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Boom, Kay-Dennis; Bower, Matt; Arguel, Amaël; Siemon, Jens; Scholkmann, Antonia

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Relationship between Computational Thinking and a Measure of Intelligence as a General Problem-Solving Ability

Kay-Dennis Boom
Faculty of Education
Universität Hamburg
Germany
kay-dennis.boom@uni-hamburg.de

Matt Bower
Faculty of Human Sciences
Macquarie University
Australia
matt.bower@mq.edu.au

Amaël Arguel
Faculty of Human Sciences
Macquarie University
Australia
amael.arguel@mq.edu.au

Jens Siemon
Faculty of Education
Universität Hamburg
Germany
jens.siemon@uni-hamburg.de

Antonia Scholkmann
Faculty of Education
Universität Hamburg
Germany
antonia.scholkmann@uni-hamburg.de

ABSTRACT

Computational thinking – the ability to solve problems using concepts from computer science – has been widely discussed in the computer science education field. However, the relationship of computational thinking to intelligence – seen as the general ability to understand and solve complex problems – is contestable and has not been extensively explored. The present study addressed the question of how computational thinking is related to intelligence. To find an answer to this question, 71 pre-service teacher students completed a survey with 20 Bebras tasks as a measure of computational thinking and a non-verbal intelligence test (TONI-3) to assess their general problem-solving ability. The large and significant correlation of $r(70) = .53$, $p < .001$, indicates that both concepts are highly related. Implications of the findings are discussed, including the meaning of the relationship between computational thinking and intelligence during teaching and assessment, and the possibility of more holistic measures of computational thinking that incorporate procedural aspects.

CCS CONCEPTS

• Social and professional topics → Computational thinking

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KEYWORDS

Computational thinking; non-verbal intelligence; Bebras Challenge; problem-solving; discriminate validity

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1 INTRODUCTION

Technology-related jobs are on the rise [17], causing a shift in the required skills for employment [16]. Several authors praise computational thinking (CT) as a one of the relevant abilities of the future [7, 9, 25] and call it even the literacy of the 21st century [29]. CT is described as a way of thinking about complex problems using computing concepts to solve them. Wing [29] initially described CT as a way to think "as a computer scientist" and emphasized CT is not like a programming technique but a set of principles for understanding and approaching problems.

If CT is presented as a way of thinking, it is relevant to point out its relationship to other cognitive abilities related to problem-solving. Intelligence is often referred as an umbrella term for related cognitive abilities such as reasoning and problem-solving [11]. Both concepts share the idea of being relevant for problem-solving, which raised the question of how similar both concepts actually are and how much variance they share. Based on the findings of such a study, educators in computer science could decide whether it is worth focusing on specific capabilities related to CT or to emphasize general problem-solving abilities.

This paper is organized as follows. We first give a brief overview about CT and intelligence, which leads to the research question and hypothesis. We then describe the data collection and how participants' level of CT and intelligence were assessed. We then discuss the findings and suggest using more sophisticated assessment for future work. The paper ends by discussing two possible implications. Either the concept of CT needs to be made more distinct from intelligence or the linear relationship indicates that CT might be part of intelligence, both of which have consequences for CT research.

2 BACKGROUND AND RELATED WORK

2.1 Computational thinking

CT has been defined as a problem-solving approach that draws upon fundamental concepts of the computer science [29]. It constitutes the ability to reformulate problems in a way that computers could be used to solve them [13, 21]. Moreover, CT includes a set of skills which are required especially in computer science. It has been a challenge in the past to identify the core capabilities of CT and still there is no definitive answer to this. However, according to different literature reviews and meta-studies, these are some CT skills that are mentioned consistently over time [2, 13, 21]:

- Decomposition: the ability to break down the problem into smaller subproblems
- Abstraction and pattern generalization: neglecting unnecessary details and identifying repeated constructs
- Organizing and analyzing data: handling and interpreting of data
- Algorithmic design: the ability to understand and implement a step-by-step procedure in order to arrive at a solution

Although CT has its origin in computer science, several authors emphasize that CT is different from coding or programming [28, 29]. However, the relationship between coding and CT is still an open issue because CT studies have used coding tasks to assess CT [2]. In order to differentiate the ability of coding and CT, it is important to find a way to assess CT independently from coding. One way to do this is using logical problems that require CT abilities to be solved, but are not related to coding or programming directly.

Examples of this kind of assessment are the tasks from the Bebras Challenge [5]. The Bebras Challenge is a contest for children and teenagers in informatics. The tasks are categorized into five different age groups and different levels of difficulty. According to the creators, the goal is to design tasks which assess abilities and skills directly or indirectly related to CT [6]. For instance, the Australian solution guides provide information for every task and what kind of CT-related skills were required to solve it [19, 20]. A distinction is made between "breaking down problems into parts", "interpreting patterns and models", "organizing data logically", and "designing and using algorithms" [20]. As previously explained, these capabilities are often mentioned in association with CT. Therefore, we conclude the Bebras tasks could be a promising way for assessing CT without involving any coding or programming activity.

2.2 Intelligence as general problem-solving ability

While intelligence has been a historically controversial construct, many definitions compromise intelligence as the ability to solve problems and to reason abstractly. According to Thurstone [26], the abilities of reasoning to identify rules and patterns are "primary mental abilities". Abstract reasoning is crucial for the latest stage in Piaget's [18] theory of cognitive development. The factor fluid intelligence in Horn and Cattell's [12] theory summarizes problem-solving abilities and general reasoning. Simon [22] saw intelligence as the ability to produce the single best or correct answer to a well-defined problem or question. Gardner [10] described intellectual competence as a summary of problem-solving skills, and Sternberg's [24] "analytical intelligence" is the ability relating to how well someone is able to solve problems. Finally, Jensen [14] presented reasoning and problem-solving as factors for an open-ended definition of intelligence. In conclusion, problem-solving and abstract reasoning are often associated with intelligence or are even synonyms in some theories. This underlines the strong relationship between these concepts.

2.3 Research question and hypothesis

There is some overlap between the concepts of computational thinking, as a special form of problem-solving that draws upon computer science concepts, and intelligence, as a general problem-solving ability. In addition, abstraction and abstract reasoning play an essential role in both concepts. This raises questions relating to the relationship between computational thinking and intelligence, and leads to the following research question:

RQ: What is the relationship between CT and intelligence?

We expect that the theoretical overlap will be shown in an empirical relationship. Therefore, we propose the following hypothesis:

H: There is a positive correlation between a measurement of CT and a measurement of intelligence.

To date, there has been no study which investigates the empirical relationship between both concepts. The goal of this study is to fill this gap.

3 METHOD

3.1 Participants

Data were collected from 71 pre-service teacher students. All participants were studying Bachelor of Education and were completing a third-year educational technology course. As part of their coursework, participants were initially asked to complete two online surveys: one to assess their computational thinking ability and one to assess their intelligence. Both tests were issued at the same time and participants were able to choose when they started and finished each test. Completion and results of both tests were independent. The study was approved by a university ethics committee.

The average age of students was 23.88 years (SD = 5.22). There were 47 (66.2%) female participants, 23 (32.2%) male participants and one participant preferred not to say. Among the students, 51 (71.8%) had no prior knowledge of programming and 19 (26.8%) described themselves as either beginners or intermediate. One student who described themself as an experienced programmer was excluded from further analyses.

3.2 Instruments

To measure CT, participants were asked to solve an online version of the Bebras tasks. To have a sufficient number of items, the test used for this investigation was composed of the two latest Australian versions of the Bebras challenge from 2014 [19] and 2015 [29]. The questions were piloted with 10 random university students two months prio in order to ascertain their appropriateness and intelligibility. It was expected that participants would need three minutes on average to solve each task, so 20 items were chosen to not exceed the overall intended test duration of 60 min.

Because participants of the present study were university students, all tasks were from the oldest group available in the Bebras challenge that is the 16 to 18 years old group (school level 11 and 12). Although the original tasks were designed to assess the level of CT for secondary school students, previous studies used the Bebras tasks to measure CT of older contestants, for instance, vocational students [15] and novice engineering students [8]. The only difference between the original Bebras questions and the ones used in the study were slight adaptations to the genre, in order to cater to the older cohort. For instance, references to beavers or other comic like pictures were replaced with a more neutral presentation.

The Bebras tasks are divided into three different levels of difficulty: easy, medium, and hard. Participants received two points when they successfully solved an easy task, three points for a medium task, and four points for a hard task. No deduction was applied for no or wrong answers. This scoring scheme relied on the recommendation for scoring the Australian Bebras challenge [19, 20]. The maximum achievable score was 57. Table 1 illustrates the composition of Bebras tasks used in the study.

Table 1: Composition of the Bebras tasks used in the study.

	Tasks from 2014	Tasks from 2015	Total
Easy (2 p.)	4 (8 p.)	4 (8 p.)	8 (16 p.)
Medium (3 p.)	3 (9 p.)	4 (12 p.)	7 (21 p.)
Hard (4 p.)	2 (8 p.)	3 (12 p.)	5 (20 p.)
Total	9 (25 p.)	11 (32 p.)	20 (57 p.)

To assess intelligence as a general problem-solving ability, participants completed the Test of Nonverbal Intelligence, third edition (TONI-3). The TONI-3 is a language-free intelligence test, developed and enhanced by Brown, Sherbeernou, and Johnson [3]. According to the authors, the test mainly estimates someone's ability "on abstract reasoning and problem-solving" as a cognitive skill. In addition Brown et al. [3] stated that the TONI-3 would estimate problem-solving as described in Thurston's and Gardner's theories as well as in Jensen's factor of reasoning thinking and Cattell and Horn's fluid intelligence.

The internal consistency of Cronbach's α=.93 and a test-retest reliability of .75 [3] can be described as high. In order to ensure high content validity, the test material of the first version was reviewed by psychologists, psychometrists, and educators with expertise in experimental and developmental psychology. Further analyses with school achievements indicated high criterion and high construct validity [1].

The TONI-3 has 45 abstract pictures as test items. Every item is divided into two parts. The first half of an item shows an uncompleted set of geometrical figures. In the second half, somewhat related figures are listed. The participants have to choose one out of six figures from the second half that completes the set of figures of the first half. In some items, the task is slightly changed so that only one figure is presented and the participants have to choose one set out of four sets of figures that complete the row. Nevertheless, in all test items the task is always about completing a set or a row of abstract figures. A correctly identified figure scores one point. All the points cumulate until the last item or until the ceiling item has been reached. The ceiling item is defined as the last item of the last five attempted items in which the participant has made three mistakes. The raw points are computed into a standardized IQ score. This demonstrates a typical test procedure to estimate intelligence based on figural and abstract problem-solving.

Many intelligence tests have different kinds of subtests, which makes them complex and external guidance might be needed during the test session. The TONI-3 is based on only one kind of task. Instructions and practice items are designed to be answered without external assistance. In addition, time does not play a role for the TONI-3 and it is completed in 20 minutes on average [3]. Therefore, we concluded that the TONI-3 was an appropriate instrument since its theoretical foundation fits well the construct of intelligence used in this study. In addition, the psychometric properties are generally described as satisfactory and the test is short and easy to administer online.

4 RESULTS

4.1 Descriptive statistics

The maximum achievable score in the Bebras tasks (i.e., 57) was set as 100%. On average, participants achieved 59.52% (*SD* = 17.61), one person reached 100% and the lowest observed score was 21.05%. We concluded that the Bebras tasks were neither too easy nor too difficult for novice participants and no floor or ceiling effects were found for any tasks which would have restricted the interpretation of the results. The average IQ-score of the participants, M = 112.81 (SD = 14.01), did not raise any suspicions about the general cognitive ability of the sample.

4.2 Tests for potential confounding effects

Before testing the hypothesis and answering the research question, prior tests were conducted to identify potential confounding effects of age, gender and prior programming knowledge on achieved Bebras and IQ scores. Neither a significant correlation between age and Bebras scores, $r(68) = .04$, $p = .769$, nor between age and IQ scores based on the TONI-3, $r(68) = .13$, $p = .278$, were found.

To analyze whether gender or prior programming knowledge had confounding effects on the Bebras and IQ scores, independent t-tests (two-sided) were conducted. For that purpose, participants who had at least some prior knowledge in programming were grouped together and were compared with students who had no prior knowledge. To correct the effect of unequal variances, the degrees of freedom for all t-tests were adjusted based on the Welch's correction. No significant differences in means were found, as presented in Table 2.

Table 2: Overview of mean differences between the percentage of achieved Bebras scores and IQ score on gender and prior programming knowledge.

		Bebras	IQ
Male	*Mean* (*SD*)	61.96 (17.21)	112.64 (14.45)
Female	*Mean* (*SD*)	58.94 (17.66)	113.38 (13.69)
	$\|t\|$ (df)	0.67 (42.13)	0.20 (39.19)
	p	.504	.840
No prior knowledge	*Mean* (*SD*)	58.41 (16.87)	113.04 (12.74)
At least some prior knowledge	*Mean* (*SD*)	62.51 (19.63)	112.21 (17.34)
	$\|t\|$ (df)	0.81 (28.50)	0.19 (25.60)
	p	.427	.851

4.3 Addressing research question

The aim of this study is to find out whether there is an empirical relationship between CT and intelligence. Based on the literature, it was expected that there would be a positive linear relationship between CT and TONI-3 scores. To test this hypothesis, a product-moment correlation between the percentage of achieved Bebras score and the IQ score based on the TONI-3 was computed. Consistent with the hypothesis, a significant positive correlation was found, $r(70) = .53$, $p < .001$. As the Bebras scores increased, the estimated IQ scores based on the TONI-3 increased as well (see Figure 1). Both constructs shared 28.4% of variance, which based on Cohen's [4] convention for interpreting effect sizes, can be considered as "large".

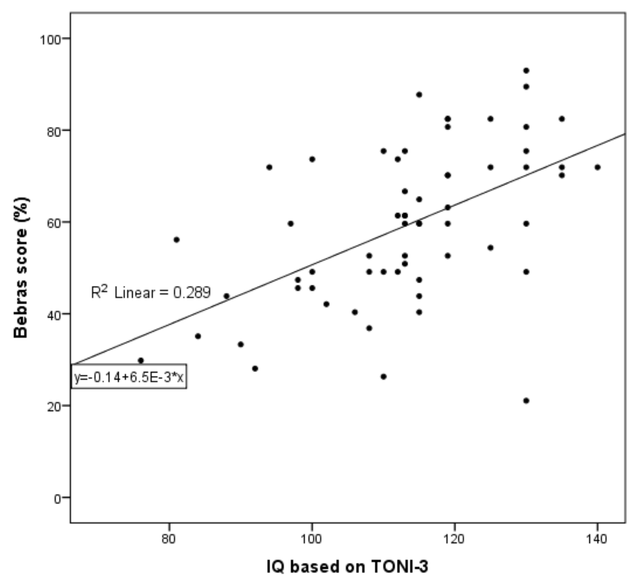

Figure 1: Scatterplot for IQ based on TONI- and achieved Bebras score, including regression coefficients and regression line.

5 DISCUSSION

The literature review revealed that CT and intelligence share some characteristics in their definitions. Both concepts are described as problem-solving approaches and the ability to abstract is crucial. CT is often referred as a problem-solving approach in computing context with features which are important in computer science, such as the ability to abstract and recognizing patterns, the ability to decompose a problem, handling of data, and the ability to design and implement algorithms. On the other side, intelligence is defined as a general problem-solving ability and also referred as the ability of abstract reasoning in many theories. Therefore, the present study predicted that higher level of CT comes along with higher IQ. The findings of this study based on 71 pre-service students support this expectation, with no confounding effects found that could have limited the interpretation of the results.

One possible explanation for the strong relationship could be that the definitions of both concepts are similar and so are their assessments. That might mean that a clearer distinction between CT and other cognitive concepts could be made. The research about CT is still in its infancy and the term is still developing. Future definitions could focus more on the unique part of CT which are not shared with other concepts. For instance, algorithmic thinking might be a unique part of CT whereas the ability of abstraction is not. A more distinct definition would increase the divergent validity of CT and could lead to instruments with higher discriminate validity.

On the other side, the strong correlation could mean that CT and intelligence are naturally related. For instance, CT could even be considered as a part of general intelligence. Some theories about intelligence based on the idea of several mental abilities [26] or even multiple intelligences [10]. According to Spearman [23], the positive correlations among these different abilities can be summarized in a g(eneral) factor of intelligence. CT might be just one of those cognitive abilities and is part of the g factor. The only reason why CT has not been seen as a part of general intelligence might be because CT is still a quite new concept and its relation to other cognitive abilities is unclear.

It is worth pointing out some limitations to this study. The Bebras tasks were used as a measuring instrument, which is independent of coding experience. Although the authors of the Bebras tasks claim to assess different capabilities of CT, it is questionable whether these abstract written tasks can cover all aspects of CT. For instance, some authors suggest debugging as a procedural evaluative skill is part of CT [2, 21]. Different from the other skills, debugging is not only shown in an end result but in a process and in developing a solution. To measure debugging competence, not only the solution but also how to derive it must be assessed. However, the Bebras tasks do not illustrate the process but only the solution. Future studies could use procedural tasks and more hands-on-problems for a more holistic measurement of CT.

Although many theories see intelligence as a problem-solving ability, they differ according to which specific capabilities are relevant. The TONI-3 is based on the theory that abstract reasoning is the best predictor for intelligence, but other theories are based on a broader set of cognitive abilities. For instance, in Horn and Cattell's [12] theory, the second factor of intelligence is called 'crystallized'. Crystallized intelligence relies on acquired knowledge, e.g. facts or vocabularies, and is not covered in the TONI-3. As for CT, different instruments for measuring intelligence could lead to different conclusions. Therefore, other intelligence tests based on a broader concept of intelligence than the TONI-3 could be used. An example of a widely accepted intelligence test with a broader set of cognitive abilities is the Wechsler Adult Intelligence Scale [27] in its fourth edition from 2008.

Another limitation of the study is the external validity of the convenience sample of novice pre-service teacher students, since they are not representative of the general population. This sample of non-computing experts can only be seen as a starting point. It gives a first glimpse how the relationship between CT and intelligence might be for the general community. However, it is possible that experienced programmers, or another subset of the population, have another level of CT and developed different kind strategies for solving problems. That might have an effect on the relationship between their CT abilities and intelligence.

6 CONCLUSION

The goal of this study is to investigate the relationship between CT and intelligence as a general problem-solving ability. To address this, 71 pre-service teacher students completed online 20 tasks based on the Bebras challenge and the Test of Nonverbal Intelligence (3rd edition).

The results revealed a significant and large positive linear relationship. As capability of CT increased, intelligence tended to increase as well. Different conclusions are possible.

One conclusion might be that there is a strong relationship between CT and intelligence because the definition and assessment of the constructs is not sufficiently differentiated. Consequently, CT might need to be rephrased so it distinguished more from other cognitive concepts.

Another conclusion could be the large relationship is no surprise because both concepts are naturally related. Intelligence just conglomerates different cognitive abilities and CT might be part of a general intelligence or g factor. That might have an impact on how we think about CT and its development.

To investigate this latter, more complex relationship, studies with more sophisticated instruments are needed to more extensively examine the place of CT amongst other mental abilities. Educators in computer science are encouraged to develop the CT capabilities of students from the earliest ages, and understanding the relationship between CT and intelligence can support this endeavor. If computational thinking is merely a manifestation of intelligence, then educators should concentrate on developing general problem-solving capabilities. On the other hand, if computational thinking is somewhat distinct from general intelligence, then it becomes more important for computing educators to focus specifically on identifying and developing those ability that relate directly and uniquely to CT.

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