Indonesian Undergraduate Students' Perception of Their Computational Thinking Ability

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Abstract

Become skilled at CT is indispensable for undergraduate students, as the proficiency in information technologies and complex problem solving increase in important in digital workplaces. This study measured Indonesian undergraduate students' self-perception of their CT ability in order to establish CT profile based on gender, majors of specialization, and university location. Study participant comprises of 527 final-year undergraduate students from three universities in Indonesia, using the Hi-ACT instrument. To examine whether statistically significant differences existed, independent sample t-test was used. The findings regarding the profile of Indonesian undergraduates' CT skill show, the students attained a moderately high CT level. In particular, statistically significant differences existed in Problem Solving and Communication between male and female students, wherein male students means were higher. Regarding majors of specialization, significant differences between STEM and non-STEM students were found in Algorithmic Thinking, Decomposition, Evaluation, Generalization, and Communication, in favor of STEM students. As for university location, significant differences were found in Algorithmic Thinking, Debugging, Teamwork, and Communication, in which suburban students performed better.

Keywords—Computational thinking, Skills, Attitudes, Undergraduate

1. INTRODUCTION

Idea that computer science concepts would be everyone's concern, particularly in education, has been sounded even since six decades ago when Perlis, in 1962, argued that programming concepts would lead to understandings of variety of topics [1]. Then, Papert suggested the 'procedural thinking', which is the use of programming symbols and representation, in solving problems [2]. However, it was not until 2006 the term 'computational thinking' gained traction in the literature, when Wing noted 'computational thinking represents a universally applicable attitude and skill set every one should learn and use.' Since then works on CT have been initiated, addressing lower education to higher education level. In higher education level, studies on CT primarily highlight the development of CT courses, both programming-based using a specific computer programming language [3]–[5] and non-programming [6], [7], also game-based approach [8]. Several studies dealed with higher education students' CT proficiency [9]–[12]. Considerable CT skills have been addressed like algorithmic-related skill [11]; processes and transformation, models and abstractions, patterns and algorithms, tools and resources, inference and logic, as well as evaluations and improvements [10]; simple algorithms, sorting, digital information storage, and file structure [9]; creativity, algorithmic thinking, critical thinking, problem solving, and cooperativity [12]. Of these studies, however, only few took notice on attitudes as factor constitute the CT; as [13] specified CT as "a universally applicable attitude and skill set everyone would be eager to learn and use".

In the recent years efforts to teach CT to Indonesian students have been undertaking. One study examined undergraduate students' CT skills (abstraction, generalization, algorithm, modularity, and decomposition) development through robotic learning activities, using Lego Mindstorm programming environment [14]. The authors claimed that overall students could adequately understand the CT knowledge despite the students had difficulties in algorithm design. CT was also used in a study that focused on enhancing energy-efficient (optimized) programming skills [15]. The study emphasized the importance of performance and resources optimization in programming, by employing four CT skills: decomposition, pattern recognition, abstraction, and algorithm. The students' CT skills were then evaluated, based on the project they developed, using Dr. Scratch tool. In another study, scientific-based instructional materials, integrated with CT, have been developed to promote CT to Education department students [16]. The instructional materials comprise of scientific literacy indicators including concept (environment theory); context (science in daily life that related to the environment, such as health, natural resources, disaster, and technological science); competencies and attitudes, which is observed in problem solving practical activities. Guideline to solve the given problems based-on CT techniques (abstraction, pattern recognition, algorithm, simulation, automation, and reasoning) is included in the teaching materials. Additionally, Indonesia also has joined with Bebras International, an international initiative whose goal is to disseminate CT among students of all ages. Referring to the Bebras Indonesia website, within the period of mid-2016 to 2017, a total of 12 seminars and workshops have been held to introduce CT [17].

In this current paper, we present the result of measuring Indonesian undergraduate students' perception of their CT concepts, using the Hi-ACT instrument. Then, profile of students' CT ability was developed based on gender, majors of specialization (Science, Technology, Engineering and Mathematics (STEM) and non-STEM), and university location. The findings of this study impart the essential insight into the students' comprehension of CT concepts, with its impact on their readiness for participating in digital workplaces. In addition, they might contribute to CT development in undergraduate level, in Indonesia. By understanding the students' strengths and weaknesses might be beneficial in incorporting the skills in the classrooms.

1.1 Gender differences issues in Computational Thinking

Gender differences is a long-standing issue in STEM-related fields, including in computer science (CS), where women's underrepresented in CS education has garnered widespread attention in academic [18], [19]. Accordingly, similar situation is happening in CT, as it basically is rooted in CS education. Gender has an effect on one's attitude and self-efficacy towards programming related activities, such as algorithm and coding, then it is believed to influence CT development [20]–[23]. However, it is noteworthy that attitudes and self-efficacy towards the stereotypical male dominated fields (mathematics, engineering, and computer) reflects lack of confidence not the ability [22].

In particular to CT, gender differences discussion can be found in the literature [23]–[28]. Of these studies, [23]–[25] found significant relationship between gender and CT level of students in secondary and high school level. On the other hand, others demonstrated that gender has no impact on CT [26], [27]. Hence, it can be said that 'like-mindedness' was failed to attain. Moreover, limited study has been conducted into gender differences in higher education. Therefore, the first goal of this study was investigate whether the distribution of CT skill is the same across categories of gender.

1.2 Major differences issues in Computational Thinking

Another issue of interest in CT studies is the disparity in STEM and non-STEM students' understanding of CT. By referring to [13] emphasis that CT should be learned and used by everyone, not only computer scientists, studies in CT have targeted different subjects at the undergraduate level. Generally, they comprise computer science (CS) [7], [9] and non-CS majors, which involved STEM [3], [6] and non-STEM majors [29].

The underlying concepts of CT are the approaches computer scientist used in solving problem process. Accordingly, researchers argued that developing CT might be strenuous for those students (non-CS majors) who are unlikely have computational mindsets and analytical methods and limited understanding of computing concepts [30]. This group of students include both STEM and non-STEM based majors. Nevertheless, it is noteworthy that CT, as a kind of analytical thinking, also acquires mathematical thinking to approach a problem, engineering thinking to design and evaluate a complex system, and scientific thinking to understand computability, intelligence and human behaviour [13]. Based on this justification, CS majors and other science, technology, engineering, and mathematics related disciplines could be classified into STEM group.

Majors differences in CT are well-documented in the literature. The study of [7] that blended computational and creative thinking in the test involving CS, physical science, and humanities majors, concluded that contrast were not found in test results of CS majors and non-majors. The result of this study is similar to [31], which also found that non-CS students performance in an interdisciplinary course to disseminate CT were comparable to CS students. Regarding STEM and non-STEM diversity, different finding was concluded in [9] in which STEM students' test scores were higher than non-STEM students. However, the CT test is limited to simple algorithm, sorting, file structure, and digital information storage. The present study seeks to learn whether the distribution of CT skill is the same across categories of majors of specialization.

1.2 University location differences issues in Computational Thinking

Indonesian context as the largest archipelago country highlights an issue of geographical imbalance, which leads to disparity in development in various sectors, including education. The graph is skewed towards Java, the most populated island as well as the home of Indonesia's capital. In particular to its higher education, the issues of accessibility to and quality of higher education institutions (HEIs) remain challenging. As per 2018, out of Indonesia's 3293 HEIs, 47.6% are in Java [32]. Moreover, most-high quality HEIs are in Java. When the Ministry of Research, Technology and Higher Education (MoRTHE) of Indonesia released the country's 2018 list of 100 top universities, 78% of them are located in Java.

Difficulty in acquiring qualified professional educators and scientists who are eager to work in underdeveloped provinces may induce disparities in teaching quality. Also, unequal technology infrastructure contributes to the already-large educational disparities between those in Java and rural provinces. The lack of adequate internet connection is a technological limitation that impacted the accessibility of electronic academic journals and available online teaching platforms [33]. This digital divide, indubitably, contributes to inequality in the knowledge and skills of students.

Digital divide, the uneven exposure to computers and advanced technology, is a critical issue when it comes to introducing CT to higher education students [2]. Going the extra mile is inevitable for those who previously have limited access to computers and information technology in order to acquire CT skills. This opinion corroborates those of [20] who argue that students' experiences in using information and communications technology may impact their level of CT proficiency.

These gaps in HEIs and digital divide between Java and those in regions outside Java are another concern in this study. Therefore, the study was also intended to investigate whether the distribution of CT skill is the same across categories of university location in Indonesia.

2. METHOD

2.1 Study group

The participants of this study were 527 final year undergraduate students were registered to both STEM and non-STEM major of specialization in three universities in Indonesia. A stratified random sampling technique was implemented to select the sample. The stratification involved was university (based on its location), major of specialization, and gender. Then, the researcher selected the sample of students randomly.

Of the total of 527 participants, 250 were male, and 277 were female. 307 (58%) were STEM-based majors students, which comprises of 161 (52.5%) female students and 146 (47.6%) male students. Of the 307 STEM-based majors students 170 (55.4%) were registered in the urban located university, while the remaining 137 (44.6%) were in the suburban located university. As for the non-STEM based major, of the 220 (42%) participants, the number of female students was 116 (52.7%), slightly higher than 104 (47.3%) male students. More non-STEM based majors students participated in the present study were registered in suburban located university (113; 51.4%) than in urban located university (107; 48.6%). The participant in this study is believed to be generally representative of Indonesian undergraduate students, as the sample involves both urban and suburban university students attending a diverse range of disciplines, and a reasonably even proportion of male and female students.

2. 2 Instrument

The Hi-ACT [34] was used as data collection instrument in this study. This scale comprises of 110 seven-point Likert type items and ten constructs. Abstraction comprises of 5 items that measure the ability to simplify a problem by removing irrelevant details or information, and choose the right representation that model the solution. Algorithmic thinking comprises of 16 items that measure the ability to formulate a set of clear procedures, based on logical thinking, to solve the problem. It involves procedural thinking, think of possible alternative actions, repetition, and parallelism. Decomposition comprises of 5 items that measure the ability to simplify a problem by dividing it into several sub-problems that are smaller and easy to manage, and otherwise creating solutions for a complex problem by compiling smaller parts of solutions. Debugging comprises of 2 items to measure the ability to identify errors in the design solution. Evaluation comprises of 10 items to measure the ability to assess solutions' performance, resource usage, and the action of refining to improve the solution's quality. Generalization comprises of 9 items that measure the ability to identify similar patterns in between problems, mapping, and reuse the common parts of a solution that has been used previously, to similar problems.

Problem Solving comprises of 20 items that measure confidence in effectively solving the problem, persistence when dealing with the difficult problem, the ability to handle ambiguity, and willingness to solve the problem. Teamwork comprises of 22 items that measure ability to cooperate and coordinate with others in a team, active participation, and ability to manage conflict work with others in a group in solving problems. Communication comprises of 5 items that measure the ability to exchange information and knowledge within the member of teamwork. Spiritual Intelligence comprises of 16 items that measure self-awareness, integrity, and creative reasoning that facilitate problem solving.

In addition, demographic data comprised of gender, type of university, year in university, majors of specialization, and university location, were also gathered. Cronbach alpha consistency coefficient calculated for the scale in this study is 0.981.

2.3 Data Analysis

We first calculated the mean values for responses to Likert type items for each construct. Then, independent sample t-test was used to determine whether statistically significant differences existed between the means of male and female (by gender), STEM and non-STEM (by majors of specialization), as well as urban and suburban (university location). Alpha was set at 0.05. The results are provided in following section.

3. RESULTS AND DISCUSSION

Figure 1 presents the mean value of all students CT competence for all ten constructs. The students' highest means were debugging, followed by communication, spiritual intelligence, teamwork, abstraction, algorithmic thinking, evaluation, decomposition, generalization, and the lowest one is problem solving.

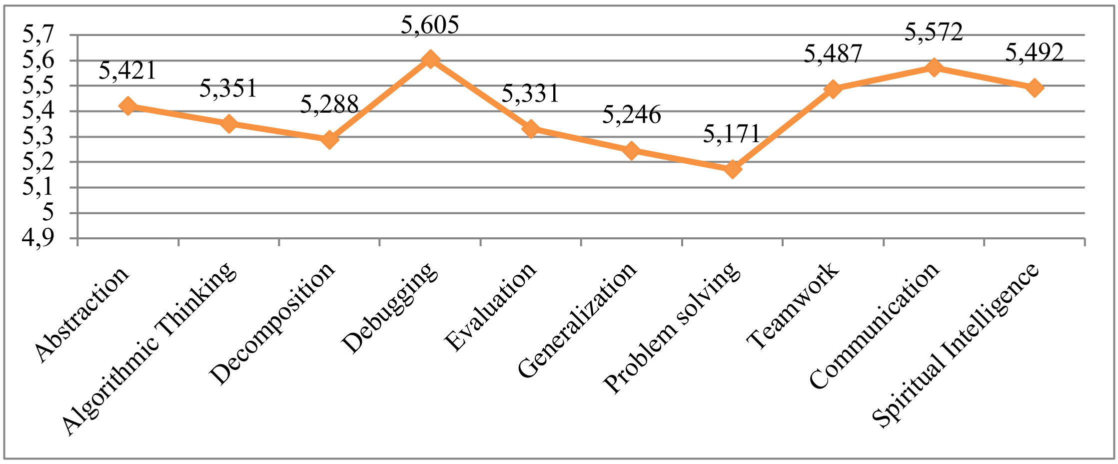

Figure 1 Students' Computational Thinking Mean Scores

The present study found that, generally, the results revealed that the students had the highest mean in debugging skill. The communication, spiritual intelligence, teamwork, abstraction, algorithmic thinking, evaluation, decomposition, generalization follow it, and the lowest one is problem solving. As can be understood from this result, in which communication, spiritual intelligence, and teamwork are ranked higher compared to other technical skills of CT besides debugging, the students were better in attitudes compare to technical skills.

Further, the highest mean of all CT aspects assessed is 5.605, which is belongs to debugging. Referring back to the scale that was used to in the Hi-ACT instrument, this value indicates, on average, the students' ability to identify and detach fault from the design solutions is only moderately high. In addition, related to the Debugging is evaluation skill. The mean of Evaluation (5.331) is slightly lower than Debugging. Evaluation, as defined in the present study, is the ability to assess whether a solution is complete and fit for its purposes to solve the problem, analyze the resources required to solve the problem, and refine the solution to improve its precision. That is to say, the students' ability in analyzing the issue when a solution does not correspond to the desired result is somewhat good; however, they are less skilled in carrying out further analysis of the solution's performance and efficiency.

The means of other CT technical knowledge indicate a moderately high level of CT skills. Based on the current data, the students still lack in ability to create a computational solution to solve a problem; the mean of Algorithmic Thinking skill was only 5.351. Similarly, the means of Abstraction (5.421), Decomposition (5.288), and Generalization (5.246) point out that the students are deficient in capability to simplify a complex problem, either by focusing on the significant details (information) or by decomposing a problem into smaller parts, as well as reutilize existing solutions to another problem. This result demonstrates that Indonesian undergraduates' have better knowledge in analyzing and fixing errors in a solution compare to formulating solutions in a systematic way. On the other hand, CT emphasizes on the use of abstraction, algorithmic thinking, decomposition, generalization, and evaluation, in solving novel and ill-defined problems of the real world, in a systematic way like the computer scientist do. The inadequacy in technical skills might leads to the students' lack of ability to solve unstructured problems in different domain.

In researchers opinion, the lack in students' technical skills might be related to other CT attitude examined in the study, i.e. Problem Solving attitude. As noted previously, mean of Problem Solving attitude (5.171), which is the lowest among the other ten CT constructs, shows that the students were relatively less skilled in self-confidence in solving complex problems, persistence when dealing with the difficult problem, ability to handle ambiguity, and willingness to solve a problem. Not only lessen ones' ability in solving challenging problems, lack of knowledge about how to solve the problem may result in low problem solving attitude. As also concluded in a study intended to examine students' higher-order thinking skills, when the students are used to practice with routine problems, they do not have confidence, and they tend to show unwillingness to solve higher-order thinking skills oriented problems which are ill-defined and complex [35]. Besides, low perseverance makes the students avoid challenging problems and be inclined to attend the ones they know (the methods) how to solve [36].

It therefore can be concluded, generally, Indonesian undergraduates have a moderately high level of CT. It is notably lesser in the knowledge of how to think like a computer scientist when solving problems, which are the technical skills. For that reason, it is an urgent necessity to incorporate CT concepts, in particular, the technical skills, across disciplines in undergraduate level in Indonesia. The reason why is because CT could develop analytical and problem-solving skills [3] which are mandatory in digital age workplaces, and should be mastered by prospective workforces. Further, we now moving forward with analysis of the students' CT level based on gender, major of specialization, and university location.

3.1 CT Skill Difference Grouped by Gender

Table 1 summarizes the results concerning students' CT skill difference by gender. By gender, means of male students' CT skills was higher than female students, however, no significant difference found ($t_{(525)}$=1.943, p=0.053). When the means of each skill and attitude assessed, the means of male students were found higher compare to female students for all skills and attitudes. Running t-tests on those means revealed statistical differences in Problem Solving ($t_{(525)}$=2.148, p=0.032) and Communication ($t_{(525)}$=2.242, p=0.025).

Male students means were higher than female students for all ten constructs. However, the differences are not significant for Abstraction, Algorithmic Thinking, Decomposition, Debugging, Evaluation, and Generalization skills, as well as in Teamwork and Spiritual Intelligence. In particular to gender indifferences in the six CT technical skills, the results are in contrast previous studies [24], [25]. The study of [24] found that male students performed higher than female students in their CT test on algorithmic thinking (sequence, loop, conditionals, operators), debugging (testing and debugging), generalization (reusing and remixing), and (abstraction) abstracting and modularizing. So as in the study of [25], statistical differences were found in algorithmic thinking, critical thinking, creativity, and cooperativity, in favour of male students. In addition, the results of the study conducted by [23] to examine the abstract thinking abilities and program understanding (algorithm) revealed that in terms of abstract thinking male students outperformed female students, which is contrary to the present study's finding. In terms of program understanding, there were no significant differences in program understanding score found in the study of [23], which is a match to the finding of the present study wherein no significant difference found in algorithmic thinking between male and female students.

Table 1 CT Skill Difference Grouped by Gender

Skills/Attitudes	Cat.	M	Std	*t*	*p*
CT	M	5.435	0.662	1.943	0.053

	F	5.326	0.628		
Abstraction	M	5.444	0.791	0.629	0.529
	F	5.401	0.749		
Algorithmic Thinking	M	5.389	0.726	1.223	0.222
	F	5.316	0.678		
Decomposition	M	5.312	0.990	0.538	0.591
	F	5.267	0.929		
Debugging	M	5.650	0.910	1.060	0.290
	F	5.565	0.928		
Evaluation	M	5.388	0.781	1.593	0.112
	F	5.279	0.784		
Generalization	M	5.285	0.817	1.081	0.280
	F	5.212	0.743		
Problem Solving	M	5.250	0.819	2.148	0.032
	F	5.100	0.778		
Teamwork	M	5.545	0.769	1.697	0.090
	F	5.434	0.725		
Communication	M	5.661	0.840	2.242	0.025
	F	5.493	0.878		
Spiritual Intelligence	M	5.553	0.779	1.784	0.075
	F	5.436	0.734		

Further, since statistical differences between male and female students in CT technical skills were not confirm, it can be said that both male and female students may have the same performance in technical skills of CT. These findings imply two things. First, the same potential both male and female students have in acquiring and understanding the fundamental concepts of computer science, which grounded the technical aspect of CT. This argument is in accordance with a study of [26] on educational robotic with 15 and 18-year-old students. The study concluded that both male and female students are likely to successfully develop their CT skill when the learning activity time is adequate. As in [20], a study to identify the variables that explain secondary and high school students' CT, gender does not affect the students' CT level.

Second, the finding regarding no statistical differences between male and female in terms of CT technical skills, which definitely are based on computer science, might indicate the narrowing in gender diversity in computer science-related disciplines. Previous studies have concluded that male demonstrate greater confidence and attitudes towards computer science [19], [37], however, there is still a possibility that diversity is not in ability, as found in the present study. Therefore, the stereotype of male dominance in the computer science domain may change under a particular condition. Teaching CT to male and female students resulting in both could reach the same level of skill, event though the time female students needed is longer [26]. Also, in another study, the differences in self-efficacy and attitudes towards programming were narrowed at the end of a teaching session, and both male and female students demonstrate similar potential in programming [21].

3.2 CT Skill Difference Grouped by Major of Specialization

Based on major of specialization, means of STEM students' CT skills was higher than non-STEM students, and the difference was found to be significant ($t_{(525)}$ =2.386, p=0.017). For all CT attitudes and skills assessed, the mean values of STEM students were found higher compare to non-STEM students'. Significant differences were found in five skills, i.e.

Algorithmic Thinking ($t_{(525)}$=2.518, p=0.012); Decomposition ($t_{(525)}$=3.056, p=0.002); Evaluation ($t_{(525)}$=2.025, p=0.043); Generalization ($t_{(525)}$=3.017, p=0.003); and Communication ($t_{(416.1)}$=2.407, p=0.017). Table 2 summarizes the results concerning students' CT skill difference by major of specialization.

Table 2 CT Skill Difference Grouped by Major of Specialization

Skills/Attitudes	Cat.	M	Sdt	t	p
CT	S	5.435	0.598	2.386	0.017
	NS	5.299	0.702		
Abstraction	S	5.474	0.704	1.875	0.061
	NS	5.347	0.847		
Algorithmic Thinking	S	5.415	0.661	2.518	0.012
	NS	5.262	0.724		
Decomposition	S	5.395	0.914	3.056	0.002
	NS	5.139	0.999		
Debugging	S	5.650	0.824	1.265	0.206
	NS	5.543	1.038		
Evaluation	S	5.389	0.786	2.025	0.043
	NS	5.249	0.775		
Generalization	S	5.332	0.745	3.017	0.003
	NS	5.126	0.811		
Problem Solving	S	5.216	0.785	1.508	0.132
	NS	5.109	0.819		
Teamwork	S	5.534	0.693	1.718	0.086
	NS	5.421	0,814		
Communication	S	5.651	0.788	2.407	0.017
	NS	5.463	0.949		
Spiritual Intelligence	S	5.542	0.720	1.801	0.072
	NS	5.422	0.802		

3.3 CT Skill Difference Grouped by University Location

Table 3 shows, suburban students' means were higher compared to urban students in most of the skills examined, i.e. abstraction, algorithmic thinking, debugging, evaluation, teamwork, communication, and spiritual intelligence. In particular, significant differences were found in algorithmic thinking, debugging, teamwork, and communication, in which suburban students performed better. As for decomposition, generalization, and problem solving, urban students performed better than suburban students; however, the differences found not significant in all of the three constructs. That is to say, in terms of abstraction, decomposition, evaluation, generalization, problem solving, and spiritual intelligence, both suburban and urban students are similar.

By referring to the existing inadequacies in Indonesian higher education, particularly the gaps in terms of educational facilities and lecturer qualities that are still disproportionately distributed which contributes to a different quality of graduates, it was astonishing that the students in the suburban area perform better than those in the urban area. Moreover, as for now, when the development of information and communication technology infrastructure is indeed still uneven in areas outside Java.

The finding of the present study regarding Indonesian undergraduates' CT based on geographic region (university location) might imply two things. First, students' experiences, exposure to, and mastery in using information and communications technology have no impact on their level of CT proficiency. This argument is contrary to previous studies [2], [41] but at the same time support [20]'s finding in which experience in using information technology has not proved to be positively effect the level of CT of the students. CT emphasizes the type of thinking process used when creating solution to a problem. Information and communication technology skill, on the other hand, focuses on the ability to use the technology to access, produce, and distribute information in a digital environment. It concentrates more on using software or an application to create digital content and solve a problem [42].

Second, the available technology today, despite its unevenness distribution, has contributed to support the students' access to information and knowledge from outside the classroom. By this means, the knowledge of CT can be disseminated without any dependence on high technology specification. As [43] recommended, exposing CT to the students does not have to involve a computer, but by using the unplugged approach. Because, CT uses the ideas from computer science, not necessarily the computer (hardware) to solve problems in the real world [13]. It is a challenge for education stakeholder, in Indonesia, to think of how to integrate CT to undergraduate curriculum that fits (doable) to different situation in urban and suburban areas in Indonesia.

Table 3 CT Skill Difference Grouped by University Location

Skills/Attitudes	Cat.	M	Sdt	*t*	*p*
CT	U	5.330	0.687	-1.798	0.073
	SU	5.431	0.594		
Abstraction	U	5.367	0.785	-1.690	0.091
	SU	5.481	0.747		
Algorithmic Thinking	U	5.279	0.716	-2.503	0.013
	SU	5.430	0.655		
Decomposition	U	5.302	0.942	0.340	0.734
	SU	5.273	0.977		
Debugging	U	5.495	0.950	-2.930	0.004
	SU	5.728	0.870		
Evaluation	U	5.295	0.777	-1.102	0.271
	SU	5.370	0.791		
Generalization	U	5.249	0.793	0.078	0.938
	SU	5.244	0.765		
Problem Solving	U	5.234	0.797	1.909	0.057
	SU	5.101	0.799		
Teamwork	U	5.373	0.782	-3.720	0.000
	SU	5.613	0.686		
Communication	U	5.391	0.855	-5.208	0.000
	SU	5.774	0.829		
Spiritual Intelligence	U	5.449	0.764	-1.348	0.178
	SU	5.538	0.748		

4. CONCLUSION

To sum up, the findings regarding the profile of Indonesian undergraduates' CT skill show, taken as a whole, the students attained a moderately high CT level. These findings have implications for computer science education teaching and learning in Indonesia; wherein they suggest urgency for Indonesia to incorporate CT into its education strategic plan, in order for the country to provide workforces with the skill compulsory in digital workplaces. The effort is required from the government to innovate the curriculum that will provide the directive policy to integrate CT into the practice of teaching and learning. CT skill should be gradually developed from an early age. Thus, such a curriculum should accommodate all educational level, starting from elementary to higher education level. In particular to CT profile based on gender, even though a significant difference was not confirmed, again, both male and female students' means of each CT construct was still moderately high. The profile based on gender gives the insight, they should develop more about technical skills of CT as well as problem solving attitude, as they lack in these subject. Regarding the result of CT profile based on major, more concern should be provided for non-STEM major as the difference between non-STEM students and STEM students was confirmed significant.

The undergraduates' CT proficiency profile found in this study impart the essential insight into the students' comprehension of CT concepts, with its impact on their readiness for participating in digital workplaces. In addition, the findings might contribute to CT development in undergraduate level, in Indonesia. By understanding the students' strengths and weaknesses might be beneficial in incorporating the skills in the classrooms. The researchers thus suggest that HEIs could adopt CT in their curriculum, such as offering an introductory course to CS. Lecturer are also encouraged to add in CT concepts in their teaching materials in order to augment the students' complex problem solving abilities, and into developing the skill required in digital workplaces.

5. FUTURE WORK

The present study was conducted mainly in Indonesia, in particular, the actual study. Due to time and resource constraints, the sample was a group of students registered in four universities located in three islands, i.e. Java, Sulawesi, and Sumatera. In addition, only one university involved from each Sulawesi and Sumatera Island, to represent the suburban region. Being subject to only this sample might not adequately represent the whole population. There is a potential that students from other provinces in eastern Indonesia have different computational thinking proficiency. For future study, involving more students from higher education institutions in other provinces in Indonesia could better represent the whole country. Such a study may result in a difference in Indonesian undergraduate students' computational thinking profile.

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