

Article

Promote students' computational thinking in rural areas: The moderating role of gender

Deddy Barnabas Lasfeto^{1,*}, Eka Budhi Santosa², Tuti Setyorini¹¹ Politeknik Negeri Kupang, Kupang 139, Indonesia² Universitas Sebelas Maret Surakarta, Surakarta 57126, Indonesia* Corresponding author: Deddy Barnabas Lasfeto, deddylasfeto@gmail.com

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Abstract: The purpose of this study was to assess rural students' computational thinking abilities. The following proofs were observed: (1) Students' abstraction affected algorithmic thinking skills; (2) Students' decomposition influenced algorithmic thinking skills; (3) Students' abstraction impacted evaluation skills; (4) Students' algorithmic thinking affected evaluation skills; (5) Students' abstraction impacted generalization skills; (6) Students' decomposition impacted generalization skills; (7) Students' evaluation affected generalization skills. Gender differences were observed in the relationship among the computational thinking factors of junior high school students. This included the abstraction-generalization skills; evaluation-generalization skills; and decomposition-generalization skills relationships, which were moderated by the gender of the students. 258 valid surveys were collected, and they were utilized in the study. Conducting the descriptive, reliability, and validity analyses used SPSS software, and the structural equation modeling (SEM) was also conducted through Smart PLS software to assess the hypothetical relationships. There were gender disparities in the correlation among computational thinking components of the junior high school students' studying in rural areas. Research has shown that male and female students may have different abstractions, evaluations, and generalizations related to computational thinking, with females being more strongly associated than males in non-programming learning contexts. These results are expected to provide relevant information in subsequent analyses and implement a computational thinking curriculum to overcome the still-existing gender gaps and promote computational thinking skills.

Keywords: computational thinking; gender; rural areas; learning; curriculum

1. Introduction

In the twenty-first century, one of the abilities required is computational thinking, and has been of great importance in the education reform policies of many countries (Nouri et al., 2020; Tsai et al., 2022). This set of problem-solving skills is often applied to solve various problems in daily life and needs to be delivered to students at a young age. By using computational thinking, students are also capable of structurally learning thinking patterns, such as when software engineers analyze requirements and plan development. Computational thinking has gained increasing attention in educational research in recent years due to its potential to equip learners with critical problem-solving and analytical skills necessary for the digital age. As technology continues to play a significant role in various aspects of our lives, including education and the workforce, computational thinking has emerged as an important skill set for learners to develop.

This study took place in rural areas in Indonesia. In developing and rising

countries, the educational gap between urban and rural areas is often more noticeable and is directly linked to a broader difference in the socio-economic development of these two types of locations. Many rural schools face challenges in recruiting and maintaining skilled instructors, as well as a lack of essential supplies. Insufficient supply of qualified instructors and resources in rural schools leads to a major issue with educational inequality and a worsening digital divide (Yang et al., 2019). In Indonesia, there is a disparity in education between the eastern and western regions as well as between urban and rural areas. Researchers have been using the students' computational thinking abilities to address the issue of digital competency since the invention of information and communication technology (ICT).

Adding computational thinking to the curriculum was highly considered (Gao and Hew, 2022). This was due to its position as technology used (Mouza et al., 2017) and subject content (Angeli et al., 2016) in the technological pedagogical content knowledge (TPACK) model. Although computational thinking has globally attracted significant interest and attention among educators and study experts (Gao and Hew, 2022), its integration into non-programming learning contexts is still a condition that has not been thoroughly addressed (Zha et al., 2021). This thinking skill is considered a specific problem-solving approach, which allows students to identify problems, think critically, and make decisions. The definition of computational thinking is also elaborated in two domains, namely specific and general. Based on the domain-specific categories, specific or knowledge skills are often need to resolve issues systematically, within the phase of computer programming or science (Avcı and Deniz, 2022; Kanaki and Kalogiannakis, 2022). Meanwhile, the general-domain category emphasizes the competencies needed to systematically solve daily problems (Guzdial, 2008).

Computational thinking is not limited to computer scientists and is very necessary for everyone, regarding the ability to read, write, and learn mathematics. In the implementation of this skill, the inductive method is the main element commonly used, to transform complex daily problems into simple ones (Théry-Schultz, 2018). Furthermore, computational thinking abilities is an important element in problem-solving abilities, through abstraction and decomposition. According to Bufasi et al., the thinking skill was applied in physics learning (Bufasi et al., 2022). In learning, the consideration of user preferences is commonly a challenge while integrating computational thinking into problem-solving techniques. This challenge is complex in determining the suitability of the thinking concept taught through educational robotics (Jamal et al., 2021; Showkat and Grimm, 2018; Sandygulova and O'Hare, 2018). Computational thinking has also been extensively evaluated in several previous reports, regarding information literacy and computer science education. As a thought process, the skill is subsequently used to systematically solve problems through computerized techniques (Wing, 2006). However, computational thinking is considered a learning outcome or performance through conceptual tests or programming tasks (Sun et al., 2022).

Based on the rapid development of artificial intelligence and communication technology, computational thinking is the most important basic concept in the computing era, due to being able to shape human thought process toward solving problems. This skill is understood as a core problem-solving skill, representing the attitudes and qualities capable of being applied universally. However, most of the

previous literature defined it as a product of thinking, compared to a thought process. The skill is also in line with the concepts used by computer scientists when writing digital programs to solve problems (Ezeamuzie and Leung, 2022). This supportive measure is emphasized despite the observation of varying components. Regarding the taxonomy of the computational thinking elements in mathematics, the following components are observed, namely problem definition, technological abstraction development, programming design, troubleshooting, and debugging. The challenges experienced by students are also the necessity to study a computational thinking-based environment, as well as apply mathematical concepts and problem-solving in the area (Cui and Ng, 2021).

According to Tang et al., the definition of computational thinking was categorized into two domains, (1) Specific domain, which is related to the computation of concepts and computer programming, and (2) General domain, where personal competence is emphasized (Tang et al., 2020). Based on the general-domain category, computational thinking emphasizes a competency necessary to systematically solve problems in daily human life (Guzdial, 2008). The thinking skill is also commonly provided in various learning environments, including economics, science, and art (Denning, 2007). This shows that the computational skill has five basic elements for all problem-solving contexts (Selby, 2013). These contexts emphasize psychological processes, as observed from the following definitions: (1) Decomposition is a skill used to break down complex problems for easy solution; (2) Abstraction is a mental process emphasizing the identification of a key information while ignoring irrelevant details to solve a problem; (3) Algorithmic thinking is the demonstration of simple problem-solving steps; (4) Evaluation is the consideration of various problem-solving resources and the determination of the best solution; and (5) Generalization is the development of connections between similar problems and experience or the application of these solution patterns to other related issues.

A previous study of the general-domain category stated that computational thinking was a basic concept foundation through algorithmic methods, to solve real-world problems and achieve specific solutions (Israel-Fishelson et al., 2021). This thinking skill is subsequently required across various contextual disciplines (Günbatır, 2019; Shute et al., 2017), with its relevance needed for a wider range of courses, including science, arts, and humanities (Kaleliolu, 2015). Regarding the perspectives of cognitive psychology, the specific domain prioritizes computational thinking as a skill related to a particular field, such as computer (Lai, 2019). Although computer programming is considered an applied science of practicing computational thinking (Buitrago Flórez et al., 2017), some experts still argued about the skill being used to solve untranslated problems (Tedre and Denning, 2016).

Computational thinking abilities is not limited to computer programming and includes cognitive skills for everyone transferrable to other learning domains. However, most of the studies in this field concentrated on the digitalized programming. A strong relationship is also observed between computational thinking and programming despite the existence of inadequate analysis to explore other operation and transfer patterns to different domains, such as humanities, and arts (domain-general category).

Gender plays a significant role in the context of computational thinking, which

refers to the cognitive skills and problem-solving strategies used in computer science and programming. Societal gender stereotypes can influence individuals' perceptions of their own abilities in computational thinking. For example, there is a pervasive stereotype that men are naturally better at computer science and programming, while women are not (Mbukanma and Strydom, 2022). These stereotypes can lead to self-doubt and reduced self-confidence among women and other gender minorities, which may affect their engagement and performance in computational thinking activities. Computational thinking often involves working with algorithms and data, which can carry biases related to gender and other social factors (Kang et al., 2023). Biases in algorithms and data can perpetuate gender stereotypes, discrimination, and inequalities (Mbukanma and Strydom, 2022). Being aware of these biases and actively addressing them in computational thinking activities is important to ensure equitable engagement and outcomes for all genders.

In computer and robot programming knowledge, the problem of gender differences has reportedly been evaluated in several previous reports (Kalelioğlu, 2015; Showkat and Grimm, 2018; Sandygulova and O'Hare, 2018), where male students performed better than female. In this context, both female and male had a positive attitude toward coding or robotic learning activities, with the emphasis of gender differences on computational skills less considered (Wu and Su, 2021). Therefore, this study evaluated the gender differences in computational thinking skills, to determine the influential factors contained. The analysis of computational thinking factors is important for the determination of women existence in computer engineering, technological courses (Espino and González, 2015), or the science, technology, engineering, and mathematics (STEM) professional arena (Kanaki and Kalogiannakis, 2022). In this study, researchers used the computational thinking scale (Tsai et al., 2021) to examine and prove the existence of gender differences in the non-computer science analyzing non-digital programming, such as social and engineering sciences or mathematics domains.

This study presents the relationship between variables as shown in **Figure 1**. In this case, five factors of computational thinking were used, with the analysis emphasizing the domain-general category, where non-computer science is studied. In this context, computational thinking is the learning domain skill required to solve humans' daily problems (Tsai et al., 2021).

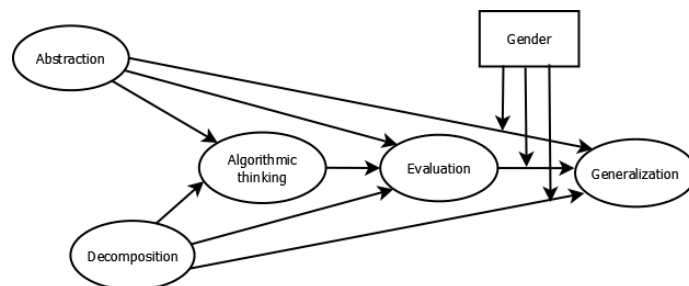


Figure 1. Proposed model of factors' relationship of computational thinking.

For examining computational thinking skills in junior high school students, the proposed model was used to determine the relationship between each influential factor based on gender. Since the model was used to examine students' computational

thinking (male and female) in junior high school, the following hypotheses are proposed:

H1: The relationship between abstraction and generalization skills is moderated by students' gender;

H2: The relationship between evaluation and generalization skills is moderated by students' gender;

H3: The relationship between decomposition and generalization skills is moderated by students' gender.

2. Materials and methods

The computational thinking (CT) scale developed by Tsai et al. (Tsai et al., 2021) was used as a measurement instrument, with five subscales found to be unobserved variables as shown in **Table 1**. These subscales were subsequently assessed using the Likert scale, from Strongly disagree (1) to Strongly agree (5).

Table 1. Scale items.

Unobserved variable (latent)	Observed variable	Text
X1	X1.1	Usually, I use analysis to approach an issue from a particular angle.
	X1.2	Usually, I consider how various issues relate to one another.
	X1.3	Usually, I attempt to identify the nuances of an issue.
	X1.4	Usually, I attempt to examine the broad trends in several issues.
X2	X2.1	I usually elaborate a problem when possible
	X2.2	I generally think about the structure of a problem
	X2.3	Typically, I divide a large difficulty into multiple smaller ones.
Y1	Y1.1	I am used to finding out step by step procedures for solutions
	Y1.2	Usually, I try to think of a workable solution.
	Y1.3	Usually, I try to describe the stages involved in completion.
	Y1.4	Usually, I look for a means to put a solution into practice.
Y2	Y2.1	I usually figure out how to solve problems.
	Y2.2	Normally, I think about the program's best option.
	Y2.3	Usually, I strive to come up with the best solution to a problem.
	Y2.4	I usually consider the quick solutions to solve a problem
Y3	Y3.1	I can solve a new problem based on my experiences
	Y3.2	Usually, I attempt to apply standard techniques to address various issues.
	Y3.3	I apply the solution of a problem to other problems
	Y3.4	I usually try to apply known solutions to solve more problems

Note: X1 = Abstraction, X2 = Decomposition, Y1 = Algorithmic thinking, Y2 = Evaluation, Y3 = Generalization.

Data were obtained through a clustered random sampling technique in Indonesia. From this context, students at junior high schools in rural areas in Indonesia were initially considered for participating in this study. This was accompanied by the distribution of 280 questionnaires to three junior high schools in rural areas of Indonesia. This study took schools in the border areas between Indonesia and Timor Leste. The students have the same culture because they came from one of the districts

in Indonesia which borders the country of Timor Leste. In this case, all questionnaires appropriately answered and returned. 258 valid surveys were collected, and they were utilized in the study. Conducting the descriptive, reliability, and validity analyses used SPSS software, and the structural equation modeling (SEM) was also conducted through Smart PLS software to assess the hypothetical relationships.

3. Results

3.1. Descriptive statistical analysis

Table 2 shows the descriptive analysis of 258 students through the following observations, (1) the proportion of male students was roughly equal to the proportion of female students, and (2) the number of students of seventh grade was greater than eighth grade.

Table 2. Students' descriptive.

Particularity	Grouping	Quantity	Percentage (%)
Gender	Female	130	50.39
	Male	128	49.61
Grade	Seventh	134	51.94
	Eighth	124	48.06

3.2. Validity and reliability analysis

CFA (Confirmatory Factor Analysis) was employed to assess construct validity was assessed by confirmatory factor analysis, indicating that the loading factor of each measured item was greater than 0.5. Moreover, the cronbach's alpha used to assess the internal reliability, which was greater than 0.7 (**Table 3**). It was also proven through composite reliability and average variance extracted (AVE), which were greater than 0.7 and 0.5, respectively (Ahrens et al., 2020).

Table 3. Validity and reliability statistics.

Unobserved variable (latent)	Observed variable	Factor loadings	CR	AVE	Cronbach's alpha
X1			0.799	0.505	0.701
	X1.1	0.517			
	X1.2	0.604			
	X1.3	0.706			
X2	X1.4	0.823			
			0.799	0.575	0.710
	X2.1	0.760			
	X2.2	0.843			
	X2.3	0.590			

Table 3. (Continued).

Unobserved variable (latent)	Observed variable	Factor loadings	CR	AVE	Cronbach's alpha
Y1	Y1.1	0.750	0.820	0.533	0.706
	Y1.2	0.672			
	Y1.3	0.728			
	Y1.4	0.710			
Y2	Y2.1	0.630	0.801	0.506	0.705
	Y2.2	0.802			
	Y2.3	0.753			
	Y2.4	0.608			
Y3	Y3.1	0.686	0.816	0.526	0.70
	Y3.2	0.695			
	Y3.3	0.699			
	Y3.4	0.702			

Note: X1 = Abstraction, X2 = Decomposition, Y1 = Algorithmic thinking, Y2 = Evaluation, Y3 = Generalization, CR = composite reliability, AVE = average variance extracted.

3.3. Hypotheses test

The hypotheses test is expected to produce similar outcome, regarding the moderation of students' computational thinking factors by gender differences. The relationship between these factors was also tested, with **Table 4** displaying a summary of the hypothetical analysis.

Table 4. Testing hypotheses using SEM path analysis.

Hypothesis	Path	T Statistics	p Values	Testing hypotheses
	X1 > Y1	5.761	0.000	Supported
	X2 > Y1	11.608	0.000	Supported
	X1 > Y2	3.383	0.001	Supported
	Y1 > Y2	6.521	0.000	Supported
	X2 > Y2	0.935	0.350	Not supported
	X1 > Y3	4.131	0.000	Supported
	X2 > Y3	1.935	0.046	Supported
	Y2 > Y3	2.395	0.017	Supported
H1	X1Z > Y3	2.782	0.011	Supported
H2	Y2Z > Y3	2.402	0.019	Supported
H3	X2Z > Y3	3.452	0.021	Supported

Note: X1 = Abstraction, X2 = Decomposition, Y1 = Algorithmic thinking, Y2 = Evaluation, Y3 = Generalization, Z = Gender.

The direct impact of the computational thinking factors and the moderating effect of gender differences on their relationships were observed based on **Table 4**. From these results, the following proofs were observed, namely (1) Students' abstraction

affected algorithmic thinking skills; (2) Students’ decomposition influenced algorithmic thinking skills; (3) Student’s abstraction impacted evaluation skills; (4) Students’ algorithmic thinking affected evaluation skills; (5) Students’ abstraction impacted generalization skills; (6) Students’ decomposition impacted generalization skills; (7) Students’ evaluation affected generalization skills; (8) the relationship between abstraction and generalization skills is moderated by students’ gender; (9) the relationship between evaluation and generalization skills is moderated by students’ gender; and (10) Students’ gender moderates the relationship between decomposition and generalization skills.

Based on the results, students’ decomposition did not significantly and directly affect their evaluation skills ($t = 0.935$ and $p = 0.350$). However, **Table 5** shows the indirect effect of both variables through Algorithmic thinking skills ($t = 5.285$ and $p = 0.001$). Students’ algorithmic thinking mediates the relationship between decomposition skills and the evaluation skills.

Table 5. Indirect effect by employing the SEM’s path analysis.

Path	T Statistics	P Values
X1 > Y1 > Y2	4.170	0.001
X2 > Y1 > Y2	5.825	0.001
X1 > Y2 > Y3	1.995	0.047
X2 > Y2 > Y3	2.036	0.042
X1 > Y1 > Y2 > Y3	1.909	0.057
X2 > Y1 > Y2 > Y3	2.033	0.043

Note: X1 = Abstraction, X2 = Decomposition, Y1 = Algorithmic thinking, Y2 = Evaluation, Y3 = Generalization.

4. Discussion

This study focused on examining gender differences in computational thinking among the junior high school students in rural areas. In the context of computational thinking, gender matters a great deal, influencing how individuals perceive themselves, access opportunities, experience learning environments, encounter pedagogical approaches, face stereotype threat, and interact with algorithms and data.

In this analysis, the similar and different relationship of each thinking skill factor was observed between male and female students. Decomposition and abstraction were also examined as independent variables, with algorithmic thinking, evaluation, and generalization being the dependent determinants. According to Tsai et al., the generated computational thinking model proved the relationship path of these factors, starting with abstraction and decomposition. These factors were then accompanied by algorithmic thinking, evaluation, and generalization (Tsai et al., 2022). For the similarities, both male and female students’ abstraction and decomposition skills predicted their algorithmic thinking skills. This was accompanied by the positive influence of algorithmic thinking on their evaluation skills, with abstraction also predicting the generalization skills.

These results proved that decomposition and abstraction were the two critical and fundamental factors of the computational thinking skills development. In this context,

decomposition and abstraction need to be initially enhanced before improving students' algorithmic thinking skills. By using the path analysis, a linear relationship was found between algorithmic and evaluation thinking. This showed that the evaluation skills were improved through the enhancement of the algorithmic thinking skills. Besides, students' abstraction also influenced their generalization skills.

Gender differences were observed in the relationship between junior high school students' thinking factors studying in rural areas. This included the abstraction-generalization skills; evaluation-generalization; and decomposition-generalization skills relationships, which were moderated by the gender of the students, with females strongly associated than males in non-programming learning contexts. Research has shown that men and women may have different abstraction, evaluation, and generalization related to computational thinking. These results are in line with the previous study that women may be more interested in applications of computational thinking in social contexts or creative domains, while men may be more interested in technical or competitive aspects. These differences in interests and motivations can influence individuals' engagement and motivation to develop their computational thinking skills (Jamal et al., 2021; Kanaki and Kalogiannakis, 2022; Showkat and Grimm, 2018). These differences can influence how individuals of different genders approach computational thinking tasks, with implications for their problem-solving strategies and outcomes. Besides, gender disparities in access to technology can impact opportunities for learning and development of computational thinking skills. Limited access to resources and underrepresentation in the field can result in fewer opportunities for women and gender minorities to engage with computational thinking, which may impact their skill development and advancement in related fields (Bufasi et al., 2022; Kanaki and Kalogiannakis, 2022; Lasfeto et al., 2018).

These results also were consistent with other previous reports, where a variation was found in improving student's computational thinking (Ikolo and Okiy, 2012). This proved that many schools provided different intervention to improve students' educational skills (Lasfeto et al., 2018) such as computational thinking, or their self-directed learning (Bhagat and Dasgupta, 2021). Based on the results, female students also obtained strong relationships than male, regarding the association of their computational thinking factors, specifically evaluation and generalization. In this case, relevant information were still provided concerning future analysis and the implementation of a computational thinking curriculum, to overcome the still-existing gender gaps (Esteve-Mon et al., 2020). However, the promotion of students' creative ability and their computational thinking skills was under exploration. Based on these results, the relationship between the implemented factors were used to improve students' computational thinking skills. The cultivation of these skills also depended on a specific course or an individual teacher, while consciously requiring the enhancement of students' ability (Espino and González, 2015; Stoilescu and Egodawatte, 2010). This study supports the development of computational thinking as one of the main competencies globally applied in the contemporary digital era. It also contributes to the learning and instructional fields, regarding the consideration of gender equality in the education curriculum (Kanaki and Kalogiannakis, 2022). From the results, students also developed confidence on their computational thinking skills. In education and learning, gender issues have become very important topics that needs

to be addressed by educators striving to close the gap masculinity and femininity (Du and Wimmer, 2019). Therefore, the applications of computational thinking skills on general or specific domain categories should be futuristically conducted, concerning the different ages and study levels of students.

5. Conclusion

Students' gender was utilized to analyze the junior high school students' computational thinking abilities studying in rural areas. Addressing gender-related considerations in computational thinking education is vital to promote equitable participation and success for individuals of all genders. Gender differences were observed in the relationship among junior high school students' computational thinking factors studying in rural areas. This included the abstraction-generalization skills; evaluation-generalization; and decomposition-generalization skills relationships, which were moderated by the gender of the students, with females strongly associated than males in non-programming learning contexts. Addressing gender-related factors in computational thinking education, such as promoting abstraction, decomposition, evaluation, and the generalization skills, can help create a more inclusive and supportive environment for individuals of all genders to engage with computational thinking and develop their skills.

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References

- Ahrens, R. de B., Lirani, L. da S., & de Francisco, A. C. (2020). Construct validity and reliability of the work environment assessment instrument WE-10. *International Journal of Environmental Research and Public Health*, 17(20), 1–19. <https://doi.org/10.3390/ijerph17207364>
- Angeli, C., Voogt, J., Fluck, A., Webb, M., Cox, M., Malyn-Smith, J., & Zagami, J. (2016). A K-6 computational thinking curriculum framework: Implications for teacher knowledge. *Educational Technology and Society*, 19(3), 47–57.
- Avci, C., & Deniz, M. N. (2022). Computational thinking: early childhood teachers' and prospective teachers' preconceptions and self-efficacy. *Education and Information Technologies*. <https://doi.org/10.1007/s10639-022-11078-5>
- Bhagat, K. K., & Dasgupta, C. (2021). *Computational Thinking for Teachers*. July, 113.
- Bufasi, E., Hoxha, M., Cuka, K., & Vrtagic, S. (2022). Developing Student's Comprehensive Knowledge of Physics Concepts by Using Computational Thinking Activities: Effects of a 6-Week Intervention. *International Journal of Emerging Technologies in Learning*, 17(18), 161–176. <https://doi.org/10.3991/ijet.v17i18.31743>
- Buitrago Flórez, F., Casallas, R., Hernández, M., Reyes, A., Restrepo, S., & Danies, G. (2017). Changing a Generation's Way of Thinking: Teaching Computational Thinking Through Programming. *Review of Educational Research*, 87(4), 834–860. <https://doi.org/10.3102/0034654317710096>
- Cui, Z., & Ng, O. L. (2021). The Interplay Between Mathematical and Computational Thinking in Primary School Students'

- Mathematical Problem-Solving Within a Programming Environment. *Journal of Educational Computing Research*, 59(5), 988–1012. <https://doi.org/10.1177/0735633120979930>
- Denning, P. J. (2007). Computing is a natural science. *Communications of the ACM*, 50(7), 13–18. <https://doi.org/10.1145/1272516.1272529>
- Du, J., & Wimmer, H. (2019). Hour of Code: A Study of Gender Differences in Computing. *Information Systems Education Journal*, 17(4), 91–100. <https://isedj.org/>; <http://iscap.info>
- Espino, E. E. E., & González, C. S. G. (2015). Influence of gender on computational thinking. *ACM International Conference Proceeding Series*, 07-09-Sept(February 2020), 3–5. <https://doi.org/10.1145/2829875.2829904>
- Esteve-Mon, F. M., Llopis, M. A., & Adell-Segura, J. (2020). Digital competence and computational thinking of student teachers. *International Journal of Emerging Technologies in Learning*, 15(2), 29–41. <https://doi.org/10.3991/ijet.v15i02.11588>
- Ezeamuzie, N. O., & Leung, J. S. C. (2022). Computational Thinking Through an Empirical Lens: A Systematic Review of Literature. *Journal of Educational Computing Research*, 60(2), 481–511. <https://doi.org/10.1177/07356331211033158>
- Gao, X., & Hew, K. F. (2022). Toward a 5E-Based Flipped Classroom Model for Teaching Computational Thinking in Elementary School: Effects on Student Computational Thinking and Problem-Solving Performance. *Journal of Educational Computing Research*, 60(2), 512–543. <https://doi.org/10.1177/07356331211037757>
- Günbatar, M. S. (2019). Computational thinking within the context of professional life: Change in CT skill from the viewpoint of teachers. *Education and Information Technologies*, 24(5), 2629–2652. <https://doi.org/10.1007/s10639-019-09919-x>
- Guzdial, M. (2008). Education: Paving the way for computational thinking. *Communications of the ACM*, 51(8), 25–27. <https://doi.org/10.1145/1378704.1378713>
- Ikolo, V. E., & Okiy, R. B. (2012). Gender differences in computer literacy among clinical medical students in selected Southern Nigerian Universities. *Library Philosophy and Practice*, 2012(MAY).
- Israel-Fishelson, R., Hershkovitz, A., Eguíluz, A., Garaizar, P., & Guenaga, M. (2021). A Log-Based Analysis of the Associations Between Creativity and Computational Thinking. *Journal of Educational Computing Research*, 59(5), 926–959. <https://doi.org/10.1177/0735633120973429>
- Jamal, N. N., Jawawi, D. N. A., Hassan, R., & Mamat, R. (2021). Conceptual Model of Learning Computational Thinking Through Educational Robotic. *International Journal of Emerging Technologies in Learning*, 16(15), 91–106. <https://doi.org/10.3991/ijet.v16i15.24257>
- Kaleliolu, F. (2015). A new way of teaching programming skills to K-12 students: Code.org. *Computers in Human Behavior*, 52, 200–210. <https://doi.org/10.1016/j.chb.2015.05.047>
- Kanaki, K., & Kalogiannakis, M. (2022). Assessing Algorithmic Thinking Skills in Relation to Gender in Early Childhood. *Educational Process: International Journal*, 11(2), 44–59. <https://doi.org/10.22521/edupij.2022.112.3>
- Kang, C., Liu, N., Zhu, Y., Li, F., & Zeng, P. (2023). Developing College students' computational thinking multidimensional test based on Life Story situations. *Education and Information Technologies*, 28(3), 2661–2679. <https://doi.org/10.1007/s10639-022-11189-z>
- Lai, R. P. Y. (2019). What underlies computational thinking: Exploring its cognitive mechanism and educational implications. *Proceedings of International Conference on Computational Thinking Education*, 204–208.
- Lasfeto, D. B., Setyosari, P., Djatmika, E. T., & Ulfa, S. (2018). Learning preference assessment: A fuzzy logic approach. *Journal of Theoretical and Applied Information Technology*, 96(10), 2862–2871.
- Mbukanma, I., & Strydom, K. (2022). Challenges to and Enablers of Women's Advancement in Academic Careers at a Selected South African University. *International Journal of Learning, Teaching and Educational Research*, 21(12), 44–64. <https://doi.org/10.26803/ijlter.21.12.3>
- Mouza, C., Yang, H., Pan, Y. C., Yilmaz Ozden, S., & Pollock, L. (2017). Resetting educational technology coursework for pre-service teachers: A computational thinking approach to the development of technological pedagogical content knowledge (TPACK). *Australasian Journal of Educational Technology*, 33(3), 61–76. <https://doi.org/10.14742/ajet.3521>
- Nouri, J., Zhang, L., Manila, L., & Norén, E. (2020). Development of computational thinking, digital competence and 21st century skills when learning programming in K-9. *Education Inquiry*, 11(1), 1–17. <https://doi.org/10.1080/20004508.2019.1627844>
- Sandygulova, A., & O'Hare, G. M. P. (2018). Age- and Gender-Based Differences in Children's Interactions with a Gender-Matching Robot. *International Journal of Social Robotics*, 10(5), 687–700. <https://doi.org/10.1007/s12369-018-0472-9>
- Selby, C. (2013). Computational Thinking : The Developing Definition. *ITiCSE Conference 2013*, 5–8.

- Showkat, D., & Grimm, C. (2018). Identifying Gender Differences in Information Processing Style, Self-efficacy, and Tinkering for Robot Tele-operation. 2018 15th International Conference on Ubiquitous Robots, UR 2018, 443–448. <https://doi.org/10.1109/URAI.2018.8441766>
- Shute, V. J., Sun, C., & Asbell-Clarke, J. (2017). Demystifying computational thinking. *Educational Research Review*, 22, 142–158. <https://doi.org/10.1016/j.edurev.2017.09.003>
- Stoilescu, D., & Egodawatte, G. (2010). Gender differences in the use of computers, programming, and peer interactions in computer science classrooms. *Computer Science Education*, 20(4), 283–300. <https://doi.org/10.1080/08993408.2010.527691>
- Sun, L., Hu, L., & Zhou, D. (2022). Single or Combined? A Study on Programming to Promote Junior High School Students' Computational Thinking Skills. *Journal of Educational Computing Research*, 60(2), 283–321. <https://doi.org/10.1177/07356331211035182>
- Tang, X., Yin, Y., Lin, Q., Hadad, R., & Zhai, X. (2020). Assessing computational thinking: A systematic review of empirical studies. *Computers and Education*, 148(May 2019), 103798. <https://doi.org/10.1016/j.compedu.2019.103798>
- Tedre, M., & Denning, P. J. (2016). The long quest for computational thinking. *ACM International Conference Proceeding Series*, 120–129. <https://doi.org/10.1145/2999541.2999542>
- Théry-Schultz, J. (2018). Les enjeux de la clarification des règles. *Concurrences*, 2018(3), 22–24.
- Tsai, M. J., Liang, J. C., & Hsu, C. Y. (2021). The Computational Thinking Scale for Computer Literacy Education. *Journal of Educational Computing Research*, 59(4), 579–602. <https://doi.org/10.1177/0735633120972356>
- Tsai, M. J., Liang, J. C., Lee, S. W. Y., & Hsu, C. Y. (2022). Structural Validation for the Developmental Model of Computational Thinking. *Journal of Educational Computing Research*, 60(1), 56–73. <https://doi.org/10.1177/07356331211017794>
- Wu, S. Y., & Su, Y. S. (2021). Visual Programming Environments and Computational Thinking Performance of Fifth- and Sixth-Grade Students. *Journal of Educational Computing Research*, 59(6), 1075–1092. <https://doi.org/10.1177/0735633120988807>
- Yang, J., Yu, H., & Chen, N. shing. (2019). Using blended synchronous classroom approach to promote learning performance in rural area. *Computers and Education*, 141(July), 103619. <https://doi.org/10.1016/j.compedu.2019.103619>
- Zha, S., Morrow, D. A. L., Curtis, J., & Mitchell, S. (2021). Learning Culture and Computational Thinking in a Spanish Course: A Development Model. *Journal of Educational Computing Research*, 59(5), 844–869. <https://doi.org/10.1177/0735633120978530>