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Computational Thinking Skill Level of Senior High School Students Majoring in Natural Science

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Abstract. Computational thinking (CT) is a skill integrated into various curricula in many countries. However, lack of student acceptance and limited assessment become challenges to integrating skill into the curriculum, specifically in developing countries like Indonesia. Therefore, this study aimed to validate the Indonesian version of the Computational Thinking Scale (CTS) and determine the CT skill level of high school students majoring in science. This study was conducted using a quantitative approach with a cross-sectional survey design. Participants were purposively selected based on certain criteria from a population of high schools in Yogyakarta, Indonesia. In this study, data were collected from 526 students with 19 items of CTS questionnaires and analysed using the Rasch model measurement. The findings showed that the adapted CTS met the fit criteria based on Rasch model measurement, except for one item. Based on the logit mean value of +1.69, the level of students' CT ability falls into the good category, where the most frequently implemented aspect is the problem-solving aspect, while the least frequently implemented aspect is algorithmic thinking. According to Differential Item Function analysis, there were differences in student responses based on coding experience. This study is expected to contribute to the field of CT assessment in science education. In addition, the results of this study can be an affirmation for educational policy makers in developing countries to integrate CT into the curriculum of natural science majors.

Keywords: coding experiences; computational thinking skill; cross-sectional survey; gender; Rasch model measurement

1. Introduction

Computational thinking (CT) is a fundamental skill crucial for individuals in the 21st century, extending the relevance beyond computer science (Li et al., 2020; Wing, 2006). This cognitive framework has seen extensive development and

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seamless integration into curriculum in developed countries such as Singapore, Finland, the United Kingdom, and Japan (Seow et al., 2019). However, the integration has not found its way into developing countries such as Indonesia. The challenges of enhancing CT skill in these settings primarily centre on the dual impediments of limited student acceptance and teacher expertise in incorporating the concepts into classroom instruction. These confirm that Indonesia is not ready to implement CT skill-oriented learning in its curriculum. Presently, Indonesia is in the nascent stages of introducing and experimenting with CT, predominantly within the domain of Mathematics (Nurwita et al., 2022) and conducted on pre-service teachers (Sondakh et al., 2022). Research in Indonesia specifically conducted to investigate CT skill of high school students is still rare, specifically in science majors. However, CT skill in science learning is very important, inseparable and needs to be integrated (Hurt et al., 2023; Weintrop et al., 2016).

The importance of CT in science learning lies in the fact that it trains students to think creatively and innovatively in solving problems with the help of computers. In many cases, science learning is carried out with data collection and analysis activities, modelling or simulation, experimentation, and observation (Barr & Stephenson, 2011; Hurt et al., 2023; Ogegbo & Ramnarain, 2022; Weintrop et al., 2016). All of these learning activities can be done based on computer technology, so that learning can be optimised. Unfortunately, high school science learning in Indonesia tends to underutilise computer technology. Thus, the integration of CT learning in Indonesia is expected to optimise science learning so that it is easier to understand because it is interactive and integrated with technology. With CT learning, students will be more literate in the function of technology in understanding science and the universe. The main key factor for this kind of learning climate to occur is the competence of science teachers' knowledge of CT teaching.

The good news is that teacher professional programmes in Indonesia have opened elective courses with a special topic of Computational Thinking. In the course book, there are interesting topics such as the integration of CT into problem-solving education, the comprehensive integration of the concept into Project-Based Learning (Pj-BL) and curriculum is a fundamental initiative. (Natali, 2022). The course in teacher professional programmes proves that there is a positive effort being made to integrate CT into the education curriculum. This is consistent with the plan of the Indonesian Minister of Education and Culture in 2020.

The Indonesian government attention to the skills of students is still not maximised, but, nevertheless, the initiative should be accepted with enthusiasm. Moreover, research in Indonesia is still relatively rare and should be more intensively conducted in the aspect of education policy, the readiness of infrastructure, the development of skill assessment and the investigation regarding readiness of students. The inclusion in CT integration is important to investigate because students are the main recipients of curriculum. Furthermore, readiness can be seen from attitude or CT intensity level in solving daily problems. Since the concept is not widely known (Natali, 2022), the exploration of skill can only be achieved based on aspects of CT, including the level of creativity, algorithmic thinking, cooperativity, critical thinking and problem-solving (Doleck et al., 2017; Korkmaz et al., 2017). The higher the level of the skill, the greater the readiness to receive the learning in the classroom.

To measure all aspects of CT skill (creativity, algorithmic thinking, cooperativity, critical thinking and problem-solving), this research used the Computational Thinking Scale (CTS) developed by Korkmaz et al. (2017). The CTS is in the form of a questionnaire to assess the level of CT skill in solving daily problems. The results of this study are expected to contribute and provide references to the field of CT assessment in natural science majors in high school. The level of students' CT ability presented in this paper is expected to be an affirmation for education policy makers in developing countries to integrate CT into the curriculum, especially for science majors.

This study aimed to validate the Indonesian version of the CTS and explore the level of CT skills of high school students majoring in natural science in Indonesia. The level of CT skills in this study shows the intensity or how often students think computationally. The intensity of computational thinking can represent the level of readiness of students in receiving CT learning in high school natural science majors. The more often students think computationally, the more the level of readiness of students to receive CT learning in the classroom. Based on these aims, this research focuses on answering the following questions.

1. Based on Rasch model measurement, does the adapted Indonesian version of the CTS fulfil the criteria of fit and reliability in use?
2. Are there questionnaire items that function differently based on gender and coding experience?
3. What is CT skill level of high school natural science students in Indonesia?

2. Literature Review

2.1 Computational Thinking (CT)

The term CT was introduced by Papert (1996) and has been popularly investigated since Jeannette Wing published 'Computational Thinking' in 2006. Previous research showed that CT is an important skill in the 21st century, not only essential for computer scientists but also for all individuals (Wing, 2006). Despite its importance, the definition is still not finalised and the development has caused worldwide debate (Barr & Stephenson, 2011). CT is authentic to the procedure of problem description, system design and solution formulation conducted creatively by using the basic concepts of computer science (Romero et al., 2017; Wing, 2006). In other literature, product-oriented CT focuses on problem-solving with thinking procedures of abstraction, decomposition, algorithmic design, evaluation and generalisation (Selby & Woollard, 2013). According to the International Society for Technology in Education (ISTE) and the Computer Science Teachers Association (CSTA) (2011), CT is a problem-solving process with characteristics of formulating, organising, analysing and representing data through abstraction, as well as automating solutions using algorithmic thinking. Cansu and Cansu (2019) concluded that the skill helps students understand and change the world for the better. However, there is no conclusive definition of the concept and its components (Voogt et al., 2015).

Decomposition, abstraction, algorithms, debugging, iteration and generalisation are related terms used in discussing the components or aspects of CT (Alfaro-Ponce et al., 2023). Other terms that have been reported from the literature are automation and analysis (Barr & Stephenson, 2011). The most popular components are decomposition, abstraction, pattern recognition and algorithms (Cansu & Cansu, 2019). In the Barefoot framework, CT is constructed of six main components, namely logic, decomposition, algorithms, patterns, abstraction and evaluation (Romero et al., 2017). Even though various experts and educational institutions have different opinions on the definition and components, CT is very close to problem-solving and creative thinking skills. Based on the various definitions and dimensions, the skill is not related to computer science or the act of using technology. However, there remains a prevalent belief among a significant number of individuals that CT is a skill primarily relevant to computer scientists (Li et al., 2020). CT is a future skill and an advanced competency for humans (Curzon & McOwan, 2016; Dolgopolovas et al., 2018) and the concept should be understood and developed by curriculum policy makers. However, in developing countries, many policy makers do not seem convinced to integrate skill into the curriculum with many challenges being faced, such as cost and the limited ability of teachers to implement the concept in teaching students (Chagas & Furtado, 2019). The adoption of CT skill-orientated learning is also affected by various factors, such as the problem of defining complex competency standards for each school level, the absence of CT-specific teacher professional development, limited facilities, and limited assessments to assess skill (Angeli & Giannakos, 2020). In Indonesia, the most frequently used assessment in measuring CT skill is the Bebras Challenge. This assessment has been adopted in several research to explore the CT skill of students in Indonesia (Natali & Nugraheni, 2023; Saad, 2020; Zamzami et al., 2020).

2.2 CT Skill of Science Students in Indonesia

In addition to limited assessment, low acceptance of students regarding CT is also an essential problem in the process of integrating the skill into the curriculum structure (Saidin et al., 2021). Due to the important role of students in the field of education, a profound understanding of CT must be provided before the integration process. Several research showed that the average CT skill among Indonesian students remains deficient and poor (Rosali & Suryadi, 2021; Wardani et al., 2022). An intriguing discovery shows that female students outperform their male counterparts in such skill (Richardo et al., 2023). In various other countries, CT skill is often synonymous with coding or programming prowess and no research has been conducted in Indonesia to investigate the particular aspect, especially in natural science majors.

However, CT is an important and influential cognitive skill in the field of STEM (Science, Technology, Engineering, and Mathematics) education in the 21st century (Cheng et al., 2023; Li et al., 2020). Weintrop et al. (2016) provided a concrete definition in mathematics and science classrooms, and Hurt et al. (2023)

proposed a specific and detailed framework as well as definition of CT for science (CT-S). CT integration in science education has been conducted in several subjects including biology, life sciences, climate science, elementary science, physics and STEM subjects (Ogegbo & Ramnarain, 2022; Rubinstein & Chor, 2014). In addition, CT skills have also been integrated in chemistry learning (Chongo et al., 2021; Matsumoto & Cao, 2017). Unfortunately, most CT research in science education is conducted to investigate the cognitive domain of students, not the affective domain. That CT research for the affective domain has not been conducted in natural science majors (Tsai et al., 2021), was affirmed by Tang et al. (2020) who stated that CT assessments for non-cognitive are rare, with only 7.53% of all currently available assessments, far below the number of cognitive assessments which is 41.78%.

The non-cognitive assessment used in this study is the Computational Thinking Scale (CTS) developed by Korkmaz et al. (2017). The CTS was developed with the aim of determining the level of students' computational thinking skills based on five aspects, namely creativity, algorithmic thinking, cooperative, critical thinking, and problem-solving (Korkmaz et al., 2017). The level of computational thinking ability means the intensity of students' computational thinking or how often students carry out the statements in the CTS. The intensity is expressed through the answer choices of never, rarely, sometimes, generally and always (Korkmaz et al., 2017).

The integration with science necessitates a thorough inquiry into the proficiency of students in the Indonesian educational context. Extensive research enhances existing academic literature and fortifies scientific efforts to incorporate CT skill into the Indonesian curriculum.

2.3 Rasch Model Analysis

To enrich the results, Rasch model analysis was used in this research and was previously used in investigating CT skill by Chan et al. (2021), Putra et al. (2022), Wardani et al. (2022) and Purnami et al. (2023) . The analysis is an alternative solution to increase the effectiveness of analysis and investigate the psychometric properties of a measurement (Bradley et al., 2015). Specifically, it was selected to provide an overview of a person's ability measures and item conditions on the same scale (Khine, 2020). Some features used to analyse survey data are the outfit mean-square fit statistic (MNSQ), outfit z-standardised fit statistic (ZSTD), and point-measure correlation (Pt-Measure Corr) to determine the fit of items to the model (Bond & Fox, 2007; Sumintono & Widhiarso, 2015). In addition, the Wright map feature was used to analyse the condition of CT skill level based on items in the same scale (logit scale). Furthermore, the Rasch model can provide information on differential item function (DIF) based on gender or coding experience.

3. Methodology

3.1 Research Design

This research was conducted using quantitative methods and the design chosen was a cross-sectional survey by collecting data at one point in time (Creswell, 2012; Wang & Cheng, 2020). This research design was chosen to describe the specific characteristics of the population (Creswell, 2012), in this case the students' level of CT skills. The study began with the submission of an ethical review to the ethics committee before proceeding with the instrument adaptation process to translate the original version of CTS into the Indonesian version. Cross-sectional research is characterised by the efficiency in terms of speed, cost-effectiveness and capacity to generate valuable findings for more in-depth research investigations (Wang & Cheng, 2020). The main orientation was to provide scientific considerations to policy makers in the process of integrating CT learning into the curriculum, specifically in high school.

3.2 Participants

Survey participants were purposively selected from schools and the target population majored in science in Yogyakarta, Indonesia, with approximately 30-40 thousand students. Several characteristics were fulfilled, including 1) coming from accredited schools A or superior, 2) being in a school that allows research, 3) students in science major, and 4) willing to fill out questionnaires voluntarily. This pilot test stage involved 290 students from the same population, but selected from different high schools as the main survey phase. In the subsequent main survey, a total of 526 high school students specialising in science participated, including 239 females and 287 males, selected from 10 public high schools located in Yogyakarta. The number of participants fulfilled the requirements of Rasch model analysis (Linacre, 1994). Based on a significance level of 95% and a margin of error of 5%, the sample size met the minimum requirement to represent the specified population (Gill et al., 2010; Krejcie & Morgan, 1970).

Table 1: Demographics of participants

Demographic Characteristics	Total	Percent
Gender		
Male	287	54.6
Female	239	45.4
Coding experience		
Ever	75	14.3
Never	451	85.7

3.3 Instruments

The instrument used is CTS as developed by Korkmaz et al. (2017) to measure CT skill level of students. In this research, CTS was adapted into Indonesian before being given to the main survey participants on a paper-based basis. The response options were created in a 5-point Likert scale organised into (1) never, (2) rarely, (3) sometimes, (4) usually, and (5) always. These options represented CT intensity level of participants in solving problems.

Validation of the Indonesian version of the instrument was conducted through an adaptation procedure of Beaton et al. (2000), which consisted of six stages, namely: 1) translation, 2) synthesis, 3) back translation, 4) expert committee review, 5) pretesting, and 6) reports. A pilot test was conducted on 290 high school students majoring in science and analysed with the Rasch model. The items have a statistical fit value except for the fifth item from the problem-solving aspect (P5). Item P5 was a misfit and did not fulfil the three criteria of validity (Outfit MNSQ, Outfit ZSTD, and Pt-Measure Corr), and was discarded (Chan et al., 2021). The Indonesian version used in the main survey consisted of five aspects, comprising 19 questionnaire items. The reliability value of Cronbach's alpha of the Indonesian version at the pilot test stage was .72, with a category sufficient for use (Nunnally, 1978; Sumintono & Widhiarso, 2015). The item reliability value was .98, with an excellent category (Sumintono & Widhiarso, 2015).

3.4 Data Analysis

The data were analysed using the Rasch model introduced by Georg Rasch in the 1960s. The model has developed from dichotomous to partial model analysis (Masters, 1982) used for rating scale (Andrich, 1988) and facets (Linacre, 1994). Rasch analysis software used was Winsteps version 3.73 and was tested at the pilot test stage. Rasch model measurement requires a minimum sample size of 30 people for stability of ±1.0 logits with 95% confidence (Azizan et al., 2021; Linacre, 1994). In addition, the assumptions of unidimensionality and local independence also need to be identified, but these assumptions are not strict and do not have to be verified prior to Rasch analysis (Sick, 2010; Sumintono & Widhiarso, 2015). The quality of the questionnaire items and the survey data suitability were measured based on the MNSQ outfit, ZSTD outfit, and Pt-Measure Correlation values. Furthermore, the internal reliability was assessed based on Cronbach's alpha, item separation, item reliability and person reliability. Wright map analysis provided a clearer and more comprehensive presentation of item and person conditions on the same scale (Boone et al., 2014).

4. Results

4.1 Based on Rasch Model Measurement, does the Adapted Indonesian Version of the CTSF the Criteria of Fit and Reliability in Use?

To affirm the validity of the adaptation stage, an additional validation process was carried out to evaluate the compatibility of the data from the main survey with the single-attribute Rasch model (Boone et al., 2014). Furthermore, reliability was also calculated based on Cronbach's alpha value (KR-20), as shown in Table 2. The mean value of Outfit MNSQ was 1.00 (very ideal) and fell in the range of acceptable values of 0.5 to 1.5 ((Boone et al., 2014; Sumintono & Widhiarso, 2015). The value of Cronbach's alpha for the Indonesian version was 0.79, which fell into the sufficient category or met the minimum limit (Isa & Naim, 2016). The reliability value was supported by person reliability, item reliability and separation index that meet good criteria. The raw variance value that could be explained by the measurement was 29.9%. This value fell in the required range of at least 20% (Sumintono & Widhiarso, 2015) and is sufficient to prove that the items in CTS were good for measurement with a logical level of prediction. Based on the values shown in Table 2, the survey data fit with the Rasch model.

Table 2: Summary of statistics

	Person	Item
Total (N)	526	19
Measure (in logit)		
Mean	1.59	0.00
Standard Deviation (SD)	0.61	0.49
Standard Error (SE)	0.3	0.12
Outfit MNSQ		
Mean	1.00	1.00
Standard Deviation (SD)	0.66	2.00
Separation	8.98	1.69
Person Reliability	0.74	
Item Reliability	0.99	
Cronsbacs's Alpha (α)	0.79	
Raw variance explained by Measures	29.9%	

To confirm the fit of the survey data, it is necessary to consider the value at the item level. The criteria used are MNSQ Outfit, ZSTD Outfit, and Pt-Measure Corr values for each item. The acceptable MNSQ and ZSTD Outfit values are in the range of 0.5 to 1.5 and -1.9 to 1.9, respectively (Boone et al., 2014). In other sources, the acceptable ZSTD Outfit value is in the range of -2.00 to 2.00 but the value is vulnerable to samples above 500 (Sumintono & Wihiarso, 2015). For the Pt-Measure Corr criterion, the required value is above .3 and a positive Pt-Measure Corr indicates the functionality of the item (T. Bond, 2015). A fit item must fulfil one of the three criteria (Chan et al., 2021), and CTS statistic fit values can be seen in Table 3.

Table 3: Analysis of item fit

Item	Measure	Infit		Outfit		Pt-Mesure Corr
		MNSQ	ZSTD	MNSQ	ZSTD	
C1	-0.99	0.97	-0.4	0.96	-0.7	.50
C4	-0.32	0.87	-2.3	0.87	-2.3	.58
C5	-0.44	0.87	-2.4	0.88	-2.2	.46
A1	0.00	0.75	-4.7	0.75	-4.7	.59
A3	0.12	1.12	2.0	1.13	2.1	.48
A4	0.26	0.70	-5.6	0.70	-5.6	.56
A6	0.59	0.96	-0.7	0.96	-0.7	.44
O1	-0.49	1.22	3.6	1.22	3.7	.45
O2	-0.16	0.95	-0.8	0.96	-0.7	.43
O3	-0.12	0.92	-1.4	0.92	-1.3	.56
O4	-0.38	0.89	-2.0	0.89	-2.0	.59
T1	0.22	0.68	-5.9	0.68	-5.9	.62
T2	-0.17	1.05	0.9	1.04	0.8	.55
T3	-0.60	1.03	0.5	1.01	0.3	.57
T5	-0.27	0.87	-2.3	0.87	-2.4	.55
P1	0.44	1.47	6.8	1.49	7.0	.12
P2	0.70	1.23	3.5	1.24	3.7	.30
P3	0.87	0.98	-0.4	1.00	0.0	.21
P4	0.75	1.46	6.6	1.47	6.8	.07

Outfit MNSQ and Pt-Measure Corr values for the items fulfil Rasch model requirements. As for ZSTD Outfit criterion, several items are not met, including items A1, A4, T1, P1, and P4. However, the values for the other criteria were still within the required range, so the items were not removed. The finalised Indonesian version of CTS consisted of 19 items in five aspects, namely three creativity aspect four algorithmic thinking items (A), four cooperativity items (O), four critical thinking items (T), and four problem-solving items (P) (see Apendix 1). Based on Outfit MNSQ, Outfit ZSTD, and Pt-Measure Corr values, the data collected from 526 high school science students fit the Rasch model measurement.

4.2 Are there Questionnaire Items that Function Differently Based on Gender and Coding Experience?

An important feature to be investigated is DIF and this analysis examines the differences in the item responses of a questionnaire based on certain variables. Questionnaire items are considered contrasting or biased with a probability figure below 5% or less than .05 (Sumintono & Widhiarso, 2015). In addition, DIF detection can be seen from DIF t value less than -2.0 or more than 2.0, as well as the contrast value less than -0.5 or more than 0.5 (Bond & Fox, 2007; Boone et al., 2014). In this research, there are two variables used to analyse DIF, namely gender and coding experience.

Table 4: DIF analysis by gender and coding experience

Item	Prob. By		DIF Contrast by			
	Gender	Coding	Gender		Coding Experience	
			Male	Famale	Ever	Never
C4	.506	.030	0.07	-0.07	0.33	-0.33
A6	.589	.031	-0.06	0.06	0.32	-0.32
O4	1.000	.009	0.00	0.00	-0.39	0.39
T1	.466	.039	-0.08	0.08	0.31	-0.31
T2	.457	.036	-0.08	0.08	0.32	-0.32
T3	.234	.046	-0.13	0.13	0.32	-0.32
P4	.748	.036	0.02	-0.02	-0.31	0.31

Considering the probability value and DIF contrast, no individual item shows significant DIF when examined in the context of the gender variable. The items have probability values above 0.05, and DIF contrasts within the required range. However, when viewed from the coding variable, DIF is detected in items C4, A6, O4, T1, T2, T3, and P4. Critical thinking (T) is the aspect of CT skill with the most DIF-detected items and Figure 1 shows the effects of the variable on coding experience.

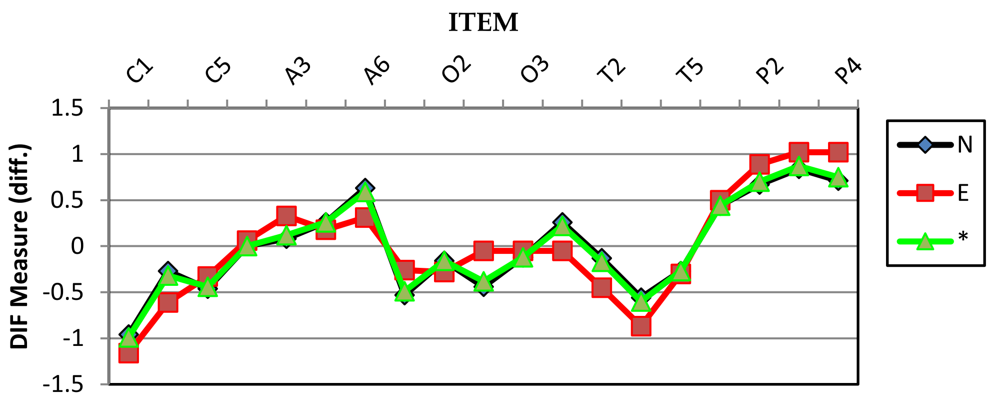

Figure 1: Person DIF plot based on coding experience

An interesting result can be seen in the items T1, T2, and T3, where students with coding experience tend to think critically less often. Possessing coding experience does not appear to enhance the skill of high school students majoring in science to devise solutions for intricate problems, or lead to a preference for complex issues. Additionally, coding experience does not seem to increase inclination of students towards embracing challenging tasks. Based on DIF contrast value on item P4, coding experience does not make students superior in generating many solution options. Furthermore, this variable has an effect on responses to CTS questionnaire items.

4.3 What is the CT Skill Level of High School Natural Science Students in Indonesia?

Important information investigated to determine the characteristics of the survey participants is seen in the Wright map in Figure 1. This map presents the distribution of CT skill level on the left side with the condition of the difficulty level of the questionnaire items on the right side.

Based on Figure 2, the statement most often implemented by students is on item C1 (-0.99 logit) followed by T3 (-0.60 logit). Meanwhile, the statements least often implemented are in items P3 (+0.87 logit) and P4 (+0.75 logit). The average level of CT skills based on its aspects is -0.58 logit for creativity (C), 0.24 logit for algorithmic thinking (A), -0.28 logit for cooperativity (O), -0.61 for critical thinking (T), and 0.69 for problem-solving (P). The logit values can be read based on positive or negative signs. A negative and positive value means that students often and rarely make statements on questionnaire items. In the problem-solving aspect (P), a positive value means that statements are often made on items because the form is negative (there is the word 'no'). Based on the average logit value in Table 3, only statements in the algorithmic thinking (A) aspect are rarely carried out by students. Other aspects such as creativity, cooperativity, critical thinking and problem-solving are performed frequently.

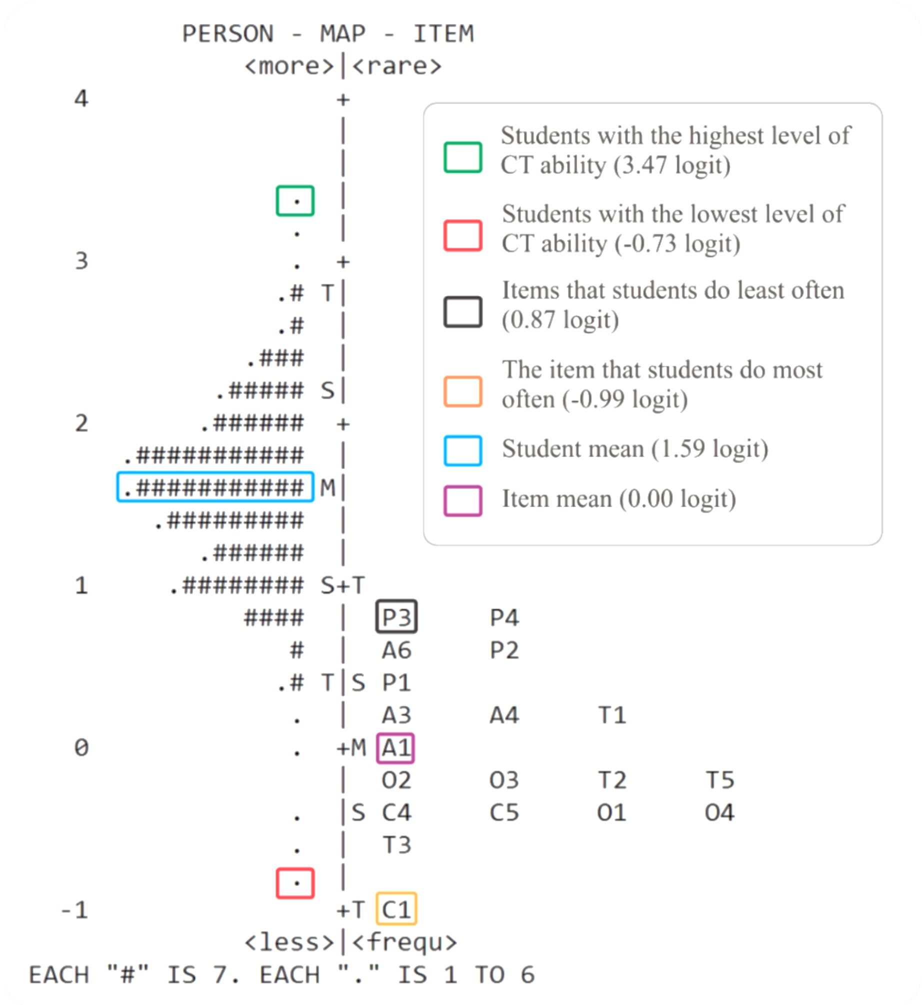

Figure 2: Analysis of Wright map

Based on the Wright map in Figure 2, students with codes 154LTC and 400LTB are males who rarely carry out the statements in the questionnaire (logit value = +3.47). Meanwhile, those with code 391LYB are males who most often conduct the statements (logit value = -0.73). The data may serve as evidence that male students show the highest and lowest level of CT skill among the population. The cut-off point of students' CT skill level can be determined based on their average logit value, which is +1.59. Students who have values above +1.59 logit are students with high CT skill levels, conversely, students with values below +1.59 logit are students with low CT skill levels.

The statement that students conduct the least was related to the problem-solving aspect (P). In item P4, only three students (1%) stated 'never' on the statement 'I cannot generate many options while thinking of possible solutions to a problem'. Therefore, most students majoring in science always come up with many solutions to a problem. In the aspect of creativity (C), they tend to agree with the statements given. Furthermore, in item C1, there were 200 (38%) and 180 (34%) students who answered 'always' and 'usually' on the statement 'I like people who are confident in the big decisions'. Based on the results, CT skill level of students falls into a fairly good category since the aspects are frequently conducted, except algorithmic thinking. This is also confirmed by the mean value of the person measure = +1.69 logit. The positive sign on the logit value proves that the average respondent tends to think computationally in facing and solving a problem.

5. Discussion

CT skill in Indonesian curriculum development is new (Natali, 2022) and has not been mastered by many teachers. However, the Indonesian government has endeavoured to prepare teachers who are competent in CT teaching. This research provides new insights and field evidence on the characteristics of CT skill. The level is closely related to the challenges of integration in the curriculum of developing countries, namely the low acceptance of students and the lack of attraction (Saidin et al., 2021; Yang et al., 2023).

This research raises three noteworthy discussion points. *Firstly*, pertaining to the assessment process, the adaptation of CTS is subjected to a meticulous phase that engages experts and students as participants. Among the 20 questionnaire items, 19 of CTS items were appropriate for use in the Indonesia language context. The results of the adaptation into the Indonesian version closed a small gap in the problem of integrating CT into the education curriculum, namely limited assessment (Angeli & Giannakos, 2020; Su & Yang, 2023). In Indonesia, the most commonly used CT assessment is the Bebras Challenge. It is a cognitive assessment, not a questionnaire like CTS. Therefore, the Indonesian version of the CTS can be an alternative assessment to determine the level of CT skills of secondary school students. In addition, the Indonesian version of the CTS adds to the literature of research adapting the CTS in various countries, as has been done in China and Turkey (Gök & Karamete, 2023; Korkmaz & Bai, 2019). It is recommended to CT researchers in Indonesia to conduct more adaptations of CT scales, so that investigations of CT ability levels can be carried out more broadly. Some CT scales that have not been adapted and tested in Indonesia include The Computational Thinking Scale for Computer Literacy (Tsai et al., 2021), Computational Thinking Self-Efficacy Scale (Kukul & Karatas, 2019), and Computational Thinking Scale (Ertugrul-Akyol, 2019). In addition, the development of a questionnaire on students' readiness to receive CT learning in the classroom seems necessary.

Secondly, DIF in the Rasch model was detected in the coding experience variable. This research supports Sun et al. (2022) and Villalustre and Cueli (2023), where this variable has different effects on CT skill level possessed by students. Despite the effect, coding experience does not necessarily make students think computationally more often than those who lack experience. The effect of coding experience on CT skill is not significant (Durak et al., 2019). Another interesting result is the absence of detectable DIF when viewed from the gender variable. This research contradicts results that have suggested a link between gender and variations in CT skill level (Sovey et al., 2022; Sun et al., 2022) due to the type of assessment. Gender-based differences are discernible when assessments take the form of tests or questions. However, a distinct pattern is developed when the assessment method is a questionnaire, as observed in CTS used. In Rasch model measurement, DIF is an important aspect that must be measured so that item bias can be known; unfortunately, in this study, there are only two aspects measured, namely gender and coding experience. Other studies are expected to add more varied aspects such as major, age difference and regional origin (city or village). In addition, investigating the correlation of CT skill level with the level of digital literacy, computer literacy and data literacy is also highly recommended.

Third, an examination of the Wright map showed that CT level among students majoring in science can be categorised as good enough. This determination is supported by the person's logit value, which is above zero or positive (+1.59). However, there exists one facet of CT that students infrequently engage with algorithmic thinking (A). Algorithmic thinking is related to skills in learning plugged and unplugged programming (Bacelo & Gómez-Chacón, 2023; Doleck et al., 2017), while science students in Indonesia have never been taught programming in school. This is one of the reasons why the algorithmic thinking aspect is rarely implemented by students. The rarity of engagement with algorithmic thinking can be attributed to the association with symbols and mathematical reasoning, which demand a higher-order thinking skill (HOTS). Meanwhile, Indonesian students have a low high-level thinking skill, specifically in the field of mathematics (OECD, 2019). One of the causes of students' low HOTS scores is that education in Indonesia does not optimally apply Bloom's taxonomy system in learning. Teachers tend to give mathematics and science questions that are only memorised and comprehended. The teaching done by teachers also does not require students to analyse, evaluate and create a product in the learning process so students are not motivated to learn (Huda & Rohaeti, 2023). This is also confirmed by the fact that students' performance on the CT (Bebras Challenge) test is also not good enough (Natali & Nugraheni, 2023; Rosali & Suryadi, 2021).

Even though students often think computationally in analysing daily problems, they are not familiar with the related problems or tests because the concept is not introduced or taught at school. The solution to overcome this problem is to integrate CT learning into the Indonesian curriculum. Therefore, students will be more accustomed to CT, as well as recognising and understanding the types of problems more deeply. Some of the ways teachers can teach CT to students is by practising the Bebras Challenge in their spare time (Natali, 2021). In classroom learning, teachers are recommended to use digital platforms to teach science topics. Teachers can teach science with the help of PhET or JavaLab as a simulation tool and Exel as a data analysis tool, so that learning is not only focused on the blackboard. Teachers should also introduce virtual labs and give instructions for students to conduct computer-assisted experiments.

This result should serve as scientific evidence for curriculum policy makers to prepare competent teachers in teaching skill. Moreover, teacher competence is one of the problems hindering skill integration in curriculum (Chagas & Furtado, 2019). Some recommended ways to improve teachers' competence in

CT teaching are by ensuring the quality of CT teaching lecturers in teacher professional programmes, providing certified CT integration training to school teachers, providing practical guidance on how to develop CT activities for teachers, and providing free digital learning platforms such as virtual labs, interactive media, data analysis software and science e-books that have integrated CT learning activities.

Finally, the Indonesian version of CTS can be a solution for other researchers and curriculum policy makers in investigating the level of CT skills of students, prospective teachers and school teachers in Indonesia. The level of CT skills of students and teachers is important to be investigated further so that there is scientific evidence that can be used as a reference to determine the CT integration measures needed at this time. Based on the results of this study, it is known that the intensity of computational thinking of students majoring in science is in the good category, so CT learning can be done by teachers, with a note that students should be given more learning activities that train them to think algorithmically. Unfortunately, currently teachers do not have guidelines on how to integrate CT in science subjects, so education policy makers in Indonesia must have the initiative to provide special guidelines for CT integration in the classroom for science teachers and teachers of other subjects.

6. Conclusion

In conclusion, the data obtained from this research fit with the Rasch model. The Indonesian version of CTS could be declared fit because it has MNSQ Outfit, ZSTD Outfit, and Pt-Measure Corr values that fall within the required range. The validated CTS proved to be used to investigate CT skill level in the good enough category. Students who participated tended to think computationally often when solving problems in the aspects of problem-solving and critical thinking, as shown by the measured aspects. However, students infrequently thought algorithmically, reflecting the relatively low performance of students' higher-order thinking skills. Based on the analysis for gender, there were no items in CTS with different functions, but DIF was detected in the coding experience. Generally, students were accustomed to CT even without receiving the learning or solving related problems. Considering CT’s skill level, students were ready to accept the integration of the concept into the education curriculum. Thus, this research is expected to encourage educational policy makers in developing countries, especially Indonesia, to integrate CT into their curricula, especially the high school curriculum for science majors.

7. Limitation

The cross-sectional research design in this study is limited to the population taken, namely the Special Region of Yogyakarta, Indonesia, so that the results of this study cannot be generalised to other regions even though they are still in Java. The participants of this study were also limited to students majoring in science, so the conclusions of this study cannot be generalised to students of other majors. The instrument used in this study was the Computational Thinking Test (CTS) in the form of a questionnaire with 1-5 Likert scale answer options. Thus, the type of data obtained do not represent the cognitive abilities of students. The CTS questionnaire measures the level of intensity of students' computational thinking, not the cognitive domain of skills or IQ.

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Appendix 1: Computational Thinking Scale (CTS) adaptation results in Indonesian

Code	Original Version	Indonesia Version
C1	I like the people who are sure of most of their decisions	Saya menyukai orang-orang yang yakin dengan keputusan besar mereka.
C4	I have a belief that I can solve the problems possible to occur when I encounter with a new situation	Saya yakin bisa menyelesaikan masalah yang mungkin terjadi dalam situasi baru.
C5	I trust my intuitions and feelings of "trueness" and "wrongness" when I approach the solution of a problem	Saya percaya pada intuisi dan perasaan saya terhadap apa yang "benar" dan "salah" ketika saya mencari solusi dari suatu masalah.
A1	I can immediately establish the equity that will give the solution of a problem	Saya dapat dengan cepat menetapkan keputusan yang akan menghasilkan solusi dari suatu masalah.
A3	I think that I learn better the instructions made with the help of mathematical symbols and concepts	Saya rasa saya belajar lebih baik dengan instruksi yang dibuat dengan bantuan simbol-simbol matematika dan konsep.
A4	I believe that I can easily catch the relation between the figures	Saya yakin bahwa saya dapat dengan mudah menangkap hubungan antara angka-angka matematika
A6	I can digitize a mathematical problem expressed verbally.	Saya dapat menjadikan (mengkonversi) masalah matematika yang disebutkan secara lisan menjadi angka-angka.
O1	I like experiencing cooperative learning together with my group friends	Saya senang melakukan pembelajaran kooperatif (kerjasama) bersama dengan kelompok saya.
O2	In the cooperative learning, I think that I attain/will attain more successful results because I am working in a group.	Dalam pembelajaran kooperatif (kerjasama), saya pikir saya akan mencapai hasil yang lebih baik karena saya bekerja dalam kelompok.
O3	I like solving problems related to group project together with my friends in cooperative learning	Saya suka memecahkan masalah yang berkaitan dengan proyek bersama teman dalam pembelajaran kooperatif (kerjasama).
O4	More ideas occur in cooperative learning	Lebih banyak ide muncul dalam pembelajaran kooperatif (kerjasama)
T1	I am good at preparing regular plans regarding the solution of the complex problems	Saya pandai menyiapkan rencana untuk solusi masalah yang kompleks.
T2	It is fun to try to solve the complex problems.	Sangat menyenangkan untuk mencoba memecahkan masalah yang rumit.
T3	I am willing to learn challenging things.	Saya bersedia belajar hal-hal yang menantang.
T5	I make use of a systematic method while comparing the options at my hand and while reaching a decision	Saya menggunakan metode yang sistematis saat membandingkan pilihan yang ada di tangan saya dan saat mengambil keputusan
P1	I have problems in the demonstration of the solution of a problem in my mind.	Saya memiliki masalah dalam menampilkan/mengungkapkan solusi dari masalah yang ada di pikiran saya
P2	I have problems in the issue of	Saya memiliki masalah saat harus

	where and how I should use the variables such as X and Y in the solution of a problem.	menggunakan variabel seperti X dan Y dalam penyelesaian suatu masalah.
P3	I cannot apply the solution ways I plan respectively and gradually.	Saya tidak dapat menerapkan solusi yang saya rencanakan secara bertahap atau sistematis (terpisah-pisah)
P4	I cannot produce so many options while thinking of the possible solution ways regarding a problem	Saya tidak dapat menghasilkan begitu banyak pilihan sambl memikirkan kemungkinan solusi dari suatu masalah