which are described in section 3.4.1 and adjusted a multiple linear regression model with CT as a dependent variable. An experimental design was implemented to answer RQ2. Children were randomly assigned to either our experimental condition (participating in an educational robotics intervention using a robot that is programmable through tangible objects) or control condition (participating in activities that included the same robot but being remotely controlled, thus excluding the programming requirements). Groups were matched in gender, mean age and their pre-test scores in our fluid intelligence task.

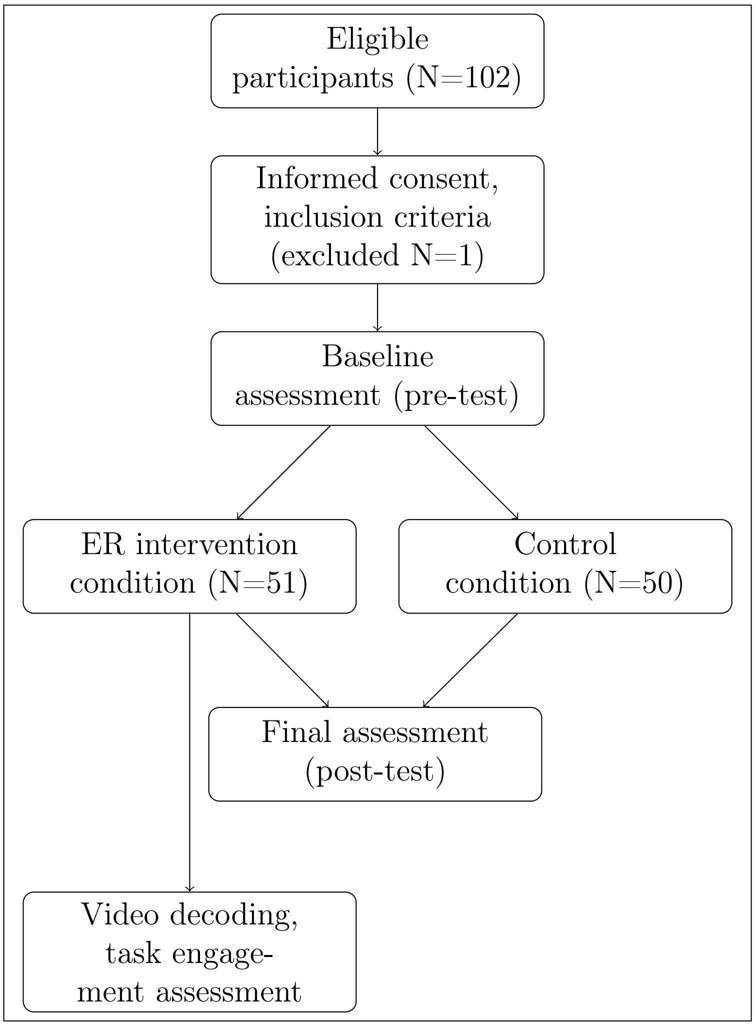


Figure 3.1: Research design

3.4 Materials

3.4.1 Assessment instruments (pre and post-test)

- **Computational thinking:** The CT assessment implemented in this study was adapted from Tran (2018) CT questionnaire for 7 year old children. This questionnaire assesses 5 CT-related abilities, namely ability to create algorithms, loops, debugging, inferring from a conditional statement and sequencing. Children's answers for each task were dummy coded for scoring (scoring range: 1-15). Scale reliability was acceptable (Cronbach's alpha: 0.72). Since CT is a theoretical umbrella term, we performed multiple correspondence analysis in order to detect possible underlying factors among our CT scale.
- **Fluid intelligence:**Raven's coloured progressive matrices (Raven and Court, 1986). This task asks children to identify the correct missing pattern from the stimuli in a 6 option multiple choice format. The test implements different kinds of problems which include pattern continuation and element abstraction.
- **Working memory:** tablet-based Corsi Block Tapping Test (Corsi, 1972) Children are tasked with repeating an incremental sequence by following the order it's been initially presented. Higher working memory spans correspond with children's ability to maintain online information for manipulation.
- **Planning:** tablet-based Tower of London task (Shallice, 1982). Two sets of coloured disks configurations are presented to children. One is a target setting, which they must try to emulate in their own setting by moving the disks in the least amount of possible steps.
- **Temporal sequencing:** We assessed children's ability to organize temporal sequences by using Langdon and Coltheart (1999) subset of mechanical stimuli. Children are tasked with organizing four picture sequences which denote temporal events.
- **Vocabulary:** PPVT-III (Peabody Picture Vocabulary Test by Dunn and Dunn (1997)) 36 item test which assesses children's receptive vocabulary by tasking them with matching a heard word with its corresponding image. Difficulty is incremental throughout the task.
- **Symbolic magnitude task:** Moyer and Landauer (1967). This task

requires children to select the highest of two arabic numbers presented on screen. Children are instructed to make the selection as fast as possible. This task quantifies children's mental representation of numerical magnitudes. Previous studies show the symbolic distance effect diminishes throughout development and is related to later math achievement (De Smedt et al., 2013; Holloway and Ansari, 2009).

- **Numerical transcoding:** This task evaluates children's ability to identify and report a herd number-word onto arabic symbols (Deloche and Seron, 1987).
- **Mental rotation:** (Quaiser-Pohl, 2003) During this test children are presented with either mirrored and rotated (incorrect) or rotated (correct) versions of a target image and tasked with identifying the correct option from three a three option setting.

3.4.2 Parent's report of home use of technology

Parents reported on their use of technology at home through a Spanish version of the Parental Perceptions of Technology Scale (Sanders et al., 2016) which explores parents self-efficacy and negative beliefs regarding technology use. Additionally, parents completed the Parent´s attitudes towards computer use scale (Mikelic Preradovic et al., 2016) which asked them to report on their perceived advantages of computer use for their children as well as technology-based activities at home.

3.4.3 Observation-based assessment of performance during the intervention

We assessed children's performance during the intervention activities through structured observation of 5 minutes per activity, which started counting once the activities' coordinator explained the task's objective for the first time during the session. The following variables were recorded:

- **ON-task time:** Defined as the total amount of seconds the child engages in either manipulating the robot or the intervention materials, answering the coordinator's inquiries, or pointing or directing his or her attention in a task-relevant way

- **Relevant interventions:** Defined as the total number of times the child participates orally during the task in ways that are relevant to solving it (whether his or her proposals lead to the correct solution or not)
- **Switches:** Defined as the total number of times the child switches between being ON-task to being OFF-task during the observation
- **Task-objective fulfillment:** Observers scored whether children could comprehend and solve the proposed task in a scale ranging from 2=Totally, 1=Partially, or 0=Not at all.

A total of 4 trained observers who did not participate of the intervention or previously knew the children collaborated in data extraction for each child of the experimental group during three tasks. Their records for each variable were averaged in order to reduce variability. Nonetheless, inter-observer reliability was high, ranging from 83% to 100% after training was concluded.

3.4.4 *RoboTito*

RoboTito was the robot used for the educational robotics intervention implemented. RoboTito was designed in the College of Engineering of the Universidad de la República, for the research project "Programming robots playing with the environment" (Funding: ANII FSED_2_2017_1_138793). Its design process took into consideration the need for a robot platform which was easily constructible, robust and user-centred (Gerosa et al., 2019). The robot is equipped with two kinds of sensors: colour and distance. While working with colour sensors, four possible colours (blue, red, green and yellow) were associated with directions (forward, left, backwards and right). When sensing a coloured card, the robot will move in the direction associated with that particular colour indefinitely until it senses a different card. The colour code associated with each direction is displayed using lights on its top LED ring so that children can infer the direction of movement depending on the selected coloured-card. While working with distance sensors the robot behaves in the following manner: (a) looks for the object that is the furthest within a predetermined range (60 cm), (b) moves towards that object and (c) goes back to condition (a). Graphic descriptions of its functioning in both sensor modes can bee seen in Figure 3.2

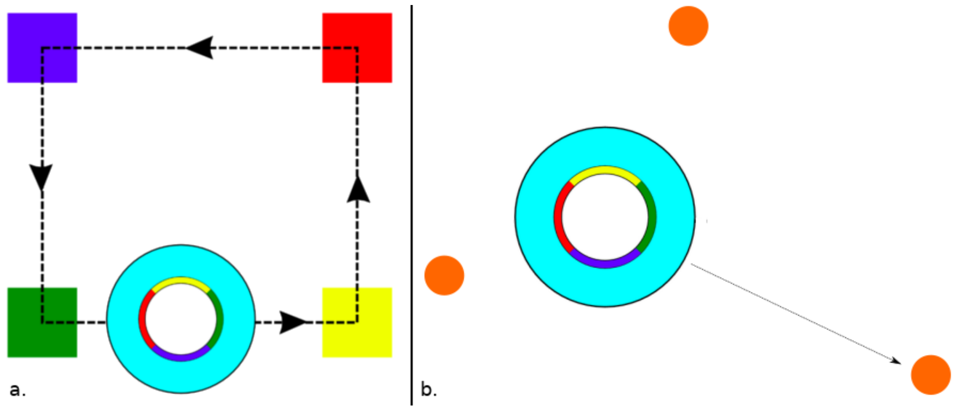


Figure 3.2: Robot behaviour according to active sensors: **a.** colour sensors mode **b.** distance sensors mode. Adapted from Bakała et al. (2019); Tejera et al. (2019)

Additionally, *RoboTito* has an android application which allows for the robot to be remotely controlled from a mobile device with WiFi connection. This function was used for control-group activities.

3.4.5 ER activities

The intervention was held in a public school in Montevideo, Uruguay. A total of four kindergarten classes (two during 2018 and two during 2019) participated in the study. Half of the children were allocated in the control group. The intervention's total duration was of 11 sessions lasting 25 minutes each. Each session was coordinated with the participating school with an average frequency of 1.5 sessions per week.

3.4.5.1 Experimental condition

Table 3.1 describes the content and progression for each activity in the experimental condition. We implemented an active control group, meaning children in this condition also participated in tasks which included the robot but did not incur in programming. Control group activities asked children to control the robot remotely using a tablet. In order to create a playful experience, the activities were presented through a story in which RoboTito was an alien from outer space looking to return to his home planet (our selected targets). This narrative was presented for both conditions.

Table 3.1: Intervention activities

N° of activity	Brief description
	Colour sensor
1	Introduction: children are familiarized with the robot and its parts. We establish the general rules of the workshop and explore the robot's basic functionalities
2	Introduction of simple objectives: children are introduced to spatial concepts such as backwards, forward, left and right. They program short trajectories and learn how to move the robot in a square loop
3	Simple planning: children use previously learnt rules to create sequences towards a pre-determined objective
4	Predicting behaviours: children are asked to observe a pre-established setting of the environment and explain the robot's sequence given those conditions. They propose alternatives to modify this trajectory
5	Sequencing and resource-efficiency: children are asked to generate sequences towards a given objective using the least amount of color-cards possible
6	Sequencing, resource-efficiency and distractor inhibition: we repeat the previous task incorporating distracting objects in the setting, which must be avoided
7	Debugging: Children are presented with an erroneous setting and asked to correct it to achieve a given objective
	Distance sensor
8	Exploratory activity of the distance sensors. Children are tasked to try to move the robot using their hands, while paying attention to what happens when we increase or decrease our distance
9	We try to infer the rules of functioning of the distance sensors and create tests to try to establish them
10	Children are introduced to the rules of the distance sensors. They are asked to imagine they are robots and perform the correct movements according to the learnt rules
11	Prediction with two rules and debugging: children are tasked to observe a given environment and predict the robot's movement. If the objective is not met, they are asked to create hypothesis regarding what actually happened

3.4.5.2 Control condition

Control activities involved children in sensory-motor games with the robot being remotely control trough a tablet device. Examples of control activities include using the controls to follow a pre-determined line, *Cat and Mouse* in which children were divided into teams (assigning one robot to each team) and one assumed the "cat" role (chaser) and the other the "mouse" role (chased), or *Robotic bowling*, in which light objects were piled up to create an obstacle which children took turns trying to tear down.

3.5 Data analysis

Statistical analysis was performed using R and R Studio software. (Team, 2019) For research question 1, Pearson correlations were performed in order to explore bivariate correlations among our variables. Mixed linear models (MLM) were implemented with CT as our dependent variable in order to create a model which accounts for the effects of our cognitive predictors to CT. Given the nature of the data collection process, it's important to clarify that no causal relation is assumed for the present analysis. We first fitted an MLR model which included all of our measured variables as fixed effects plus the random effect of classroom grouping. Model reduction was performed using backward step-wise deletion by the Akaike Information Criteria (AIC). ANOVA was used to test for significant differences between our initial and final models, if testing proved non significant, the simpler model was selected per the parsimony principle. For research question 2, mixed effects linear models were used for analysis. We included principal and interaction effects of time (pre and post test measures) and group (both experimental groups and control), fluid intelligence scores were used as a control variable, while random effects were composed of individuals nested within classrooms.

Chapter 4

Results

4.1 Descriptive statistics

Descriptive statistics for our sample are shown in Table 4.1. Experimental and control groups were matched in regards to age, gender and pre-test scores on fluid intelligence. Figure 4.1 presents CT scores' distribution for our entire sample.

	Control group (N=50)	Experimental group (N=51)	Overall (N=101)
Age			
Mean (SD)	68.8 (4.80)	67.8 (5.34)	68.3 (5.07)
Median [Min, Max]	69.0 [54.0, 76.0]	68.0 [55.0, 76.0]	68.5 [54.0, 76.0]
Missing	2 (4.0%)	3 (5.9%)	5 (5.0%)
Sex			
Boys	24 (48.0%)	28 (54.9%)	52 (51.5%)
Girls	26 (52.0%)	23 (45.1%)	49 (48.5%)
Fluid intelligence			
Mean (SD)	12.2 (5.92)	11.9 (5.86)	12.1 (5.86)
Median [Min, Max]	12.0 [0, 25.0]	12.0 [2.00, 26.0]	12.0 [0, 26.0]
Missing	5 (10.0%)	3 (5.9%)	8 (7.9%)
Class			
Classroom 1	12 (24.0%)	12 (23.5%)	24 (23.8%)
Classroom 2	14 (28.0%)	12 (23.5%)	26 (25.7%)
Classroom 3	12 (24.0%)	12 (23.5%)	24 (23.8%)
Classroom 4	12 (24.0%)	15 (29.4%)	27 (26.7%)

Table 4.1: Descriptive statistics.

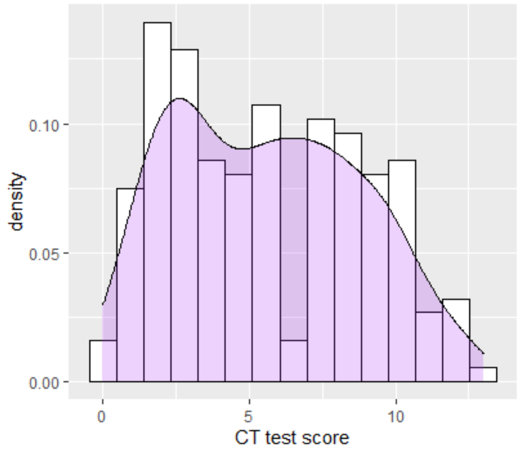


Figure 4.1: Density plot of CT assessment scores

4.2 Research question 1: Which cognitive abilities are associated with CT outcomes?

4.2.1 Correlation results

In this section we present our results in regards to the exploration of associations between the CT assessment implemented in the present study and our battery of cognitive assessments. Results from bivariate Pearson correlations between the explored variables and CT outcomes are summarised in 4.2. We found moderate positive associations between children's CT outcomes and their sequencing ability, $r(100) = 0.51$, $p < 0.001$; number comparison accuracy, $r(100) = 0.49$, $p<0.001$; numerical transcoding, $r(100) = 0.39$, $p < 0.001$ and fluid intelligence $r(100) = 0.36$, $p < 0.001$. Weak positive associations were also found with children's vocabulary, $r(100)= 0.23$, $p < 0.05$; working memory, $r(100) = 0.21$, $p < 0.05$; and planning abilities, $r(100) = 0.22$, $p < 0.05$. Associations between CT outcomes and children's accuracy in our mental rotation task and their age in months proved to be non significant. We then performed partial correlations controlling for children's fluid intelligence scores. Our results show that findings regarding the association to sequencing ability, working memory, vocabulary, number transcoding and comparison remain, while the association with planning doesn't. No significant associations were found between CT and children's frequency in technology use, parental technological self-efficacy or parental negative attitudes towards technology.

Table 4.2: Pearson correlations between CT and cognitive assessments, simple and controlled by fluid intelligence

Variable	CT (Simple)	CT (Controlled)
sequencing	0.51***	0.57***
working memory	0.21*	0.44*
mental rotation	0.10	0.00
vocabulary	0.23*	0.64***
num. transcoding	0.39***	0.51***
num. comparison	0.49***	0.45*
planning	0.22*	0.33
age (months)	0.16	0.01

4.2.2 Mixed effects linear model

Data was fitted into a mixed effects linear regression with CT as our dependent variable. First, we created Model 0 by including every assessed variable. Model reduction was performed using backward stepwise deletion by the Akaike Information Criteria (AIC). ANOVA results between our model 0 and our final model proved not to be statistically significant (DF=10, Chisquare=8.25, p=0.6), therefore, our simplified model was selected per the parsimony principle. 2 Our final model results are shown in Table 4.3. Model diagnostics can be seen in figure 4.2.

	scale(CT)		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.00	-0.29 – 0.29	0.998
Sequencing	0.40	0.23 – 0.57	**<0.001**
Num.comp	0.26	0.09 – 0.44	**0.004**
Random Effects			
σ^2	0.61		
$\tau_{00\ class}$	0.06		
ICC	0.09		
N_{class}	4		
Observations	101		
Marginal R^2 / Conditional R^2	0.313 / 0.378		

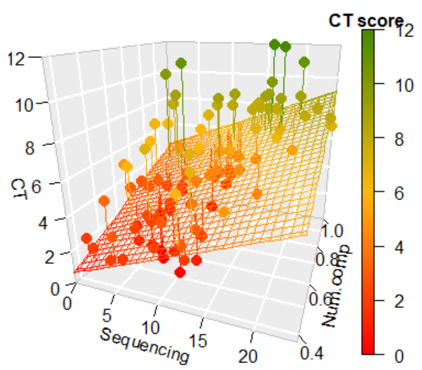


Table 4.3: Final model results and visualization of associations between fixed effects.

As shown in Table 4.3, our temporal sequencing and number comparison tasks are significant predictors of CT. The standardized coefficients of the model are β(Sequencing)=0.40 and β(Num.com)=0.26. Conditional R^2 for our model was 0.37, meaning our resulting model was capable of explaining 37% of our CT test scores' variance. Model assumptions of normality and variance homogeneity were assessed with satisfactory results, (see figure 4.2). Possible multicollinearity was assessed via the variance inflation factor (VIF) obtaining scores below 1.2 for both independent variables, suggesting only low intercorrelation.

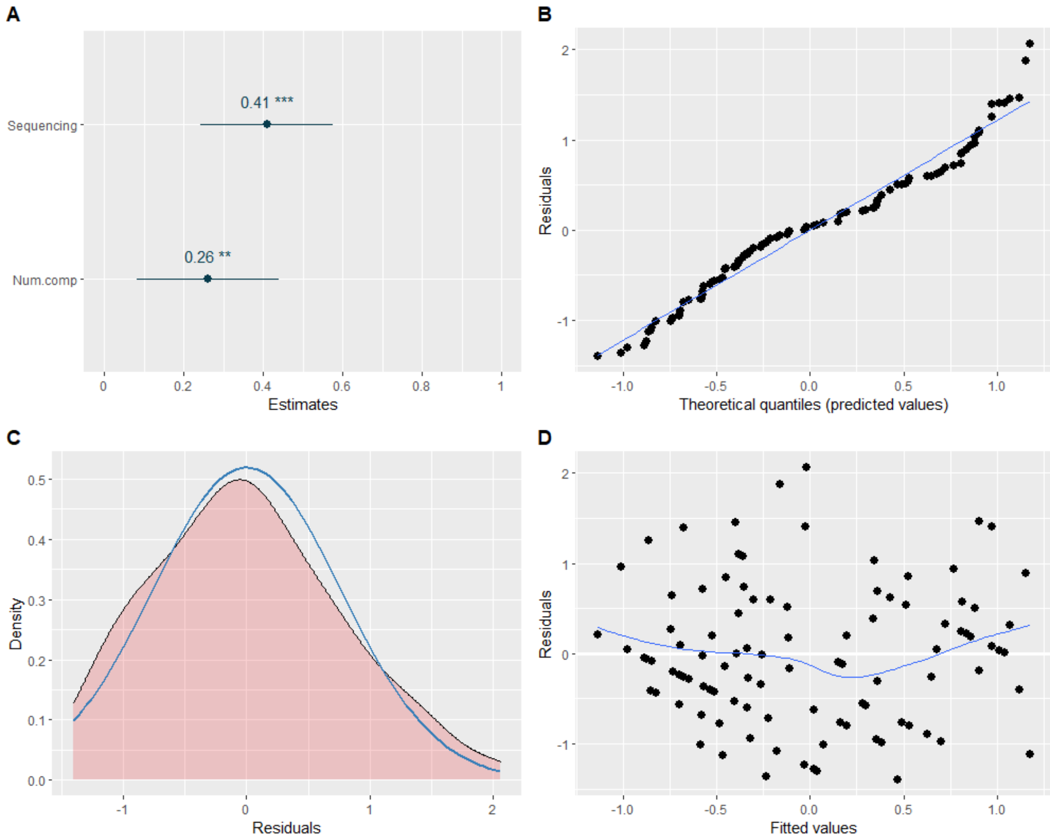


Figure 4.2: A. Fixed-effects estimates. B. QQplot for model 1. C. Normality of residuals (Shapiro-Wilke test W = 0.98, p= 0.13). D. Homoscedasticity: Levene test F=2.11, p=0.14

4.2.3 Association between CT and ER task fulfillment

Additionally, we analyzed the scores of children in the experimental condition with video-recorded data and found a positive significant association between children's CT scores at pre-test and their ability to fulfill the required task objectives while working with the robot, $r(27) = 0.50$, $p<0.05$. Further correlation analysis for children's objective fulfillment in ER tasks and cognitive variables are shown in table 4.4, both simple and controlling for children's fluid intelligence.

Table 4.4: Pearson correlations between objective fulfillment in robotics tasks and cognitive assessments, simple and controlled by fluid intelligence

Variable	ER (Simple)	ER (Controlled)
CT	0.50*	0.55***
sequencing	0.23	0.10
working memory	0.58***	0.56***
mental rotation	0.30	0.23
vocabulary	0.50*	0.49*
num. transcoding	0.44*	0.34
num. comparison	0.48*	0.43*
planning	0.38	0.16
age (months)	0.36	0.40

4.3 Research question 2: Could an educational robotics intervention have an effect on CT outcomes?

In this section we will summarise the results obtained after the implementation of our 12-session educational robotics intervention with *RoboTito*. In subsection 4.3.1 we will present results stemming from the cognitive assessments performed pre and post-intervention, conducted on our overall sample (N=101).In section 4.3.2 we present results from observational assessments of children's task engagement during the intervention and analyse their effect on CT outcomes

4.3.1 Pre and post-test assessment outcomes

Table 4.5 presents pre-test and post-test results for our experimental and control groups. Mixed effects linear models were used in order to examine possible effects of the intervention. We included the variable of interest as the dependent variable and principal and interaction effects of time (pre and post test measures) and group (control and experimental), fluid intelligence scores were used as a control variable, while random effects were composed of individuals nested within classrooms. No significant interactions were found between time of testing and group.

Table 4.5: Summary of intervention results

	Control group		Experimental group		Interaction effect
Variable: Mean (SD)	Pre (N=50)	Post (N=50)	Pre (N=51)	Post (N=50)	P-value
Computational thinking	4.59 (2.87)	6.00 (2.87)	5.10 (3.17)	6.90 (3.22)	0.30
Sequencing	9.44 (5.97)	12.1 (6.63)	9.14 (6.09)	12.5 (5.73)	0.50
Mental rotation	0.40 (0.16)	0.42 (0.18)	0.39 (0.15)	0.43 (0.19)	0.18
Num. transcoding	0.40 (0.27)	0.48 (0.28)	0.38 (0.24)	0.43 (0.28)	0.56
Num. comparison	0.74 (0.18)	0.80 (0.17)	0.77 (0.18)	0.81 (0.15)	0.69
Planning	8.29 (3.61)	12.6 (3.27)	6.25 (4.29)	11.4 (3.74)	0.23
Working memory	3.10 (1.37)	3.76 (1.32)	2.97 (1.30)	3.80 (1.21)	0.38
Vocabulary	32.6 (6.40)	33.9 (5.24)	34.6 (8.16)	34.2 (6.86)	0.32

4.3.2 Task engagement outcomes

Task engagement outcomes for children in the experimental group were assessed using the categories described in subsection 3.4.3. Delta (Δ) CT scores were calculated for each child by subtracting baseline scores to their post-test outcomes. Figure 4.3 presents Spearman correlation results between Δ CT scores and children's mean time spent *ON*-task, mean number of switches between *ON*-task and *OFF*-task status, mean number of meaningful interventions and mean objective fulfillment scores. Positive and significant correlations were found between children's Δ CT scores and their mean time spent *ON*-task (rs(26) = .51, $p < .05$) and their mean number of relevant interventions during task (rs(26)= .47, $p < 0.05$). A negative non-significant association was found with the number of switches between the *ON* and *OFF* task status (rs(26) = -.28, p = ns), while a positive non-significant association was found with objective fulfillment (rs(26) = .38, p = ns).

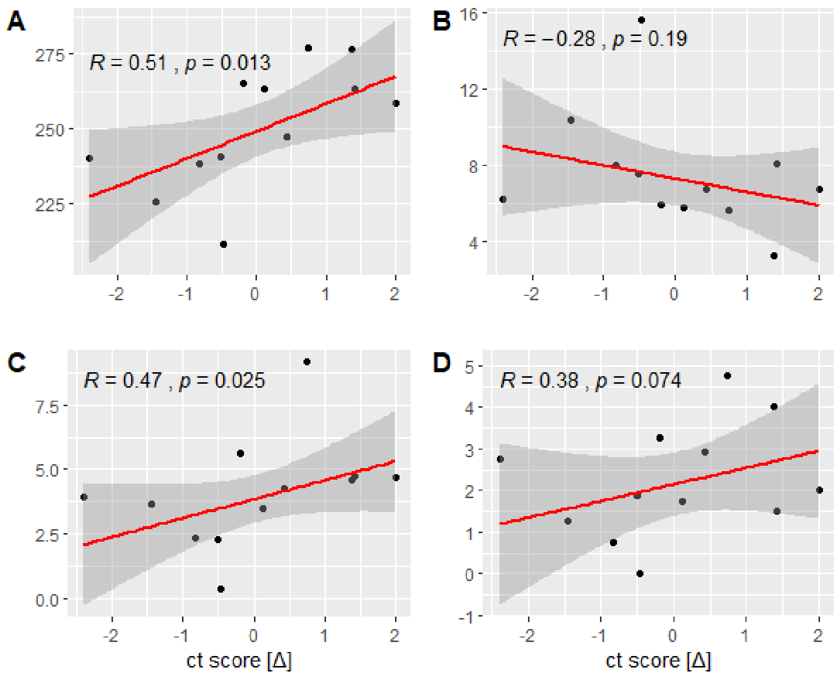


Figure 4.3: Spearman correlations between CT Δ scores and observable engagement variables. **A.** Mean on-task time as a function of CT Δ score. **B.**Mean number of switches during tasks as a function of CT Δ score. **C.** Mean number of meaningful interventions during task as a function of CT Δ score. **D.** Observed ER task objective fulfillment score as a function of CT Δ score

In order to contrast whether our task engagement variables (specifically, time spent ON task, participation, and switching) were factors capable of modulating intervention effects, we divided children in our experimental group into high and low engagement groups. Each variable was thus discretized into two separate factor levels using the median. Fluid intelligence used as a control variable in order to prevent a confounding effect. Figure 4.4 presents pre-test and post-test CT outcomes as a function of grouping for task engagement, participation and number of switches during task. ANOVA on our mixed effects linear models showed significant group*measure interactions in task engagement F(2)=4,25; p<0.05; post-hoc Tukey contrasts revealed non-significant pre-test to post-test gains for the control (p=0.92) and low engagement (p=0.99) groups, and significant for the high engagement group (p<0.01). Participation, switching and objective fulfillment did no present statistically significant effects. Post-hoc analysis are presented in Table 4.6

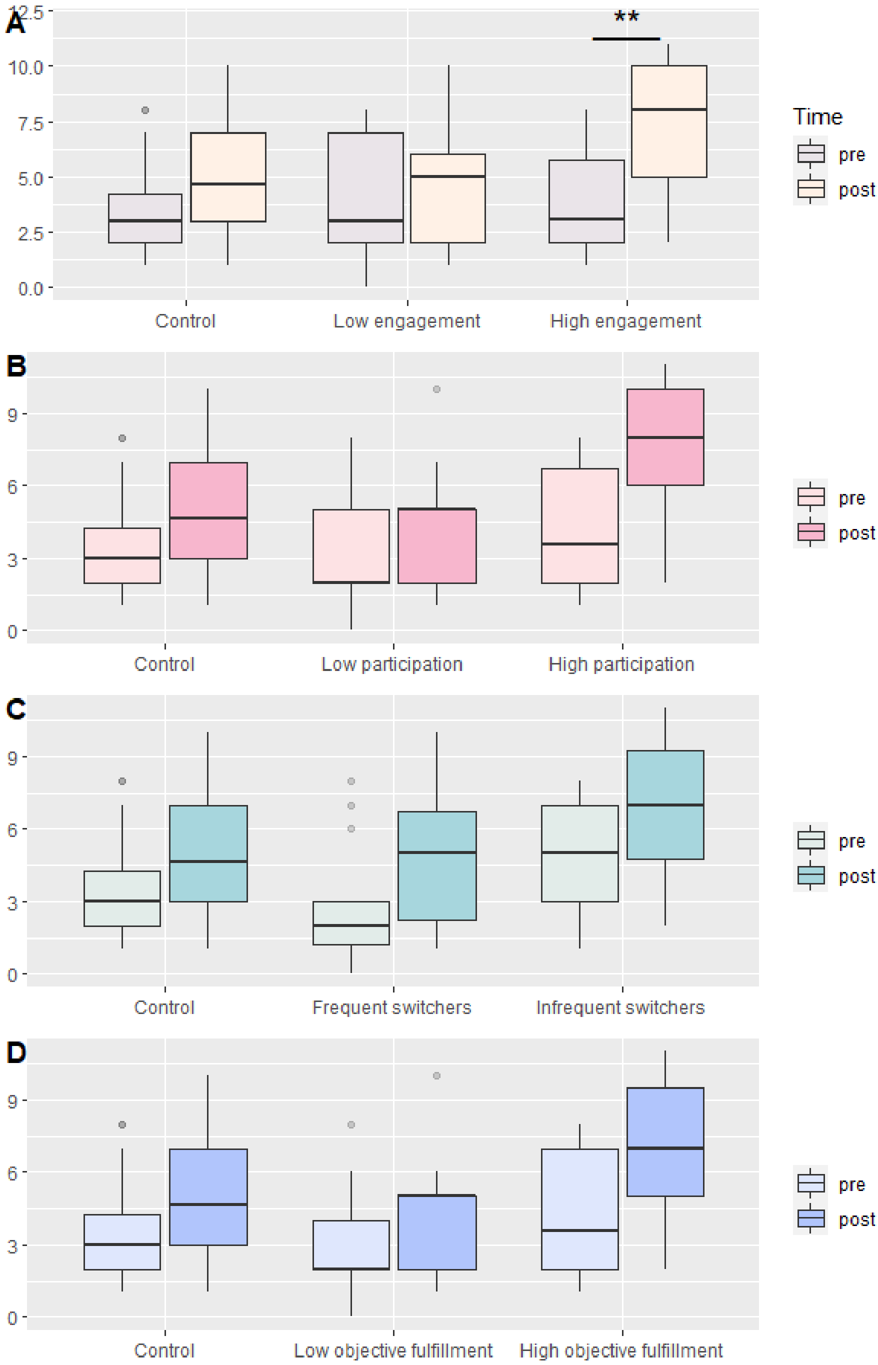


Figure 4.4: CT scores for each group condition and time of assessment (pre-test or post-test). **A.**Mean CT scores as a function of task engagement condition: high engagement (n=14), low engagement(n=13) or control (n=24) groups**B.**Mean CT scores as a function of participation during task condition: high participation (n=14), low participation(n=13) or control (n=24) groups **C.** Mean CT scores as a function of number of switches between on/off status during task: infrequent switching (n=13), frequent switching (n=14) and control (n=24) groups. **D.** Mean CT scores as a function of objective fulfillment: low (n=11), high (n=16) and control (n=24) groups

Table 4.6: Results from engagement variables' effect on CT. Within-group post-hoc contrasts

Variable	Pre:Post Contrast	Estimate	SE	df	t ratio	p value
Time ON task	Control	-0.66	0.67	55	-0.98	0.92
	Low engagement	0.22	0.90	52	0.24	0.99
	High engagement	-3.17	0.86	50	-3.67	0.00**
Number of interventions	Control	-0.75	0.70	54	-1.07	0.89
	Low participation	-0.60	0.93	50	-0.64	0.98
	High participation	-2.52	0.90	50	-2.78	0.07 ·
Number of ON/OFF switches	Control	-0.74	0.72	54	-1.03	0.90
	Frequent switchers	-1.51	0.92	51	-1.64	0.57
	Infrequent switchers	-1.64	0.96	50	-1.70	0.53
Objective fulfillment	Control	-0.72	0.70	47	-1.02	0.90
	Low obj. fulfillment	-0.53	1.02	50	-0.52	0.99
	High obj. fulfillment	-2.27	0.85	50	-2.67	0.09 ·

Chapter 5

Discussion

5.1 Computational thinking's association with cognitive outcomes

The present study aimed to contribute to the current evidence on young children's computational thinking skills by providing empirical evidence of its association with other cognitive abilities at an early age. Our results point to sequencing and the ability to compare symbolic numerical magnitudes as significant predictors of CT. A mixed effects linear model composed of these variables was able to explain 37% of our dependent variable. Previous evidence on mathematical cognition has consistently found a strong association between performance on symbolic magnitude comparison tasks and mathematics achievement (Ashcraft and Moore, 2012; Butterworth, 2011; Fazio et al., 2014; Siegler and Booth, 2004; Siegler and Pyke, 2013; Siegler et al., 2011), while temporal sequencing skills relate to children's ability to understand causal events (Sanefuji and Haryu, 2018). Thus, our results align with the previous evidence presented by Tsarava et al. (2019) in slightly older children, and Guggemos (2020) in high schoolers, but contrasts with the results found by Román-González et al. (2017) in pre-teens, in which the numerical factor of the Primary Mental Abilities (PMA) assessment was not significantly correlated. Additionally, the lack of correlation between CT and mental rotation ability found in the present study does not corroborate the findings of Città et al. (2019). The heterogeneity between the existing evidence so far might be related to a diversity in assessment approaches. In this study, CT skills were assessed through a pencil and paper set of tasks and applied individually to each child. While most of the reported assessments covered similar theoretical constructs, such as creating algorithms, debugging, conditional statements, sequencing and loops, it is possible that there are differences in the emphasis and weight of each construct within the tests. Another possible explanation for this heterogeneity is that the studies are conducted with participants at varied stages in development, which could suggest that the underlying cognitive abilities required for CT might change throughout children's development. Further scientific inquiry on this subject should continue this line of research by not only replicating and corroborating these results but also expanding on the explored variables. For example, the current study focused primarily on children's cognitive development, however certain definitions of CT such as the one proposed by the Computer Science Teachers Association (ISTE and CSTA, 2011) or the one by Brennan and Resnick (2012) propose CT is supported by computational perspectives or socio-emotional dispositions such as self-regulation, persistence and cooperation. To our knowledge, there have not been studies which explore the association between socio-emotional factors and CT skills in young children, while a few studies have been conducted in teenagers (Román-González et al., 2018). Social aspects of acquiring CT such as parental expectations or opinion on STEM subjects might also impact children's abilities. While the present study incorporated parent-report questionnaires which assessed parent's negative attitudes and self efficacy towards technology, as well as children's frequency of use of several devices, it was limited in the fact that the questionnaires conducted were focused on parents' experiences and not their expectations for their children. We did not find any significant associations between higher parental technological self-efficacy and children's CT, or between lower negative attitudes towards technology and higher CT. It would be desirable for further studies to focus specifically on children's attitudes towards STEM, as well as parent's STEM-related expectations towards their children and whether they promote their children's interest in these subjects through at-home activities. Budding evidence from teen participants suggests that environmental factors might play a key role in promoting CT, for example, Guggemos (2020) found that participant's parent's socioeconomic and cultural status, teen's computer use and past computer science instruction were significant predictors of their CT. To our knowledge, this is the first study focused on empirically exploring the associations between CT and other abilities in early childhood, and thus contributes in the establishment of

CT's nomological network at this stage of development. Our resulting mixed effects linear model proved adequate and benefited from more explanatory power in relation to similar models performed in previous studies (Román-González et al., 2017, 2018). Recent evidence by Guggemos (2020) in high schoolers suggests taking into account more context-related variables might improve the existing results, as a model taking into account variables such as parents' socio-economic and cultural status and migration status showed these factors as significant predictors in a model with adj. R2 of 0.70. However, it is important to acknowledge our approximation is limited in the fact that it explores CT as a general construct. Consequently, we adjusted our models using the overall score on the CT assessment as the dependent variable, following similar procedures to those conducted by Román-González et al. (2017). As was previously introduced in section 2.3 most authors define CT by breaking it down into multiple components. Nonetheless, while there is a wide variety of theoretical proposals for defining CT, few studies have provided empirical evidence of these taxonomies through factorial analyses. Overall, psychometric aspects of CT assessments are severely underreported and should be thoroughly examined in further studies. As a recent review by Haseski and Ilic (2019) reported, 23% of the reviewed studies did not report on the tests' factorial composition, while up to 59% failed to report reliability. Besides reporting on the associations between children's cognitive abilities and CT scores, this study presented results from an educational robotics (ER) intervention in which over 100 kindergarten children learnt playfully with *RoboTito*, a robot programmable through tangible elements. In the present study, we contrasted the results obtained with the CT assessment by providing a similar analysis using children´s performance on an educational robotics task (ER) as the dependent variable, as performance on ER tasks have been previously used as a proxy to CT assessment in young children (Angeli and Valanides, 2020; Bers et al., 2014; Saxena et al., 2020). Our findings yielded interesting results: firstly, as expected, both outcomes were significantly correlated. Additionally, both assessments were correlated to similar cognitive abilities, namely working memory, vocabulary, and symbolic magnitude comparison and transcoding. Since CT is often defined as a general problem solving ability, we presented results of both simple and partial correlations using fluid intelligence as a control variable in order to rule out this variable as a confounding for CT. We observed most of the reported associations strengthened when controlling for fluid intelligence scores, with the exception of planning, which became non-significant and would thus suggest the initial association was better explained by fluid intelligence. Interestingly, while sequencing presented significant associations with the CT test, it was not significantly associated with the ER tasks score. This result was unexpected, as previous evidence has linked ER training to gains in sequencing ability (Kazakoff et al., 2013) in young children. A possible explanation for this is that our sequencing test focused primarily on temporal sequencing. While the CT assessment implemented requires both temporal and spatial sequencing skills, our robotics tasks might require primarily the use of spatial sequences. While we were able to find a positive significant correlation between CT and children's ER performance, our ER assessment is limited in that it stems from the intervention sessions. While this could be considered a more ecological approach, it arguably lacks the controlled nature of an individually applied pre-test and post-test assessment. Additionally, observational methods could be considered susceptible to observers' intrinsic biases. We strived to reduce these factors by averaging observations by different trained observers and made sure inter-observer reliability was satisfactory. Overall, the present study contributed to understanding the concept of CT by studying its associations between previously described cognitive variables in preschoolers. Results suggest temporal sequencing and numerical skills are strongly associated with CT, even when controlling for several variables. Additionally, we found a significant correlation between children's CT test scores and their performance during ER tasks and showed both tasks were associated with similar cognitive abilities.

5.2 Effects of an educational robotics intervention on computational thinking

For our second research question, we were interested in finding out whether a controlled ER intervention using a robot programmable through its environment could have positive effects on young children's skills. In order to accomplish this, we used an experimental design with an active control group. Additionally, we conducted structured observation on filmed material from the ER sessions in order to account for context related variables, namely child engagement, distractibility, participation and task objective fulfillment. The ER activities implemented in the present study were based on previous literature regarding robotics interventions in early childhood (Bers et al., 2014; Ioannou and Makridou, 2018; Kazakoff et al., 2013; Sullivan et al., 2017; Sullivan and Bers, 2013), thus, the resulting intervention programme was based on mostly goal-oriented problems which were solved through the robots' spatial navigation and had a reduced number of possible solutions. Our results showed 5 year old children in the experimental condition who presented high engagement in the activities significantly increased their overall CT skills, while children with low engagement and children in the control condition did not. Thus, our results suggest that motivational and attentional factors such as children's engagement could modulate the benefits of ER on children's CT. However, the confounding nature of attention and motivation in a natural educational setting does not allow us to infer (through observation of filmed material) which of these processes is causing this effect. Hence, children who are highly motivated by ER will probably pay more attention to the tasks and tools, while children with better executive functioning development (thus more attentive) might have better cognitive resources to engage in the tasks. Further research should be conducted in order to control these variables: for example, this could be achieved by including questionnaires in order to account for children´s intrinsic motivation towards ER before the intervention. Generally, our results are aligned with previous evidence on the possibility of improving CT through ER at an early age and contributed to understanding how context-related factors might impact controlled interventions. Nonetheless, one of the major differences between this study and previous work is that CT was assessed through a questionnaire that was independent from the intervention tools. While most previous studies opted to rely on ER performance as a proxy to CT (Bers et al., 2019; González and Muñoz-Repiso, 2018; Roussou and Rangoussi, 2019; Saxena et al., 2020; Sullivan et al., 2017), it was important to us to be able to infer that any benefits would be indeed related to a cognitive skill rather than resulting from training in a specific task. It is noteworthy that the use of these methods is a strength of the present study, as much of the current evidence on ER interventions is often limited by the lack of control groups and quantitative assessments. In a recent review on empirical research on CT through robotics in early childhood by Bakala et al. (2021) found that only 26% of the reviewed studies reported the use of control groups and pre-test post-test designs. It is important to mention that a few of the previous empirical studies in ER to promote CT did include assessments that were independent from the intervention tools, such is the case of work by Nam et al. (2019), who used picture sequencing and mathematical problem solving tasks as proxies to CT, as well as Cho and Lee (2017) in which children were asked to self-report on their efficacy and interest in the subject. In the last year, diagnostic CT assessments which could be independently applied to young children have been developed and validated, thus, future studies should gradually incorporate these types of assessments (Relkin and Bers, 2019; Zapata-Cáceres et al., 2020). As previously discussed in section 5.1, a limiting factor of our ER assessment was that scores were extracted from structured observation of the natural ER learning setting. This is somewhat restricting, as filmed material lacks the flexibility of in-person assessment and the more controlled nature of individual evaluation. For example, temperamental factors or personality traits at play during group dynamics might have skewed the observer's ability to determine children's skills. Arguably, children who are more extroverted might have had more chances to showcase their skills than introverted children. Thus, further studies should consider adding a brief individual ER assessment through a structured task before and after the intervention in order to expand upon the current findings. A possible structure of tasks for the purpose of CT assessment through tangible materials has been proposed recently by Barnabé et al. (2020). Despite its limitations, the examination of context-related variables through structured observation of the experimental condition allowed us to shed light into some of the factors that could enhance or prevent the success of these types of interventions. Thus, our results highlight the importance of maintaining children's engagement and fostering their interest throughout the process. Further studies should examine how individual factors such as children's interest in robotics, as well as previous exposure to similar activities, could enhance their ability to succeed in these tasks. Furthermore, aspects such as scaffolding techniques, group size, child:adult ratio and other variables that could potentially impact proper engagement should be further examined in order to identify the best practices for maximizing positive results. So far, most of the existing data consists of case studies or small-scale research (Jung and Won, 2018). For example, a case study by Janka (2008) indicated introducing storytelling to their activities was an integral part of succeeding in promoting meaningful learning instances using educational robots. Additionally, the authors recommend small-groups with up to five children per teacher as the most adequate way to organize classrooms for effective learning. As to the amount and types of scaffolding received during tasks, a review by Atmatzidou et al. (2018) confirms that studies with strong levels of guidance generally obtain better results, while their own experimental data from 11-16 year olds showed groups which received more questions and prompts to help understand the problems, design and evaluate solutions throughout the tasks were more successful than those who were allowed to explore freely. Recent studies such as those performed by Angeli and Valanides (2020); Wang et al. (2021); Zhong and Si (2020) pose interesting questions and provide budding evidence on the way different scaffolding techniques impact children and teenagers' performance during robotics' tasks. All of the aforementioned variables are determinant to the feasibility and scalability of the ER interventions proposed. Thus, further evidence is required in order to identify best practices and extract guidelines that are useful for teachers interested in introducing ER and CT as classroom activities. Finally, the present study included a broad range of cognitive assessments in its pre-test and post-test evaluations. Interestingly, our results were specific to CT, as we did not find any significant impact of the intervention on either of the other cognitive assessments implemented. This is somewhat contradictory to previous evidence. For example, Kazakoff et al. (2013) found positive effects of ER on children's sequencing skills, as assessed through a picture sequencing task (Baron-Cohen et al., 1986) that is similar in nature to the one used in the present study. Recent evidence by Di Lieto et al. (2020) found a positive impact of an ER intervention on children's working memory as assessed through the Matrix Path Test, a task in which the child is asked to indicate in a matrix the final destination reached following a sequence of progressively longer steps read aloud by the examiner, but did not find any significant effects in working memory as assessed through Corsi Block Tapping (Corsi, 1972), which was the task used in the current study. These results could be interpreted as more cohesive to our own, as it could be argued that our CT assessment contains items (specifically 1-6) in which tasks require similar visuo-spatial working memory to maintain a sequence online to those of the Matrix Path test.

Chapter 6

Conclusion

Computational thinking is an emerging concept stemming from computer science that has been embraced by educators and policy makers and promoted by academia in order to transmit problem-solving strategies similar to those used in these disciplines. As such, it is imperative we acquire a better understanding of what this term means and which specific skills are at play during these kinds of tasks. The present study provided evidence on the association between a previously established CT questionnaire and various cognitive abilities in preschool aged children. Our results suggest computational thinking in early childhood was largely explained by participants' temporal sequencing skills and numerical abilities regarding their understanding of symbolic magnitude, further establishing the existing notions from previous evidence regarding CT's associations with reasoning and early math skills. Additionally, we tested the effects of an 11-session educational robotics' intervention using a robot programmable through tangible objects on children's CT outcomes. Using an experimental design with an active control group, we provided budding evidence for the positive effects of this particular intervention in children who were highly engaged throughout the activities. This finding could have important implications for practice, as it contributes to existing evidence on how motivational and attentional factors mediate effectiveness in targeted interventions.

Bibliography

Aho, A. V. (2012). Computation and computational thinking. *The Computer Journal*, 55(7):832–835.

Almeida, L. S., Antunes, A. M., Martins, T. B., and Primi, R. (1997). Bateria de provas de raciocínio (bpr-5): Apresentação e procedimentos na sua construção. In *Actas do I Congresso Luso-Espanhol de Psicologia da Educação*, pages 295–298.

Alves, N. D. C., Von Wangenheim, C. G., and Hauck, J. C. (2019). Approaches to assess computational thinking competences based on code analysis in k-12 education: A systematic mapping study. *Informatics in Education*, 18(1):17.

Ambrosio, A. P., Almeida, L. S., Macedo, J., and Franco, A. H. R. (2014). Exploring core cognitive skills of computational thinking.

Anderson, N. D. (2016). A call for computational thinking in undergraduate psychology. *Psychology Learning & Teaching*, 15(3):226–234.

Andrews, G. (2019). Reasoning and problem solving. *The Encyclopedia of Child and Adolescent Development*, pages 1–11.

Angeli, C. and Valanides, N. (2020). Developing young children's computational thinking with educational robotics: An interaction effect between gender and scaffolding strategy. *Computers in Human Behavior*, 105:105954.

Ansari, D., Dhital, B., and Siong, S. C. (2006a). Parametric effects of numerical distance on the intraparietal sulcus during passive viewing of rapid numerosity changes. *Brain research*, 1067(1):181–188.

Ansari, D., Fugelsang, J. A., Dhital, B., and Venkatraman, V. (2006b). Dissociating response conflict from numerical magnitude processing in the brain: an event-related fmri study. *Neuroimage*, 32(2):799–805.

Ansari, D., Garcia, N., Lucas, E., Hamon, K., and Dhital, B. (2005). Neural correlates of symbolic number processing in children and adults. *Neuroreport*, 16(16):1769–1773.

Ashcraft, M. H. and Moore, A. M. (2012). Cognitive processes of numerical estimation in children. *Journal of experimental child psychology*, 111(2):246–267.

Assembly, U. G. (1989). Convention on the rights of the child. *United Nations, Treaty Series*, 1577(3).

at School Working Group, C. et al. (2012). Computer science: A curriculum for schools. *Computing at School Working Group.*

Atmatzidou, S. and 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.

Atmatzidou, S., Demetriadis, S., and Nika, P. (2018). How does the degree of guidance support students' metacognitive and problem solving skills in educational robotics? *Journal of Science Education and Technology*, 27(1):70–85.

Attout, L. and Majerus, S. (2018). Serial order working memory and numerical ordinal processing share common processes and predict arithmetic abilities. *British Journal of Developmental Psychology*, 36(2):285–298.

Attout, L., Noël, M.-P., and Majerus, S. (2014). The relationship between working memory for serial order and numerical development: A longitudinal study. *Developmental psychology*, 50(6):1667.

Bakala, E., Gerosa, A., Hourcade, J., and Tejera, G. (2021). Preschool children, robots, and computational thinking: a systematic review. *Unpublished manuscript.*

Bakała, E., Visca, J., Tejera, G., Seré, A., Amorin, G., and Gómez-Sena, L. (2019). Designing child-robot interaction with robotito. In *2019 28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, pages 1–6. IEEE.

Barbey, A. and Barsalou, L. (2009). Reasoning and problem solving: models. *Encyclopedia of neuroscience*, 8:35–43.

Barnabé, S., Denet, L., Manrique, M., Menon, D., Pascual, É., Romero, M., and Viéville, T. (2020). *A low-cost tabletop game to collect learning analytics during computational thinking using unplugged or tangible activities*. PhD thesis, Inria.

Baron-Cohen, S., Leslie, A. M., and Frith, U. (1986). Mechanical, behavioural and intentional understanding of picture stories in autistic children. *British Journal of developmental psychology*, 4(2):113–125.

Barr, V. and Stephenson, C. (2011). Bringing computational thinking to k-12: what is involved and what is the role of the computer science education community? *Acm Inroads*, 2(1):48–54.

Belsky, J. (2007). Social-contextual determinants of parenting. *Encyclopedia on Early Childhood Development, Topic Ed; Tremblay, RE, Bolvin, M., Peters, RDV, Eds.*

Bermúdez, J. L. (2014). *Cognitive science: An introduction to the science of the mind*. Cambridge University Press.

Bers, M. U. (2018). Coding and computational thinking in early childhood: the impact of scratchjr in europe. *European Journal of STEM Education*, 3(3):8.

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

Bers, M. U., Flannery, L., Kazakoff, E. R., and Sullivan, A. (2014). Computational thinking and tinkering: Exploration of an early childhood robotics curriculum. *Computers & Education*, 72:145–157.

Bers, M. U., González-González, C., and Armas-Torres, M. B. (2019). Coding as a playground: Promoting positive learning experiences in childhood classrooms. *Computers & Education*, 138:130–145.

Bers, M. U. and Resnick, M. (2015). *The official ScratchJr book: Help your kids learn to code*. No Starch Press.

Binet, A. and Simon, T. (1905). Upon the necessity of establishing a scientific diagnosis of inferior states of intelligence. *L'Année psychologique*, 11:163–191.

Blair, C. (2016). Developmental science and executive function. *Current directions in psychological science*, 25(1):3–7.

Bocconi, S., Chioccariello, A., Dettori, G., Ferrari, A., Engelhardt, K., et al. (2016). Developing computational thinking in compulsory education-implications for policy and practice. Technical report, Joint Research Centre (Seville site).

Boom, K.-D., Bower, M., Arguel, A., Siemon, J., and Scholkmann, A. (2018). Relationship between computational thinking and a measure of intelligence as a general problem-solving ability. In *Proceedings of the 23rd Annual ACM Conference on Innovation and Technology in Computer Science Education*, pages 206–211.

Boucinha, R. M., Barone, D. A. C., Reichert, J. T., Brackmann, C. P., and Schneider, A. M. (2019). Relationship between the learning of computational thinking and the development of reasoning. *International Journal of Advanced Engineering Research and Science*, 6(6).

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

Brennan, K. and Resnick, M. (2012). New frameworks for studying and assessing the development of computational thinking. In *Proceedings of the 2012 annual meeting of the American educational research association, Vancouver, Canada*, volume 1, page 25.

Britto, P. R., Lye, S. J., Proulx, K., Yousafzai, A. K., Matthews, S. G., Vaivada, T., Perez-Escamilla, R., Rao, N., Ip, P., Fernald, L. C., et al. (2017). Nurturing care: promoting early childhood development. *The Lancet*, 389(10064):91–102.

Brown, A. L. and French, L. A. (1976). Construction and regeneration of logical sequences using causes or consequences as the point of departure. *Child Development*, pages 930–940.

Brown, L., Sherbenou, R. J., and Johnsen, S. K. (1997). *TONI-3, test of nonverbal intelligence: A language-free measure of cognitive ability*. Pro-ed.

Butterworth, B. (2011). Foundational numerical capacities and the origins of dyscalculia. In *Space, Time and Number in the Brain*, pages 249–265. Elsevier.

Cantlon, J. F., Brannon, E. M., Carter, E. J., and Pelphrey, K. A. (2006). Functional imaging of numerical processing in adults and 4-y-old children. *PLoS Biol*, 4(5):e125.

Cardenas Peralta, Maria Cristina, S. d. E. P. (2018). Marco referencial de pensamiento computacional para la educacion basica.

Cattell, R. B. (1963). Theory of fluid and crystallized intelligence: A critical experiment. *Journal of educational psychology*, 54(1):1.

CEIBAL, P. (2019). Memoria anual 2019.

Ceruzzi, P. E., Paul, E., Aspray, W., et al. (2003). *A history of modern computing*. MIT press.

CFE, C. F. d. E. (2018). Núcleos de aprendizajes prioritarios: Educacion digital, programacion y robotica.

Chiazzese, G., Arrigo, M., Chifari, A., Lonati, V., and Tosto, C. (2019). Educational robotics in primary school: Measuring the development of computational thinking skills with the bebras tasks. In *Informatics*, volume 6, page 43. Multidisciplinary Digital Publishing Institute.

Ching, Y.-H., Hsu, Y.-C., and Baldwin, S. (2018). Developing computational thinking with educational technologies for young learners. *TechTrends*, 62(6):563–573.

Cho, Y. and Lee, Y. (2017). Possibility of improving computational thinking through activity based learning strategy for young children. *Journal of Theoretical and Applied Information Technology*, 95(18).

Città, G., Gentile, M., Allegra, M., Arrigo, M., Conti, D., Ottaviano, S., Reale, F., and Sciortino, M. (2019). The effects of mental rotation on computational thinking. *Computers & Education*, 141:103613.

Clements, D. H. (1986). Effects of logo and cai environments on cognition and creativity. *Journal of Educational Psychology*, 78(4):309.

Clements, D. H. and Gullo, D. F. (1984). Effects of computer programming on young children's cognition. *Journal of Educational psychology*, 76(6):1051.

Cohen, G. N., Bronson, M. B., and Casey, M. B. (1995). Planning as a factor in school achievement. *Journal of applied developmental psychology*, 16(3):405–428.

Coolidge, F. L., Overmann, K. A., Ansari, D., Ardila, A., Bruner, E., De Cruz, H., Malafouris, L., Nieder, A., Orban, G. A., Tattersall, I., et al. (2012). Numerosity, abstraction, and the emergence of symbolic thinking. *Current Anthropology*, 53(2):000–000.

Corsi, P. (1972). Human memory and the medial temporal region of the brain (ph. d.). *McGill University.*

Cuny, J., Snyder, L., and Wing, J. (2010). Computational thinking: a definition. *Unpublished manuscript.*

Dagienė, V. and Futschek, G. (2008). Bebras international contest on informatics and computer literacy: Criteria for good tasks. In *International conference on informatics in secondary schools-evolution and perspectives*, pages 19–30. Springer.

Dapozo, G. N., Greiner, C. L., and Petris, R. H. (2017). Programación en las escuelas. experiencia de formación docente en el nordeste argentino. *Memorias del Encuentro Internacional de Educación a Distancia*, 5(5).

Dasgupta, A., Rynearson, A. M., Purzer, S., Ehsan, H., and Cardella, M. E. (2017). Computational thinking in k-2 classrooms: Evidence from student artifacts (fundamental). In *2017 ASEE Annual Conference & Exposition.*

De Smedt, B., Noël, M.-P., Gilmore, C., and Ansari, D. (2013). How do symbolic and non-symbolic numerical magnitude processing skills relate to individual differences in children's mathematical skills? a review of evidence from brain and behavior. *Trends in Neuroscience and Education*, 2(2):48–55.

del Olmo-Muñoz, J., Cózar-Gutiérrez, R., and González-Calero, J. A. (2020). Computational thinking through unplugged activities in early years of primary education. *Computers & Education*, 150:103832.

Deloche, G. and Seron, X. (1987). Numerical transcoding: A general production model.

Di Lieto, M. C., Pecini, C., Castro, E., Inguaggiato, E., Cecchi, F., Dario, P., Cioni, G., and Sgandurra, G. (2020). Empowering executive functions in 5-and 6-year-old typically developing children through educational robotics: An rct study. *Frontiers in psychology*, 10:3084.

Diamond, A. (2013). Executive functions. *Annual review of psychology*, 64:135–168.

Diamond, A. (2016). Why improving and assessing executive functions early in life is critical.

Dunn, L. M. and Dunn, L. M. (1997). *PPVT-III: Peabody picture vocabulary test*. American Guidance Service.

Eickelmann, B. (2019). Measuring secondary school students' competence in computational thinking in icils 2018—challenges, concepts, and potential implications for school systems around the world. In *Computational Thinking Education*, pages 53–64. Springer, Singapore.

Fazio, L. K., Bailey, D. H., Thompson, C. A., and Siegler, R. S. (2014). Relations of different types of numerical magnitude representations to each other and to mathematics achievement. *Journal of experimental child psychology*, 123:53–72.

Feigenson, L., Dehaene, S., and Spelke, E. (2004). Core systems of number. *Trends in cognitive sciences*, 8(7):307–314.

Fessakis, G., Gouli, E., and Mavroudi, E. (2013). Problem solving by 5–6 years old kindergarten children in a computer programming environment: A case study. *Computers & Education*, 63:87–97.

Fivush, R. and Hamond, N. R. (1990). Autobiographical memory across the preschool years: Toward reconceptualizing childhood amnesia.

Flannery, L. P. and Bers, M. U. (2013). Let's dance the "robot hokey-pokey!" children's programming approaches and achievement throughout early cognitive development. *Journal of research on technology in education*, 46(1):81–101.

Flannery, L. P., Silverman, B., Kazakoff, E. R., Bers, M. U., Bontá, P., and Resnick, M. (2013). Designing scratchjr: Support for early childhood learning through computer programming. In *proceedings of the 12th international conference on interaction design and children*, pages 1–10.

Fraillon, J., Ainley, J., Schulz, W., Duckworth, D., and Friedman, T. (2018). Preparing for life in a digital age: Iea international computer and information literacy study 2018 international report. international association for the evaluation of educational achievement (iea) website.

Friedman, W. J. (1991). The development of children's memory for the time of past events. *Child development*, 62(1):139–155.

Friedman, W. J. (2005). Developmental and cognitive perspectives on humans' sense of the times of past and future events. *Learning and Motivation*, 36(2):145–158.

García, J. M. (2020). La expansión del pensamiento computacional en uruguay. *Revista de Educación a Distancia*, 20(63).

García-Valcárcel-Muñoz-Repiso, A. and Caballero-González, Y.-A. (2019). Robotics to develop computational thinking in early childhood education. *Comunicar. Media Education Research Journal*, 27(1).

Gerosa, A., Koleszar, V., Gómez-Sena, L., Tejera, G., and Carboni, A. (2019). Educational robotics and computational thinking development in preschool. In *2019 XIV Latin American Conference on Learning Technologies (LACLO)*, pages 226–230. IEEE.

Gioia, G. A., Isquith, P. K., Guy, S. C., and Kenworthy, L. (2015). *BRIEF-2: Behavior rating inventory of executive function*. Psychological Assessment Resources Lutz, FL.

González, M. R. (2015). Computational thinking test: Design guidelines and content validation. In *Proceedings of EDULEARN15 conference*, pages 2436–2444.

González, Y. A. C. and Muñoz-Repiso, A. G.-V. (2018). A robotics-based approach to foster programming skills and computational thinking: Pilot experience in the classroom of early childhood education. In *Proceedings of the Sixth International Conference on Technological Ecosystems for Enhancing Multiculturality*, pages 41–45.

Grover, S. and Pea, R. (2013). Computational thinking in k–12: A review of the state of the field. *Educational researcher*, 42(1):38–43.

Guggemos, J. (2020). On the predictors of computational thinking and its growth at the high-school level. *Computers & Education*, 161:104060.

Haffner, J. (2005). *HRT 1-4: Heidelberger Rechentest; Erfassung mathematischer Basiskompetenzen im Grundschulalter*. Hogrefe.

Haseski, H. İ., Ilic, U., and Tugtekin, U. (2018). Defining a new 21st century skill-computational thinking: Concepts and trends. *International Education Studies*, 11(4):29–42.

Haseski, H. I. and Ilic, U. (2019). An investigation of the data collection instruments developed to measure computational thinking. *Informatics in Education*, 18(2):297–319.

Heckman, J. J. and Masterov, D. V. (2007). The productivity argument for investing in young children. *Applied Economic Perspectives and Policy*, 29(3):446–493.

Heikkilä, M. and Mannila, L. (2018). Debugging in programming as a multimodal practice in early childhood education settings. *Multimodal Technologies and Interaction*, 2(3):42.

Heller, K. A. and Perleth, C. (2000). Kognitiver fähigkeitstest für 4. bis 12. *Klassen, Revision*, 3.

Heydasch, T., Haubrich, J., and Renner, K.-H. (2013). The short version of the hagen matrices test (hmt-s): 6-item induction intelligence test. *methods, data, analyses*, 7(2):26.

Holloway, I. D. and Ansari, D. (2009). Mapping numerical magnitudes onto symbols: The numerical distance effect and individual differences in children's mathematics achievement. *Journal of experimental child psychology*, 103(1):17–29.

Holloway, I. D. and Ansari, D. (2010). Developmental specialization in the right intraparietal sulcus for the abstract representation of numerical magnitude. *Journal of Cognitive Neuroscience*, 22(11):2627–2637.

Hsu, T.-C., Chang, S.-C., and 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.

Hunter, J. E. (1983). The dimensionality of the general aptitude test battery (gatb) and the dominance of general factors over specific factors in the prediction of job performance for the us employment service.

Ioannou, A. and Makridou, E. (2018). Exploring the potentials of educational robotics in the development of computational thinking: A summary of current research and practical proposal for future work. *Education and Information Technologies*, 23(6):2531–2544.

ISTE, I. and CSTA, C. (2011). Operational definition of computational thinking for k–12 education. *National Science Foundation.*

Izard, V., Sann, C., Spelke, E. S., and Streri, A. (2009). Newborn infants perceive abstract numbers. *Proceedings of the National Academy of Sciences*, 106(25):10382–10385.

Janka, P. (2008). Using a programmable toy at preschool age: Why and how. In *Teaching with robotics: didactic approaches and experiences. Workshop of International Conference on Simulation, Modeling and Programming Autonomous Robots*, pages 112–121.

Jung, S. E. and Won, E.-S. (2018). Systematic review of research trends in robotics education for young children. *Sustainability*, 10(4):905.

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

Kalogiannakis, M. and Papadakis, S. (2017). Pre-service kindergarten teachers acceptance of "scratchjr" as a tool for learning and teaching computational thinking and science education. In *Proceedings of the 12th Conference of the European Science Education Research Association (ESERA), Research, practice and collaboration in science education*, pages 21–25.

Kaufmann, L., Vogel, S., Starke, M., Kremser, C., and Schocke, M. (2009). Numerical and non-numerical ordinality processing in children with and without developmental dyscalculia: Evidence from fmri. *Cognitive Development*, 24(4):486–494.

Kazakoff, E. R., Sullivan, A., and Bers, M. U. (2013). The effect of a classroom-based intensive robotics and programming workshop on sequencing ability in early childhood. *Early Childhood Education Journal*, 41(4):245–255.

Kurland, D. M., Pea, R. D., Clement, C., and Mawby, R. (1986). A study of the development of programming ability and thinking skills in high school students. *Journal of Educational Computing Research*, 2(4):429–458.

Langdon, R. and Coltheart, M. (1999). Mentalising, schizotypy, and schizophrenia. *Cognition*, 71(1):43–71.

Lemos, G. C., Almeida, L. S., and Guisande, M. A. (2006). Bateria de provas de raciocínio: suas versões, validação e normalização.

Lin, Y.-T., Wu, C.-C., Hou, T.-Y., Lin, Y.-C., Yang, F.-Y., and Chang, C.-H. (2015). Tracking students' cognitive processes during program debugging—an eye-movement approach. *IEEE transactions on education*, 59(3):175–186.

Lockwood, J. and Mooney, A. (2018). Developing a computational thinking test using bebras problems.

Lorenceau, A., Marec, C., and Mostafa, T. (2019). Upgrading the ict questionnaire items in pisa 2021.

Lowe, T. and Brophy, S. (2017). An operationalized model for defining computational thinking. In *2017 IEEE Frontiers in Education Conference (FIE)*, pages 1–8. IEEE.

Lyons, I. M. and Ansari, D. (2015). Numerical order processing in children: From reversing the distance-effect to predicting arithmetic. *Mind, Brain, and Education*, 9(4):207–221.

Lyons, I. M., Price, G. R., Vaessen, A., Blomert, L., and Ansari, D. (2014). Numerical predictors of arithmetic success in grades 1–6. *Developmental science*, 17(5):714–726.

Magnuson, K. and Duncan, G. J. (2016). Can early childhood interventions decrease inequality of economic opportunity? *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 2(2):123–141.

McCauley, R., Fitzgerald, S., Lewandowski, G., Murphy, L., Simon, B., Thomas, L., and Zander, C. (2008). Debugging: a review of the literature from an educational perspective. *Computer Science Education*, 18(2):67–92.

McColgan, K. L. and McCormack, T. (2008). Searching and planning: Young children's reasoning about past and future event sequences. *Child Development*, 79(5):1477–1497.

Mikelic Preradovic, N., Lešin, G., and Šagud, M. (2016). Investigating parents' attitudes towards digital technology use in early childhood: A case study from croatia. *Informatics in education*, 15(1):127–146.

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., and 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.

Moreno-León, J., Robles, G., and Román-González, M. (2015). Dr. scratch: Automatic analysis of scratch projects to assess and foster computational thinking. *RED. Revista de Educación a Distancia*, (46):1–23.

Moyer, R. S. and Landauer, T. K. (1967). Time required for judgements of numerical inequality. *Nature*, 215(5109):1519–1520.

Nahin, P. J. (2017). *The logician and the engineer: How George Boole and Claude Shannon created the information age*. Princeton University Press.

Nam, K. W., Kim, H. J., and 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.

O'Connell, B. G. and Gerard, A. B. (1985). Scripts and scraps: The development of sequential understanding. *Child Development*, pages 671–681.

O'Connor, P. A. (2019). *The role of mental representations of order in mathematical cognition: a developmental approach.* PhD thesis, Queen's University Belfast.

Oxford, E. D. S. (2007). Shorter oxford english dictionary.

Papadakis, S., Kalogiannakis, M., and Zaranis, N. (2016). Developing fundamental programming concepts and computational thinking with scratchjr in preschool education: a case study. *International Journal of Mobile Learning and Organisation*, 10(3):187–202.

Papert, S. (1980). Mindstorms: children, computers, and powerful ideas basic books. *Inc. New York, NY.*

Papert, S. and Harel, I. (1991). Situating constructionism. *Constructionism*, 36(2):1–11.

Pea, R. D., Soloway, E., and Spohrer, J. C. (1987). The buggy path to the development of programming expertise.

Perone, S., Almy, B., and Zelazo, P. D. (2018). Toward an understanding of the neural basis of executive function development. In *The neurobiology of brain and behavioral development*, pages 291–314. Elsevier.

Pfeiffer, J. E. (1962). *The thinking machine.* Lippincott.

Piaget, J. (1963). *La naissance de l'intelligence chez l'enfant*, volume 968. Delachaux et Niestlé Neuchatel-Paris.

Pichot, P. (1949). *Les tests mentaux en psychiatrie*, volume 1. Presses universitaires de France.

Piget, J. (1969). *The child's Conception of time.* Routledge & Kegan Paul.

Pila, S., Aladé, F., Sheehan, K. J., Lauricella, A. R., and Wartella, E. A. (2019). Learning to code via tablet applications: An evaluation of daisy the dinosaur and kodable as learning tools for young children. *Computers & Education*, 128:52–62.

Quaiser-Pohl, C. (2003). The mental cutting test" schnitte" and the picture rotation test-two new measures to assess spatial ability. *International Journal of Testing*, 3(3):219–231.

Raven, J. C. and Court, J. (1986). Raven's progressive matrices and raven's coloured matrices. *London: HK Lewis.*

Relkin, E. and Bers, M. U. (2019). Designing an assessment of computational thinking abilities for young children. *STEM for early childhood learners: how science, technology, engineering and mathematics strengthen learning. New York: Routledge. https://doi. org/10.4324/9780429453755-5.*

Rich, K. M., Binkowski, T. A., Strickland, C., and Franklin, D. (2018). Decomposition: A k-8 computational thinking learning trajectory. In *Proceedings of the 2018 ACM Conference on International Computing Education Research*, pages 124–132.

Rich, K. M., Strickland, C., Binkowski, T. A., and Franklin, D. (2019). A k-8 debugging learning trajectory derived from research literature. In *Proceedings of the 50th ACM Technical Symposium on Computer Science Education*, pages 745–751.

Richter, L. M., Daelmans, B., Lombardi, J., Heymann, J., Boo, F. L., Behrman, J. R., Lu, C., Lucas, J. E., Perez-Escamilla, R., Dua, T., et al. (2017). Investing in the foundation of sustainable development: pathways to scale up for early childhood development. *The lancet*, 389(10064):103–118.

Robertson, J., Gray, S., Toye, M., and Booth, J. (2020). The relationship between executive functions and computational thinking. *International Journal of Computer Science Education in Schools*, 3(4):35–49.

Román-González, M., Moreno-León, J., and Robles, G. (2019). Combining assessment tools for a comprehensive evaluation of computational thinking interventions. In *Computational thinking education*, pages 79–98. Springer, Singapore.

Román-González, M., Pérez-González, J.-C., and Jiménez-Fernández, C. (2017). Which cognitive abilities underlie computational thinking? criterion validity of the computational thinking test. *Computers in Human Behavior*, 72:678–691.

Román-González, M., Pérez-González, J.-C., Moreno-León, J., and Robles, G. (2018). Extending the nomological network of computational thinking with non-cognitive factors. *Computers in Human Behavior*, 80:441–459.

Roussou, E. and Rangoussi, M. (2019). On the use of robotics for the development of computational thinking in kindergarten: educational intervention and evaluation. In *International Conference on Robotics and Education RiE 2017*, pages 31–44. Springer.

Sanders, W., Parent, J., Forehand, R., Sullivan, A. D., and Jones, D. J. (2016). Parental perceptions of technology and technology-focused parenting: Associations with youth screen time. *Journal of applied developmental psychology*, 44:28–38.

Sanefuji, W. and Haryu, E. (2018). Preschoolers' development of theory of mind: The contribution of understanding psychological causality in stories. *Frontiers in psychology*, 9:955.

Sapounidis, T. and Demetriadis, S. (2016). Educational robots driven by tangible programming languages: A review on the field. In *International Conference EduRobotics 2016*, pages 205–214. Springer.

Sasanguie, D. and Vos, H. (2018). About why there is a shift from cardinal to ordinal processing in the association with arithmetic between first and second grade. *Developmental science*, 21(5):e12653.

Saxena, A., Lo, C. K., Hew, K. F., and Wong, G. K. W. (2020). Designing unplugged and plugged activities to cultivate computational thinking: An exploratory study in early childhood education. *The Asia-Pacific Education Researcher*, 29(1):55–66.

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

Seisdedos, N. (2002). Test resolución de problemas [problem resolution test]. *Madrid: TEA Ediciones.*

Selby, C., Dorling, M., and Woollard, J. (2014). Evidence of assessing computational thinking.

Selby, C. and Woollard, J. (2013). Computational thinking: the developing definition.

Shallice, T. (1982). Specific impairments of planning. *Philosophical Transactions of the Royal Society of London. B, Biological Sciences*, 298(1089):199–209.

Shannon, C. E. (1938). A symbolic analysis of relay and switching circuits. *Electrical Engineering*, 57(12):713–723.

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

Siegler, R. S. and Booth, J. L. (2004). Development of numerical estimation in young children. *Child development*, 75(2):428–444.

Siegler, R. S. and Pyke, A. A. (2013). Developmental and individual differences in understanding of fractions. *Developmental psychology*, 49(10):1994.

Siegler, R. S., Thompson, C. A., and Schneider, M. (2011). An integrated theory of whole number and fractions development. *Cognitive psychology*, 62(4):273–296.

So, H.-J., Jong, M. S.-Y., and Liu, C.-C. (2020). Computational thinking education in the asian pacific region.

Sondakh, D. E. (2018). Review of computational thinking assessment in higher education. *Retrieved May*, 29:2019.

Sternberg, R. J. (1998). Thinking and problem solving.

Stoeckelmayr, K., Tesar, M., and Hofmann, A. (2011). Kindergarten children programming robots: a first attempt. In *Proceedings of 2nd International Conference on Robotics in Education (RIE).*

Strawhacker, A., Lee, M., Caine, C., and Bers, M. (2015). Scratchjr demo: A coding language for kindergarten. In *Proceedings of the 14th International Conference on Interaction Design and Children*, pages 414–417.

Sullivan, A. and Bers, M. (2019). Computer science education in early childhood: the case of scratchjr. *Journal of Information Technology Education: Innovations in Practice*, 18(1):113–138.

Sullivan, A., Bers, M., and Pugnali, A. (2017). The impact of user interface on young children's computational thinking. *Journal of Information Technology Education: Innovations in Practice*, 16(1):171–193.

Sullivan, A. and Bers, M. U. (2013). Gender differences in kindergarteners' robotics and programming achievement. *International journal of technology and design education*, 23(3):691–702.

Tang, X., Yin, Y., Lin, Q., Hadad, R., and Zhai, X. (2020). Assessing computational thinking: A systematic review of empirical studies. *Computers & Education*, 148:103798.

TEA (1997). *PMA:(aptitudes mentales primarias): manual*. Tea.

Team, R. C. (2019). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Tejera, G., Amorin, G., Sere, A., Capricho, N., Margenat, P., and Visca, J. (2019). Robotito: programming robots from preschool to undergraduate school level. In *2019 19th International Conference on Advanced Robotics (ICAR)*, pages 296–301. IEEE.

Thalheim, B. (1999). *Fundamentals of entity-relationship modeling*. Springer.

Tran, Y. (2018). Computational thinking equity in elementary classrooms: What third-grade students know and can do. *Journal of Educational Computing Research*, 57(1):3–31.

Tsarava, K., Leifheit, L., Ninaus, M., Román-González, M., Butz, M. V., Golle, J., Trautwein, U., and Moeller, K. (2019). Cognitive correlates of computational thinking: Evaluation of a blended unplugged/plugged-in course. In *Proceedings of the 14th Workshop in Primary and Secondary Computing Education*, pages 1–9.

Tsarava, K., Moeller, K., and Ninaus, M. (2018). Training computational thinking through board games: The case of crabs & turtles. *International Journal of Serious Games*, 5(2):25–44.

Turing, A. (1936). 1937. on computable numbers, with an application to the decision problem. *Proceedings of the London Mathematical Society*, 2(42):230–265.

Uscanga, E. A. V., Bottamedi, J., and Brizuela, M. L. (2019). Pensamiento computacional en el aula: el desafío en los sistemas educativos de latinoamérica. *Revista Interuniversitaria de Investigación en Tecnología Educativa.*

van de Vijver, F. J. and Willemsen, M. E. (1993). Abstract thinking. In *Advances in psychology*, volume 103, pages 317–342. Elsevier.

Vandell, D. L., Belsky, J., Burchinal, M., Steinberg, L., Vandergrift, N., and Network, N. E. C. C. R. (2010). Do effects of early child care extend to age 15 years? results from the nichd study of early child care and youth development. *Child development*, 81(3):737–756.

Vandell, D. L., Burchinal, M., and Pierce, K. M. (2016). Early child care and adolescent functioning at the end of high school: Results from the nichd study of early child care and youth development. *Developmental psychology*, 52(10):1634.

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

Voogt, J., Fisser, P., Good, J., Mishra, P., and Yadav, A. (2015). Computational thinking in compulsory education: Towards an agenda for research and practice. *Education and Information Technologies*, 20(4):715–728.

Wang, X. C., Choi, Y., Benson, K., Eggleston, C., and Weber, D. (2021). Teacher's role in fostering preschoolers' computational thinking: An exploratory case study. *Early Education and Development*, 32(1):26–48.

Wechsler, D. (1944). The measurement of adult intelligence.

Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., and Wilensky, U. (2014). Defining computational thinking for science, technology, engineering, and math. In *Poster presented at the Annual Meeting of the American Educational Research Association (AERA 2014). Philadelphia. USA. Retrieved from http://ccl. northwestern. edu/2014/CT-STEM_-AERA_2014. pdf.*

Weiß, R. H. (2006). *CFT 20-R: grundintelligenztest skala 2-revision*. Hogrefe.

Wing, J. (2017). Computational thinking's influence on research and education for all. *Italian Journal of Educational Technology*, 25(2):7–14.

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

Wing, J. M. (2008). Computational thinking and thinking about computing. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 366(1881):3717–3725.

Wong, G. K. and Jiang, S. (2018). Computational thinking education for children: Algorithmic thinking and debugging. In *2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE)*, pages 328–334. IEEE.

Xu, S. and Rajlich, V. (2004). Cognitive process during program debugging. In *Proceedings of the Third IEEE International Conference on Cognitive Informatics, 2004.*, pages 176–182. IEEE.

Yu, J. and Roque, R. (2019). A review of computational toys and kits for young children. *International Journal of Child-Computer Interaction*, 21:17–36.

Zapata-Cáceres, M., Martín-Barroso, E., and Román-González, M. (2020). Computational thinking test for beginners: Design and content validation. In *2020 IEEE Global Engineering Education Conference (EDUCON)*, pages 1905–1914. IEEE.

Zapata-Ros, M. (2019). Pensamiento computacional desenchufado.

Zelazo, P. D., Blair, C. B., and Willoughby, M. T. (2016). Executive function: Implications for education. ncer 2017-2000. *National Center for Education Research*.

Zelazo, P. D., Carter, A., Reznick, J. S., and Frye, D. (1997). Early development of executive function: A problem-solving framework. *Review of general psychology*, 1(2):198–226.

Zhong, B. and Si, Q. (2020). Troubleshooting to learn via scaffolds: Effect on students' ability and cognitive load in a robotics course. *Journal of Educational Computing Research*, page 0735633120951871.

Zhong, B., Wang, Q., Chen, J., and Li, Y. (2016). An exploration of three-dimensional integrated assessment for computational thinking. *Journal of Educational Computing Research*, 53(4):562–590.

APPENDIXES

Appendix 1

Systematic review of CT definitions in early childhood empirical studies

1.1 Methodology supplement

Systematic search was performed on Scopus, ScienceDirect and IEEE. Data extraction was performed using a spreadsheet with publications' relevant information. Table 1.1 details the selected search terms, while figure 2.3 presents a flowchart of the search procedure.

Table 1.1: Search terms implemented

Search engine	Search terms
IEEE	"All Metadata":"computational thinking" AND ("All Metadata":"preschool*" OR "All Metadata":"young children" OR "All Metadata":"early childhood*" OR "All Metadata":"kindergarten*")
ScienceDirect	"computational thinking" AND ((preschool) OR ("young children") OR ("early childhood") OR (kindergarten)
Scopus	TITLE ("computational thinking") AND TITLE-ABS-KEY ("early childhood" OR "young children" OR "preschool" OR "kindergarten")

1.1.1 Inclusion Criteria

- Peer-reviewed articles on computational thinking
- Empirical studies
- 3-6 year old participants

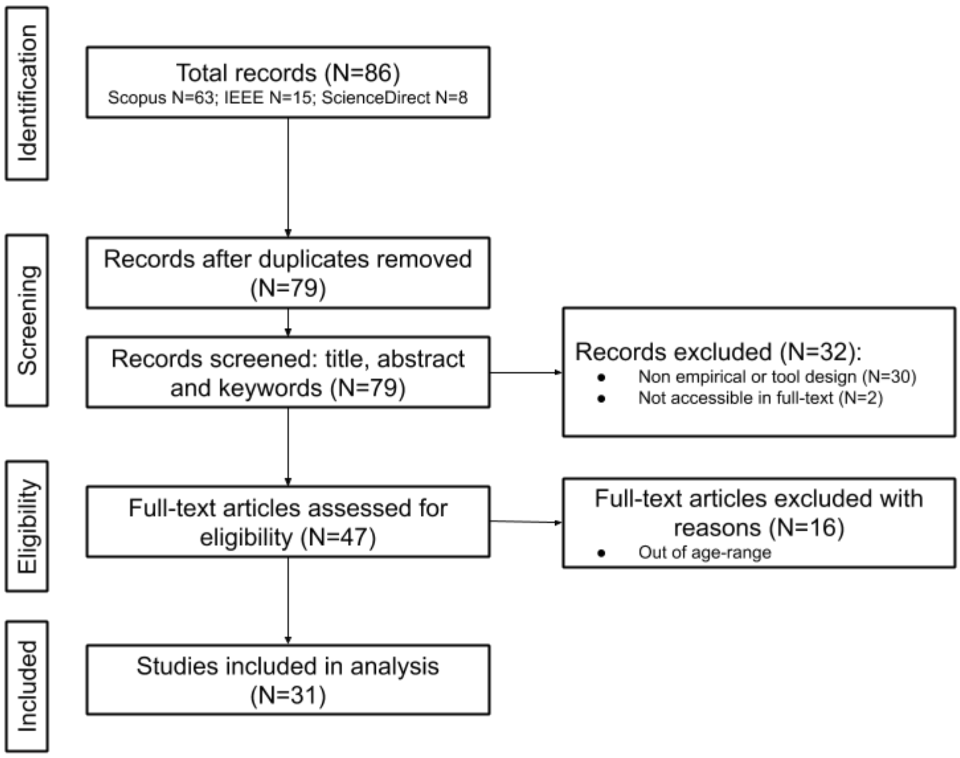


Figure 1.1: Selection of articles

Appendix 2

Consent forms

UNIVERSIDAD
DE LA REPÚBLICA
URUGUAY

cicea

Hoja de Información

Estimados madres, padres y tutores:

El centro educativo al que acude su hijo/a ha sido seleccionado para participar en el proyecto de investigación titulado: *"Programando robots jugando con el entorno"* del Centro Interdisciplinario en Cognición para la Enseñanza y el Aprendizaje, de la Universidad de la República (CICEA-UdelaR). Este proyecto tiene por objetivo desarrollar una plataforma robótica que le permita a niños preescolares y escolares en edades tempranas comenzar a desarrollar conceptos relacionados al pensamiento computacional. Los resultados obtenidos permitirán evaluar el impacto del uso del robot en el desarrollo de los niños.

¿Qué implica la participación?

1. Su hijo/a participará en actividades semanales realizadas en subgrupos que apuntan a la interacción lúdica con un robot.
2. Se evaluarán algunos aspectos del desarrollo cognitivo del niño/a, en dos instancias y le solicitaremos por única vez que complete un breve formulario con preguntas que nos informan acerca del uso de la tecnología en el hogar del niño/a.

Es importante aclarar que las evaluaciones a realizar no tienen objetivos diagnósticos, ni suponen ningún tipo de riesgos para los participantes.

El proyecto es dirigido por el Dr. Leonel Gómez (Facultad de Ciencias) y el Dr. Gonzalo Tejera (Facultad de Ingeniería), y cuenta con un equipo interdisciplinario que incluye a su vez investigadores de Facultad de Psicología, Información y Comunicación, y Maestros. El proyecto ha sido otorgado financiación de los Fondos Sectoriales en Educación de la Agencia Nacional de Investigación e Innovación (ANII) y avalado por el comité de ética en investigación de la Facultad de Psicología.

Las diferentes instancias del proyecto estarán a cargo del equipo de investigación, y la información recogida será utilizada únicamente por este equipo, siguiendo los procedimientos adecuados para preservar la identidad de los participantes (cambio de nombres personales, supresión de referencias que identifiquen a los participantes, etc.). Se realizarán registros audiovisuales de uso exclusivo del equipo de investigación.

En el caso de que usted o su hijo/a opten por retirarse de la investigación, lo pueden hacer en cualquier momento sin tener que dar explicaciones, lo cual no supondrá ningún tipo de inconveniente.

Ante cualquier duda o consulta, el equipo de investigación se encuentra disponible para organizar una reunión informativa en el centro educativo con los padres que así lo soliciten, o puede comunicarse con el investigador responsable del proyecto, Dr. Leonel Gómez, enviando un correo electrónico a cicea@ei.udelar.edu.uy o llamando telefónicamente al Centro Interdisciplinario en Cognición para la Enseñanza y el Aprendizaje, tel. 24020297.

Figure 2.1: Study information

Hoja de consentimiento

Declaro haber leído el comunicado sobre el proyecto de investigación *"Programando robots jugando con el entorno"* del Centro Interdisciplinario en Cognición para la Enseñanza y el Aprendizaje, de la Universidad de la República (CICEA-UdelaR).

Declaro además que:

- Se me ha informado que la participación de mi hijo en el proyecto implica dos instancias de evaluación individual de algunos aspectos del desarrollo cognitivo y la participación del niño/a en las actividades que se realicen semanalmente en el aula con sus docentes y compañeros.
- Se me ha brindado la posibilidad de hacer cualquier pregunta sobre esta investigación y en caso de haber formulado preguntas, las mismas fueron respondidas de forma satisfactoria.
- He sido informado/a de que la participación de mi hijo/a en este estudio es voluntaria, que no supone ningún tipo de riesgos, y que los datos recabados serán sistematizados y analizados de forma confidencial por el investigador responsable, quien utilizará procedimientos adecuados para preservar nuestra identidad (cambio de nombres personales, supresión de referencias que identifiquen a los participantes, etc.). A su vez, he sido informado/a de que, en el caso de que mi hijo/a se quiera retirar de la investigación, lo podrá hacer en cualquier momento sin tener que dar explicaciones, lo cual no supondrá ningún tipo de inconveniente.

Acepto las condiciones acordadas en el presente documento y permito que mi hijo/a participe de esta investigación

Nombre del niño:			
Cédula de identidad:		**Fecha de nacimiento del niño:**	
Institución educativa:			
Firma del padre, madre o tutor:			
Aclaración de firma:			
Fecha de hoy:			

Figure 2.2: Informed consent

Appendix 3

Supplementary analyses

3.1 CT assessment

Table 3.1: CT test items by construct and difficulty

Item	CT construct	Correct proportion
A1	Algorithm/Sequence	0.57
A2	Algorithm/Sequence	0.39
A3	Algorithm/Sequence	0.39
A4	Algorithm/Sequence	0.48
A5	Algorithm/Sequence	0.40
A6	Algorithm/Sequence	0.31
L1	Loops	0.04
L2	Loops	0.24
P1	Patterns	0.29
D1	Debugging	0.42
D2	Debugging	0.45
D3	Debugging	0.16
S1	Algorithm/Sequence	0.25
C1	Conditionals	0.37
C2	Conditionals	0.44

3.2 Parent-report questionnaires

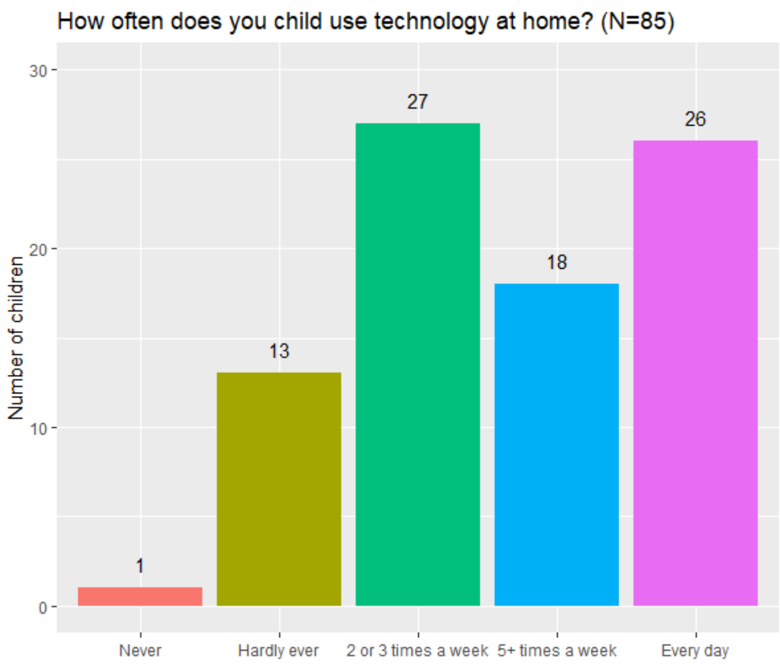


Figure 3.1: Frequency of technology use overall

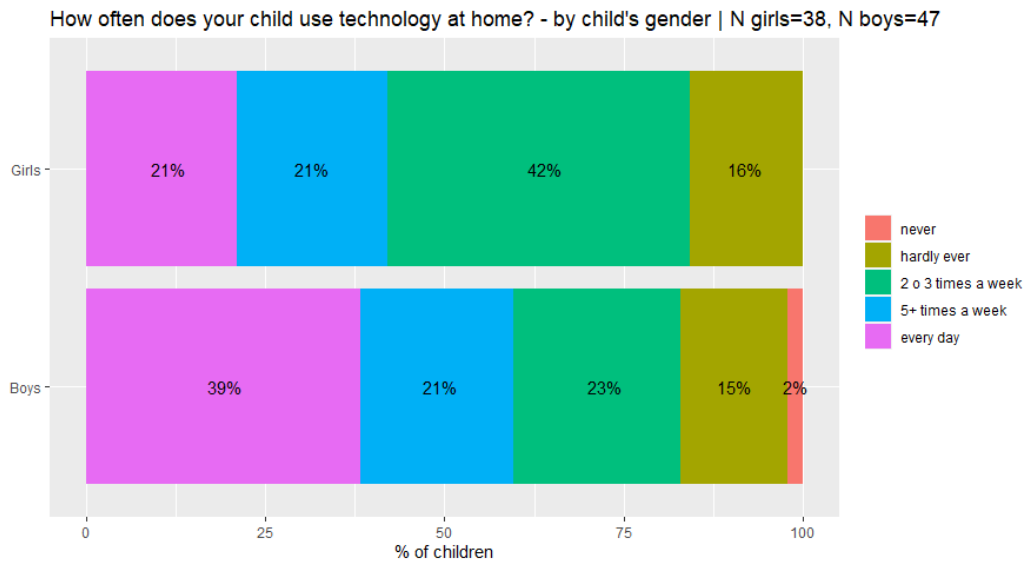


Figure 3.2: Frequency of technology use overall, by child's gender

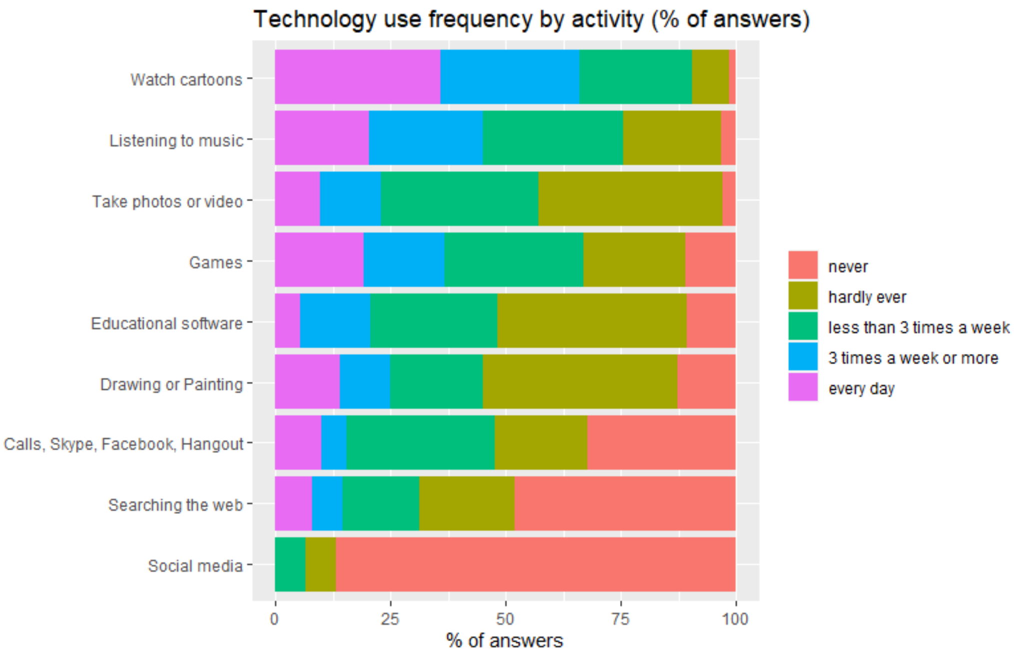


Figure 3.3: Frequency of technology use by activity (% of answers)

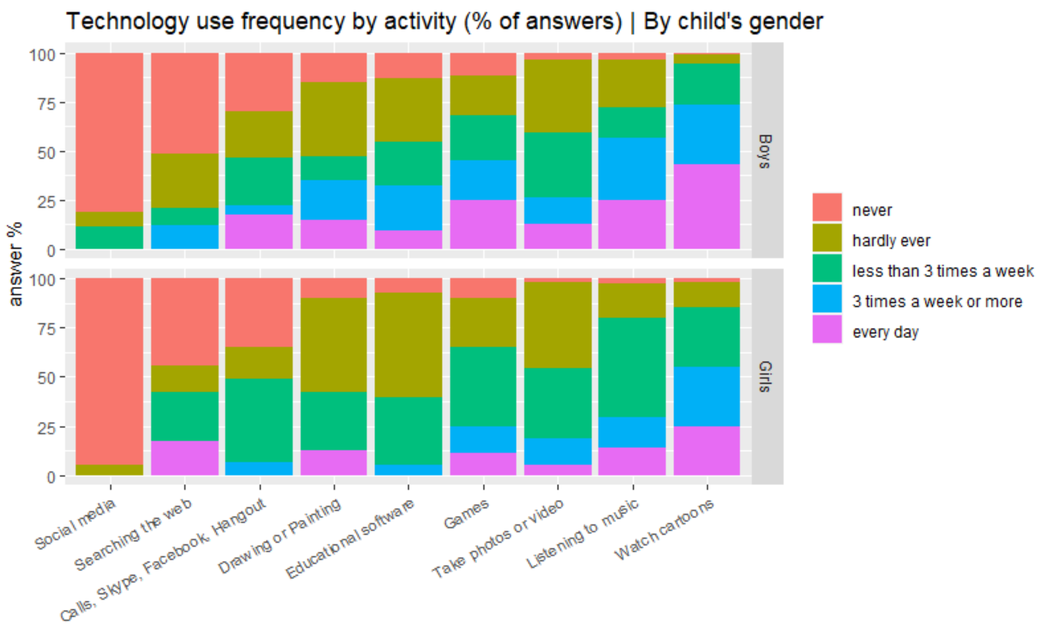


Figure 3.4: Frequency of technology use by activity (% of answers) by child's gender

ANNEXES

Annex 1

CT assessment

Test de Pensamiento Computacional (Tran, 2018)

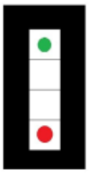
Nombre del niño: ____

Escuela: ______________________

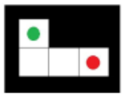
Clase: _____________. Fecha del día de hoy: ___/___/2019.Evaluador:____________

1.En este ejercicio queremos llegar desde el puntito verde al puntito rojo, usando las flechas que ves debajo. Las flechas van hacia abajo, arriba, derecha, e izquierda. (Nota: señalar las flechas a medida que las vamos nombrando). Cada vez que usamos una flecha avanzamos un cuadradito. Por ejemplo, (1.a)si yo quisiera ir desde este punto verde hasta este punto rojo, haría una flecha para abajo, y otra flecha para abajo, y luego otra más. ¿Ves? Ahora vamos a mirar el segundo (1.b) ¿Podrías decirme señalando las flechas cómo hacemos para llegar hasta el punto rojo? (Repetir para cada imagen, si el niño no logra hacer dos seguidos pasar al ítem 2)

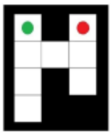
1.a (Ítem de práctica, no registrar)



____
____
____



1.c
1. ___________
2. ___________
3. ___________
4. ___________



1. ___________
2. ___________
3. ___________
4. ___________
5. ___________
6. ___________

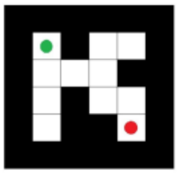


Figure 1.1: CT assessment (1)

2. Ahora, vamos a hacer lo mismo que hicimos en la actividad anterior, pero esta vez queremos llegar desde el punto rojo hasta el verde. ¿Podrías decirme las instrucciones para este caso? (Repetir para imagen 2, 3 y 4, en reverso, si el niño no logra 2 seguidos pasar al ítem 3)

2.b

1. ____________
2. ____________
3. ____________

2.c

1. ____________
2. ____________
3. ____________
4. ____________

2.d

1. ____________
2. ____________
3. ____________
4. ____________
5. ____________
6. ____________

3. Ahora, te voy a leer una frase sobre la forma en que Emma hace ejercicio, es importante prestar atención porque luego te voy a hacer dos preguntas sobre esto ¿si? Esta es la frase:

Emma está haciendo ejercicio antes de la clase de gimnasia.

Primero, Emma hace dos saltos.
Luego, Emma repite el primer paso dos veces más, y se toca los dedos de los pies cuando termina cada repetición.

¿Cuántos saltos hizo Emma? _____
¿Cuántas veces se tocó los dedos de los pies? _____

4. Ahora te voy a mostrar estas instrucciones sobre cómo Emma hace sus ejercicios. En estos ejercicios hay partes que se repiten, que se llaman patrones. Por ejemplo (patrón de prueba) ahora: ¿Podés dibujar un círculo sobre los patrones que se repiten? (Mostrar patrón de ejercicio 4)

Logrado: Sí ___
No___

5.a

Ahora vamos a leer una lista de pasos que sigue Belén cuando se levanta por la mañana. Pero cuidado! Hay un paso que está fuera de su orden.

1. Abrir los ojos
2. Sacar a pasear a su perro

Figure 1.2: CT assessment (2)

3. Salir de la cama
4. Vestirse y tomar el desayuno

¿Cuál de estos pasos está desordenado?

5.b

1. Comprar los ingredientes
2. Mezclar los ingredientes
3. Comer la torta
4. Poner la masa en el horno
5. Esperar a que se cocine la masa

¿Cuál de estos pasos está desordenado?

5.c

1. Despertarse
2. Vestirse y tomar el desayuno
3. Manejar hasta la escuela
4. Ponerse la mochila para ir a la escuela
5. Subirse al auto
6. Entrar a la clase

¿Cuál de estos pasos está desordenado?

6. Ahora te voy a leer los pasos del ejercicio anterior nuevamente y tu tienes que intentar ordenarlos ¿sí? Nota: solo con el reverso de 5.a

6.a
1________
2________
3________
4________

7. Este es otro ejercicio en el que tienes que estar muy atento porque luego te voy a hacer una pregunta sobre lo que vas a escuchar:
Nota: señalar si lo logró o no con un círculo

Si Emily tiene 3 o más manzanas, puede hacer una torta de manzana. Emily tiene 5 manzanas y una calabaza. ¿Puede hacer torta de manzana?.

SI NO

8. Si John tiene dos bananas, va a compartir una con su amigo. Si no, John se va a quedar con su banana. John tiene una banana y dos zanahorias. ¿Qué va a hacer John?

SI NO

Figure 1.3: CT assessment (3)

Annex 2

Parental reports on technology use and perceptions

cicea

Estimados padres:

Como saben, su hijo/a se encuentra actualmente, junto a sus compañeros de clase, participando en el proyecto "Programando Robots Jugando con el Entorno" del Centro Interdisciplinario en Cognición para la Enseñanza y Aprendizaje (Cicea), Universidad de la República. Este proyecto tiene por objetivo desarrollar una plataforma robótica que le permita a niños preescolares y escolares en edades tempranas comenzar a desarrollar conceptos relacionados al pensamiento computacional. En esta oportunidad, les pedimos nuevamente de su amable colaboración completando el siguiente cuestionario. A través del mismo, buscamos conocer sus opiniones generales en cuanto a algunos aspectos de la tecnología, y las actividades que realiza su hijo/a al utilizar ciertos dispositivos.

Al igual que durante todo el transcurso del proyecto, los datos recabados permanecerán estrictamente confidenciales y serán tratados acorde a las normas éticas vigentes.

Yo, (nombre del padre, madre o tutor) ____ accedo a completar el presente cuestionario a los efectos de colaborar con la presente investigación a cargo de CICEA, Universidad de la República.

Firma: ____

El llenado de este cuestionario tiene un tiempo estimado de 10 min.
Por favor intente responder todas las preguntas de acuerdo a su opinión. No hay respuestas incorrectas
Le agradecemos ampliamente su colaboración

Nombre del niño/a: ________________________________Fecha de nacimiento del niño/a:____/____/____ Fecha del día de hoy: ____/____/2018

Por favor, responda señalando su nivel de acuerdo con las siguientes afirmaciones:						
1.	Los objetos tecnológicos como las computadoras, tablets, o smartphones son demasiado difíciles de utilizar	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
2.	Mi hija/o será expuesto a material ilícito si usan estos dispositivos	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
3.	Mi hija/o sabe más de estos dispositivos de lo que yo sabré jamás	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
4.	No me molesto en poner contraseñas o controles parentales porque mis hijos encuentran la manera de "hackearlo" de todas formas	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo

Figure 2.1: Parent report questionnaire on technology use and perception (1)

5.	Me siento confiado en mis habilidades para utilizar dispositivos tecnológicos	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
6.	Es demasiado difícil poner contraseñas o controles parentales en mis dispositivos	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
7.	La tecnología hace a la gente más haragana	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
8.	Mi hija/o estaría mejor si no hubiera aparatos tecnológicos en la escuela	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
9.	Encuentro a las nuevas tecnologías intimidantes	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
10.	La vida era más fácil antes que los dispositivos tecnológicos fueran de uso común	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
11.	¿Qué tan a menudo usa su hija/o dispositivos tecnológicos? (Por ejemplo computadora, tablet o celular)	❑ 1.Nunca	❑ 2.Casi nunca	❑ 3. Dos o tres veces a la semana	❑ 4. Cinco o más veces a la semana	❑ 5. Todos los días
12.	Los niños aprenden cosas nuevas y útiles usando la computadora	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
13.	Los niños que usan la computadora regularmente están en riesgo de generar dependencia	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
14.	Cuando usan computadoras, los niños desarrollan habilidades tecnológicas que serán útiles para ellos en el futuro	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
15.	La tecnología sólo puede tener una influencia negativa en el desarrollo infantil	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
16.	En lugar de jugar con sus pares, los niños pasan su tiempo en la computadora, tablet o celular	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
17.	Los niños pueden desarrollar habilidades jugando juegos de computadora, tablet o celular	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
18.	Los niños practican menos deporte debido al incremento del uso de la tecnología	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
19.	El uso excesivo de la computadora podría separar a los niños de sus padres o sus amigos	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo

Figure 2.2: Parent report questionnaire on technology use and perception (2)

20.	Gracias a las computadoras, la inteligencia de los niños ha aumentado	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo
21.	Los niños pasan más tiempo de calidad usando la computadora que mirando televisión	❑ 1.Muy en desacuerdo	❑ 2.En desacuerdo	❑ 3.Neutral	❑ 4.De acuerdo	❑ 5. Muy de acuerdo

22. ¿Con qué frecuencia realiza su hija/o estas actividades con la computadora, tablet o celular?					
Mirar dibujos animados/ Contenido para niños	❑ 1.Nunca	❑ 2.Casi nunca	❑ 3. Dos o tres veces a la semana	❑ 4. Cinco o más veces a la semana	❑ 5. Todos los días
Jugar videojuegos	❑ 1.Nunca	❑ 2.Casi nunca	❑ 3. Dos o tres veces a la semana	❑ 4. Cinco o más veces a la semana	❑ 5. Todos los días
Escuchar música	❑ 1.Nunca	❑ 2.Casi nunca	❑ 3. Dos o tres veces a la semana	❑ 4. Cinco o más veces a la semana	❑ 5. Todos los días
Utilizar software educativo	❑ 1.Nunca	❑ 2.Casi nunca	❑ 3. Dos o tres veces a la semana	❑ 4. Cinco o más veces a la semana	❑ 5. Todos los días
Dibujar/Pintar	❑ 1.Nunca	❑ 2.Casi nunca	❑ 3. Dos o tres veces a la semana	❑ 4. Cinco o más veces a la semana	❑ 5. Todos los días
Comunicarse con aplicaciones como Skype, Whatsapp o Hangouts	❑ 1.Nunca	❑ 2.Casi nunca	❑ 3. Dos o tres veces a la semana	❑ 4. Cinco o más veces a la semana	❑ 5. Todos los días
Navegar la red	❑ 1.Nunca	❑ 2.Casi nunca	❑ 3. Dos o tres veces a la semana	❑ 4. Cinco o más veces a la semana	❑ 5. Todos los días
Usar redes sociales como Facebook, Instagram o Snapchat	❑ 1.Nunca	❑ 2.Casi nunca	❑ 3. Dos o tres veces a la semana	❑ 4. Cinco o más veces a la semana	❑ 5. Todos los días
Sacar fotos o videos	❑ 1.Nunca	❑ 2.Casi nunca	❑ 3. Dos o tres veces a la semana	❑ 4. Cinco o más veces a la semana	❑ 5. Todos los días
Otra actividad:____________________ ____________________________	❑ 1.Nunca	❑ 2.Casi nunca	❑ 3. Dos o tres veces a la semana	❑ 4. Cinco o más veces a la semana	❑ 5. Todos los días

Figure 2.3: Parent report questionnaire on technology use and perception (3)