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# Evaluating primary students' motivation and computational thinking in scratch-based learning: a confusion matrix analysis

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| Article info | Abstract |
|---|---|
| Keywords: confusion matrix, computational thinking (ct), motivation, scratch-based learning | This study examined the relationship between student motivation and computational thinking (CT) skills within a Scratch-based learning environment for primary school students. Utilizing a quantitative research design with a pretest-posttest framework, the research involved 28 primary school students engaged in a computational learning program centered on the Jumping Bean concept. A confusion matrix analysis was employed to assess the predictive relationship between motivation levels and improvements in CT skills. The results showed that motivation is a reliable predictor of CT gains, with high precision indicating that highly motivated students are very likely to demonstrate measurable progress. However, the recall score suggests motivation alone is not a conclusive factor, as some motivated students did not achieve the expected CT improvements. This implies that other instructional elements, such as prior knowledge, cognitive differences, teaching methods, and learning design, also significantly impact outcomes. The implications of this research suggest that educators should cultivate motivating learning environments to foster students' CT skills effectively. Recommendations include integrating gamified elements and personalized feedback to enhance student engagement and motivation in computational learning contexts. |

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## 1. Introduction

In today's linked society, STEM education is becoming increasingly important in early education, especially at the elementary school level. According to Spektor-Levy et al. (2013), these early years are ideal for introducing STEM courses since children are curious and ready to investigate novel ideas. Early STEM education can, therefore, spark students' enthusiasm and interest in science and technology, resulting in a lifetime quest for learning and creativity (Hakim et al., 2020; Hermita et al., 2023a). In addition to teaching fundamental knowledge in Science and Technology, Hudson et al. (2015) asserted that STEM education develops a wide range of cognitive abilities critical for negotiating the complexity of the twenty-first century (Ah-Namand & Osman, 2018). Heritage et al. (2023b) further state that STEM education gives students the skills they need to meet difficulties and take advantage of the opportunities of the digital age by encouraging critical thinking, creativity, and problem-solving skills. Additionally, STEM education gives students the tools to apply their knowledge to real-world problems, advance society, and prepare them for future employment prospects in STEM-related industries (Hudson et al., 2015).

According to Wang et al. (2022), Computational Thinking (CT) is emerging as a key skill within STEM education, integral for tackling complex, technology-driven problems. Logical reasoning, decomposition, and pattern detection are all part of CT (Sands et al., 2018), equipping students to tackle classroom and real-world problems methodically (Zhang et al., 2024). Li and Hu (2024) also add that teaching CT skills in primary school promotes resilience and adaptation while laying the foundation for later study in subjects like coding and artificial intelligence. As Tsortanidou et al. (2019) claimed, incorporating CT into early education helps students cultivate a digital mentality, preparing them to be capable problem solvers and innovators in a tech-centric environment as technology continues to impact daily life.

A widespread tool for encouraging CT in young learners is Scratch (Zhang & Nouri, 2019), a visual programming language created by MIT. Fagerlund et al. (2021) assert that its block-based interface makes CT ideas approachable and enjoyable by allowing beginners to create interactive projects without sophisticated coding skills. Marcelino et al. (2018) maintain that Scratch helps students make the connection between abstract computational principles and practical applications by encouraging logical thinking, experimentation, and problem-solving in an enjoyable setting through the creative process of coding. As students experiment with the interface, Scratch encourages creativity, perseverance, and a sense of success while supporting the development of fundamental CT skills (Zhang & Nouri, 2019; Fagerlund et al., 2021).

Student motivation greatly influences learning outcomes (Li et al., 2012; Sugiyanto et al., 2020), especially in subjects like computational learning that call for persistence (Dörnyei & Henry, 2022). Mega et al. (2014) state that motivation is a critical component of academic success since it substantially impacts student engagement, effort, and accomplishment (Sugiyanto et al., 2020). According to research, students who are highly driven are more likely to succeed in challenging, complicated learning situations because they are better prepared to put in the time and effort necessary to understand complex ideas and overcome challenges (Mega et al., 2014; Alizadeh 2016; Filgona et al., 2020; Sugiyanto et al., 2020). Therefore, motivation is essential in computational thinking because developing abilities like problem-solving, logical reasoning, and algorithmic thinking requires a high level of perseverance and dedication from students (Fagerlund et al., 2022). However, despite the established link between motivation and success, there is a gap in research specifically examining how motivation influences CT outcomes in a Scratch-based setting, particularly at the primary level. Thus, by analyzing the predicted relationship between motivation and CT performance using a confusion matrix, this study fills this gap and offers educators fresh perspectives on best utilizing computational learning environments.

## 2. Theoretical

### *2.1 Computational thinking*

Computational thinking (CT), which gives students the problem-solving skills necessary for success in an increasingly complex society (Wang et al., 2022), is becoming more and more acknowledged as a critical competency in 21st-century education (Nouri et al., 2020). Fundamentally, Moschella and Basso (2020) claim that CT consists of several interrelated abilities: logical reasoning, which enables students to interpret information rationally; decomposition, which simplifies the process of solving complicated problems; and pattern recognition, which allows students to extrapolate and apply knowledge to related issues in the future. These abilities help students succeed academically in various subjects, including science, math, and technology (Rich et al., 2019). They

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also help students think critically and be flexible in real-world scenarios, equipping them to handle various problems (Zhang et al., 2024).

As technology continues to permeate daily life and transform industries, there is a growing emphasis on introducing computational thinking skills early in education, including in primary school settings (Fagerlund et al., 2021; Li & Hu, 2024). By incorporating CT into the curriculum, teachers are assisting young students in cultivating a mentality that will allow them to use digital tools and technology confidently, approach challenges systematically, and become more self-reliant thinkers (Tsortanidou et al., 2019). Early CT exposure lays the groundwork for more complex learning in fields like artificial intelligence, data processing, and coding, as well as more abstract skills like creativity and problem-solving resilience (Fagerlund et al., 2021). In the end, cultivating computational thinking in primary school gives students employable, high-demand skills for their future jobs and enables them to contribute to and create in a rapidly changing digital world.

### *2.2 Scratch Media*

MIT created the visual programming language Scratch, which has grown to be an effective tool for encouraging computational thinking in young students (Fagerlund et al., 2021; Fagerlund et al., 2022). Scratch's user-friendly, block-based interface allows students to make interactive stories, games, and animations without knowing how to write complicated code (Marcelino et al., 2018). This easy-to-use software builds sequential and logical thinking in primary school students, key elements of computational thinking (Jiang & Li, 2021). According to Piedade and Dorotea (2023), because Scratch views coding as an interactive, creative challenge rather than a difficult technical one, it allows students to learn problem-solving skills in an enjoyable and captivating way. The platform will enable students to experiment, make mistakes, and learn by doing as they go while simultaneously allowing them to investigate computational ideas like loops, variables, and conditional expressions (Jiang & Li, 2021).

Beyond only teaching coding, Scratch is a valuable tool for hands-on learning and creative expression (Fagerlund et al., 2022). As Pérez-Marín et al. (2020) state, building projects help students develop their computational thinking abilities while teaching them how to solve problems creatively, cooperate with others, and improve their work. Therefore, students can better understand the connection between technology and their creative pursuits using Scratch to connect abstract computational concepts with concrete, real-world applications (Piedade & Dorotea, 2023). For this reason, Scratch helps students grasp computational ideas more deeply while promoting curiosity, resiliency, and a sense of achievement—all critical for young students navigating a technologically advanced future.

### *2.3 Confusion matrix*

The confusion matrix is a valuable tool for evaluating the performance of a classification model (Salmon et al., 2015). It provides a breakdown of expected results versus actual ones, which are organized into four primary categories: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). Therefore, this offers vital information on the accuracy and reliability of a particular model or prediction (Beauxis-Aussalet & Hardman, 2014). In this study, the confusion matrix is used to assess the predictive power of student motivation on computational thinking (CT) skills within a Scratch-based learning environment.

This study uses the confusion matrix to evaluate how effectively motivation predicts computational thinking (CT) outcomes in primary students using Scratch-based learning. Here, the matrix categorizes student performance into "Pass" or "Fail" based on post-test results, allowing a detailed analysis of motivational impact. The matrix compares actual CT outcomes with projections based on motivation levels to determine the degree and precision of motivation as a predictor of CT success. Accuracy and recall, two critical metrics from the confusion matrix, demonstrate how closely motivation matches students' CT accomplishments, facilitating a more complex understanding of motivation's function in computational learning.

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## 3. Method

### *3.1 Research Design*

Using a quantitative research methodology with a pretest-posttest setup, the research explored the impact of student motivation on computational thinking (CT) abilities in a Scratch-based learning environment. The participants in this study comprised students in a primary school who were enrolled in a Scratch-based computational learning program that concentrated on the Jumping Bean concept. All 28 students who participated in the study worked on Scratch-based tasks to enhance their computational thinking abilities. In particular, the study used a confusion matrix analysis to classify and interpret predictive outcomes about students' computational thinking abilities according to their motivation levels.

### *3.2 Research instrument*

Motivation levels were measured using a Likert scale questionnaire to quantify students' motivation toward computational activities. This questionnaire included items related to students' interest and engagement in learning with Scratch.

**Table 1.** Scratch motivation instrument

| No | Statement | SA | A | D | SD |
|---|---|---|---|---|---|
| 1 | The use of Scratch media makes me eager to learn | | | | |
| 2 | The use of Scratch media makes learning Science more fun. | | | | |
| 3 | The use of Scratch media does not make you feel bored to study. | | | | |
| 4 | The use of Scratch media makes me more interested in learning science. | | | | |
| 5 | The use of Scratch media added to my curiosity. | | | | |
| 6 | Scratch media helps me learn independently. | | | | |
| 7 | Scratch media increases my participation in learning science. | | | | |
| 8 | Scratch media helps me solve problems with science material. | | | | |
| 9 | Scratch media causes me to think more creatively. | | | | |

Meanwhile, computational thinking skills were measured through pretest and post-test assessments. Both tests used the same six multiple-choice questions directly from the reliable test developed by Putra et al. (2022). These questions evaluated students' capacity to apply computational thinking principles to solve problems and reason logically.

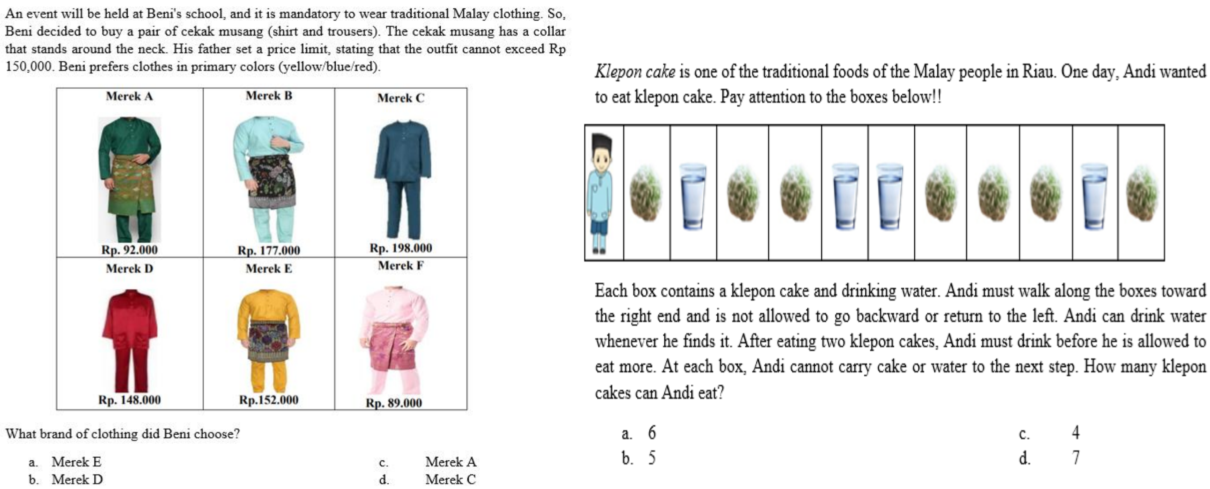


**Figure 1.** Question examples

***Data Analysis***

To examine the predictive relationship between motivation and CT improvement, a confusion matrix was constructed with the following components:

1) True Positives (TP): Students who were motivated and showed improved CT skills.
2) False Positive (FP): Motivated students who did not show improvement in CT skills.
3) False Negatives (FN): Unmotivated students who improved CT skills.
4) True Negatives (TN): Unmotivated students who did not show improvement in CT skills.

Key metrics calculated from the confusion matrix include:

1) Accuracy: The overall correctness of predictions regarding CT improvement based on motivation levels. The formula is as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

2) Precision: The accuracy of identifying students likely to improve based on high motivation. The formula is as follows:

$$\text{Precision} = \frac{TP}{TP+FP}$$

3) Recall (Sensitivity): The effectiveness in identifying all students who improved in CT. The formula is as follows:

$$\text{Recall} = \frac{TP}{TP+FN}$$

4) F1-Score: The harmonic mean of Precision and Recall, providing an overall measure of the model's reliability. The formula is as follows:

$$\text{F1-Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

These measurements demonstrate the accuracy of motivation as a predictor of student achievement and provide insights into the predictive relationship between motivation and CT performance.

## 4. Results

Based on the Likert scale of the motivation questionnaire (1-4, with one being "Strongly Disagree" and four being "Strongly Agree"), students were categorized as having high or low motivation with these decisions: Students with a motivation score ≥ 3 are predicted to improve (because they have high motivation), and Students with a motivation score < 3 are predicted not to improve (because they have low motivation). Therefore, the confusion matrix format is shown in **Table 2**.

**Table 2.** Confusion matrix

| | **Predicted (Improvement)** | **Predicted (No Improvement)** |
|---|---|---|
| **Actual (Improved)** | True Positive (17) | False Negative (6) |
| **Actual (Not Improved)** | False Positive (3) | True Negative (2) |

In other words, the classification of the students is:

a) 17 students who improved were correctly predicted to improve (TP = 17).
b) 6 students who improved were incorrectly predicted not to improve (FN = 6).
c) 3 students who did not improve were incorrectly predicted to improve (FP = 3).
d) 2 students who did not improve were correctly predicted not to improve (TN = 2).

The breakdown of each metric regarding the connection between motivation and computational thinking is provided below:

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***4.1 Accuracy***

This measures the proportion of correct predictions out of all predictions.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Accuracy} = \frac{17+2}{17+6+3+2} = \frac{19}{28} = 0.679\ (67.9\%)$$

Based on the result, the model correctly predicted the improvement status of students about 67.9% of the time. This overall accuracy illustrates that the program can somewhat reliably predict improved computational thinking based on observed motivation levels. While this is a good indicator of general performance, it can still be asserted that accuracy alone does not reveal the nuances between positive and negative cases.

***4.2 Precision***

This measures the model's accuracy in predicting positive outcomes (students who improved) out of all optimistic predictions.

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Precision} = \frac{17}{17+3} = \frac{17}{20} = 0.85\ (85\%)$$

Based on the result, the model has high precision, meaning when the model predicts a student will improve in computational thinking, the prediction is correct 85% of the time. This exhibits that motivation is likely a key role in improvement because when students are more motivated, they will also show measurable gains in computational thinking skills. Thus, motivation can be seen as a reliable predictor of improvement in this case.

*4.3* ***Recall***

This measures the ability of the model to correctly identify positive outcomes (students who improved) out of all actual positive cases.

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{Recall} = \frac{17}{17+6} = \frac{17}{23} = 0.739\ (73.9\%)$$

The recall score indicates that the model successfully identified 73.9% of the students who improved. This confirms that those who were motivated ultimately demonstrated an increased capacity for computational thinking. However, while most motivated students improved, some did not achieve the expected growth, implying that motivation is a significant but inconclusive component in driving these skills.

***4.4 F1-Score***

This is the harmonic mean of Precision and Recall, providing a balanced measure when there is an uneven distribution between positive and negative predictions.

$$\text{F1-Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

$$\text{F1-Score} = 2 \times \frac{0.85 \times 0.739}{0.85 + 0.739} = 2 \times \frac{0.6281}{1.589} = 0.79\ (79\%)$$

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The F1 score of 79% suggests a reliable model, especially when identifying all improving students, which is essential. This implies that the model's predictions are pretty balanced between correctly identifying those who improved and minimizing false positives. This balance shows that while students with high motivation frequently move in the right direction, not all achieve the expected progress in computational thinking, indicating differences in how motivation translates into skill acquisition.

## 5. Discussion

The research results highlight the crucial role that motivation plays in promoting the development of computational thinking abilities, making it a primary target for boosting the efficacy of learning programs based on Scratch. As Kong et al. (2018) studied, motivation is a reliable indicator of students' capacity for computational thinking and affects their involvement. The high precision score underlines motivation's dependability as a predictor of learning achievement. Yağcı (2019) states that highly motivated students are likelier to make quantifiable progress in computational thinking. Thus, Renon and Pasia (2024) emphasize, in their study, how crucial it is to create a constructive and engaging learning environment using techniques like gamified components, interactive exercises, and tailored feedback, all of which can raise students' levels of motivation both internally and externally.

Although motivation plays a substantial role in predicting improvements in computational thinking, the recall score of 73.9% suggests it is not always the case. Some motivated students did not make the expected progress in computational thinking, which indicates that other factors are essential in determining learning outcomes. One essential factor is prior knowledge, significantly impacting how effectively students understand new concepts. As maintained by Lee and Lee (2022), if students come into the program with a strong foundation in computational principles or related abilities, such as logical reasoning or problem-solving, they can better understand challenging programming tasks. On the other hand, even if they are highly motivated, students with little core knowledge could find it challenging to keep up (Hooshyar, 2022). In addition, Lee and Lee (2022) further add that another important consideration is individual cognitive differences, which involve variances in processing rates, learning styles, memory retention, and problem-solving skills. For example, students with strong abstract thinking skills might find programming topics easier to understand, whereas others may find it difficult even if motivated. These variations emphasize the need for specialized teaching methods considering students' cognitive profiles (Fagerlund et al., 2021; Fagerlund et al., 2022; Hooshyar, 2022; Lee & Lee, 2022). Personalized learning approaches, such as adaptive technologies, can assist students in getting past cognitive obstacles and improving their performance (Dumont & Ready, 2023).

Furthermore, the high F1 score of 79% demonstrates a reliable balance between correctly identifying and improving students and minimizing false positives. This implies that even though motivation is essential, it should be considered alongside other instructional factors to optimize computational thinking development. As stated by Hsu et al. (2018), motivation alone might not be sufficient to handle the complexity of learning. Besides, its effects are greatly amplified when paired with efficient teaching techniques and supportive settings (Kong et al., 2018). Factors such as teaching methods, task design, and student support may also play relevant roles. Chen and Law (2016) explain that teaching approaches that actively engage students and scaffold their learning could enhance the impact of motivation. Therefore, the best results can come from implementing a multimodal strategy that fosters student motivation and focused computational thinking training (Yağcı, 2019; Renon & Pasia, 2024). By taking motivation into account in addition to other critical instructional components, teachers may design learning environments that meet the different needs of their students and allow them to utilize their desire to acquire critical computational thinking abilities fully.

## 6. Conclusion

The findings of this study highlight the critical role that motivation plays in fostering the development of computational thinking abilities in primary school students engaged in Scratch-based learning. The confusion matrix analysis revealed that motivation is a very accurate predictor of gains in computational thinking, meaning that highly motivated students will likely show quantifiable improvements in these abilities. However, given that some motivated students did not make the anticipated advancement in computational thinking, the recall score indicates that motivation alone is not a decisive element. This implies that other instructional elements, like prior knowledge, cognitive differences, teaching methods, and learning environment design, also significantly impact student outcomes.

To further enhance the effectiveness of Scratch-based learning programs, it is recommended that educators implement targeted motivational strategies, such as incorporating gamification elements, providing timely feedback, and encouraging a collaborative learning environment. Future research should examine how motivation affects CT skills in various age groups and educational contexts and how various motivating elements influence students' success and involvement in computational thinking.

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