Original Research Article

Journal of Educational Computing Research
2022, Vol. 0(0) 1–49

DOI: 10.1177/07356331221081753
journals.sagepub.com/home/jec
SAGE

The competent Computational Thinking Test: Development and Validation of an Unplugged Computational Thinking Test for Upper Primary School

Laila El-Hamamsy[1,2], María Zapata-Cáceres[3], Estefanía Martín Barroso[3], Francesco Mondada[1,2], Jessica Dehler Zufferey[2], and Barbara Bruno[4]

Abstract

With the increasing importance of Computational Thinking (CT) at all levels of education, it is essential to have valid and reliable assessments. Currently, there is a lack of such assessments in upper primary school. That is why we present the development and validation of the competent CT test (cCTt), an unplugged CT test targeting 7–9 year-old students. In the first phase, 37 experts evaluated the validity of the cCTt through a survey and focus group. In the second phase, the test was administered to 1519 students. We employed Classical Test Theory, Item Response Theory, and Confirmatory Factor Analysis to assess the instruments' psychometric properties. The expert evaluation indicates that the cCTt shows good face, construct, and content validity. Furthermore, the psychometric analysis of the student data demonstrates adequate reliability, difficulty, and discriminability for the target age groups. Finally, shortened variants of the test are established through Confirmatory Factor Analysis.

[1]MOBOTS Group, École Polytechnique Fédérale de Lausanne, Lausanne, Switzerland
[2]LEARN, Center for Learning Sciences, École Polytechnique Fédérale de Lausanne, Lausanne, Switzerland
[3]Department of Computer Science, Universidad Rey Juan Carlos, Madrid, Spain
[4]Computer Human Interaction in Learning and Instruction (CHILI) Laboratory, École Polytechnique Fédérale de Lausanne, Lausanne, Switzerland

Corresponding Author:
Laila El-Hamamsy, MOBOTS Group, École Polytechnique Fédérale de Lausanne, ME B3 435 (Batiment ME), Station 9, CH-1015 Lausanne, Switzerland.
Email: laila.elhamamsy@epfl.ch

To conclude, the proposed cCTt is a valid and reliable instrument, for use by researchers and educators alike, which expands the portfolio of validated CT assessments across compulsory education. Future assessments looking at capturing CT in a more exhaustive manner might consider combining the cCTt with other forms of assessments.

Keywords
Computational Thinking, assessment, primary education, expert evaluation, psychometric validation

Introduction and Related Work

The Increasing Position of CT in Research and Formal Education

An international debate sparked with Wing (2006)'s article presenting Computational Thinking (CT) as a universally applicable attitude and skill set, as important as reading, writing and arithmetic. While a consensus has not been reached on the definition of CT, nor on where its boundaries lie, one prominent definition is the one by Brennan and Resnick (2012). Brennan and Resnick (2012) decompose CT into: (i) computational concepts (the concepts most closely related to computer science and programming, that is, "sequences, loops, parallelism, events, conditionals, operators, and data"), (ii) computational practices (the strategies and practices required to be apply said concepts), and (iii) computational perspectives ("the perspectives designers form about the world around them and about themselves"). While CT is traditionally considered to be the "thought processes that facilitate framing and solving problems using computers and other technologies" (Relkin & Bers, 2021), more and more researchers argue that CT is not specific to "those interested in computer science and mathematics". These researchers consider that CT has a "multi-faceted theoretical nature" and can be considered more generally as an example of "models of thinking" (Li et al., 2020). Under this new light, CT is envisioned to have a broader role to play in education, from STEM-related disciplines (Li et al., 2020; Peel et al., 2020; Weintrop, 2016), to languages (Rottenhofer et al., 2021), and transversal competences[1] such as "creative problem solving" (Grover et al., 2017; Chevalier et al., 2020). Some researchers thus consider CT to be one of the fundamental competences that every citizen must acquire in the 21st century (Li et al., 2020). The growing importance of CT as a transversal competence has led, in the past decade, to an increase in the research around CT (Ilic et al., 2018; Li et al., 2020; Tang et al., 2020) as well as in the initiatives seeking to equip K-12 students with CT competences (Basu et al., 2020). Such initiatives operate through informal education (Weintrop et al., 2021), extra-curriculars, and formal education settings (Weintrop et al., 2021), some even starting at the level of kindergarten (Bocconi et al., 2016).

The Need for CT Assessments at all Levels of Education

With this “tremendous growth in curricula, learning environments, and innovations around CT education” (Weintrop et al., 2021), the design of tools to assess CT competences in a developmentally appropriate and reliable way throughout compulsory education becomes crucial (Hsu et al., 2018). Indeed, “CT assessment is important [to document] learning progress, [measure] lesson effectiveness, [assist] in curriculum development and [help] identify students in need of greater assistance or enrichment” (Relkin & Bers, 2021). As CT is also becoming popular among K-9 educators (Chen et al., 2017; Mannila et al., 2014), it is also paramount to develop assessments for that age range. Indeed, as mentioned by Relkin and Bers (2021), “one of the greatest challenges to integrating CT into early elementary school education has been a lack of validated, developmentally appropriate assessments to measure young students’ CT skills in classroom and online settings” (Lockwood & Mooney, 2017; Román-González et al., 2019). Assessment tools should therefore be adapted for use, not only by researchers looking to design CT learning experiences (Weintrop et al., 2021) and investigate how best to foster CT competences (Chevalier et al., 2020), but also by teachers aiming to ensure that their students are acquiring the desired competences, and this starting from kindergarten onward (Zapata-Cáceres et al., 2020). Provided the pressing need to clarify the question about how best to assess CT competences (Tang et al., 2020; Lockwood & Mooney, 2017; Hsu et al., 2018), it is not surprising to find that CT assessment “is at the forefront of CT research [and] gathering the greatest interest of researchers” (Tikva & Tambouris, 2021). However, as stated by Zapata-Cáceres et al. (2020) and Román-González et al. (2019), most efforts to develop assessments for CT have focused on secondary school and tertiary education.

The Importance of Validated and Reliable Instruments Which Do Not Conflate with Programming Abilities

Developing CT assessments must consider, in addition to the developmental appropriateness for the target age group, the different assessment formats which exist, their use cases, and their scalability. From a design perspective, four main formats have been used to assess CT (Tang et al., 2020): traditional tests (often used in combination with other assessment methods), portfolios (to “[situate] CT assessment in a real-world context and further allows teachers and researchers to provide formative feedback”), interviews (“to support or elaborate on the results of traditional or portfolio assessment by specifying students’ thinking processes”) and surveys (to assess dispositions and attitudes towards CT). The most common approach seems to consist in the use of portfolios to “analys[e] projects performed by students in specific programming environments” (Tang et al., 2020). Unfortunately, assessment tools following this approach carry the risk of “conflating CT with coding abilities” (Relkin & Bers, 2021), which may limit their use in (i) pre-post test designs (Chen et al., 2017), (ii) when validating new learning environments, and (iii) in cases where Computer Science (CS) unplugged activities (Bell & Vahrenhold, 2018) are employed to develop students' CT competences[2]. Because of the transversal nature of Computational Thinking and the "variety of methods by which CT is taught and contexts in which students learn CT" (Weintrop et al., 2021), researchers advocate the development of CT tests that go beyond self-reporting, and are more general (Tikva & Tambouris, 2021). Such assessments should be agnostic of the specific content of the study and the programming environments. The past few years have thus seen a rise in age appropriate unplugged CT assessments targeting CT skills[3] which

i) Can be administered without employing screens (referring to the definition of Unplugged provided by Bell & Vahrenhold, 2018) and can thus be easily deployed in various settings and at a large scale,
ii) Do not require any prior knowledge pertaining to programming or coding (including that of a specific programming language) and are therefore adapted for use in pre-post test experimental designs,
iii) Put a strong emphasis on the reliability and validity said instruments (Chen et al., 2017; Relkin et al., 2020; Román-González et al., 2017, 2018, 2019; Zapata-Cáceres et al., 2020; Wiebe et al., 2019), something which has been identified so far as lacking in the CT assessment literature (Tang et al., 2020).

The Lack of Existing Validated and Reliable CT Assessments Spanning Compulsory Education

Considering the importance of having unplugged CT assessments which are (i) agnostic of programming skills and (ii) have undergone psychometric analyses for validity and reliability, we find ourselves lacking full coverage from kindergarten to upper secondary school (see Table 1).

Starting from the lower end of the spectrum, the TechCheck-K was recently developed by Relkin and Bers (2021) to assess CT at the level of kindergarten, considering the requirements of that age group in terms of cognitive, literacy and motor development.

Two assessment tools exist for lower primary school: the TechCheck (Relkin et al., 2020) and the Beginner's CT test (BCTt, Zapata-Cáceres et al., 2020). The TechCheck (Relkin et al., 2020) was developed for grades 1–2 and proved reliable through Classical Test Theory and Item Response Theory and valid in comparison with the original TACTIC-KIBO instrument (Relkin et al., 2020), thus speaking to the instruments' convergent validity. The BCTt draws inspiration from the CT test (CTt, Román-González et al., 2017; 2019), specifically adapting the original CTt in terms of format and content to take into account students' limited reading and understanding skills (Tikva & Tambouris, 2021; Zhang & Nouri, 2019) and ensure the use of "developmentally appropriate language and tasks to assure that factors such as literacy and fine motor skills are not limiting" (Relkin et al., 2021). The instrument, which follows a multiple choice format, was validated with both experts and primary school students (ages 5–10) without prior coding experience, but showed a ceiling effect for students aged 7–10, with the developmental

Table 1. Synthesis of decontextualised unplugged CT assessments and corresponding validation processes.

Test	Format	Target age group	Underlying CT definition	Validation process	Sample	Validity established for
TechCheck-K (Relkin and Bers 2021)	15 item MCQ	kindergarten (5–6 year old students)	Algorithms, Modularity, Design Process, Debugging, Control Structures, Hardware/Software	Classical Test Theory	89 kindergarten students without coding experience	Full sample
TechCheck (Relkin et al. 2020)	15 item MCQ	1st and 2nd grade (6–9 year old students)		Expert validation (face validity), psychometric analysis (reliability and validity through Classical Test Theory and Item Response Theory - IRT) and convergent validation with the TACTIC-KIBO	768 5–9 year old students participating in a robotics coding curriculum	Full sample
Beginner's CT test (Zapata-Caseres et al. 2020)	25 item MCQ	Primary school (5–12 year old students)	Computational concepts, practices, perspectives (Brennan and Resnick 2012)	Expert validation, and psychometric analysis (reliability and validity Classical Test Theory)	299 primary school students from grades 1–6	5–7 year old students

(continued)

Table 1. (continued)

Test	Format	Target age group	Underlying CT definition	Validation process	Sample	Validity established for
Bebras challenge (Hubwieser and Muhling 2014)	15 item MCQ (3 sets of 5 tasks for 6 age groups with easy, medium & difficult questions)	Secondary school (10–16 year old students)	Problem solving, algorithm design, pattern recognition, pattern generalization and abstraction (see bebras.org)	Psychometric analysis (IRT) to identity constructs	55088 10–16 year old students	
Bebras challenge (Bellettini et al. 2015)			Sequence, repetition, conditionals, decomposition, variables, and debugging	Psychometric analysis (IRT) to determine the difficulty of the questions	2736 students aged 11–18	2 instruments for students in grades 3–4
[unnamed test] (Gane et al 2021)	6 instruments (10 items each) with assessment rubrics	Grades 3–4 (age not specified)	Sequences and loops	Inferential (Classical Test Theory and IRT) and cognitive (design methodology) validation	144 grade 3 and 4 primary school students following an integrated instruction	Full sample
ACES (Paeker et al 2021)	10 item MCQ including block based and Bebras-style questions	Grades 3–5 (age not specified)	CT as "thinking in a way that can be represented and processes by machines to formulate and solve problem"	Cognitive interviews and psychometric analysis through Classical Test Theory	57 4th grade students who completed a CT curriculum	Full sample

(continued)

Table 1. (continued)

Test	Format	Target age group	Underlying CT definition	Validation process	Sample	Validity established for
[unname test] (Chen et al. 2017)	23 items (15 MCQ, 8 open ended with assessment rubrics)	Grade 5 (age not specified)	Computational concepts, practices, perspectives (Brennan and Resnick 2012)	Psychometric analysis through (IRT, construct validity) and demonstration of student learning (pre-post test)	121 5th grade students following a robotics curriculum	Full sample
CT test Gonzalez (2015)	28 item MCQ with Scratch style questions	Secondary school (10–16 year old students)		Expert validation		
CT test (Roman-Gonezalez et al. 2017)				Psychometric analysis (Classical Test Theory) and criterion validity (comparison with spatial, reasoning, and problem solving abilities)	1,251 middle school students (10–16 years old)	Full sample
CT test (Roman-Gonzalez et al. 2018)				Predicative validity	314 middle school students (12–14 years old)	Full sample

appropriateness in regards to the length of the test (45 minutes) for lower primary being put into question by (Relkin et al., 2021). Indeed, provided the objective of having developmentally appropriate instruments, which can also be used in a diverse range of settings, including researchers in pre-post intervention study designs, and practitioners evaluating the impact of educational reforms (notably digital and computing education), length of administration also becomes a major factor of adoption.

While certain researchers have looked into developing assessments for upper primary school (Gane et al., 2021; Parker et al., 2021), they suffer from numerous limitations. The Bebras challenge (Román-González et al., 2017), for example, is an international competition for students throughout compulsory school. While it is sometimes used to assess CT skills, it has undergone limited psychometric validation (Hubwieser & Mühling, 2014; Bellettini et al., 2015). At the same time, the assessment by Gane et al. (2021) requires manual grading and multiple annotators, limiting the test's scalability. Finally, the assessment by Parker et al. (2021), which relies on a combination of block-based and Bebras-style questions, has been piloted with just 57 4th graders.

Lastly, we find the CTt by Román-González et al. (2017, 2018, 2019), a multiple choice test designed and adapted for secondary school (ages 10–16). The CTt has undergone several stages of validation (including reliability, criterion validity in relation to other cognitive tests Román-González et al., 2017, predictive validity Román-González et al., 2018, and convergent validity Román-González et al., 2019).

There thus appears to be a gap in validated unplugged assessments for students in upper primary school (ages 7–9, Román-González et al., 2017).

Research Questions

Therefore, to expand the portfolio of validated CT tests across compulsory education, specifically filling the gap in upper primary school, in this article we present the competent CT test (cCTt), the steps undertaken to develop it on the basis of the BCT test, and its psychometric validation with 37 experts and 1519 students. In the following, we specifically consider the following research questions:

- RQ1: Is the cCTt a valid measure of CT skills for students in third and fourth grade (aged 7–9)?
- RQ2: Is the cCTt a reliable measure of CT skills for students in third and fourth grade (aged 7–9)?
- RQ3: Is the length of the cCTt developmentally appropriate for students in third and fourth grade? If not, can it be shortened?

Methodology

The objective of the study was to design a CT assessment adapted for students in upper primary school, with adequate psychometric properties: the competent CT test (cCTt). In section *The competent Computational Thinking Test*, we describe the format of the cCTt and its development, before presenting its validation in section *Validation of the competent Computational Thinking Test*. Validation was done in two stages. First, the cCTt underwent an expert evaluation (see section *Expert evaluation*). Subsequent adjustments were made based on their recommendations before administering the cCTt to 1519 students to evaluate the psychometric properties of the test (see section *Psychometric reliability and construct validation from student data*).

The competent Computational Thinking Test

The cCTt was developed by adapting the BCTt in terms of format and content to the target age group, as was done by researchers to develop the TechCheck-K from the TechCheck (Relkin et al., 2021) and to develop the BCT test from the CT test (Zapata-Cáceres et al., 2020). Both the BCTt and the cCTt are unplugged (i.e., paper-based) multiple choice exams composed of 25 questions of progressive difficulty which employ questions in two formats (see Figure 1). The majority of questions (21 out of 25) use a 3×3 or a 4×4 grid that a chick must navigate to reach a hen, possibly satisfying side-goals as well, such as picking up a flower or avoiding a cat. The remaining questions are canvas-type questions where students have to replicate a drawing pattern. In both formats, each question presents itself with four possible answers from which the students must choose from. As shown in Table 2, both tests address CT concepts, as defined by Brennan and Resnick (2012), by successively assessing notions of sequences, simple loops, nested loops, conditionals (if-then and if-then-else), and while statements, but with varying number of questions per concept. While designing the cCTt, adaptations in terms of *content* aimed at rendering the test more complex by

i) Mainly employing 4 × 4 grids,
ii) Removing questions of low difficulty (i.e., which exhibited notable ceiling effects in Zapata-Cáceres et al., 2020, in particular questions on 3 × 3 grids and questions involving sequences and simple loops)

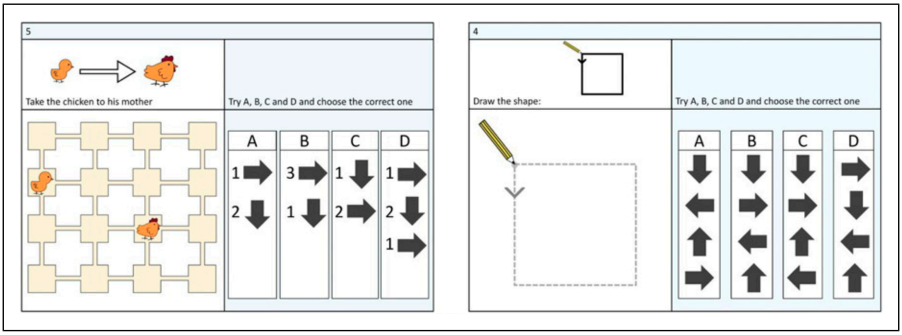

5
Take the chicken to his mother
Try A, B, C and D and choose the correct one
A
B
C
D
1
2
3
1
1
2
1
2
1
4
Draw the shape:
Try A, B, C and D and choose the correct one
A
B
C
D

Figure 1. The two main question formats of the cCTt: grid (left) and canvas (right).

Table 2. Comparison between the BCTt and the cCTt in terms of question concepts and question types.

	BCTt				cCTt			
Blocks	Grid (3×3)	Grid (4×4)	Canvas	Total	Grid (3×3)	Grid (4×4)	Canvas	Total
Sequences	3	1	2	6	1	1	2	4
Simple loops	3	2	0	5	0	4	0	4
Complex loops	0	5	2	7	0	5	2	7
Conditional statements	1	3	0	4	1	3	0	4
While statements	1	2	0	3	1	3	0	4
Combinations	0	0	0	0	0	2	0	2
Total	8	13	4	25	3	18	4	25

iii) Adding more questions related to complex concepts (e.g., while statements)

iv) Creating a new subset of questions which looks to determine whether students had assimilated the range of concepts addressed in the test (referred to as “combinations”)

v) Altering the disposition of objects (starting point, targets and or obstacles) on the grid, and/or the selection of responses students could choose from, so that identifying the correct response requires more reflection on the students’ part.

Adaptations in terms of *format* primarily concerned the while statements: to convey the notion of repetition, and to make the statement more clearly distinct from the simple sequences, the symbols were adapted as shown in Figure 2.

The individual questions of the cCTt are described in Table 3 and the full subset of questions is provided in appendix A.

Validation of the competent Computational Thinking Test

The validation of instruments generally falls under the field of psychometrics, which we briefly introduce here before detailing the approach undertaken for the cCTt.

Psychometric theories are part of a field which seeks to understand the structure of intelligence and “portrays intelligence as a composite of abilities measured by mental tests”[4]. Psychometric theories help evaluate the quality of assessments through two main properties: validity and reliability. Reliability is “the ability to reproduce a result consistently in time and space”. Validity on the other hand “refers to the property of an instrument to measure exactly what it proposes” (Souza et al., 2017) and is typically presented under four forms (Taherdoost, 2016):

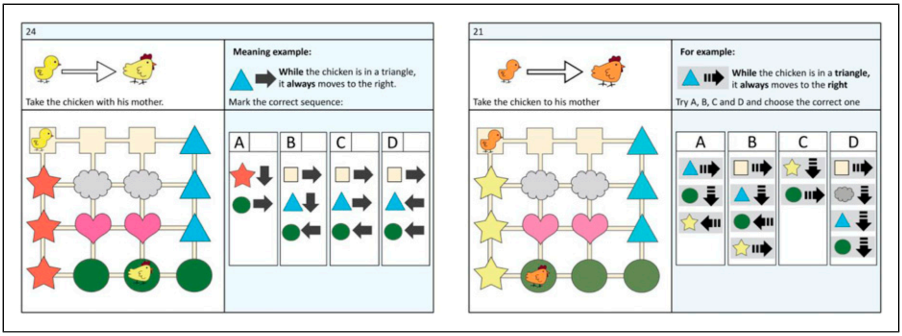

24
Take the chicken with his mother.
Meaning example:
While the chicken is in a triangle, it always moves to the right.
Mark the correct sequence:
A
B
C
D
21
Take the chicken to his mother
For example:
While the chicken is in a triangle, it always moves to the right
Try A, B, C and D and choose the correct one
A
B
C
D

Figure 2. Example of a format and content adaptation (Q24 in the BCTt on the left, which became Q21 in the cCTt on the right), including the recommendations made by the experts.

- Construct validity, or the "extent to which there is evidence consistent with the assumption of a construct of concern being manifested in subjects' observed performance of the instrument" (Raykov & Marcoulides, 2011). Simply put, does our test measure the skills/abilities it intends to measure?
- Content validity, or the "degree to which test components represent adequately a performance domain or construct of interest" (Raykov & Marcoulides, 2011), that is, "whether the particular items in the test adequately represent the domain of possible items one could construct" (Raykov & Marcoulides, 2011). Simply put, is the test fully representative of the content it aims to measure?
- Criterion validity, or how closely the results of the test correspond to the results of a different test.
- Face validity, or the extent to which the content of the test appears to be suitable to its aims.

Both validity and reliability must be considered to adequately validate an assessment instrument. As such, we employ expert evaluation to look into the face, construct and content validity of the test (see section *Expert evaluation*) and analyse student performance to establish both construct validity and reliability of the cCTt (see section *Psychometric reliability and construct validation from student data*). Criterion validity, generally established by comparing the assessment with other validated instruments (Román-González et al., 2017, 2019), is lacking in the present study.

Expert evaluation is an approach that has been used by many researchers to validate CT assessments (Djambong et al., 2018; Zapata-Cáceres et al., 2020; Relkin et al., 2021). That is why, prior to administering the test to the students, a panel of experts was organized to (i) "evaluate if the test [content corresponds] to the intended constructs" (Tang et al., 2020, construct validity), (ii) if the test is an adequate measurement of CT competence (content validity), and (iii) whether the test appears adequate for students in upper primary school (face validity). In total, 37 experts of diverse backgrounds

Table 3. Description of the cCTt, as administered to the students for validation. Note that this format includes error profiles associated to each response (see section *Expert evaluation* and *Expert validation*), with similar distributions of profiles across options A, B, C and D, as suggested by the experts in the expert evaluation. Q: question, O: obstacles, P: pickups.

					Profile for answer							
Block (CT concept)	Q	O	P	Format	A	B	C	D	Profile 1	Profile 2	Profile 3	Profile 4
Sequences	1	x	x	Grid (3 × 3)	3	4	2	1	Incorrect interpretation of the displacements	Correct displacements but lacking objectives	Partial error with the objectives	Correct
	2	x	-	Canvas	2	3	1	4				
	3	-	x	Grid (4 × 4)	4	1	3	2				
	4		-	Canvas	1	2	4	3				
Simple loops	5			Grid (4 × 4)	1	3	4	2	Ignoring the distances / numbers	Incorrect target	Incomplete objectives	Correct
	6			Grid (4 × 4)	4	2	3	1				
	7	x	x	Grid (4 × 4)	3	1	2	4				
	8	x	x	Grid (4 × 4)	2	4	1	3				
Complex loops	9			Grid (4 × 4)	3	4	2	1	Ignoring the loops	Incorrect target	Incomplete objectives	Correct
	10			Canvas	1	2	4	3				
	11			Grid (4 × 4)	4	2	1	3				
	12	x	x	Grid (4 × 4)	4	3	2	1				
	13	x	x	Grid (4 × 4)	2	1	3	4				
	14	-	-	Canvas	1	3	4	2				
	15	x	x	Grid (4 × 4)	2	1	3	4				
Conditional statements	16			Grid (3 × 3)	2	3	1	4	Ignoring the conditional statements	Incorrect target, misinterpretation of the statements	Interpretation as a while	Correct
	17			Grid (4 × 4)	1	2	4	3				
	18			Grid (4 × 4)	3	4	2	1				
	19			Grid (4 × 4)	4	1	3	2				
While statements	20			Grid (3 × 3)	1	2	4	3	Ignoring the while statements	Starting point misinterpretation	Interpretation as a go to	Correct
	21			Grid (4 × 4)	3	4	2	1				
	22			Grid (4 × 4)	2	3	1	4				
	23			Grid (4 × 4)	4	1	3	2				
Combinations	24			Grid (4 × 4)	1	2	3	4	Ignoring the symbols	Misinterpreting the while	Misinterpreting distances & loops	Correct
	25			Grid (4 × 4)	3	1	4	2				

participated in the evaluation of the cCTt (see Table 4). The experts were recruited from:

1. The panel of experts having participated in the validation of the BCTt (Zapata-Cáceres et al., 2020).
2. Researchers in education and computer science working on the question of fostering and/or assessing CT.
3. Practitioners involved in the local digital education reform to gain additional insight into the developmental appropriateness of the instrument. These included (a) experts in assessment from the department of education, (b) professors from the university of teacher education, and (c) teachers having been

Table 4. Experts' profiles. Note that the experts had the possibility to select multiple occupations. Two early childhood education teachers were part of the experts who have been teaching CT to their students for years and participated in the evaluation of the BCTt (Zapata-Cáceres et al., 2020), while the other one is a former primary school teacher who is presently working as a teacher trainer and doing a PhD in a CT-related field.

Occupation and Expertise	Number of Experts
Early childhood education teacher	3
Elementary education teacher	5
High school teacher	1
Teacher in the field of computer science or information technology	4
Teacher trainer	5
Background in computer science or information technology (or related)	4
PhD student in education	5
Researcher in education	10
Teacher/Professor at a University	13
Professor at a teacher education University	1
Undisclosed	7
Age	Number of experts
≤30	2
Between 31 and 45	21
Between 46 and 60	8
Undisclosed	6
Gender	Number of experts
Female	15
Male	16
Undisclosed	6
Expertise teaching computer science, programming and/or Computational Thinking	5-point Likert scale
(From 1 = no knowledge to 5 = expert)	μ = 3.7

trained to introduce digital education (including computer science and CT) and presently teaching said concepts to students in the target age group.

The expert evaluation was conducted in two stages. First, the experts were asked to respond to the survey described in Table 5, with the possibility to leave comments and provide suggestions for improvements after each block of questions. In a second stage, the experts were invited to a short presentation of the development of the test and objectives, which was followed by an unstructured focus group to discuss the experts' impressions of the test and their suggestions for improvements.

Psychometric reliability and construct validation from student data. *Administration* of the cCTt was done after implementing the adjustments suggested by the experts (see section *Expert validation*). Using a paper-based format, generated with the Auto-Multiple-Choice software[6], 1519 students (77 classes) in grade 3 and grade 4 (ages 7–9) did the cCTt in February 2021 (see Table 6). The students belonged to 7 establishments

Table 5. Questions used in the expert evaluation survey.

	Question	Validity Type	Format
Evaluation of the individual questions of the cCTt	Please select the correct response		Multiple choice
	Indicate in your opinion the level of difficulty of the question for students aged 7–10	Face	7-Point Likert
Evaluation of the individual blocks of the cCTt	In your opinion, the questions you just did are adapted to measure students' knowledge of the [concept]	Construct	7-Point Likert
	In your opinion, the questions you just did are relevant to evaluation Computational Thinking skills[5]	Content	7-Point Likert
	Have clear illustrations and instructions	Face	7-Point Likert
	We are open to any suggestions you may have to help improve the quality of the test	Face, construct, and content	Open-ended
Evaluation of the cCTt	Do you think the number of questions is adequate? (yes, too much, not enough)	Face	Multiple choice
	Indicate, in your opinion, the level of adequacy of the test for students aged 7–10	Face	5-Point Likert
Demographics	Indicate your knowledge in terms of teaching computer science and or programming, and Computational Thinking		5-Point Likert
	Age, gender, occupation		Checkboxes

Table 6. Student demographics.

	Grade 3	Grade 4	Grade 3–4 (Mixed Classrooms)
Female	337	372	28
Male	386	385	31

in the Canton Vaud in Switzerland that were selected to be representative of the demographics of the region (El-Hamamsy, Chessel-Lazzarotto, et al., 2021). Due to COVID-19 restrictions the researchers could not be present to administer the tests, which is why a detailed protocol was provided to teachers. In particular, teachers were asked to demonstrate an explanatory example (see appendix B) on the board for each computational concept, and adhere to the recommended time frame (i.e., 40 minutes and 1.5 hours maximum as in the BCTt). The data was then scanned and integrated into a spreadsheet using the Auto-Multiple-Choice software. Additional data pre-processing for the validity and reliability analyses included replacing the lack of responses, "I don't know" and multiple checked-boxes with a score of 0.

Construct validity was assessed through factor analysis, a technique which groups "observed variables [(here, the questions of the test)] into latent [variables, (here, the associated concept)] based on commonalities within the data" (Atkinson et al., 2011). Two main approaches exist for factorial analyses (exploratory and confirmatory). Confirmatory Factor Analysis (CFA) is used when there is an assumption about the underlying structure of the data and to "confirm the structural model of an instrument" (de Souza et al., 2019), while exploratory factor analysis is usually used to explore the dimensionality of the data at hand. In our case, the objective being to evaluate whether the blocks of questions presented in Table 3 constitute coherent groups of questions (i.e., factors, or latent variables which cannot be directly observed—e.g., intelligence, motivation, happiness—but are inferred from others), we employed CFA. When conducting CFA one must employ multiple fit indices as they provide "a more holistic view of goodness of fit, accounting for sample size, model complexity, and other considerations relevant to the particular study" (Alavi et al., 2020). Two types of fit indices exist and must be employed in parallel: (i) global model fit indices assess "how far a hypothesized model is from a perfect model" (Xia & Yang, 2019) (such as the chi-square χ^2 statistic, the root mean square error of approximation or RMSEA, and standardized root mean square residual or SRMR), while (ii) local or incremental fit indices "compare the fit of a hypothesized model with that of a baseline model (i.e., a model with the worst fit)" (Xia & Yang, 2019) (such as the comparative fit index CFI and the Tucker-Lewis index TLI). Cutoffs frequently employed for these metrics are (Hu & Bentler, 1999; Xia & Yang, 2019) CFI and TLI > 0.95, RMSEA < 0.06, SRMR < 0.08 $p_{\chi 2} > 0.05$. It is important to point out that these thresholds are conventional and were established in a specific context, thus meaning that they should be considered as indicative of levels of miss-specification, rather than absolute judges of bad model fit (Xia & Yang, 2019).

Additionally, the χ^2 statistic is sensitive to sample size, with larger samples decreasing the *p*-value (Alavi et al., 2020; Prudon, 2015), and should thus not be considered as “the final word in assessing fit” (Alavi et al., 2020). Some authors therefore suggest employing the ratio between the χ^2 statistic and the degrees of freedom with a cutoff at χ^2 /df ≤ 3 (Kyriazos, 2018). Finally, as the input data is binary (with a score of 0 or 1 per question), the CFA analysis is conducted using an estimator which is adapted to non-normal data and employs diagonally weighted least squared to estimate the model parameters and tetrachoric correlations (Rosseel, 2020; Schweizer et al., 2015).

Reliability was evaluated through two means: Classical Test Theory and Item Response Theory (IRT), as recommended in the context of instrument validation (Cappelleri et al., 2014; Embretson & Reise, 2000; Relkin et al., 2020). Classical Test Theory “comprises a set of principles that allow us to determine how successful our proxy indicators are at estimating the unobservable variables of interest” (DeVellis, 2006) and focuses on test scores (Hambleton & Jones, 1993). Main metrics include (i) difficulty (proportion of students responding correctly), (ii) reliability (proportion of the item’s variation that was shared with the true score, often computed using Cronbach’s alpha when considering scale reliability), and (iii) discrimination (i.e., to what extent the question helps distinguish between the top performers and the low performers, estimated using the Point-biserial correlation). Unfortunately, Classical Test Theory suffers from several limitations. As its focus is at the test level, the observed scores and true scores are test-dependent, and sample-dependent (Hambleton & Jones, 1993). In other words, “different samples with different variances will not yield equivalent data or data that can easily be compared across samples” (DeVellis, 2006). While Classical Test Theory can be used to compare groups against one another, this can also put into question the reliability of the test. Moreover, “a score value on one item should mean the same thing as the same score value on another item of the same scale” (DeVellis, 2006), which is not necessarily true when we consider assessments that have questions of increasing difficulty. That is why researchers have advocated the use of ability scores which are test independent. Item Response Theory (IRT) addresses this limitation, as it helps estimate the ability of an examinee, which is test independent. IRT is based on latent trait theory and assumes that there is an underlying student ability which leads to consistent performance, that is, that the probability of a student getting a given item correct is a function of said students’ ability. IRT thus operates at the item level and estimates parameters for the population (and not just the sample), but is based on high assumptions which are often hard to meet (Hambleton & Jones, 1993).

The data analysis was conducted in R (version 3.6.0, R Core Team 2019) using R Studio (version 1.2) with the lavaan (version 0.6–7, Rosseel, 2012), CTT (version 2.3.3, Sheng, 2019), psych (version 2.1.3, Revelle, 2021) and ltm (version 1.1.1, Rizopoulos, 2006) packages.

Shortening the competent Computational Thinking Test

A further objective of our work is to determine whether the length of the test if developmentally appropriate through the expert evaluation and by gathering feedback from teachers in the field having participated in the test's administration. Provided their responses, if inadequate, the objective is to propose several versions of the cCT test which can be selected according to researchers' and/or practitioners' needs. To that effect, Confirmatory Factor Analysis will be employed once more, this time not to validate the underlying structure of the test, but to identify questions exhibiting high correlations with other factors or other questions. Indeed, CFA fit indices tend to improve with parsimonious models, that is, which are less complex (Alavi et al., 2020).

Results

RQ1: Validity of the competent Computational Thinking Test

As anticipated, we establish the validity of the cCTt through two means: expert validation, reported in section *Expert validation*, and Confirmatory Factor Analysis, detailed in section *Confirmatory Factor Analysis for construct validity.* Considering the validity measures, the experts appear in agreement on the face and content validity of the test, and both the expert validation and the factor analysis point to adequate construct validity. While content validity is evaluated positively, the experts highlight that the test is best suited for computational concepts and does not measure the full range of competences related to CT, notably computational practices (i.e., thought processes) and computational perspectives (i.e., perception). This is indeed an identified limitations of summative assessments (Román-González et al., 2019), which, if one desires a more exhaustive CT assessment, may be addressed by combining multiple assessment methods (Grover et al., 2015; Román-González et al., 2019).

Expert validation. *Face Validity* of the cCTt was evaluated based on several criteria (see Figure 3). The evaluation of each individual question's difficulty points to a progressive increase in difficulty as intended, with an average overall difficulty of $-0.4 \pm 1.0\%$ (between "neither easy nor difficult" and "somewhat difficult" on a scale of -3 to $+3$). The experts, unaware that there was a protocol with examples that was provided to teachers at the time of the survey administration, believed that the symbolism would be difficult to understand without prior explanations, notably in the case of the for loops, the if-else statements, while statements and their combinations. This accounts for the more negative ratings obtained in terms of illustrations for those blocks of questions, and confirms the importance of providing examples to the students beforehand to grasp the key mechanics of the test. As for the test length, 52% of respondents believed it was adequate, 41% that it was too long, and 7% that it was not enough. All in all, 63% believed the test was adequate to measure upper primary school students' CT skills, 26% were neutral, and just 11% were in disagreement.

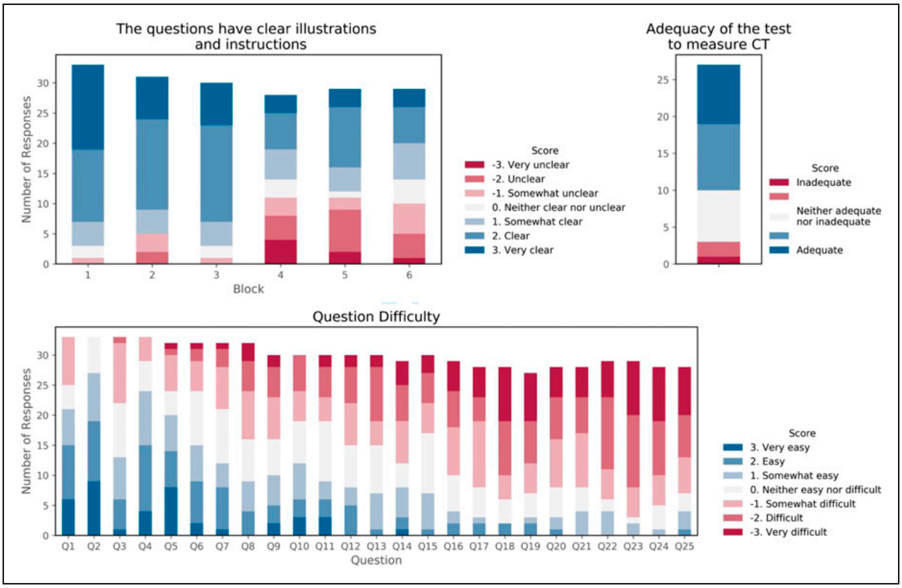


Figure 3. Face Validity of the cCTt.

Construct validity is established in Figure 4. The experts were asked to what extent they believed the blocks of questions adequately measure the concepts defined in Table 3. In the worst case, that is, for the while statements, 76% of the experts agreed that the block of questions adequately measures the targeted concept, with an average agreement of 1.2 ± 0.4% (between "agree" and "totally agree" on a scale of −3 to +3). This seems to point to an adequate construct validity.

Content validity was assessed on the basis of whether the experts believed each block of questions was an adequate representation of CT skills. Results were mainly positive with an average approval rating of 1.5 ± 0.3% (on a scale of −3 to +3). In the worst case, a 71% approval was obtained for the conditional statements (see Figure 4). The experts provided additional insight into their perception of the content validity of the test through the open comments, and in particular in the focus group. The latter, which was unstructured, was primarily focused on what it entails to assess CT considering the fact that (i) CT highly multi-dimensional, (ii) suffers from a lack of consensus around what CT encompasses, and (ii) can be considered both in disciplinary and non-disciplinary contexts. For the experts, the cCTt, although it assesses adequately computational concepts, it does not assess CT in all its dimensions. The cCTt, like the CTt and the BCTt before it, mainly focuses on computational concepts and while it includes certain notions of computational practices, it disregards computational perspectives. Indeed, the cCTt does not provide insight into students' thought processes when engaged in CT-related problem solving tasks (Chevalier et al., 2020), their

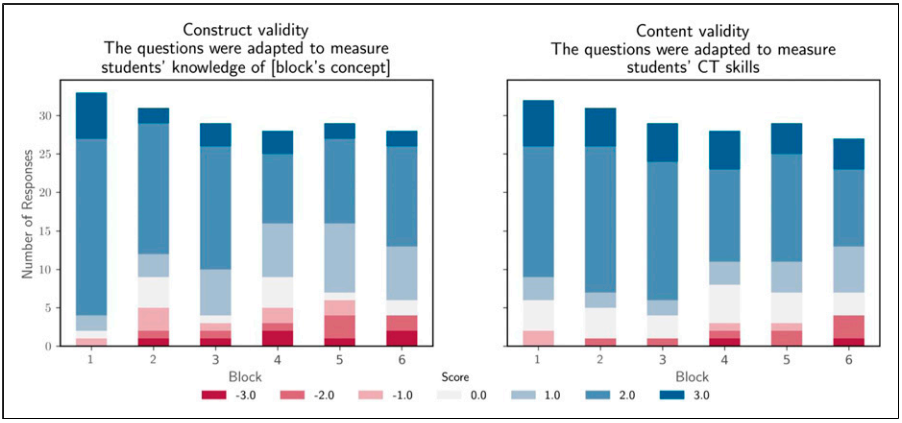


Figure 4. Construct and content validity of the cCTt.

transversal competences (both inter-personal and intrapersonal), and their perception of "of themselves and their relationships with others and the technological world" (Lye & Koh, 2014). This is a limitation of most summative assessments (Román-González et al., 2019) which, despite having excellent adequacy for computational concepts and little adequacy for computational practices, are considered inadequate for computational perspectives. Indeed, both the literature and the experts highlighted the importance of combining the cCTt with other instruments in a system of assessments to get a comprehensive evaluation of CT interventions (Grover et al., 2015; Román-González et al., 2019). Multiple assessment methods help provide complementary information on the acquisition of CT competences. In particular, computational practices relate to processes and are best assessed through direct observations as in the case of the study by Chevalier et al. (2020) who looked into the students' thought processes using the Creative Computational Problem Solving model.

Other suggestions, both in terms of format and content, emerged from the focus group discussion and open questions of the survey. While we will not detail the format related suggestions that were implemented, we present the remaining content related suggestions that were provided. A primary school educator recommended adding an "I don't know" option so students would not feel pressured into selecting a response. Such an addition also helps distinguish between students who did not have time to answer the question and those who did not know what the correct answer was. Another expert with experience in didactics, pedagogy, research and teacher training also emphasized the importance of establishing error profiles in the selection of responses. Concretely, the idea is that each response should correspond to a type of error, so teachers may also use the test to identify specific learning difficulties and intervene accordingly. Ideally, a teacher would like to know where the students are struggling in order to remedy the situation. Both suggestions were included in the version of the cCTt that was administered to the students (see Table 3 for the error profile attributed to each response).

Confirmatory Factor Analysis for construct validity. Based on the test results, a CFA analysis was conducted on the 25 items of the cCTt-25 using the blocks of questions (i.e., CT constructs) as latent factors (see Table 3). This analysis was conducted on three subsets of the data (full, grade 3 and grade 4) to ensure the construct validity was adequate both in general, and for each grade individually. The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's test of sphericity were computed to determine whether the data was suitable for structure detection (see Table 7). KMO values were above 0.8 indicating that the sampling is adequate (superior to the 0.5 acceptable limit, Field et al., 2012). Bartlett's test of sphericity is significant with p-values below 0.05, indicating that a factor analysis may be used. Multiple fit indices are then provided for the cCTt-25 model for the different data subsets (see Table 7). The χ^2 statistic is significant in all three cases although this is likely due to the large sample size. That is why the χ^2/df is considered and is below three in all cases indicating an adequate fit. The RMSEA and the SRMR are also below their cutoffs and indicate a good fit. This is also the case for the CFI and TLI which are above the 0.95 cutoff.

Table 8 provides, for each question in the test, its factor and factor loadings. The factor loadings are positive and significant for all questions, with standardized coefficients ranging from 0.540 for question 17 to 0.867 for question 2. Table 9 shows that there are significant positive correlations between the factors themselves. As each factor is related to the performance in a given block of the cCTt, these correlations indicate that students who perform well in one block are likely to perform well in the others.

Table 7. Confirmatory Factor Analysis for the cCTt-25, with latent variables and observed variables corresponding to the distribution in Table 3.

cCTt-25	Initial Conditions (KMO: Kaiser, Meyer, Olkin Sampling Adequacy)		Robust Model Fit Indices (CFI: Comparative Fit Index, TLI: Tucker-Lewis Index, RMSEA: Root Mean Square Error of Approximation, SRMR: Standardized Root Mean Square Residual)					
	KMO	Bartlett's Test of Sphericity	$\chi 2$	χ^2/df	CFI	TLI	RMSEA	SRMR
All	.90	χ^2 (300) = 7106, $p < .001$	χ^2 (260) = 551, $p = .000$	2.1	.978	.974	.027	.052
Grade 3	.88	χ^2 (300) = 3101, $p < .001$	χ^2 (260) = 378, $p = .000$	1.45	.977	.974	.025	.061
Grade 4	.88	χ^2 (300) = 3614, $p < .001$	χ^2 (260) = 403, $p = .000$	1.6	.975	.971	.027	.070

Table 8. cCTt-25 Factor Loadings for CFA on the full dataset.

Latent Factor	Question	B (Factor Loading)	Standard Error of B	Z-scores	Beta (Standardized Factor Loading)	Significance
f1 (sequences)	1	0.699	0.053	13.154	0.699	***
	2	0.867	0.039	22.216	0.867	***
	3	0.596	0.041	14.504	0.596	***
	4	0.694	0.033	20.775	0.694	***
f2 (simple loops)	5	0.738	0.027	27.415	0.738	***
	6	0.778	0.031	24.868	0.778	***
	7	0.635	0.030	21.125	0.635	***
	8	0.792	0.025	31.521	0.792	***
f3 (complex loops)	9	0.608	0.032	19.013	0.608	***
	10	0.715	0.025	29.122	0.715	***
	11	0.771	0.021	36.155	0.771	***
	12	0.769	0.021	36.626	0.769	***
	13	0.844	0.019	45.050	0.844	***
	14	0.612	0.027	22.423	0.612	***
	15	0.768	0.022	34.956	0.768	***
f4 (conditionals)	16	0.721	0.030	24.231	0.721	***
	17	0.540	0.047	11.494	0.540	***
	18	0.688	0.029	23.688	0.688	***
	19	0.652	0.030	21.765	0.652	***
f5 (while statements)	20	0.626	0.032	19.645	0.626	***
	21	0.765	0.026	29.423	0.765	***
	22	0.576	0.034	16.903	0.576	***
	23	0.540	0.034	15.862	0.540	***
f6 (combinations)	24	0.547	0.049	11.102	0.547	***
	25	0.836	0.050	16.786	0.836	***

These results indicate that the cCTt-25 fits well, and that the blocks are representative of the CT concepts they intend to measure.

RQ2: Reliability of the cCTt

Reliability of the cCTt was established through two means which are considered complimentary: Classical Test Theory (see section *Reliability through Classical Test Theory and item analysis*) and Item Response Theory (see section *Reliability through item response theory*). Both approaches appear to indicate that the test has a wide range of question difficulties and adequately discriminates between students. The IRT contributes to this by showing that the test is best suited to discriminate between students with low and medium abilities, while Classical Test Theory adds that the cCTt

Table 9. cCTt-25 Latent Factor Correlations for CFA on the full dataset.

Factor 1	f1	f1	f1	f1	f1	f2	f2	f2	f2	f3	f3	f3	f4	f4	f5
Factor 2	f2	f3	f4	f5	f6	f3	f4	f5	f6	f4	f5	f6	f5	f6	f6
Correlation	.686	.663	.559	.489	.367	.758	.552	.559	.426	.607	.583	.510	.803	.671	.808
Significance	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***

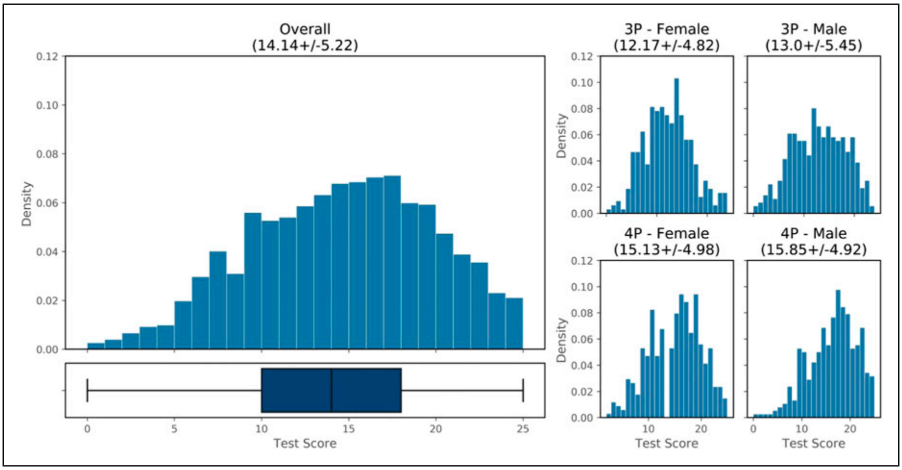


Figure 5. Score distribution per grade and gender.

has a good level of internal consistency and exhibits no clear ceiling or flooring effects, with students in grade 4 scoring significantly better than students in grade 3.

Reliability through Classical Test Theory and item analysis. The distribution of scores obtained by the students is shown in Figure 5. Students score on average 14.14 ± 5.22 out of a total of 25, with no evident ceiling effect, and 8% of students scoring below chance (i.e., < 25/4). Considering the minimum effect size that can be considered in the study to achieve a power of 0.8 (Cohen's $D = 0.14$), significant differences are observed between grades ($p < 0.001$, +2.9pt in grade 4, Cohen's $D = 0.57$), and gender ($p = 0.013$, +0.6pt for boys, Cohen's $D = 0.15$). Although the effect size for gender is small, this brings up the question of when (and *why*) gender differences arise in STEM and disciplines related to Computer Science (CS), and the need to effectively addressed them in ongoing CS and CT curricular reforms (El-Hamamsy, Chessel-Lazzarotto, et al., 2021). Provided the small effect size for gender, we only distinguish between grades in the rest of the Classical Test Theory analysis.

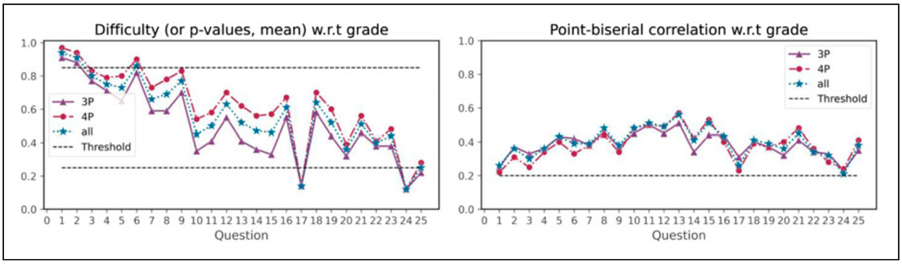


Figure 6. Question difficulty and point-biserial correlation distribution per question. Items with a difficulty below .25 are considered too hard while items with a difficulty above .85 are considered too easy. A point-biserial correlation between .2 and .3 is considered good, and above .3 excellent.

Figure 6 shows the proportion of correct responses for students in grade 3, grade 4 and for the full sample. The questions appear to be increasingly difficult with certain earlier questions being too easy (difficulty index > 0.85 for questions 1 and 2 for all, and question 6 for grade 4), and later questions being too hard (difficulty index < 0.25 for question 17 and 24 for all, and question 25 for grade 3). Students in grade 4 appear to score consistently better than students in grade 3 over all questions. Looking at the point-biserial correlation, which is the difference between the high scorers and the low scorers of the sample population, all questions score above 0.2 which is considered acceptable.

Finally, we consider the reliability of the cCTt with respect to Cronbach's α measure of internal consistency. The overall test reliability is high (Taherdoost, 2016) with an alpha of .85 for the full sample and .84 for grade 3 and grade 4 individually. The drop alpha was computed for each question in the test to determine whether removing a given question would improve the internal consistency of the test. The results in Table 10 show that internal consistency does not improve when removing questions. When considering the reliability of the individual blocks of questions, whether for the full sample of each grade, the reliability is high for blocks 1–3 and 5 ($0.7 < \alpha < 0.9$), and moderate for 4 and 6 ($0.5 < \alpha < 0.7$), according to the thresholds of Hinton et al. (2014) (referenced by Taherdoost, 2016), yielding acceptable levels of internal consistency for psychological assessments (Relkin et al., 2020).

Reliability through Item Response Theory. Item Response Theory complements the results of the Classical Test Theory analysis by considering the relationship between (a) the probability that a student answers a question correctly and (b) an underlying latent ability. Two models were tested: (i) the one-parameter model (called 1-Parameter Logistic, or 1-PL) which considers that only difficulty varies between items, and (ii) the two-parameter model (called 2-Parameter Logistic, or 2-PL), which considers that both difficulty and discrimination varies across items. Table 11 shows the comparison between the two models. Here, the test is significant ($p < 0.001$) indicating that one

Table 10. Classical Test Theory item analysis. Items with a difficulty below .25 are considered too hard while items with a difficulty above .85 are considered too easy. A point-biserial correlation between .2 and .3 is considered good, and above .3 excellent. Q: question, 3P: grade 3, 4P: grade 4.

		Block alpha			1. Difficulty (or p-values, mean)			2. Standard Deviation			3. Point-biserial correlation (or item discrimination, item-total correlation)			Individual drop alpha		
Block	Q	all	3P	4P	all	3P	4P	all	3P	4P	all	3P	4P	all	3P	4P
1	1	.76	.75	.79	.94	.91	.97	.23	.28	.17	.26	.25	.22	.85	.84	.84
	2				.91	.88	.94	.28	.33	.24	.36	.37	.31	.85	.84	.84
	3				.8	.77	.83	.4	.42	.38	.3	.33	.25	.85	.84	.84
	4				.75	.71	.79	.43	.46	.41	.36	.36	.34	.85	.84	.84
2	5	.78	.77	.77	.73	.65	.8	.44	.48	.4	.43	.43	.4	.84	.84	.84
	6				.86	.82	.9	.34	.38	.3	.39	.42	.33	.85	.84	.84
	7				.66	.59	.73	.47	.49	.44	.39	.38	.38	.85	.84	.84
	8				.69	.59	.78	.46	.49	.41	.48	.46	.44	.84	.83	.84
3	9	.83	.81	.83	.77	.7	.83	.42	.46	.38	.38	.37	.34	.85	.84	.84
	10				.45	.35	.54	.5	.48	.5	.48	.45	.48	.84	.83	.83
	11				.5	.41	.58	.5	.49	.49	.51	.5	.5	.84	.83	.83
	12				.63	.55	.7	.48	.5	.46	.49	.45	.49	.84	.83	.83
	13				.52	.41	.62	.5	.49	.49	.56	.51	.57	.84	.83	.83
	14				.47	.36	.56	.5	.48	.5	.41	.34	.42	.85	.84	.84
	15				.46	.33	.57	.5	.47	.5	.51	.44	.53	.84	.83	.83
4	16	.67	.7	.62	.61	.55	.67	.49	.5	.47	.43	.44	.4	.84	.83	.84
	17				.14	.14	.14	.34	.34	.35	.26	.31	.23	.85	.84	.84
	18				.64	.58	.7	.48	.49	.46	.41	.4	.39	.85	.84	.84
	19				.52	.44	.6	.5	.5	.49	.39	.37	.37	.85	.84	.84
5	20	.72	.7	.73	.36	.32	.39	.48	.47	.49	.36	.32	.4	.85	.84	.84
	21				.51	.46	.56	.5	.5	.5	.45	.41	.48	.84	.84	.83
	22				.4	.38	.41	.49	.49	.49	.34	.34	.36	.85	.84	.84
	23				.44	.38	.48	.5	.49	.5	.32	.33	.28	.85	.84	.84
6	24	.57	.58	.57	.12	.12	.12	.32	.33	.33	.21	.23	.24	.85	.84	.84
	25				.25	.22	.28	.43	.41	.45	.38	.35	.41	.85	.84	.84
Overall		.85	.85	.83	.59	.53	.65	.49	.50	.48	-	-	-	-	-	-

Table 11. Comparison of the 1-PL and 2-PL model.

Model	AIC	BIC	Log Likelihood	LRT	df	p.value
1-PL	39156.40	39294.87	−19552.20			
2-PL	38904.32	39170.61	−19402.16	300.08	24	<0.001

model offers a better fit. As lower AIC and BIC scores are obtained with the 2-PL model, this indicates that the 2-PL model is to be preferred.

The IRT analysis results with the 2-PL model are shown in Figure 7, 8 and 9. The Item Characteristic Curves (or ICC) show the probability of selecting the correct response for a given question of the cCTt with respect to the students' ability. In Figure 7, easier questions are those with a curve which begins to increase already at lower abilities. Additionally, questions which better discriminate between students with high and low ability are those with a steeper slope. The objective is to have a test that is composed of questions with varying degrees of difficulty, thus covering a wide spectrum of abilities, and which discriminate well (steep slopes). The ICCs in Figure 7 show curves at varying levels of ability, with easy and medium questions discriminating better than harder ones. Indeed the average test difficulty is equal to 0.032 ± 1.2 on the logit scale, with the easiest question yielding a difficulty index of -2.4 and the hardest a difficulty index of 2.8 (see Table 12). The Item Information Curves (IIC) in Figure 8 offer complementary information by indicating the amount of information that each question provides for a given ability. This means that more precise items at a given ability level are higher on the IIC scale. As higher peaks appear in the low to medium ability range, the test would appear to be better suited to discriminate between students at that level. This is confirmed by the Test Information Function (TIF, sum of the IICs, Hambleton & Jones, 1993) in Fig. 9 which is centered around 0 (medium ability) and slightly higher on the left than on the right, thus providing more information about students with lower abilities than with higher abilities.

RQ3: Shortening the cCTt through Confirmatory Factor Analysis

Administration times lasted on average 35 minutes for students in grade 3 and 30 minutes for students in grade 4, according to an estimation with 453 grade 3 students and 680 grade 4 students. Teachers reported having taken a an average of 65 ± 35 minutes (minimum 25 minutes, median of 50 minutes, and a maximum of 4 sessions) to administer the test, including explanations, examples provided to students and breaks. Provided the expert evaluation where 41% of experts considered that the test was too long, as well as the teachers' feedback following the test administration, in addition to the reported duration of administration, it is important to consider how the test may be shortened. Since the results of the Classical Test Theory analysis (see section *Reliability through Classical Test Theory and item analysis*) showed that the

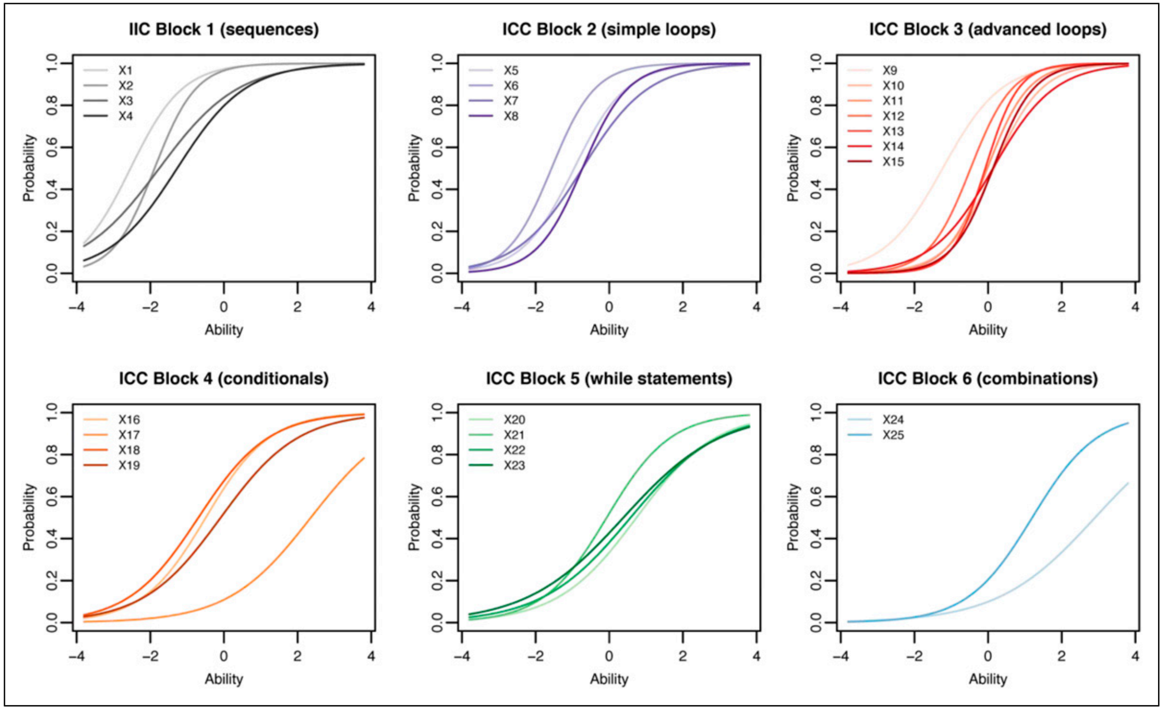


Figure 7. 2-PL model IRT Item Characteristic Curves (ICC).

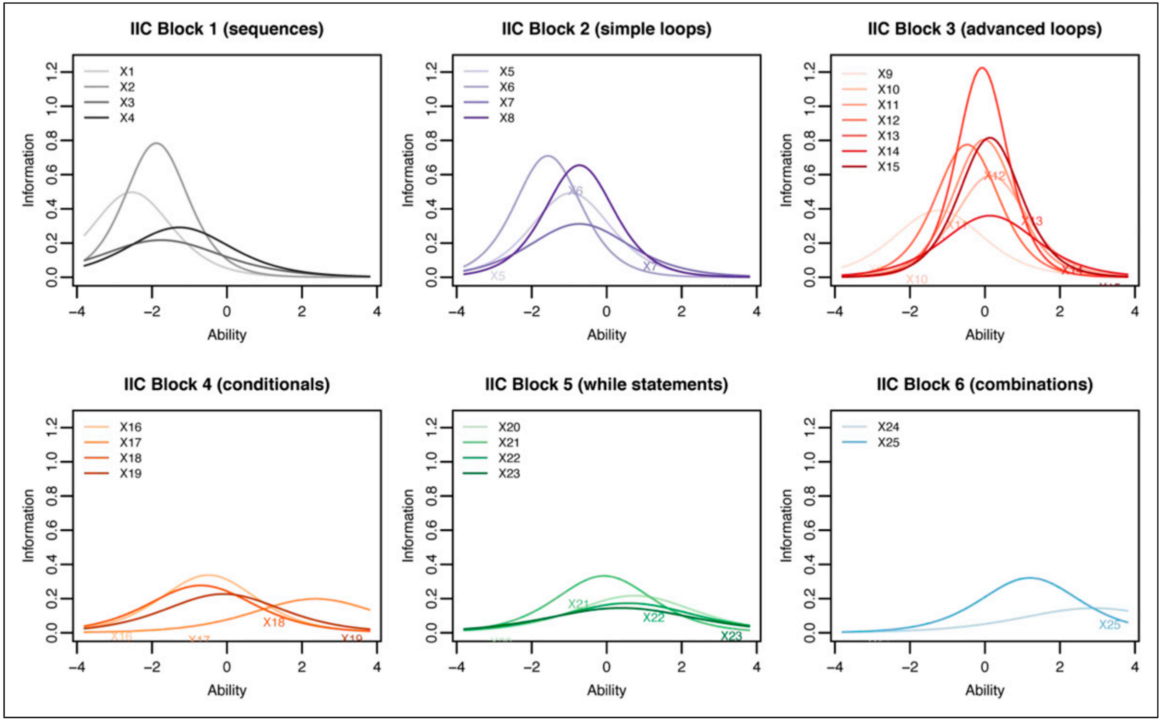


Figure 8. 2-PL model IRT Item Information Curves (IIC).

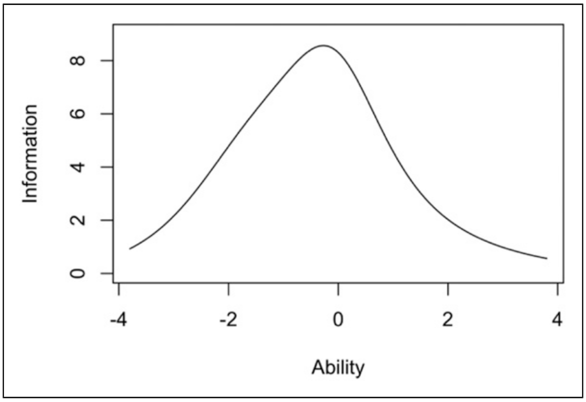


Figure 9. 2-PL model IRT Test Information Function (TIF).

Table 12. IRT Item difficulty and discrimination indices.

Question	IRT Item difficulty index	IRT item discrimination index
1	−2.40	1.18
2	−1.67	1.70
3	−1.42	1.03
4	−1.01	1.07
5	−0.63	1.28
6	−1.28	1.75
7	−0.43	1.03
8	−0.37	1.41
9	−0.92	1.13
10	0.57	1.43
11	0.30	1.68
12	−0.19	1.44
13	0.32	1.78
14	0.69	0.95
15	0.67	1.42
16	−0.23	1.18
17	2.07	1.08
18	−0.37	1.01
19	0.29	0.93

(continued)

Table 12. (continued)

Question	IRT Item difficulty index	IRT item discrimination index
20	1.04	0.80
21	0.16	1.03
22	0.66	0.83
23	0.65	0.83
24	2.80	0.79
25	1.47	1.06
$\mu \pm \sigma$	0.032 ± 1.2	1.2 ± 0.31

Table 13. Iterative procedure to shorten the cCTt based on CFA.

	Successive Editions to the cCTt-25	Model Fit Statistics					
Model		$\chi 2$	χ^2/df	CFI	TLI	RMSEA	SRMR
cCTt-17	1. Removing Q17: Correlates with Q24 and has a high difficulty	χ^2 (237) = 464, p = .000	1.96	.982	.979	.025	.047
	2. Removing Q22: Correlates with Q2 and also loads on factor 4	χ^2 (215) = 394, p = .000	1.83	.985	.983	.023	.045
	3. Removing Q9: Also loads on factors 1 and 2	χ^2 (194) = 336, p = .000	1.73	.988	.986	.022	.044
	4. Removing Q10: Correlates with Q4 and loads on factors 1 and 2	χ^2 (174) = 294, p = .000	1.69	.989	.986	.021	.043
	5. Removing Q2: Correlates with Q4, and is too easy	χ^2 (155) = 260, p = .000	1.68	.989	.987	.021	.041
	6. Removing Q4: Loads on factors 4, 5 and 6	χ^2 (137) = 228, p = .000	1.66	.990	.988	.021	.040
	7. Removing Q8: Also loads on factor 3	χ^2 (120) = 201, p = .000	1.68	.991	.988	.021	.040
	8. Removing Q14 (last remaining canvas question)	χ^2 (104) = 176, p = .000	1.69	.991	.988	.021	.040
cCTt-15	9–10. Removing Q24 and Q25 (block 6, the combination of constructs)	χ^2 (80) = 137, p = .000	1.71	.992	.989	.022	.038

Table 14. Questions in the variants of the cCTt.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
cCTt-25	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
cCTt-17	x		x		x	x	x				x	x	x		x	x		x	x	x	x		x	x	x
cCTt-15	x		x		x	x	x				x	x	x		x	x		x	x	x	x		x		

problematic questions were the same for students in grade 3 and grade 4 alike (despite students in grade 3 scoring less), we believe that there is not enough difference to justify having an ad-hoc test for each grade. That is why we chose to apply the same shortening procedure, independently of the students' grade, to propose several shorter versions of the cCTt which we validate on the full dataset. The chosen approach is Confirmatory Factor Analysis, more specifically using the provided modification indices (i.e., the amount by which the χ^2 statistic would improve) to identify questions which are highly correlated and thus redundant, or load on other factors (and thus reduce the model's fit). Therefore, taking into consideration that we would like to have blocks which are somewhat balanced in length, we iteratively removed questions as described in Table 13. The resulting variants of the test are presented in Table 14:

- The cCTt-25, the longest version of the test which meets all the traditional thresholds for the model fit statistics.
- The cCTt-17, which covers the same breadth of constructs of the cCTt-25 but lacks a certain number of redundancies over the different blocks of questions.
- The cCTt-15, the fastest and most focused test, which does not include the final block of questions that evaluate the combination of concepts and were the most difficult for students.

Discussion and Conclusion

With the introduction of CT in curricula worldwide, there is a pressing need to have validated and reliable instruments to assess Computational Thinking throughout mandatory schooling. It is not surprising to see that CT assessment is one of the most prominent topics in CT research (Tikva & Tambouris, 2021), with researchers working to develop instruments from kindergarten (Relkin et al., 2021), through primary school (Relkin et al., 2020; Zapata-Cáceres et al., 2020) and up to middle school (Román-González et al., 2017, 2019). However, and to the best of our knowledge, none have proven to be both valid and reliable measurements of CT in upper primary school. Therefore, building up on the CT test (Román-González et al., 2017, 2019) designed for middle school, and the subsequent BCT test which adapted the CT test and validated it for use in lower primary school, we developed the cCT test to pally the lack of validated instruments in upper primary school.

The cCT test is an unplugged CT assessment adapted from the BCT test in terms of format and content, to be administered to students in the 7–9 age range regardless of their prior coding experience. The test is composed of 25 multiple choice questions of increasing difficulty and addressing notions of sequences, loops, conditionals and while statements. To assess the tests' validity (face, construct, and content validity) we conducted an expert evaluation with 37 participants. The survey results and focus group indicate that the test has good face, content and construct validity. Then, to validate the psychometric properties of the cCTt (in terms of validity and reliability), the test was administered to 1519 students from 77 classes in grades 3 and 4 (ages 7–9) enrolled in 7 schools of the same region. The analysis of the results involved three stages and the outcomes can be summarized as follows. In the first stage, Confirmatory Factor Analysis confirmed the construct validity of the different blocks of the test. In the second stage, the results from Classical Test Theory showed that there was no evident ceiling or flooring effect, with scores distributed around 14/25, although students in grade 3 score significantly lower than those in grade 4. The Classical Test Theory analysis also indicated adequate reliability with good internal consistency (Cronbach's $\alpha = 0.85$), levels of discrimination (Point-biserial correlations > 0.2) and a wide range of question difficulties (proportion of correct responses). In the final stage, the Item Response Theory analysis supported these findings and further indicated that the test was better suited at evaluating and discriminating between students with low and medium abilities. In addition to the psychometric analyses, and to pally the limitations posed by administration time that were brought up both by teachers and experts, several shortened versions of the cCT test are proposed (cCTt-17 and cCTt-15), having been established through an iterative shortening procedure using Confirmatory Factor Analysis.

While the test has adequate face, content, and construct validity, as determined through expert validation, and good psychometric properties, there are two main limitations. Firstly, to achieve a more exhaustive measurement of CT is important to consider combining assessments such as the cCTt with other forms of assessments (Grover et al., 2015; Román-González et al., 2019), thus improving the content validity of the overall assessment scheme. This is because the cCTt, as a paper-based test, does not measure all aspects of CT. The cCTt specifically focuses on computational concepts and practices while lacking computational perspectives (Román-González et al., 2019), and more generally competences (Lye & Koh, 2014), an identified limitation of many summative CT assessments. Secondly, criterion validity needs to be established with respect to a "gold standard". Three main approaches exist. Typically, researchers make a comparison with other assessment methods (convergent validity, Relkin et al., 2020, 2021; Román-González et al., 2017). More classically however, criterion validity is established through

i) Determining the test's predictive validity (i.e., does the test predict something that it should predict, such as academic performance and coding achievement, as done in Román-González et al., 2018)
ii) Determining its concurrent validity (can the test distinguish between two populations that are distinct, for example, can we distinguish between students who partake in CT-related activities and those who don't?).

Provided that validation is a multi-step process which requires "collect[ing] multiple sources of evidence to support the proposed interpretation and use of assessment result

[s]" and "multiple methodologies, sources of data, and types of analysis" (Gane et al., 2021), future work should continue to validate the instrument in consideration of the test's content and criterion validity, for both the target and older age groups (namely grades 5 and 6).

To conclude, the cCTt appears to be a valid and reliable instrument for CT assessment in grades 3 and 4 (students aged 7–9), which should be combined with other assessments to include computational perspectives and practices. The test is easy to administer and score on a large scale. With this work, we therefore extend the portfolio of CT assessments designed for use by researchers and teachers in formal education. In particular, the BCTt, cCTt, and CTt now jointly cover the range needed for CT assessment throughout primary and secondary school, by means of unplugged tests. It would be desirable, however, to extend the study by applying the cCTt to other populations, and to specifically study the age limits for using one test or the other.

Appendix A

cCTt-25 question set

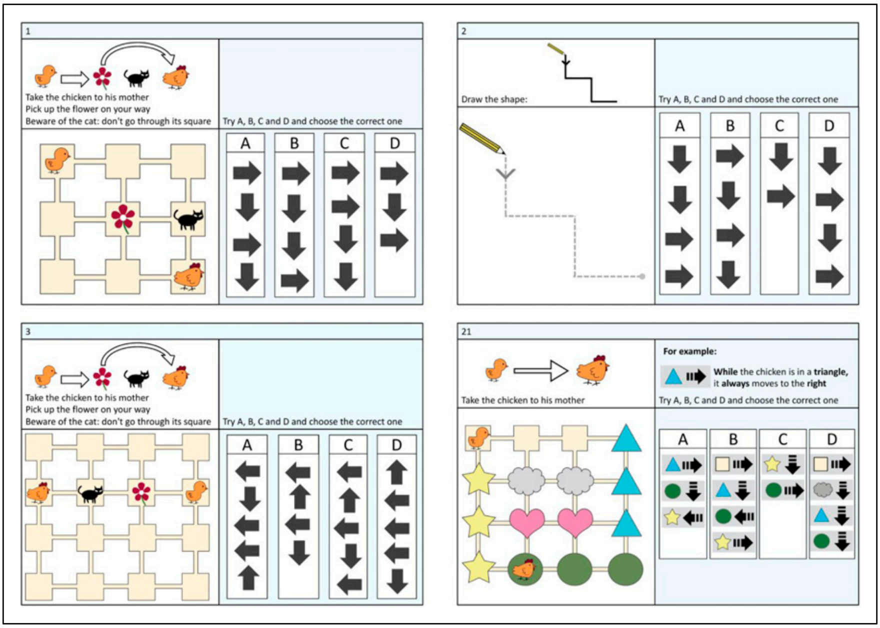

1
Take the chicken to his mother
Pick up the flower on your way
Beware of the cat: don't go through its square
Try A, B, C and D and choose the correct one
A
B
C
D
2
Draw the shape:
Try A, B, C and D and choose the correct one
A
B
C
D
3
Take the chicken to his mother
Pick up the flower on your way
Beware of the cat: don't go through its square
Try A, B, C and D and choose the correct one
A
B
C
D
21
Take the chicken to his mother
For example:
While the chicken is in a triangle, it always moves to the right
Try A, B, C and D and choose the correct one
A
B
C
D

Figure A1. Questions of the block 1 (sequences) of the cCTt.

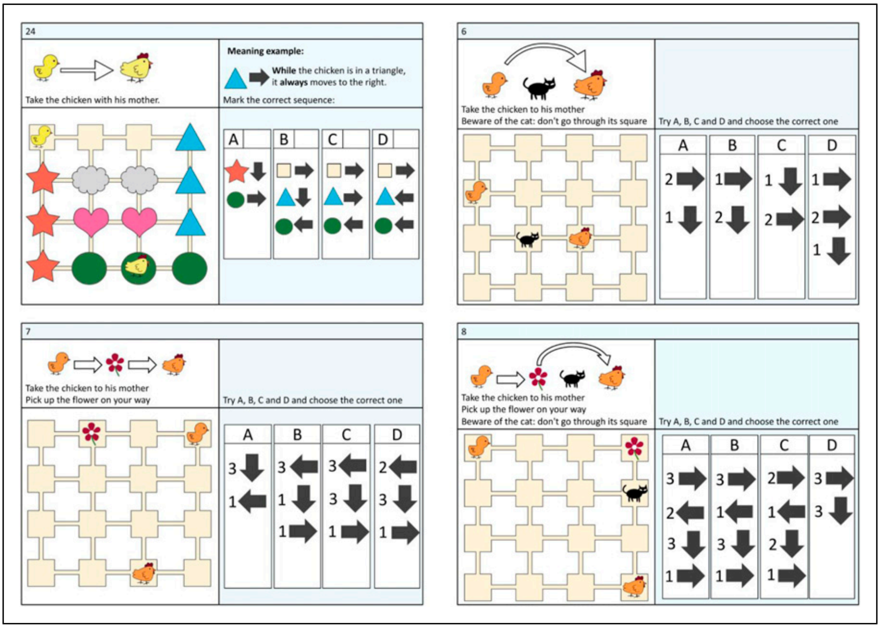

24
Take the chicken with his mother.
Meaning example:
While the chicken is in a triangle, it always moves to the right.
Mark the correct sequence:
A
B
C
D
6
Take the chicken to his mother
Beware of the cat: don't go through its square
Try A, B, C and D and choose the correct one
A
B
C
D
2
1
1
2
1
2
1
2
1
7
Take the chicken to his mother
Pick up the flower on your way
Try A, B, C and D and choose the correct one
A
B
C
D
3
1
3
1
1
3
3
1
2
3
1
8
Take the chicken to his mother
Pick up the flower on your way
Beware of the cat: don't go through its square
Try A, B, C and D and choose the correct one
A
B
C
D
3
2
3
1
3
1
3
1
2
1
2
1
3
3

Figure A2. Questions of the block 2 (simple loops) of the cCTt.

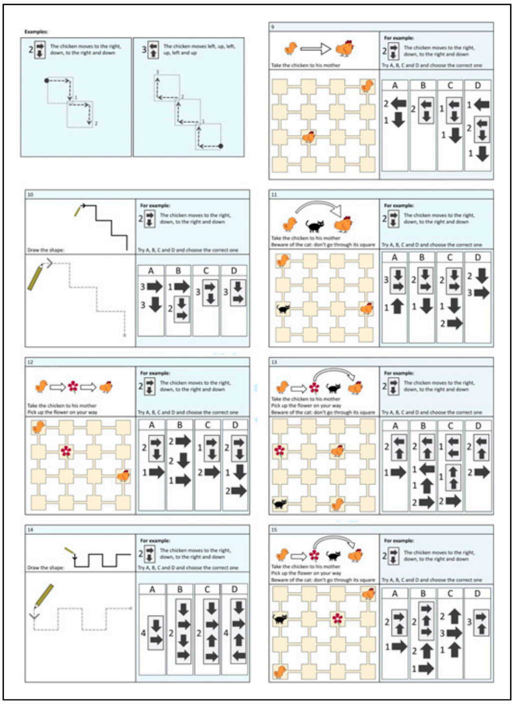
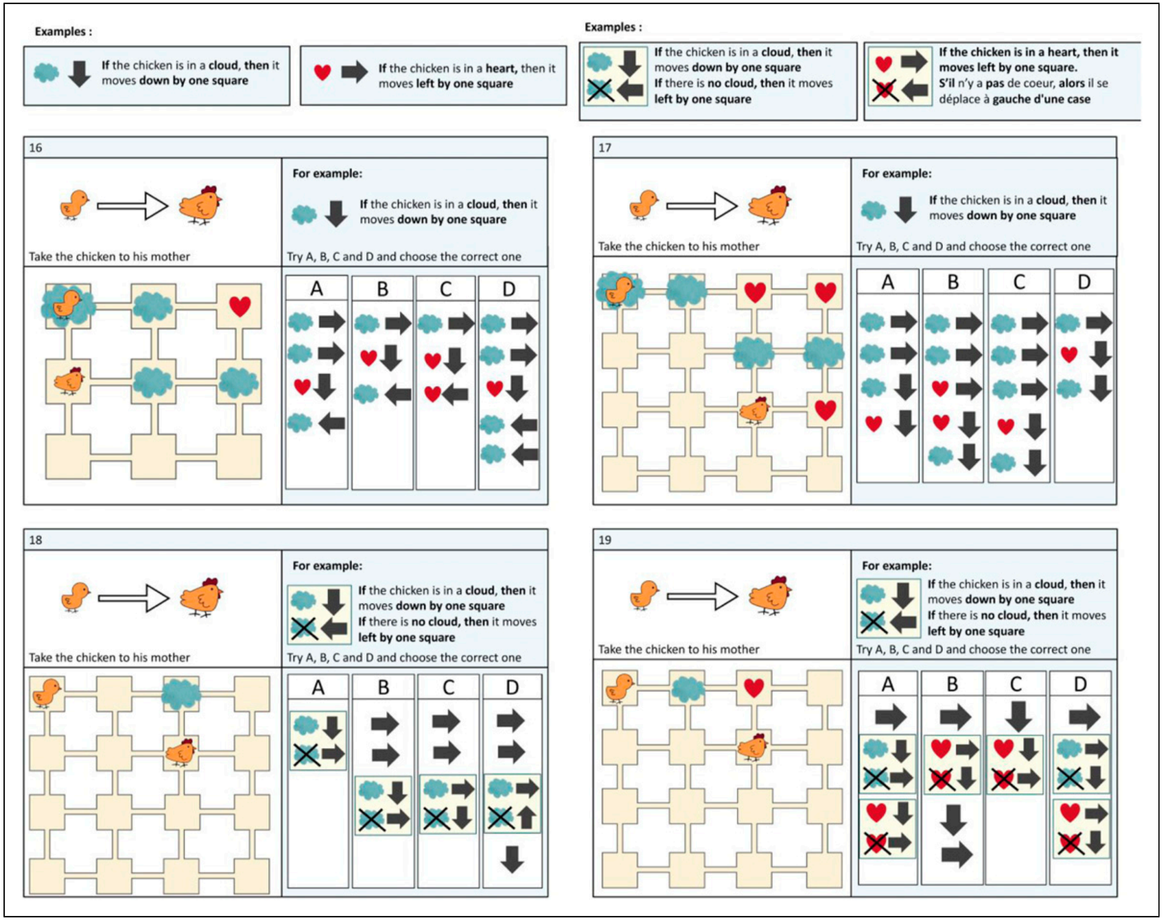

Examples:
The chicken moves to the right, down, to the right and down
The chicken moves left, up, left, up, left and up
9
Take the chicken to his mother
For example:
The chicken moves to the right, down, to the right and down
Try A, B, C and D and choose the correct one
10
Draw the shape:
11
Take the chicken to his mother
Beware of the cat: don't go through its square
12
Take the chicken to his mother
Pick up the flower on your way
13
Take the chicken to his mother
Pick up the flower on your way
Beware of the cat: don't go through its square
14
Draw the shape:
15
Take the chicken to his mother
Pick up the flower on your way
Beware of the cat: don't go through its square
A
B
C
D

Figure A3. Questions of the block 3 (complex loops) of the cCTt.



Examples :

If the chicken is in a **cloud**, **then** it moves **down by one square**

If the chicken is in a **heart**, then it moves **left by one square**

Examples :

If the chicken is in a **cloud**, **then** it moves **down by one square**
If there is **no cloud**, **then** it moves **left by one square**

If the chicken is in a heart, then it moves left by one square.
S'il n'y a **pas** de coeur, **alors** il se déplace à **gauche d'une case**

16

Take the chicken to his mother

For example:

If the chicken is in a **cloud**, **then** it moves **down by one square**

Try A, B, C and D and choose the correct one

17

Take the chicken to his mother

For example:

If the chicken is in a **cloud**, **then** it moves **down by one square**

Try A, B, C and D and choose the correct one

18

Take the chicken to his mother

For example:

If the chicken is in a **cloud**, **then** it moves **down by one square**
If there is **no cloud**, **then** it moves **left by one square**

Try A, B, C and D and choose the correct one

19

Take the chicken to his mother

For example:

If the chicken is in a **cloud**, **then** it moves **down by one square**
If there is **no cloud**, **then** it moves **left by one square**

Try A, B, C and D and choose the correct one

Figure A4. Questions of the block 4 (conditionals) of the cCTt.

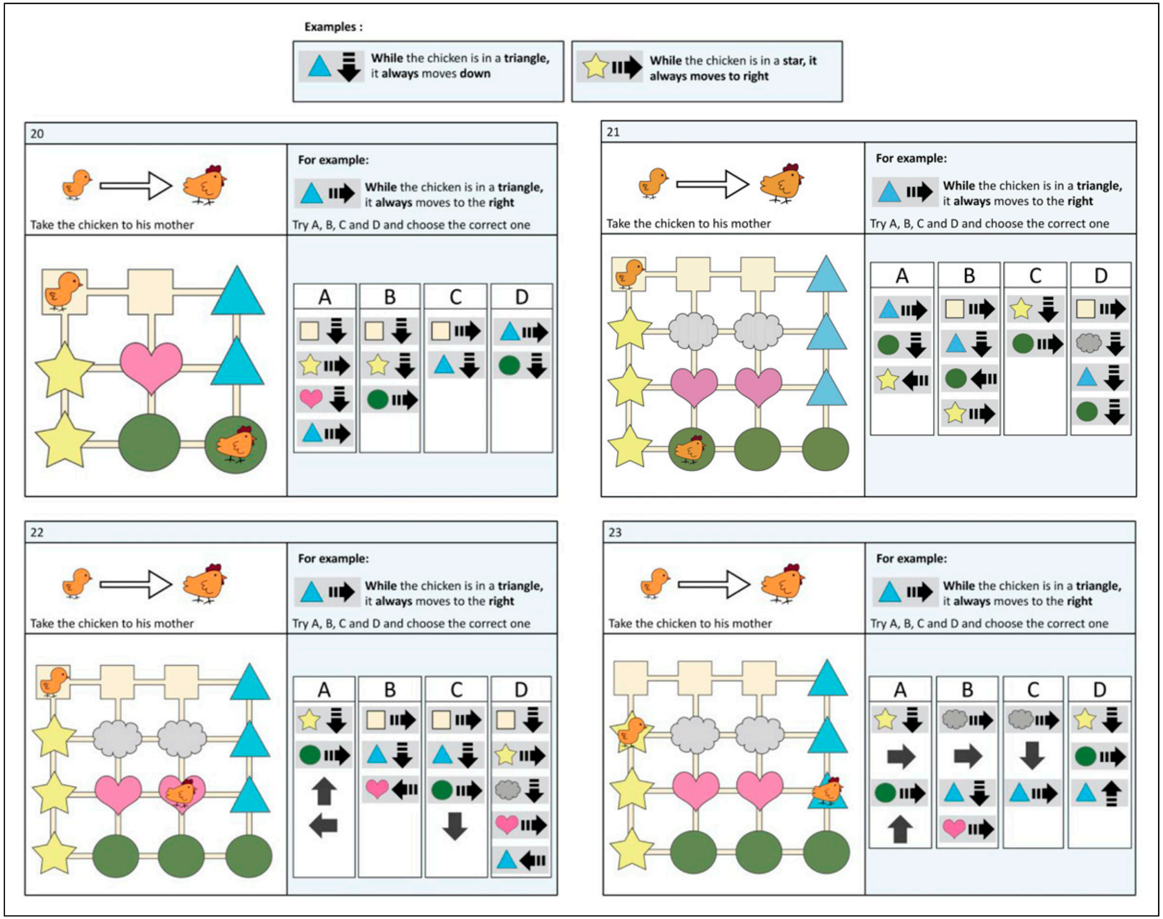
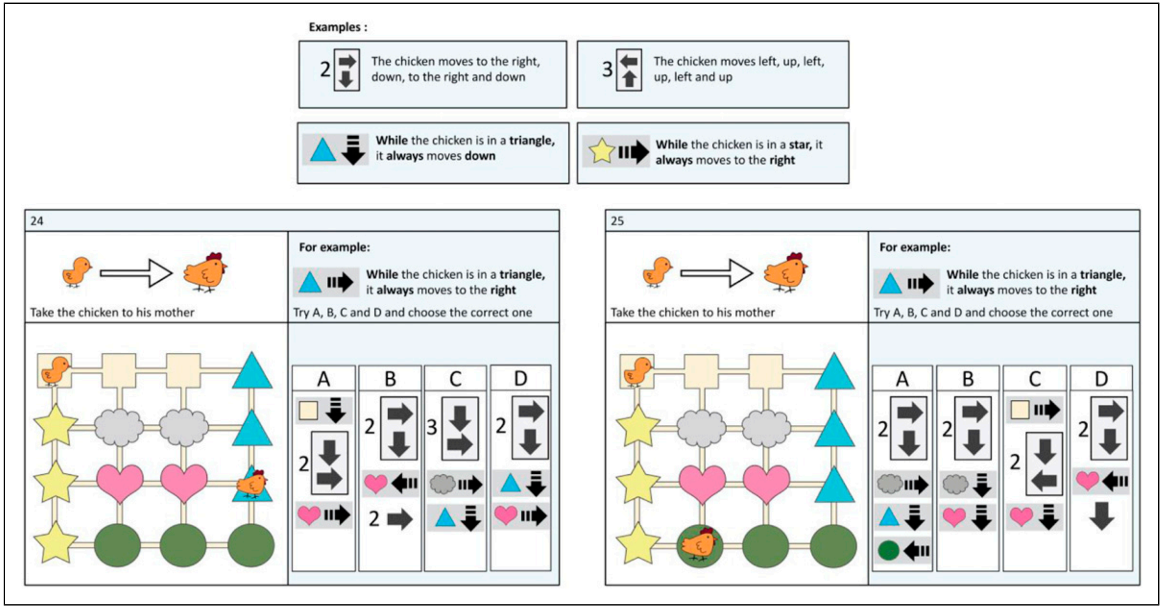

Examples :
While the chicken is in a triangle, it always moves down
While the chicken is in a star, it always moves to right
20
Take the chicken to his mother
For example:
While the chicken is in a triangle, it always moves to the right
Try A, B, C and D and choose the correct one
A
B
C
D
21
Take the chicken to his mother
For example:
While the chicken is in a triangle, it always moves to the right
Try A, B, C and D and choose the correct one
A
B
C
D
22
Take the chicken to his mother
For example:
While the chicken is in a triangle, it always moves to the right
Try A, B, C and D and choose the correct one
A
B
C
D
23
Take the chicken to his mother
For example:
While the chicken is in a triangle, it always moves to the right
Try A, B, C and D and choose the correct one
A
B
C
D

Figure A5. Questions of the block 5 (while statements) of the cCTt.



Examples :

2 The chicken moves to the right, down, to the right and down

3 The chicken moves left, up, left, up, left and up

While the chicken is in a **triangle,** it **always** moves **down**

While the chicken is in a **star,** it **always** moves to the **right**

24

Take the chicken to his mother

For example:

While the chicken is in a **triangle,** it **always** moves to the **right**

Try A, B, C and D and choose the correct one

25

Take the chicken to his mother

For example:

While the chicken is in a **triangle,** it **always** moves to the **right**

Try A, B, C and D and choose the correct one

Figure A6. Questions of the block 6 (combination of concepts) of the cCTt.

Appendix B

cCTt Example questions

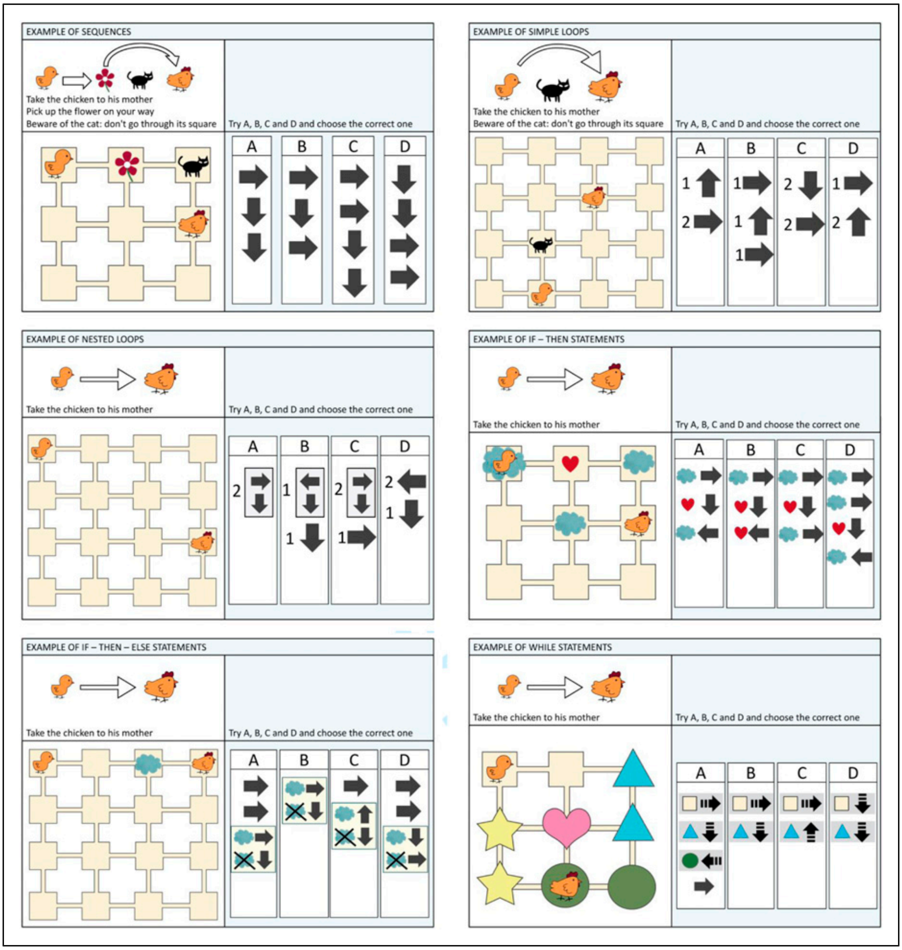

EXAMPLE OF SEQUENCES
Take the chicken to his mother
Pick up the flower on your way
Beware of the cat: don't go through its square
Try A, B, C and D and choose the correct one
A
B
C
D
EXAMPLE OF SIMPLE LOOPS
Take the chicken to his mother
Beware of the cat: don't go through its square
Try A, B, C and D and choose the correct one
A
B
C
D
EXAMPLE OF NESTED LOOPS
Take the chicken to his mother
Try A, B, C and D and choose the correct one
A
B
C
D
EXAMPLE OF IF – THEN STATEMENTS
Take the chicken to his mother
Try A, B, C and D and choose the correct one
A
B
C
D
EXAMPLE OF IF – THEN – ELSE STATEMENTS
Take the chicken to his mother
Try A, B, C and D and choose the correct one
A
B
C
D
EXAMPLE OF WHILE STATEMENTS
Take the chicken to his mother
Try A, B, C and D and choose the correct one
A
B
C
D

Figure B1. Example questions of the cCTt. C Factor Loadings for the Confirmatory Factor Analysis of the cCTt variants.

Appendix C

cCTt-17

Table 15. cCTt-17 Factor Loadings for CFA on the full dataset.

Latent Factor	Question	B (Factor Loading)	Standard Error of B	Z-scores	Beta (Standardized Factor Loading)	Significance
f1	1	0.694	0.068	10.281	0.694	***
(Sequences)	3	0.612	0.051	11.993	0.612	***
	5	0.759	0.030	25.253	0.759	***
f2	6	0.805	0.034	24.021	0.805	***
(Simple loops)	7	0.640	0.033	19.133	0.640	***
	11	0.784	0.023	34.546	0.784	***
f3	12	0.807	0.021	38.091	0.807	***
(Complex loops)	13	0.857	0.021	41.788	0.857	***
	15	0.786	0.023	33.875	0.786	***
	16	0.721	0.031	23.437	0.721	***
f4	18	0.702	0.030	23.446	0.702	***
(Conditionals)	19	0.668	0.031	21.382	0.668	***
	20	0.644	0.033	19.690	0.644	***
f5	21	0.798	0.028	28.793	0.798	***
(While statements)	23	0.585	0.034	17.341	0.585	***
f6	24	0.520	0.051	10.279	0.520	***
(Combinations)	25	0.879	0.056	15.683	0.879	***

Table 16. cCTt-17 Latent Factor Correlations for CFA on the full dataset.

Factor 1	f1	f1	f1	f1	f1	f2	f2	f2	f2	f3	f3	f3	f4	f4	f5
Factor 2	f2	f3	f4	f5	f6	f3	f4	f5	f6	f4	f5	f6	f5	f6	f6
Correlation	.792	.615	.528	.365	.300	.676	.554	.517	.407	.561	.551	.474	.730	.569	.756
Significance	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***

cCTt-15

Table 17. cCTt-15 Factor Loadings for CFA on the full dataset.

Latent Factor	Question	B (Factor Loading)	Standard Error of B	Z-scores	Beta (Standardized Factor loading)	Significance
f1	1	0.697	0.067	1.350	0.697	***
(Sequences)	3	0.609	0.051	11.909	0.609	***
	5	0.759	0.030	25.492	0.759	***
f2	6	0.808	0.034	24.118	0.808	***
(Simple loops)	7	0.636	0.033	19.141	0.636	***
	11	0.788	0.023	34.896	0.788	***
f3	12	0.809	0.021	38.214	0.809	***
(Complex loops)	13	0.856	0.021	41.606	0.856	***
	15	0.780	0.024	33.123	0.780	***
	16	0.721	0.031	22.954	0.721	***
f4	18	0.716	0.030	23.730	0.716	***
(Conditionals)	19	0.654	0.032	20.496	0.654	***
	20	0.643	0.035	18.635	0.643	***
f5	21	0.788	0.030	26.665	0.788	***
(While statements)	23	0.596	0.035	16.989	0.596	***

Table 18. cCTt-15 Latent Factor Correlations for CFA on the full dataset.

Factor 1	f1	f1	f1	f1	f2	f2	f2	f3	f3	f4
Factor 2	f2	f3	f4	f5	f3	f4	f5	f4	f5	f5
Correlation	.792	.616	.530	.366	.676	.553	.519	.561	.552	.731
Significance	***	***	***	***	***	***	***	***	***	***

Acknowledgments

We would like to thank all those who were implicated in the expert evaluation, test administration in the schools, as well as the teachers and students who participated in the validation process.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the NCCR Robotics, a National Centre of Competence in Research, funded by the Swiss National Science Foundation (grant number 51NF40_185543), and the Madrid Regional Government, through the project e- Madrid-CM (P2018/TCS-4307) which is also co-financed by the Structural Funds (FSE and FEDER).

Data availability

The data used for the study is available on Zenodo at https://doi.org/10.5281/zenodo.5865572.

ORCID iDs

Laila El-Hamamsy https://orcid.org/0000-0002-6046-4822
María Zapata-Cáceres https://orcid.org/0000-0002-8817-5889
Barbara Bruno https://orcid.org/0000-0003-0953-7173

Notes

1. A competence refers to "the proven ability to use knowledge, skills and personal, social and/or methodological abilities, in work or study situations and in professional and personal development" (European Union, 2006).
2. Computer Science Unplugged activities (Bell & Vahrenhold, 2018) are defined as activities which develop core CS competences without using screens. These activities have numerous advantages including i) making use of embodied cognition, ii) being adapted to a wide range of learners by reducing the cognitive load pertaining to use of technological devices and programming artefacts (Romero et al., 2018), iii) saving time pertaining to the mastery of specific tools and programming interfaces (Webb et al., 2017), and iv) not requiring any specific technological devices. Owing to these benefits, CS unplugged activities have gained in popularity over the past two decades, with the term "unplugged" now referring to a type of pedagogy (Bell & Vahrenhold, 2018) with a wide range of applications in outreach initiatives and more recently teacher training and classrooms to support formal curricula. Once example which can be cited is the case of Switzerland where the lower primary school (grades 1–4) CS curricular reform is heavily focused on unplugged content which teachers favor and employ more largely than their plugged counterparts (El-Hamamsy, Bruno, et al., 2021) in big part due

to a reticence towards the presence of screens in classrooms (Negrini, 2020). While there is often a debate around the relevance of such types of activities to develop CT competences, there is an increasing amount of research being done on the topic. While certain small scale studies were undertaken and showed that CS Unplugged activities could be as effective as traditional approaches (Thies & Vahrenhold, 2013; 2016; Hermans & Aivaloglou, 2017), more and more large scale studies at the level of primary school show the benefits of CS Unplugged activities compared to traditional approaches for learning (Brackmann et al., 2017; del Olmo-Muñoz et al., 2020; Sun et al., 2021; Zhan et al., 2022; Kirçali & Özdener, 2022), in addition to the benefits in terms of motivation and gender issues (del Olmo-Muñoz et al., 2020), engagement (Zhan et al., 2022), and self-efficacy (Hermans & Aivaloglou, 2017), thus contributing to the promotion of CS for all and the development of CT competencies (Huang & Looi, 2021).

3. CT skills here refers to the definition of skills provided by the European Union (2006) as "the ability to apply knowledge and use know-how to complete tasks and solve problems". Measuring CT skills thus implies assessing the outcome of the application of the knowledge of the underlying CT concepts, without looking into the processes involved. Such assessments therefore do not evaluate the full range of CT competences involved in the resolution of CT-tasks.
4. See the section of the Encyclopedia Britannica on Psychometric Theories here https://www.britannica.com/science/ human-intelligence-psychology/Psychometric-theories.
5. Please note that experts considered this question from a content perspective, that is, whether the test grasps all facets of CT, despite the use of the word "evaluation".
6. See https://www.auto-multiple-choice.net/index.en for the link to the Auto-Multiple-Choice software.

References

Alavi, M., Visentin, D. C., Thapa, D. K., Hunt, G. E, Watson, R., & Cleary, M. (2020). Chi-square for model fit in confirmatory factor analysis. *Journal of Advanced Nursing*, *76*(9), 2209–2211. https://doi.org/10.1111/jan.14399.

Atkinson, T. M, Rosenfeld, B. D., Sit, L., Mendoza, T. R., Fruscione, M., Lavene, D., et al. (2011). Using confirmatory factor Analysis to evaluate construct validity of the brief pain inventory (BPI). *J Pain Symptom Manage*, *41*(3), 558–565. https://doi.org/10.1016/j.jpainsymman.2010.05.008.

Basu, S., Rutstein, D., Xu, Y., & Shear, L. (2020). A principled approach to designing a Computational Thinking practices assessment for early grades. Proceedings of the 51st ACM Technical Symposium on Computer Science Education, SIGCSE '20, Portland, OR, 11–14 March , 2020 (p. 912). Association for Computing Machinery. https://doi.org/10.1145/3328778.3366849.

Bellettini, C., Lonati, V., Malchiodi, D., Monga, M., Morpurgo, A., & Torelli, M. (2015). How challenging are bebras tasks? An IRT analysis based on the performance of Italian students. Proceedings of the 2015 ACM Conference on Innovation and Technology in Computer

Science Education, ITiCSE ’15, Vilnius, Lithuania, 4–8 July, 2015 (pp. 27–32). Association for Computing Machinery.

Bell, T., & Vahrenhold, J. (2018). CS unplugged—How is it used, and does it work? In Bockenhauer H.-J., Komm D., & Unger W. (Eds.), *Adventures Between Lower Bounds and Higher Altitudes: Essays Dedicated to Juraj Hromkovic on the Occasion of His 60tȟ Birthday, Lecture Notes in Computer Science*, (pp. 497–521). Springer International Publishing.

Bocconi, S., Chioccariello, A., Dettori, G., Ferrari, A., & Engelhardt, K. (2016). *Developing Computational Thinking in compulsory education - Implications for policy and practice*. Technical Report JRC104188, Joint Research Centre (Seville site).

Brackmann, C. P., Román-González, M., Robles, G., Moreno-León, J., Casali, A., & Barone, D. (2017). Development of Computational′ thinking skills through unplugged activities in primary school. Proceedings of the 12th Workshop on Primary and Secondary Computing Education, WiPSCE ’17, Nijmegen, Netherlands, 8–10 November, 2017. (pp. 65–72). Association for Computing Machinery.

Brennan, K., & Resnick, M. (2012). *New frameworks for studying and assessing the development of Computational Thinking* (p. 25).

Cappelleri, J. C., Jason Lundy, J., & Hays, R. D. (2014). Overview of Classical Test Theory and Item Response Theory for the quantitative assessment of items in developing patient-reported outcomes measures. *Clinical Therapeutics*, *36*(5), 648–662. https://doi.org/10.1016/j.clinthera.2014.04.006.

Chen, G., Shen, J., Barth-Cohen, L., Jiang, S., Huang, X., & Eltoukhy, M. (2017). Assessing elementary students’ Computational Thinking in everyday reasoning and robotics programming. *Computers & Education*, *109*, 162–175. https://doi.org/10.1016/j.compedu.2017.03.001.

Chevalier, M., Giang, C., Piatti, A., & Mondada, F. (2020). Fostering Computational Thinking through educational robotics: a model for creative computational problem solving. *IJ STEM Ed*, *7*(1), 39. https://doi.org/10.1186/s40594-020-00238-z.

de Souza, A. A., Barcelos, T. S., Munoz, R., Villarroel, R., & Silva, L. A. (2019). Data mining framework to analyze the evolution of computational thinking skills in game building workshops. *IEEE Access*, *7*, 82848–82866. https://doi.org/10.1109/access.2019.2924343.

del Olmo-Muñoz, J., Cózar-Gutiérrez, R., & González-Calero, J. A. (2020). Computational Thinking through unplugged activities in early years of primary education. *Computers & Education*, *150*, 103832. https://doi.org/10.1016/j.compedu.2020.103832.

DeVellis, RF (2006). Classical Test Theory. *Medical Care*, *44*(11 Suppl 3), S50-S59. https://doi.org/ 10.1097/01.mlr.0000245426.10853.30.

Djambong, T., Freiman, V., Gauvin, S., Paquet, M., & Chiasson, M. (2018). Measurement of Computational Thinking in K-12 education: the need for innovative practices. In D. Sampson, D. Ifenthaler, J. M. Spector, & P. Isaías (Eds.), *Digital technologies sustainable innovations for improving teaching and learning* (pp. 193–222). Springer International Publishing. https://doi.org/10.1007/978-3-319-73417-0_12.

El-Hamamsy, L., Bruno, B., Chessel-Lazzarotto, F., Chevalier, M., Roy, D., Zufferey, J. D., et al. (2021). The symbiotic relationship between educational robotics and computer science in formal education. *Education and Information Technologies*, *26*(5), 5077–5107. https://doi.org/10.1007/s10639-021-10494-3.

El-Hamamsy, L., Chessel-Lazzarotto, F., Bruno, B., Roy, D., Cahlikova, T., Chevalier, M., et al. (2021). A computer science and robotics integration model for primary school: evaluation of a large-scale in-service K-4 teacher-training program. *Education and Information Technologies*, *26*(3), 2445–2475. https://doi.org/10.1007/s10639-020-10355-5.

Embretson, S. E., & Reise, S. P. (2000). Item Response Theory for psychologists. *Item Response Theory for psychologists*. Lawrence Erlbaum Associates Publishers.

Field, A. P., Miles, J., & Field, Z. (2012). *Discovering statistics using R*. Sage.

Gane, B. D., Israel, M., Elagha, N., Yan, W., Luo, F., & Pellegrino, J. W. (2021). Design and validation of learning trajectory-based assessments for Computational Thinking in upper elementary grades. *Computer Science Education*, *31*(2), 141–168. https://doi.org/10.1080/08993408.2021.1874221.

González, M. R. (2015). *Computational Thinking test: Design guidelines and content validation*.

Grover, S., Basu, S., Bienkowski, M., Eagle, M., Diana, N., & Stamper, J. (2017). A framework for using hypothesis-driven approaches to support data-driven learning analytics in measuring Computational Thinking in block-based programming environments. *ACM Trans. Comput. Educ*, *17*(3), 1425. https://doi.org/10.1145/3105910.

Grover, S., Pea, R., & Cooper, S. (2015). Systems of assessments" for deeper learning of Computational Thinking in K-12. Proceedings of the 2015 annual meeting of the American educational research association, Chicago, IL, (pp. 15–20).

Hambleton, R. K., & Jones, R. W. (1993). Comparison of Classical Test Theory and item response theory and their applications to test development. *Educational Measurement: Issues and Practice*, *12*(3), 38–47.

Hermans, F., & Aivaloglou, E. (2017). To scratch or not to scratch? A controlled experiment comparing plugged first and unplugged first programming lessons. Proceedings of the 12th Workshop on Primary and Secondary Computing Education, WiPSCE '17, Nijmegen, Netherlands, 8–10 November, 2017. (pp. 49–56). Association for Computing Machinery.

Hinton, P., McMurray, I., & Brownlow, C. (2014). *SPSS explained*. Routledge.

Hsu, T.-C., Chang, S.-C., & Hung, Y.-T. (2018). How to learn and how to teach Computational Thinking: Suggestions based on a review of the literature. *Computers & Education*, *126*(1), 296–310. https://doi.org/10.1016/j.compedu.2018.07.004.

Huang, W., & Looi, C.-K. (2021). A critical review of literature on "unplugged" pedagogies in K-12 computer science and Computational Thinking education. *Computer Science Education*, *31*(1), 83–111. https://doi.org/10.1080/08993408.2020.1789411. Publisher: Routledge eprint.

Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118.

Hubwieser, P., & Mühling, A. (2014). Playing PISA with Bebras. Proceedings of the 9th Workshop in Primary and Secondary Computing Education, WiPSCE '14, Berlin, Germany, 5–7 November, 2014. (pp. 128–129). Association for Computing Machinery. https://doi.org/10.1145/2670757.2670759.

Ilic, U., Haseski, H. I., & Tugtekin, U. (2018). Publication trends over 10 Years of Computational Thinking research. *Cont ED Technology*, *9*(2), 131–153. https://doi.org/10.30935/cet.414798.

Kirçali, A., & Özdener, N. (2022). A comparison of plugged and unplugged tools in teaching algorithms at the K-12 level for Computational Thinking skills. *Tech Know Learn*.

Kyriazos, T. A. (2018). Applied psychometrics: writing-up a factor Analysis construct validation study with examples. *Psychology*, *09*(11), 2503–2530. https://doi.org/10.4236/psych.2018.911144.

Li, Y., Schoenfeld, A. H, diSessa, A. A., Graesser, A. C., Benson, L. C., English, L. D., et al. (2020). Computational Thinking is more about Thinking than computing. *Journal for STEM Educ Res*, *3*(1), 1–18. https://doi.org/10.1007/s41979-020-00030-2.

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

Lye, S. Y., & Koh, J. H. L. (2014). Review on teaching and learning of Computational Thinking through programming: What is next for K-12? *Computers in Human Behavior*, *41*, 51–61. https://doi.org/10.1016/j.chb.2014.09.012.

Mannila, L., Dagiene, V., Demo, B., Grgurina, N., Mirolo, C., Rolandsson, L., et al. (2014). Computational Thinking in K-9 education. Proceedings of the Working Group Reports of the 2014 on Innovation & Technology in Computer Science Education Conference, ITiCSE-WGR '14, 23–25 June, 2014, Uppsala, Sweden. (pp. 1–29). Association for Computing Machinery. https://doi.org/10.1145/2713609.2713610.

Negrini, L. (2020). Teachers' attitudes towards educational robotics in compulsory school. *Italian Journal of Educational Technology*. Online First.

Parker, M., Kao, Y., Saito-Stehberger, D., Franklin, D., Krause, S., Richardson, D., et al. (2021). *Development and preliminary validation of the assessment of computing for elementary students (ACES)* (pp. 10–16).

Peel, A., Dabholkar, S., Anton, G., Wu, S., Wilensky, U., & Horn, M. (2020). *A case study of teacher professional growth through Co-design and Implementation of computationally enriched biology units* (*8*).

Prudon, P. (2015). Confirmatory factor Analysis as a tool in research using questionnaires: a critique. *Comprehensive Psychology*, *4*(1), 03.CP.4.10. https://doi.org/10.2466/03.cp.4.10.

R Core Team (2019). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing.

Raykov, T., & Marcoulides, G. A. (2011). *Introduction to psychometric theory*. Routledge.

Relkin, E., & Bers, M. (2021). Techcheck-k: A measure of computational thinking for kindergarten children. In *2021 IEEE Global Engineering Education Conference (EDUCON)*, pp. 1696–1702. https://doi.org/10.1109/educon46332.2021.9453926.

Relkin, E., de Ruiter, L., & Bers, M. U. (2020). TechCheck: development and validation of an unplugged assessment of Computational Thinking in early childhood education. *J Sci Educ Technol*, *29*(4), 482–498. https://doi.org/10.1007/s10956-020-09831-x.

Relkin, E., de Ruiter, L. E., & Bers, M. U. (2021). . Learning to code and the acquisition of Computational Thinking by young children. *Computers & education*, *169*, 104222. https://doi.org/10.1016/j.compedu.2021.104222.

Revelle, W. (2021). *psych: Procedures for psychological, psychometric, and personality research*. Northwestern University.

Rizopoulos, D. (2006). Ltm: an R package for latent variable modelling and Item Response Theory analyses. *Journal of Statistical Software*, *17*(5), 1–25. https://doi.org/10.18637/jss.v017.i05.

Román-González, M., Moreno-León, J., & Robles, G. (2019). Combining assessment tools for a comprehensive evaluation of Computational Thinking interventions. In S.-C. Kong, & H. Abelson (Eds.), *Computational Thinking education* (pp. 79–98). Springer.

Román-González, M., Pérez-González, J.-C., & Jiménez-Fernández, C. (2017). Which cognitive abilities underlie Computational Thinking? Criterion validity of the Computational Thinking test. *Computers in Human Behavior*, *72*, 678–691. https://doi.org/10.1016/j.chb.2016.08.047.

Román-González, M., Pérez-González, J.-C., Moreno-León, J., & Robles, G. (2018). Can Computational talent Be detected? Predictive validity of the Computational Thinking Test. *International Journal of Child-Computer Interaction*, *18*, 47–58. https://doi.org/10.1016/j.ijcci.2018.06.004.

Romero, M., Duflot-Kremer, M., & Vieville, T. (2018). *Le jeu du robot : Analyse d’une activité d’informatique débranchée sous la perspective de la cognition incarnée*. https://doi.org/10.26220/rev.3089.

Rosseel, Y. (2012). Lavaan: an R package for structural equation modeling. *Journal of Statistical Software*, *48*(2), 1–36. https://doi.org/10.18637/jss.v048.i02.

Rosseel, Y. (2020). *Structural equation modeling with lavaan [PowerPoint slides]*. Department of Data Analysis, Ghent University. https://users.ugent.be/~yrosseel/lavaan/geneve2020/lavaan_oneday_geneve2020.pdf.

Rottenhofer, M., Sabitzer, B., & Rankin, T. (2021). Developing Computational Thinking skills through modeling in language lessons. *Open Education Studies*, *3*(1), 17–25. https://doi.org/10.1515/edu-2020-0138.

Schweizer, K., Ren, X., & Wang, T. (2015). A comparison of confirmatory factor Analysis of binary data on the basis of tetrachoric correlations and of probability-based covariances: a simulation study. In R. E. Millsap, D. M. Bolt, L. A. van der Ark, & W.-C. Wang (Eds.), *Quantitative Psychology Research, Springer Proceedings in Mathematics & Statistics* (pp. 273–292). Springer International Publishing. https://doi.org/10.1007/978-3-319-07503-7_17.

Sheng, Y. (2019). CTT package in R. *Measurement: Interdisciplinary Research and Perspectives*, *17*(4), 211–219. https://doi.org/10.1080/15366367.2019.1600839.

Souza, A. C. d., Alexandre, N. M. C., Guirardello, E. d. B., Souza, A. C. d., Alexandre, N. M. C., & Guirardello, E. d. B. (2017). *Epidemiologia e Serviços de Saúde*, *26*(3), 649–659. https://doi.org/10.5123/s1679-49742017000300022.

Sun, L., Hu, L., & Zhou, D. (2021). Improving 7th-graders’ computational thinking skills through unplugged programming activities: A study on the influence of multiple factors. *Thoracic Surgery Clinics*, *42*, 100926. https://doi.org/10.1016/j.tsc.2021.100926.

Taherdoost, H. (2016). Validity and reliability of the research instrument; How to test the validation of a questionnaire/survey in a research. *SSRN Journal*, *5*(3), 28–36. https://doi.org/10.2139/ssrn.3205040.

Tang, X., Yin, Y., Lin, Q., Hadad, R., & Zhai, X. (2020). Assessing Computational Thinking: A systematic review of empirical studies. *Computers & Education*, *148*(1), 103798. https://doi.org/10.1016/j.compedu.2019.103798.

Thies, R., & Vahrenhold, J. (2013). On plugging ”unplugged” into CS classes. Proceeding of the 44th ACM Technical Symposium on Computer Science Education, SIGCSE '13, Denver, CO. (pp. 365–370). ACM.

Thies, R., & Vahrenhold, J. (2016). Back to school: computer science unplugged in the wild. Proceedings of the 2016 ACM Conference on Innovation and Technology in Computer Science Education, ITiCSE '16, Arequipa, Peru. (pp. 118–123). ACM.

Tikva, C., & Tambouris, E. (2021). Mapping Computational Thinking through programming in K-12 education: A conceptual model based on a systematic literature Review. *Computers & Education*, *162*(1), 104083. https://doi.org/10.1016/j.compedu.2020.104083.

European Union (2006). *Recommendation of the European Parliament and of the Council of 18 December 2006 on key competences for lifelong learning*. Technical report.

Webb, M., Davis, N., Bell, T., Katz, Y. J., Reynolds, N., Chambers, D. P., et al. (2017). Computer science in K-12 school curricula of the 21st century: Why, what and when? *Educ Inf Technol*, *22*(2), 445–468. https://doi.org/10.1007/s10639-016-9493-x.

Weintrop, D. (2016). Defining Computational Thinking for mathematics and science classrooms. *Journal Science Education Technology*, *25*(1), 21. https://doi.org/10.1007/s10956-015-9581-5.

Weintrop, D., Wise Rutstein, D., Bienkowski, M., & McGee, S. (2021). *Assessing Computational Thinking: An Overview of the fieldComputer Science Education*, *31*(2), 113–116. https://doi.org/10.1080/08993408.2021.1918380.

Wiebe, E., London, J., Aksit, O., Mott, B. W., Boyer, K. E., & Lester, J. C. (2019). Development of a lean Computational Thinking abilities assessment for middle grades students. Proceedings of the 50th ACM Technical Symposium on Computer Science Education, SIGCSE '19, Minneapolis MN27 February, 2019–2 March, 2019 (pp. 456–461). Association for Computing Machinery. https://doi.org/10.1145/3287324.3287390.

Wing, J. M. (2006). Computational Thinking. *Commun. ACM*, *49*(3), 33–35. https://doi.org/10.1145/1118178.1118215.

Xia, Y., & Yang, Y. (2019). RMSEA, CFI, and TLI in structural equation modeling with ordered categorical data: the story they tell depends on the estimation methods. *Behav Res*, *51*(1), 409–428. https://doi.org/10.3758/s13428-018-1055-2.

Zapata-Cáceres, M., Martín-Barroso, E., & Román-González, M. (2020). Computational Thinking test for beginners: Design and content validation. 2020 IEEE Global Engineering Education Conference (EDUCON), 28–31 March, 2022, Tunisia, Africa. (pp. 1905–1914). IEEE.

Zhang, L., & Nouri, J. (2019). A systematic review of learning computational thinking through scratch in K-9. *Computers & Education*, *141*, 103607. https://doi.org/10.1016/j.compedu.2019.103607.

Zhan, Z., He, W., Yi, X., & Ma, S. (2022). Effect of unplugged programming teaching aids on children's Computational Thinking and classroom interaction: with respect to piaget's four stages theory. *Journal of Educational Computing Research*. https://doi.org/10.1177/07356331211057143. Publisher: SAGE Publications Inc.

Author Biography

Laila El-Hamamsy is a PhD candidate at the École Polytechnique Fédérale de Lausanne (EPFL) with the MOBOTS Group and LEARN, the Center for Learning Sciences. Her research focuses the introduction of Computer Science and Educational Robotics into teacher practices, within the context of a digital education curricular reform and the associated teacher professional development program. Prior to that, she received a MSc. in Robotics and a BSc. in Micro-engineering from EPFL.

María Zapata-Cáceres received the Architect BSc Degree and MEng at the Universidad Politécnica de Madrid (UPM) in 2002, M.S. Degrees in Virtual Environments (CSA) in 2002, and Videogames Design and Production (UEM) in 2005, and Computer Science BSc Degree at Universidad Nacional de Educación a Distancia (UNED) in 2018. She is currently a researcher and visiting professor in the Games Design and Development BSc Degree at the Computer Science Department at the Universidad Rey Juan Carlos (URJC) in Madrid. Her main area of research includes video games as learning instruments for computer science. She has more than 15 years of professional experience as an entrepreneur with activities related to 3D design, video games, technology, and teaching.

Estefanía Martín Barroso received the Computer Science BSc Degree and MEng Degree in 2002 and 2004. She obtained her PhD degree in Computer Science and Telecommunications in 2008 at Universidad Autónoma de Madrid (UAM). Her thesis was focused on mobile adaptive learning systems for collaborative contexts. From 2003 to 2008, she was an Assistant Professor at UAM and Universidad Rey Juan Carlos (URJC). Currently, she is an associate professor in the Computer Science Department at the URJC. She leads Blue Thinking project, an application that allows the person with ASD to learn programming; DEDOS project, which provides authoring tools for creating educational activities on multiple devices, and ClipIt, a video-based social network platform developed in the EU project JuxtaLearn. Her research interests include learning systems, HCI and disabilities.

Francesco Mondada is a professor at the École Polytechnique Fédérale de Lausanne (EPFL), Switzerland and director of the Center for Learning Sciences at EPFL. After a master and a PhD received at EPFL, he led the design of many miniature mobile robots, commercialized and used worldwide in thousands of schools and universities. He co-founded several companies selling these robots or other educational tools. He is author of more than a hundred publications in the field of robot design. He received several awards, including the Swiss Latsis University prize, as best young researcher at EPFL and the Credit Suisse Award for Best Teaching as best teacher at EPFL.

Jessica Dehler Zufferey earned her PhD from University of Tübingen in the field of computer-supported collaborative learning (CSCL) with a focus on knowledge awareness. She held post-doctoral positions at University of Fribourg in university didactics, working on gender neutral teaching, and at École Polytechnique Fédérale de Lausanne (EPFL) in the Computer- Human-Interaction in Learning and Instruction CHILI lab, working on technology-enhanced vocational training. After 4 years in a R&D role in the educational technology industry, she is now executive director of the EPFL Center for Learning Sciences.

Barbara Bruno is a post-doctoral researcher at the École Polytechnique Fédérale de Lausanne (EPFL), in Lausanne, Switzerland, in the CHILI lab. She is a co-founder of the start-up company Teseo, Italy. Barbara received the M.Sc. and the PhD in Robotics from the University of Genoa in 2011 and 2015, respectively. She is part of the NCCR Robotics organization and currently involved in the EU ITN ANIMATAS. In 2017-2019 she was Technical Manager of the H2020 project CARESSES. She has published more than 45 articles in international journals and peer-reviewed international conferences. Her research interests are in Social Robotics and Human–Robot Interaction and Cooperation.