Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 5, 52-73
2024
Publisher: Learning Gate
DOI: 10.55214/25768484.v8i5.1630

Exploring the impact of makerspace-based learning materials on students' computational thinking skills: Using machine learning to address challenges in smart coffee agroforestry

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Abstract: This research aimed to develop teaching materials to improve students' computational thinking skills in solving smart coffee agroforestry problems through machine learning, using the RBL-STEM makerspace. Computational thinking skill goes beyond coding and programming and is related to the students' higher-order thinking skills. This research uses the ADDIE development model in developing the learning materials. The learning material products consist of assessment instruments, students' worksheets, and lesson plans. The research employed questionnaires, validation sheets (including content, construct, programming, and language), and observation sheets to collect data regarding the instruments' effectiveness, practicality, and validity. We evaluated the effectiveness of the teaching materials in a single classroom using a paired-test, examining the significant difference between the pre-test and post-test scores. The research subjects are 42 students of the Science Education Department at the University of Jember for the academic year 2023-2024. The average overall score, including content, construct, programming, and language, is 92.97%. The results show that the learning materials satisfy in all aspects. We did in-depth interviews with some selected students at low, medium, and high levels of computational thinking skills and compared the interview results using NVIVO software to making project maps. Furthermore, the score of paired t-test shows α-value = 0.003< 0.05. We concluded that RBL-STEM makerspace learning materials significantly contribute to the development of students' computational thinking skills. It implies that the learning materials developed in this research are ready to be used in the learning activities to foster students' computational thinking skills.

Keywords: *ADDIE, Computational thinking skills, Learning materials, Machine learning, RBL-STEM makerspace, Smart coffee agroforestry.*

1. Introduction

Computational thinking skills are the ability to solve problems systematically and logically, using approaches inspired by concepts and techniques in computation. These skills involve understanding how computers work, problem modelling, data analysis, and solving problems, as well as abstract and logical information. In the ever-evolving digital era, computational thinking skills have become increasingly important in various aspects of life, including education, careers, and technological development. In the rapidly increasing technology-dependent work environment, computational thinking skills are highly valuable [1]. Furthermore, the ability to solve problems, analyze data, and make decisions based on logical thinking is needed for many company jobs. Some studies show that the computational approach in education can help students improve 21st century skills such as 4C (critical thinking, creativity, communication, and collaboration). The ability to develop new technologies and innovate is based on computational thinking skills. The ability to design algorithms, analyze data, and solve problems

History: Received: 28 February 2024; Revised: 29 July 2024; Accepted: 16 August 2024; Published: 11 September 2024
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effectively plays a crucial role in developing better technological solutions. These skills support the development of artificial intelligence, data science, data analytics, data engineering, and various other technological fields [2].

Machine learning challenges in smart coffee agroforestry can enhance students' computational thinking abilities. The importance of machine learning is growing in the current technological era [3, 4]. The demand for professionals with machine learning skills continues to rise [5, 6]. Companies and industries across sectors, including technology, finance, healthcare, and marketing, are increasingly adopting machine learning technology to improve efficiency, decision-making, and innovation [7]. Here are some research activities that contributed fostering students' computational thinking skills in solving smart coffee agroforestry problems using machine learning. The importance of integrating research-driven approaches, promoting active learning methodologies, and addressing real-world challenges in STEM education through the development of innovative learning instruments [8]. The importance of this focuses on addressing the need for personalized learning materials to enhance students' computational thinking skills [9]. The problems in coffee agroforestry focus on making an ideal condition for coffee plantations by monitoring soil conditions and parameters on shade trees [10]. The integration of IoT (Internet of Things) into smart coffee agroforestry involves deploying sensors and connected devices throughout coffee farms to collect real-time data on environmental conditions, soil moisture, and other factors [11]. The integration of machine learning into smart coffee agroforestry revolutionizes coffee cultivation by leveraging advanced algorithms to analyze data and optimize management practices. Machine learning models analyze various datasets, including sensor data and satellite imagery, to provide insights and support decision-making for farmers [12]. The development of teaching materials for smart coffee agroforestry based on IoT and machine learning involves creating educational resources that showcase the application of these technologies in agriculture [13].

The support system and instruments for this research project would aim to create an immersive and interactive learning environment where students can apply STEM principles to real-world problems in smart coffee agroforestry while developing essential computational thinking skills. There are some support systems and instruments, namely research team, makerspace facilities, rbl-stem curriculum, learning instruments, machine learning models, assessment tools, hardware and software [14].

Research-based learning (RBL) was a groundbreaking approach that gained widespread recognition among academics in the 2009. Jenkins and Healey [15] are two of the educational figures who pioneered RBL learning and provided invaluable research guidelines, highlighting the crucial relationship between learning and research [15]. Academics continue to explore the potential of RBL through numerous studies. Healey and Jenkins [16] define research-based learning as when students learn as researchers, and the curriculum is largely designed for research-based activities Healey and Jenkins [16]. Badley [17] strongly supports this, stating that Research-Based Learning (RBL) is one of the most effective ways for learners to gain various benefits from research [17]. In fact, many other researchers have also contributed to the study of RBL learning, highlighting its numerous advantages and potential for success. Research-Based Learning (RBL) has proven to be an incredibly effective approach to education, enhancing academic achievement, promoting the learning process, and encouraging learners to construct their knowledge [18]. With RBL, students are able to control their own learning and achieve their full potential. The RBL learning model empowers students to actively construct their knowledge. We achieve this by providing ample space for student activities, including research activities.

The research on the integration of RBL and STEM focuses on research about the implementation model of RBL with a STEM approach using local antimagic graph coloring techniques in designing wallpaper decorations [19]. The research about learning activity framework of RBL-STEM on CCTV placement using dominating set technique Humaizah, et al. [20]. Puji and Ridlo [8] explore the research focuses on improving student historical literacy in designing Batik motifs using RBL-STEM [8].

Research about integration of machine learning in education discusses how machine learning applies to learning activities in classroom [3]. The importance of machine learning integration in education in the human age [6]. The survey about the deep implementation of machine learning in education is very important for learning activities [7]. It is critical to integrate deep learning as part of machine learning in agriculture [21]. By teaching IoT and machine learning to solve smart coffee agroforestry problems, we are preparing the younger generation with good computational thinking skills. They are ready to face the challenges and leverage the opportunities offered by these rapid technological advancements [22].

The study aims to address the following research questions: 1) How is the process and result of developing RBL-STEM learning materials improving students' computational thinking skills in solving Smart Coffee Agroforestry problems using Machine Learning? 2) Can the implementation of RBL-STEM learning materials improve students' computational thinking skills in solving Smart Coffee Agroforestry problems using Machine Learning? Based on these research questions, we can formulate the following research goals: 1) To analyze the process and the result of developing RBL-STEM learning materials for improving students' computational thinking skills in solving Smart Coffee Agroforestry problems using Machine Learning. 2) To evaluate whether the implementation of RBL-STEM learning materials can improve the students' computational thinking skills in solving Smart Coffee Agroforestry problems using Machine Learning or not.

The study formulates the null hypothesis (H0) and alternative hypothesis (H1) as pair. H0 is as follows: the implementation of RBL-STEM makerspace-based learning materials with machine learning techniques cannot improve students' computational thinking skills. H1 is as follows: the implementation of RBL-STEM makerspace-based learning materials with machine learning techniques can improve students' computational thinking skills. In order to accept the hypothesis, the following rules must be satisfied: If the value of Sig. (2-tailed) is greater than 0.05, then H0 is accepted and H1 is rejected. Conversely, if the value of Sig. (2-tailed) is less than 0.05, then H0 is rejected and H1 is accepted [19].

The development of RBL-STEM (Research-Based Learning in Science, Technology, Engineering, and Mathematics) learning materials is very important in enhancing students' computational thinking skills, particularly in addressing complex issues such as Smart Coffee Agroforestry problems through Machine Learning. Research-Based Learning (RBL) in the STEM fields provides an innovative educational framework that encourages students to engage actively with real-world problems, fostering a deep understanding of the subject matter. When applied to Smart Coffee Agroforestry, an interdisciplinary challenge that combines agricultural practices with smart technology, RBL-STEM becomes instrumental in developing critical computational thinking skills. Machine Learning (ML), a core component of this educational approach, serves as a powerful tool that students can leverage to analyze and solve agroforestry issues. Educators can enhance students' ability to apply computational methods and foster a comprehensive understanding of how technology can optimize agricultural practices by integrating ML into RBL-STEM learning materials. This educational strategy empowers students to tackle complex problems, analyze vast data sets, and develop innovative solutions that improve efficiency and sustainability in agroforestry. Consequently, the development of such specialized learning materials is pivotal in preparing students to meet the demands of modern agricultural industries and to contribute effectively to the advancement of Smart Coffee Agroforestry.

2. The Literature Review

The RBL stands for research-based learning, which is part of scientific learning models. It encourages mind-on and hand-on learning in the classroom, which is needed in makerspace learning. RBL education promotes inquiry-based learning and provides authentic research experiences [19]. Students engage in original investigations, conduct experiments, and make discoveries, fostering a deeper understanding of real-life projects. Research-based activities encourage students with open-ended problems or challenges to devise innovative solutions. The implementation of RBL learning model will improve the research competencies of students in the classroom. stated that Research-based learning is effective because it integrates research activities into teaching and learning activities [19]. RBL is a learning model that contains some approaches inside, namely cooperative learning, inquiry discovery, contextual learning, problem-solving learning, authentic learning, and direct learning, which are implemented by using constructivism as learning philosophy. The RBL also facilitates students to improve 21st century skills (critical thinking, creativity, communication, and collaboration) [23, 24].

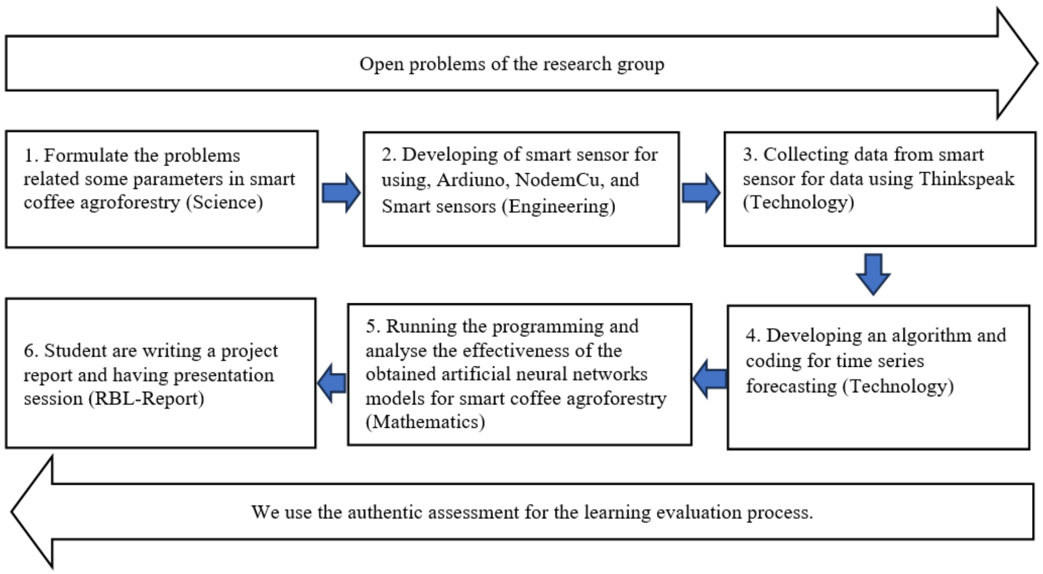

Figure 1.
The learning activities framework of RBL-STEM makerspace on solving smart coffee agroforestry problems.

STEM is a learning approach in education that consists of four aspects: technology, science, mathematics, and engineering [25]. STEM can enhance students' ability to work effectively in diverse groups, particularly when interacting with STEM makerspaces [26]. The development of students' innovative and creative thinking skills will be improved using STEM approach [27]. Engaging the research-based learning in STEM makerspace will connect theory with real-world relevance [28, 29]. The integration of RBL-STEM makerspace will enhance the student's learning activities. Humaizah, et al. [20] describe the learning activity framework for the integration of RBL-STEM makerspace in their paper. The integration of internet-based learning and problem-solving in STEM fosters critical thinking and creativity skills [30]. The framework of learning activities in the RBL-STEM makerspace is shown in Figure 1.

Moreover, the smart sensor is a smart device to monitor and control parameters related to Smart Coffee Agroforestry [30, 31]. A smart sensor is used with Arduino development board. In Smart Coffee Agroforestry, smart sensors with Arduino can be used for various purposes. Some of them are: (i) Coffee plantation condition monitor: soil moisture sensors, light sensors, and soil hydrogen concentration can be connected to the Arduino to monitor and collect data on coffee plantations [32]. The data obtained from these sensors can be used to optimize the growth of shading trees; (ii) carbon dioxide; (iii) condition of shading trees: temperature sensors, relative humidity sensors, and gas sensors. These sensors can identify the existence of pests or diseases in plants.

Smart sensors connected to the Arduino and NodemCu can be easily monitored through an online computer by means of the ThinkSpeak application software [33]. For example, by using soil moisture sensors, soil hydrogen concentration sensors, Digital Humidity Temperature sensors (DHT 11) and Methane Quality sensor (MQ 135) as carbon dioxide sensor, Arduino can collect carbon dioxide and relative data from shading tree [34, 35]. It can improve efficiency and optimize coffee growth. The advantages of using smart sensors with Arduino in Smart Coffee Agroforestry include real-time

DOI: 10.55214/25768484.v8i5.1630

monitoring capabilities; saving resources, increasing productivity, and the ability to optimize environmental factors that affect plant growth regarding the protection of Ultraviolet (UV)[35].The sensors and board utilise the NodeMCU ESP8266, DHT 11, jumper wires, MQ135 gas sensor, DC adaptor, and solar panel as a power source. Figure 2 illustrates the type of smart sensors employed in precision farming.

Figure 2.
Some Arduino boards and smart sensors used in precision farming.

Computational thinking as the cognitive element related to student mind-on and hand-on activities on solving smart coffee agroforestry spread into elements, definitions, indicators, and sub-indicators as shown in Table 1.

The research gap identified in the studies concerning computational thinking skills in science education underscores a significant challenge in reaching optimal levels of these skills among students. Despite various educational interventions, the results suggest that there is still room for improvement in cultivating computational thinking capabilities effectively. Ridlo, et al. [1] explored the impact of a project-based learning model on enhancing computational thinking skills, revealing that students achieved only 59% and 54% in algorithmic and debugging skills, respectively. These figures indicate that while there is some improvement, students have not reached an optimal level of competency in these crucial areas of computational thinking. Similarly, Ulfa, et al. [29] investigated the use of an electronic module to boost computational thinking skills and reported an average post test score of 77, which falls short of the highest criteria. The N-Gain score of 0.57, categorized as moderate, further suggests that the intervention's effectiveness in enhancing computational thinking was limited. Furthermore, Ridlo, et al. [24] examined the integration of computational thinking skills with computer simulation, finding that the generalization aspect of computational thinking was still at a moderate level. This outcome points to a need for more robust educational strategies that can elevate students' computational thinking skills beyond moderate levels.

ISSN: 2576-8484
Vol. 8, No. 5: 52-73, 2024
DOI: 10.55214/25768484.v8i5.1630

Table 1.
Indicator of computational thinking skills using smart sensor on precision farming problems.

Aspect	Definition	Indicator	Sub-indicators
Abstraction	The skill of deciding what information should be kept and what should be ignored.	The student will be able to identify and determine the key information on smart coffee agroforestry.	The student can identify the soil moisture, Rh, and CO_2concentration as parameter on smart coffee agroforestry.
Generalization	Being able to create a formulation for one item and then apply it to different items.	The student can make a combination the concept of Arduino integrated development environment(IDE) project and computer programming.	Combination of algorithm in Arduino IDE in design smart sensors for smart coffee agroforestry, and algorithm in computer programming for time series forecasting using machine learning.
Decomposition	The ability to break down a complex issue into simple steps, making the parts more comprehensible and the issues easier to solve.	The students can analysis the parameter on smart coffee agroforestry.	The students can analysis the effect of soil moisture for soil health on coffee plantation and Rh, and O_2concentration for shade tree.
Algorithms	A crucial skill in science is the process of deducing a series of step-by-step operations to solve a problem.	The student can make integration Arduino and computer programming for multi-step time series forecasting.	The student can develop the coding for Arduino programming and develop the coding in time series forecasting the soil moisture, Rh, and CO2 concentration.
Debugging	Capability to detect, remove and correct system errors.	The student will be able to identify and correct syntax errors within an Arduino and within a machine learning program.	The student can identify and find error and fix the Arduino programming, and computer programming for multi-step time series forecasting.

The collective findings from these studies highlight a research gap: existing educational models and tools have not fully succeeded in optimizing computational thinking skills in students. This gap underscores the necessity for innovative approaches, such as integrating RBL-STEM-based learning tools with machine learning, to tackle complex, interdisciplinary problems like those found in Smart Coffee Agroforestry. By adopting such a multifaceted educational approach, there is potential to significantly enhance students' computational thinking skills, equipping them with the necessary competencies to solve real-world challenges effectively.

3. Methodology

3.1. Research Design

Research and Development (R&D) is the type of study in this research. We implemented the ADDIE design for this research type. The analysis stage is the first step in ADDIE. The analysis stage involves collecting data to characterize the necessary requirements. The second stage is called the design stage. In the design stage, we created a blueprint outlining the specifications needed to develop the learning materials. The design step involves prototyping the learning materials, including the lesson plan, student's worksheet, assessment tools, content analysis, smart sensor chart diagram, RBL model, STEM problems, and learning activities framework. The third stage is called the development stage. In the development step, all materials were developed based on the validation sheet with specific criteria using Likert scale rubric from 1 to 5 for learning material validation. The validation process includes content validity, construct validity, programming validity, language validity, and the practicality tests and effectiveness tests.

The fourth stage is the implementation stage. In the fourth stage, we implemented the learning materials developed in the development stages and observed the implementation of learning activities by students, as well as analyzed the significant differences between pre-test and post-test to know the significant contribution of the developed learning materials. The evaluation is used to measure the effectiveness of the developed learning materials so that they will be ready to be used to improve the students' computational thinking skills.

3.2. Research Population

The research population comprises students of the Science Education Department at the Faculty of Teacher and Training of Education, University of Jember, Jember. We selected the sample using the purposive random sampling technique. The research subjects comprised one class of 42 students from the Science Education Department in the Faculty of Teacher and Training of Education at the University of Jember in Indonesia, enrolled in the 2023-2024 academic year. The study was approved by the Social Research Ethics Committee of the University of Jember (No. 2564/UN25.5.1/LL/2023).

3.3. Instrument

The data analysis method used in R&D follows the stage of ADDIE, whose main aim is to develop ready-to-use learning materials to increase the students' computational thinking skills in solving time series forecasting problems in precision farming using machine learning. In the implementation stage of ADDIE, we used a paired sample t-test, considering that the sig value (2-tailed) of paired t-test should be ($p =< 0.05$). Next, the research activities were continued by interviewing three students from three levels of computational thinking skills. The first student is from the high-level group, the second student is from medium-level group, and the last student is from the low-level group. The purpose of interviewing the student was to triangulate the data analysis results and analyze their computational thinking skills. The aim of doing in-depth interviews is to develop the students' meta-analysis of their computational thinking skills. The results of the in-depth interviews are a student-phase portrait. The steps of making the student portrait phase start by choosing students from three levels of computational thinking skills: high, medium, and low level. The three level student interview using questioner's sheet focused on designing and developing smart sensors and using computer programming for time series forecasting related to some parameters in precision farming. The responses of the students were noted and drawn on the interview cards, which contain the sub-indicators of computational thinking skills. The interviewer has understood the response of student due to the activities. The interviewer develops the relationship between sub indicators of computational thinking skills represented by nodes and edges. Lastly, we analyzed the interview results using NVIVO and WordCLOUD applications to explore the students' perceptions about solving time series forecasting problems in precision farming using machine learning.

3.4. Validity and Reliability Tests

The validity of a learning tool refers to the extent to which the tool developed is valid. Validity plays a crucial role in ensuring that the instrument's results accurately reflect the construct or numeracy skill under evaluation. There is content validity, construct validity, programming validity, and language validity validated by three reviewers as doctoral degrees in science education, whose research focused on STEM education, learning media, and learning materials. All validators assess the semester lesson plan, student's worksheet, students' assessment instruments, and the student's learning media. The validity and reliability tests were analysed by employing inferential statistical techniques, namely Pearson correlation [8]. The criteria for determining the validity of each question item are as follows: Each question is considered valid and warrants further analysis if it's associated significance value (2-tailed) falls below 0.05. Furthermore, the Alpha Cronbach test was employed in order to assess the reliability of the data. The criteria for reliability are as follows: if the alpha Cronbach score of an instrument exceeds 0.6, it is considered reliable [8].

4. The Result and Discussion

4.1. Result

In the first stage, we conducted two analyses, namely performance and needs analysis. The results of performance analysis are derived from the contextualization of teaching and learning activities, including STEM activities. The real problems of precision farming are given to the students in the class so that they can solve them. The lecturers give some homework or assignments, but not in the form of makerspace. Thus, the implementation of RBL-STEM makerspace model is important, since the combination of the model and approach will foster the students learning activities so that their computational thinking skills are increased. As a result, we consider developing RBL-STEM makerspace-based learning materials to improve the students' computational thinking skills in solving precision farming problems using machine learning.

We have reached the second phase, which is the design phase. Knowing the performance and needs results, we continue to design the format of lesson plan, student's worksheet on using machine learning for solving precision farming problems, assessment instrument tools, learning media for utilizing smart sensors, Arduino, and ThinkSpeak channel, as well as the programming utilized in analyzing the precision farming model. Figure 3 illustrates the prototype for precision farming using smart sensors and machine learning.

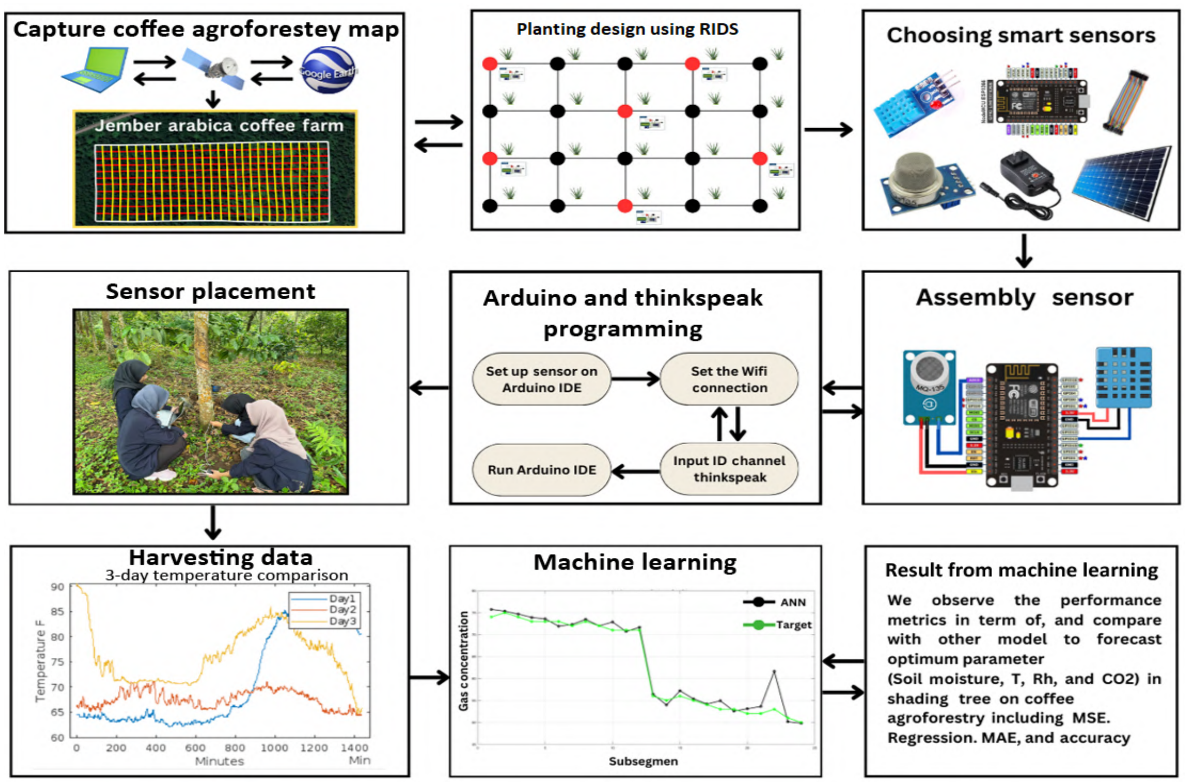

Figure 3.
The prototype of smart sensors on precision farming technology for smart coffee agroforestry using machine learning.

The third stage, known as the development stage, begins. There are four steps in this stage, namely content validity, construct validity, programming validity, and language validity. The class assesses the Science, Technology, Engineering, and Mathematics (STEM) makerspace problem using the content validation. This research encompasses the appropriateness, completeness, and representativeness of the concepts, theories, instruments, or programming under development or evaluation. The construct validity is used to measure the extent to which the construction of the guide is reviewed in terms of composition, framework, and presentation appropriately in regards to the semester lesson plan, student's worksheet on using machine learning for solving precision farming problems, assessment instrument tools, and learning media. The programming validity is to test the models in accordance with the machine learning architectures used, models used, Mean Squared Error (MSE), learning rate, the regression, and the number of epochs. Once we have determined the good models, we bring the machine learning model into a class to use it together with the RBL-STEM makerspace-based learning materials to foster the students' computational thinking skills. The last is the language validity. It refers to the consistency and accuracy of language used, clarity of the learning materials, word choice and writing style, data interpretation, and interpolation.

The content validity, construct validity, programming validity, and language validity are validated by three validators by means of assessment rubric instruments using a Likert. The average results of the semester lesson plan, student's worksheet, students' assessment instruments, and the student's learning media are shown in Table 2.

Table 2.
The validity recapitulation results on RBL-STEM makerspace-based learning materials.

Aspect	Content	Construct	Programming	Language	Average
Semester lesson plan	87.5%	93.75%	93.75%	93.75%	92.18%
Student's worksheet	87.5%	93.75%	100%	93.75%	93.75%
Students' assessment instruments	87.5%	87.5%	100%	93.75%	92.18%
Learning media	87.5%	93.75%	93.75%	93.75%	93.75%
Average	87.5%	92.19%	96.88%	93.75%	92.97%

From now on, we are working on the fourth stage of ADDIE, namely implementation stage. This includes practicality test and an effectiveness test. Table 3 displays the results of the practicality test. The overall average score of practicality test is 93.13%, indicating that the learning materials meet the practicality criteria. The result of the reliability test of the instrument shows that the score of Cronbach's Alpha of 0.824 means the instrument is reliable. The score of reliability can be seen in Table 4.

Table 3.
The practicality test results on RBL-STEM makerspace-based learning instruments.

RBL-STEM model of teaching	Score
Syntax	94.37%
Social interaction	91.66%
Lecturer guidance	95.15%
Support system	90.31%
Instructional effect	93.08%
Nurturing effect	94.75%
Average	93.13%

Table 4.
The results of the reliability test of the pretest instrument.

Reliability statistics		
Cronbach's alpha	**Cronbach's alpha based on standardized items**	**N of items**
0.824	0.754	18

The next step of the effectiveness test is to implement the RBL-STEM makerspace-based learning materials, and at the end of the learning cycle, we did a post-test. The post-test question items are similar to the pre-test; thus, we do not need to do validity and reliability tests. However, prior to analyzing the paired sample t-test, we need to do the normality test. Table 5 shows the results of the normality test. The significance value (p) in the Kolmogorov-Smirnov test is 0.112 ($p>0.05$), thus the data are normally distributed on the basis of the Kolmogorov-Smirnov normality test. The significance value (p) in the Shapiro-Wilk test is also 0.475 ($p > 0.05$), which means that based on the Shapiro-Wilk normality test, the data is also normally distributed.

Table 5.
The normality test results for the post-test data.

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Value	0.148	51	0.122	0.867	51	0.475

Note: a. Lilliefors significance correction.

Additionally, we performed statistical analysis using the paired sample t-test to determine if there is a noteworthy difference between the pre-test and post-test scores in the RBL-STEM makerspace-based learning materials. As shown in Table 6, the results have indicated a significant difference at a 5% level of confidence, with a two-tailed value of Sig. (2-tailed) = $0.003<0.05$. Further, the correlation between pre-test and post-test scores is 0.854. There appears to be a noteworthy contrast between the pre-test and post-test results following the utilization of RBL-STEM makerspace-based learning materials. The study suggests that makerspace-based learning materials in RBL-STEM can enhance students' computational thinking abilities in addressing problems related to precision farming using machine learning techniques. Thus, the learning materials developed in this study are ready to be used in learning process of RBL-STEM makerspace. See also Table 7 for mean comparison between pretest score and post-test score. The data indicates that the average pre-test score is 57.2778, while the post-test score stands at 84.2565. It indicates that post-test score is greater than pre-test score. Table 8 shows a significance value of 0.000, which is less than the threshold of 0.05, indicating that implementing RBL-STEM makerspace learning materials has a significant positive effect on improving computational thinking skills.

Table 6.
The correlation of the pre- and post-test.

Correlation		N	Correlation	Sig.
Pair 1	Pre-test and post-test	42	0.854	0.003

Table 7.
Mean comparison results between pre-test and post-test.

Comparison		Mean	N	Std. deviation	Std. error mean
Pair 1	Pre-test	57.2	42	9.45	1.57
	Post-test	84.2	42	6.05	1.00

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 5: 52-73, 2024
DOI: 10.55214/25768484.v8i5.1630

Table 8.
The results of the paired samples t-test comparing the pre-test and the post-test.

Result		Paired differences		*t*	*df*	Sig. (2-tailed)
		Mean	Std. deviation			
Pair 1	Pre-test and post-test	-20.94	9.85	-12.75	35	0.000

Finally, we end up with the fifth stage, namely the evaluation stage. In the subsequent stage, we triangulate to demonstrate the substantial influence of RBL-STEM makerspace-related learning resources on promoting computational thinking abilities. We aim to determine whether the RBL-STEM makerspace-based learning materials are suitable for implementation in broader learning contexts. For these purposes, we choose three students, namely student who have high-level computational thinking skill denoted by S1, those who have medium-level computational thinking skills denoted by S2, and those who have low-level computational thinking skills denoted by S3. We did an in-depth interview with those three students, and the script of the interview is recorded in the "compare file" feature. The results of the comparison of S1, S2, and S3 in regards to the interview items for specific terms are presented in Figure 4. This picture is depicted using the NVIVO application software.

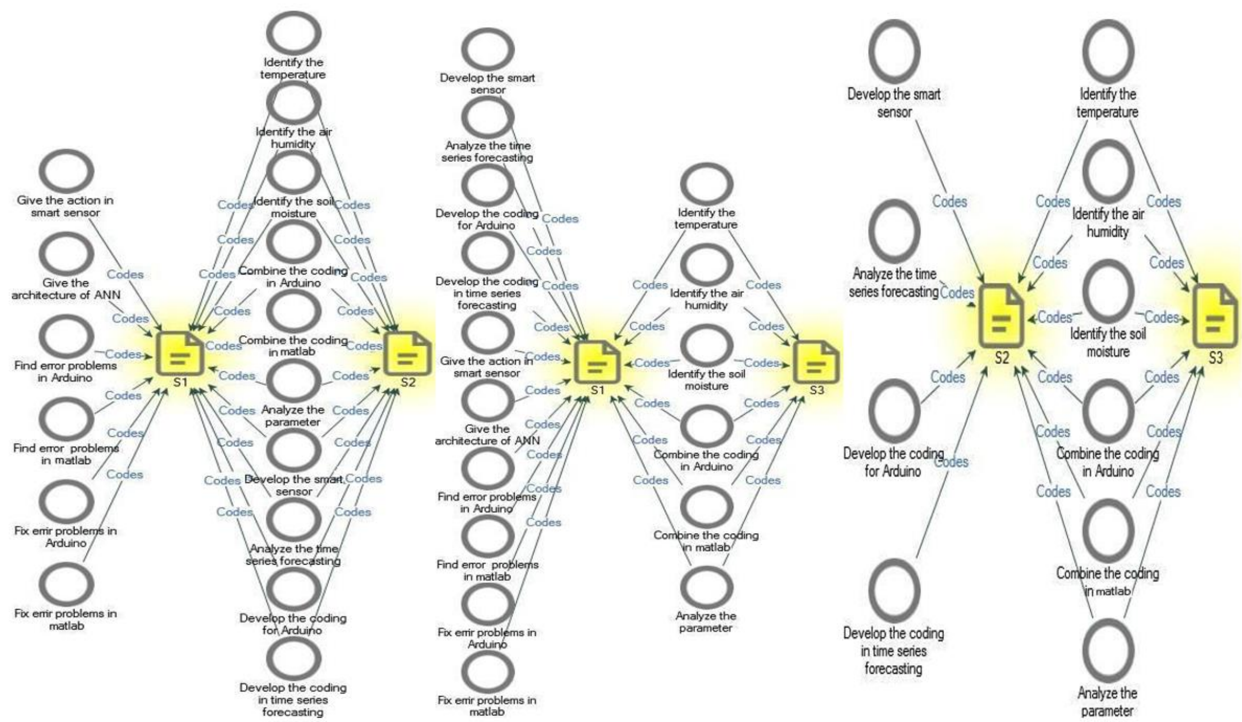

Figure 4.
The comparison of S1, S2, and S3 in regards with the interview items of specific terms derived from the computational thinking skill indicators and sub-indicators.

Based on Figure 4, we can determine the knowledge terms possessed by both S1 and S2, namely identifying the temperature, identifying the air humidity, identifying the soil moisture, installing an Arduino, writing a code, analyzing parameters, developing smart sensors, developing coding for Arduino, and developing coding for time series forecasting. The additional knowledge terms that are only possessed by S1 are giving action to smart sensors, providing the architecture of Artificial Neural Network (ANN), finding error problems in Arduino, finding error problems in computer programming,

DOI: 10.55214/25768484.v8i5.1630

fixing error problems in Arduino, and fixing error problems in computer programming. Furthermore, the differences between S1 and S3 are related as follows: developing smart sensors, analyzing time series forecasting, developing coding for Arduino, developing coding for time series forecasting, giving action in smart sensors, providing the architecture of machine learning, finding error problems in Arduino, finding error problems in computer programming, fixing error problems in Arduino, and fixing error problems in computer programming. S2 and S3 diverge in the areas of smart sensor development; time series forecast analysis, Arduino, and time-series forecasting coding. The project map is NVIVO's next feature. The project map covers a comprehensive picture of indicators and sub-indicators achieved by three students' categories at once. Figure 5 displays the results of the project map.

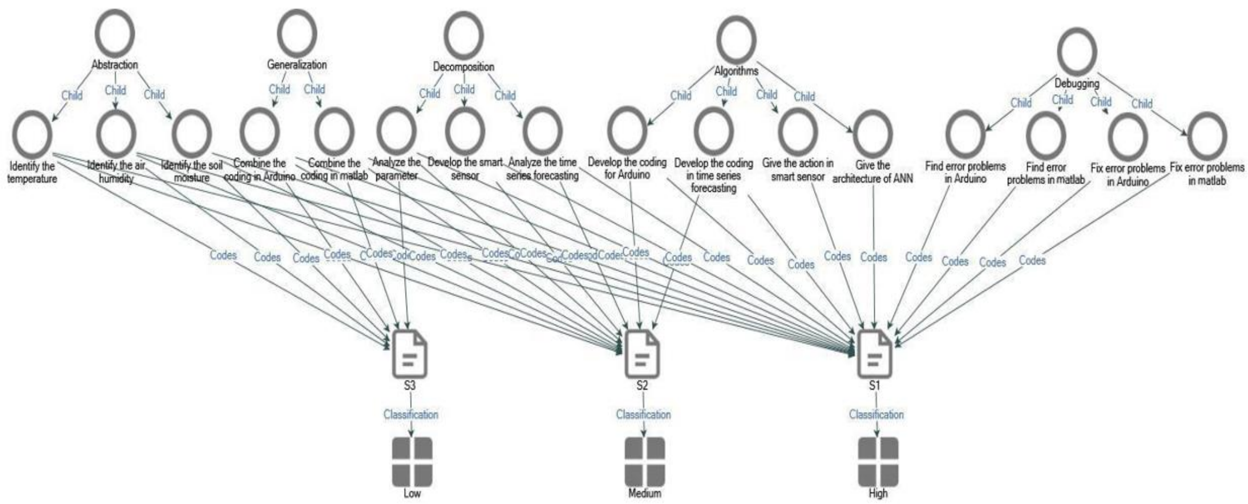

Figure 5.
The project map of subject S1, S2, and S3 in regards with the interview items of specific terms derived from the computational thinking skill indicators and sub-indicators.

The matrix coding query is NVIVO's next feature. This feature provides information about the coding frequency. In this case, the coding frequency refers to indicators and sub-indicators of students' computational thinking skills. This feature allows us to visualize the data in a graphic to easily understand the data distribution. Figure 6 illustrates the distribution of students' computational thinking skills at three levels, namely high (S1), medium (S2), and low (S3).

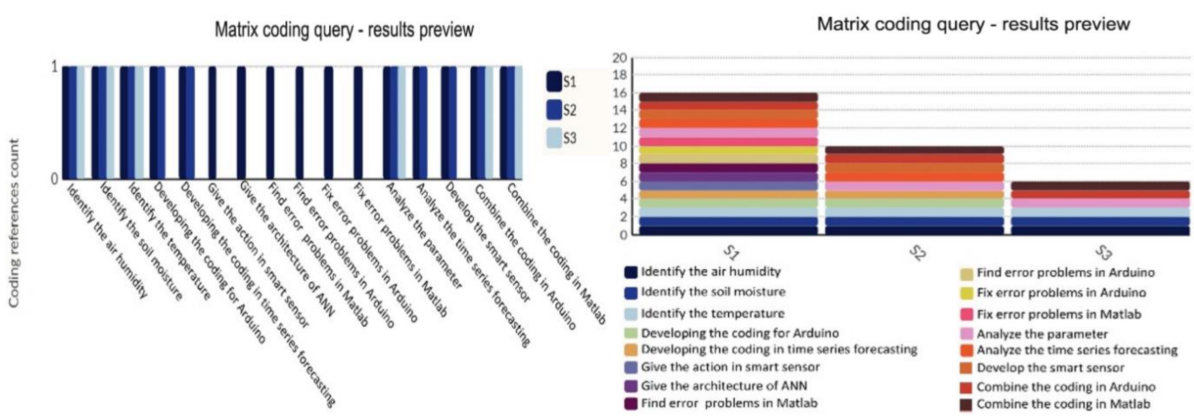

Figure 6.
The distribution of students' computational thinking skills at three levels of subject S1, S2, and S3.

ISSN: 2576-8484
Vol. 8, No. 5: 52-73, 2024
DOI: 10.55214/25768484.v8i5.1630

Furthermore, we will show the wordCLOUD feature of the computational thinking skills indicators and sub-indicators of subjects S1, S2, and S3. We use it to identify the most frequently occurring words in the interview transcripts. The results of the NVIVO word cloud can be seen in Figure 7. It shows that the most frequently occurring word is "Arduino," with a percentage of 3.47%. Another commonly occurring word is "moisture," with a frequency of 2.7%.

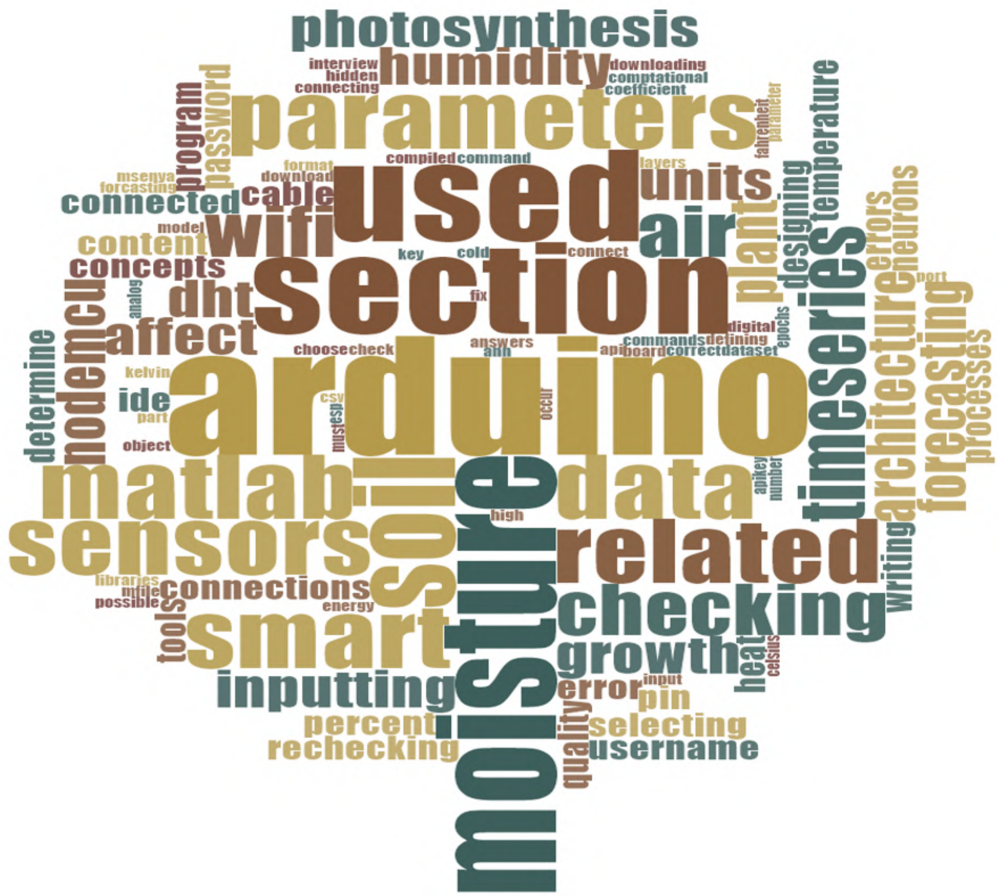

Figure 7.
The word cloud feature in regards with the computational thinking skills indicators and sub-indicators of subject S1, S2, and S3.

The next feature of NVIVO is item clustered by-word similarity. Table 9 displays the results of the item clustered by-word similarity. It shows that the Pearson correlation coefficient value between S3 and S2 is 0.86025, the Pearson correlation coefficient value between S3 and S1 is 0.519035, and the Pearson correlation coefficient value between S2 and S1 is 0.519035.

Table 9.
Pearson correlation of item clustered by-word similarity.

Student	Student	Pearson correlation coefficient
S3	S2	0.86
S3	S1	0.51
S2	S1	0.51

The last stage of the evaluation process involves examining the students' phase portrait of their computational thinking abilities. We will present the phase-portrait of three research subjects, each with high, medium, and low-level computational thinking skills. Phase portraits are schematic visualizations derived from interviewing selected students using phase portrait interview cards to assess their computational thinking skills. A phase portrait interview card comprises sub-indicators of computational thinking skills intended for conducting comprehensive interviews by researchers. There are 17 sub-indicators of computational thinking skills, which correspond to the number of cards. These interview cards are designated with codes ranging from A1, A2, A3, G1, G2, up to DB4. During the interview, there was no awareness of the card codes. The researcher presented a problem from one of the post-test inquiries and interviewed the participant to obtain the solution sequence based on the card. Each response was matched with its code, and then demonstrated in a phase portrait image. Based on the interview results, we then draw a students' portrait phase in terms of high computational skills and low computational skills. Figure 8 shows the phase portrait of computational thinking skill of student S1 with high level of computational thinking skill. Student S1 travels the thinking process from stage A1, A2 to A3, and then from G1 goes to G2, continue to D1, D2, and back to D1. After that, D1 jumps to the D3, D4, AG1, back to D4, continue to AG2, AG1, jump to the S and back to AG1, continue to F, back to S continue the debugging stages, and start from DB1 jumps to DB3, back to DB2 stages, and the last one is DB4. Figure 9 illustrates the adjacency matrix for the student S1 phase portrait.

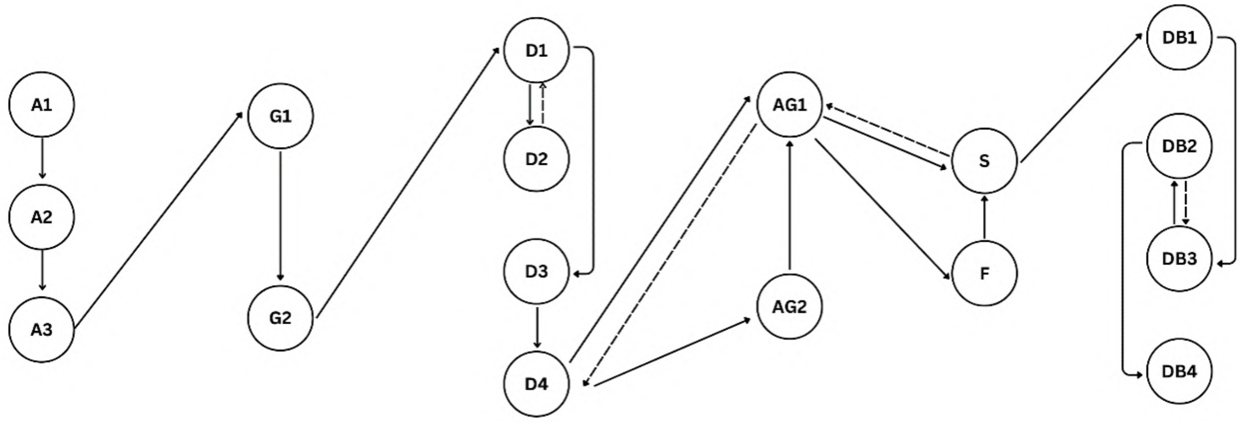

Figure 8.
The phase portrait of computational thinking skill of subject S1.

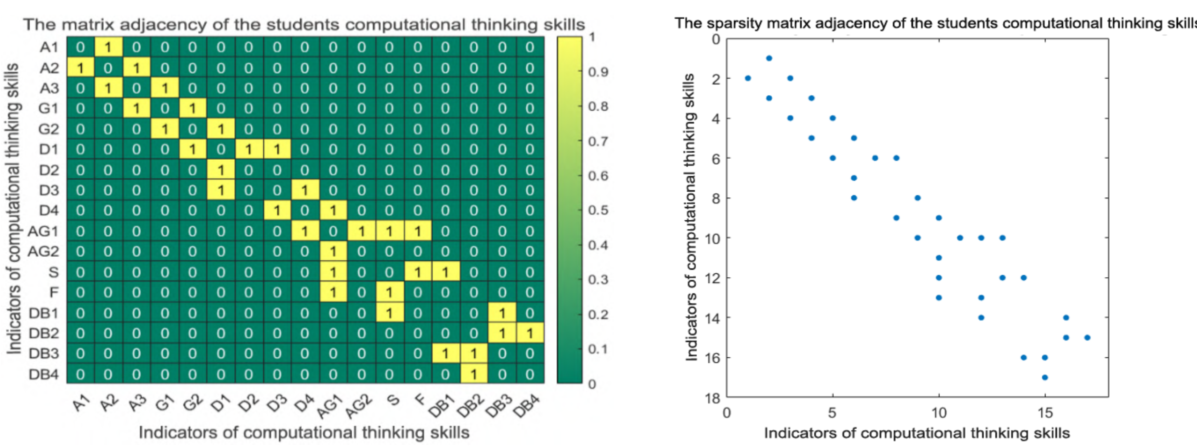

Figure 9.
The adjacency matrix of the student phase portrait of subject S1.

Furthermore, Figure 10 shows the phase portrait of computational thinking skills of subject S2 with medium level of computational thinking skill. The student S1 travels the thinking process from stages A1, A2, and A3, and then G1 goes to G2, and back to G1. After that, G1 moves to D3, D2, and D1 and jumps to D4. It continues by entering the algorithm stage from D4 to AG2, AG1, S, F, and DB1, DB2, DB3, and the last one is to DB4. The neighbourhood matrix of student S2 phase portrait can be seen in Figure 10. The adjacency matrix of student S2 phase portrait can be seen in Figure 11.

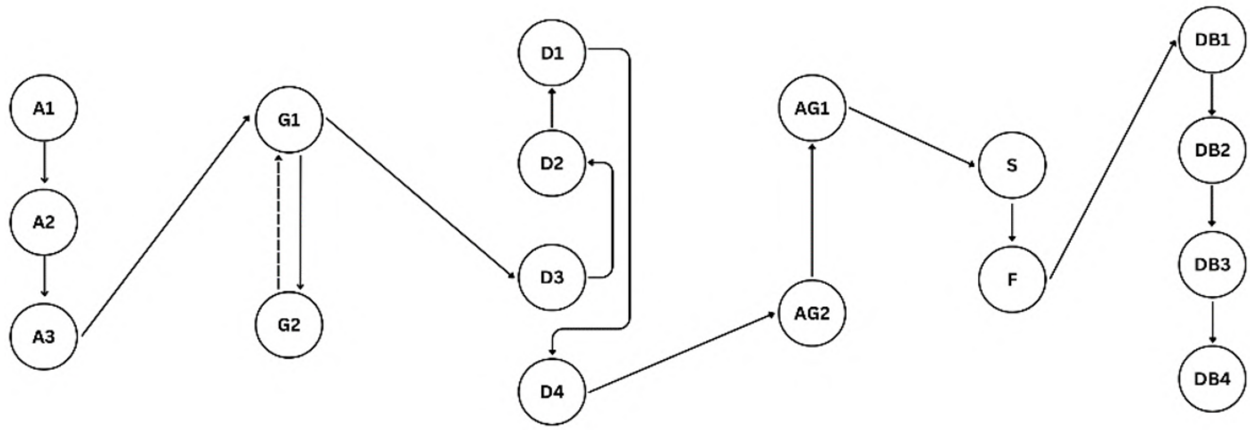

Figure 10.
The phase portrait of computational thinking skill of subject S2.

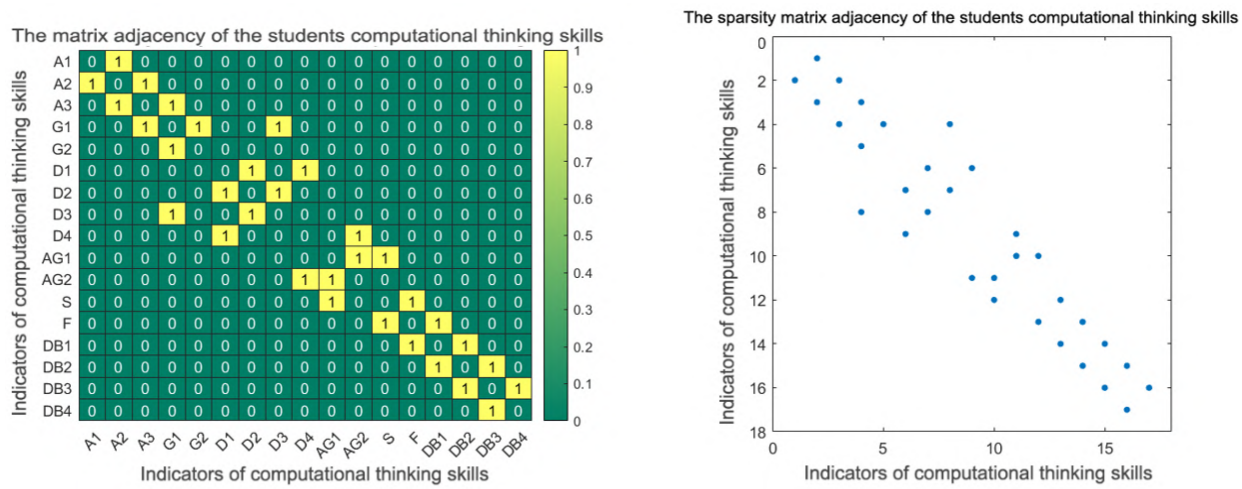

Figure 11.
The adjacency matrix of the student phase portrait of subject S2.

Last, Figure 12 shows the phase portrait of computational thinking skills of subject S3 with low level of computational thinking skill. Student S1 travels the thinking process from stages A1, A2, and A3, and then G1 goes to stage G2, after that G1 moves to D1, D2, and D3 and jumps to stages AG1, S, AG2, and F. After that, enter the debugging stage for DB1, DB2, DB3, and the last one, DB4. The neighborhood matrix and adjacency matrix for the S3 student phase portrait can be observed in Figures 12 and 13.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 5: 52-73, 2024
DOI: 10.55214/25768484.v8i5.1630

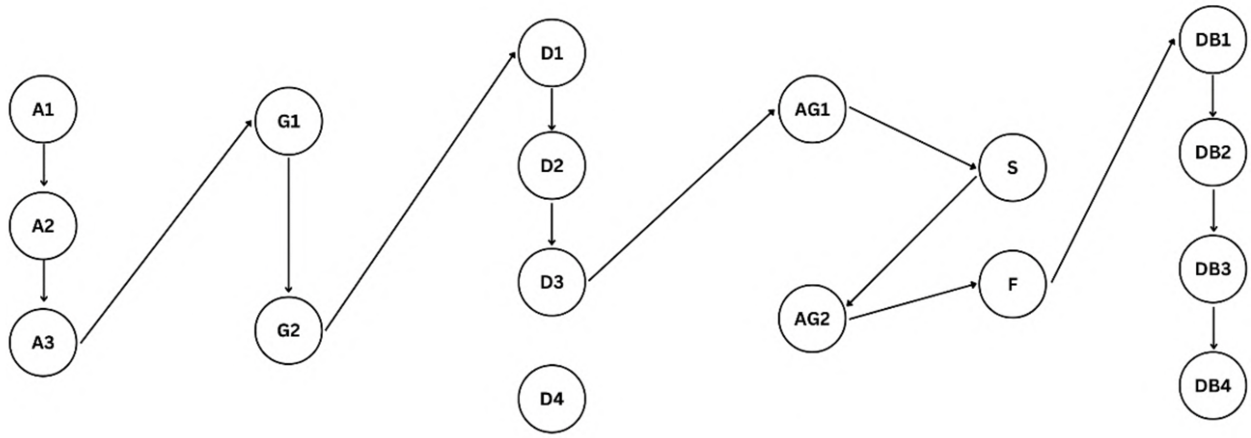

Figure 12.
The phase portrait of computational thinking skill of subject S3.

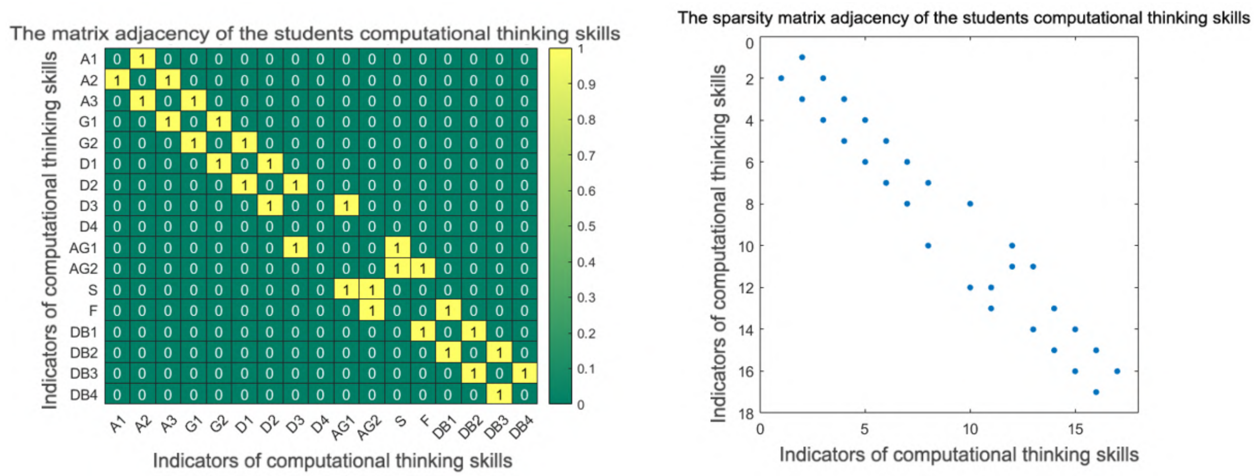

Figure 13.
The adjacency matrix of the student phase portrait of subject S3.

Based on the three students' phase portraits of computational thinking skills above, we can show that the most comprehensive computational thinking skill is student S1. Since the maximum degree of the distance adjacency matrix of S1 is greater than that of other phase portrait, namely AG1, with an in-out degree of 6. This indicates that the students' computational thinking process is more flexible than the others since the computational thinking flow shows more alternative paths for solving problems over a long period of time. In contrast, the phase portraits of student S3 show a discontinuity from D3 to D4, which illustrates that the computational thinking process is not optimal. The greater the degree of phase portrait element, the higher their computational thinking skill. We are convinced that the RBL-STEM educational resources produced in this study are suitable for broader use in the classroom.

4.2. Discussion

There is a lot of meaningful information from ADDIE development process for RBL-STEM makerspace-based Learning Material. The average score of validity is 92.97%, meaning that the learning instrument meets good validity criteria. The reliability score of instruments is 0.824, which means the instrument is reliable. The practicality test of learning instrument is 93.13%, meaning that the learning instrument meets good practicality. The subsequent stage involves evaluating the efficiency of the educational resources. During implementation, we scrutinize both the pretest and post-test scores, as well as the attributes of the students. The average pre-test score is 57.2778, while post-test is 84.2565. It means the average post-tests score is much better than pre-test score. The sig-value from paired t-test is 0.003 $< \alpha$ (0.005). It implies that there is a relationship between pre-test and post-test scores. The correlation between pretest score and posttest score is 0.854, meaning that the correlational score is 85.4%. Furthermore, under the implementation of RBL-STEM makerspace, students can learn individually without much help or interference from the lecturer. They become autonomous learners during the implementation of RBL-STEM makerspace-based learning materials on solving precision farming problems using machine learning. The learning materials developed in this study are deemed suitable for use in the learning process of RBL-STEM makerspace.

The last stages are evaluation stages. There are several evaluation steps in these stages. The first evaluation is about student competencies in analyzing the parameters in precision farming. Based on the student interview results, most of the students have some difficulties with the programming of machine learning for time series forecasting in precision farming. According to the triangulation analysis using NVIVO, the most frequently occurring word is "Arduino," accounting for 3.47% of the total. Another commonly occurring word is "sensors," with a frequency of 2.7%. It indicates that there are some problems faced by students, especially in designing smart sensors, writing programming to connect the smart sensors to Arduino IDE, integrating smart sensors with ThinkSpeaks, collecting the data, and applying machine learning for time series forecasting.

This research and development carried out in this study strengthens the benefits of RBL-STEM makerspace. STEM makerspaces play an important role in education and development of students, offering an effective and innovative learning environment that improves creativity, problem-solving skills, minds-on activity, and hands-on experience [36, 37]. It encourages students to think outside the box, experiment with ideas, and innovate [38]. They provide a space where students can design, prototype, and create, allowing them to explore their creative potential in STEM field [39-41]. STEM makerspaces also offer a practical, hands-on approach to learning [42, 43]. Students will be able to integrate theoretical and practical knowledge from classroom into the real-world projects and do cooperative activities reinforcing their understanding and retention of STEM concepts [44, 45]. Furthermore, RBL-STEM makerspaces are typically collaborative environments where students work together on projects. This fosters teamwork, communication, and the ability to collaborate effectively, skills that are highly valuable in today's workforce [46, 47]. Engaging in hands-on projects in a makerspace environment challenges students to identify problems and find solutions. They learn to troubleshoot, iterate, and adapt their designs, honing their critical thinking and problem-solving skills [48, 49]. RBL-STEM makerspaces often blend multiple disciplines, allowing students to see the interconnectedness of mathematics, technology, science, and engineering [50, 51]. The interdisciplinary approach helps students gain a more holistic understanding of complex real-world issues.

Moreover, RBL-STEM makerspaces often incorporate cutting-edge technologies and tools such as 3D printers, laser cutters, robotics kits, and more. Students have the opportunity to familiarize themselves with emerging technologies, preparing them for future careers in STEM [52]. Many projects in makerspaces have real-world applications, which can make learning more relevant and engaging for students [53]. Whether they are designing sustainable solutions or building prototypes, students can see the direct impact of their work [54]. Employers highly value the skills and knowledge that student develop in RBL-STEM makerspaces. As the job market becomes increasingly competitive in STEM fields, hands-on experience gained in makerspaces can give students a competitive edge. RBL-STEM makerspaces often prioritize inclusivity and diversity, providing opportunities for students from various backgrounds to participate in STEM activities [22]. This can help address the gender and diversity gap in STEM fields by making STEM more accessible to all students [55]. RBL-STEM makerspaces instill a passion for lifelong learning. Long after their formal education is complete. RBL-STEM makerspaces encourage students to explore their interests and continue experimenting and creating. Lastly, RBL-STEM makerspaces are invaluable educational resources that empower students to become creative problem solvers, critical thinkers, and future innovators in STEM fields. They equip students to meet the challenges and seize the opportunities of today's world by providing an environment where theory and practice can merge. Thus, the implementation of RBL-STEM makerspace-based learning materials developed in these results is significantly useful to foster students' computational thinking skills.

5. Conclusions

The ADDIE research and development model has been employed in the creation of learning materials for the RBL-STEM makerspace. The results demonstrated that the learning materials exhibited satisfactory levels of language validity, construct validity, content validity, and programming validity, with an overall average score of 92.97%. These findings suggest that the learning materials developed possess robust and well-founded criteria. The results of the practicality test of the RBL-STEM makerspace demonstrated an average practicality score of 93.13%, indicating that the RBL-STEM makerspace is highly practical to utilise. The reliability of the scores produced by the instruments used was demonstrated by the consistency of the results. The results of the paired t-test indicate that the value of $\alpha = 0.003$ is less than 0.05, thereby demonstrating a statistically significant increase in the average posttest score, which now stands at 84.2.

The RBL-STEM makerspace learning model provides students with the opportunity to develop their ability to integrate research activities into their learning process through the utilisation of smart sensors and machine learning. It is of great importance to establish a comprehensive knowledge and practice base in order to facilitate students' capacity to utilise machine learning for the resolution of everyday problems. By employing the STEM approach, students are trained to analyse specific scientific concepts, utilise technology based on big data and cloud computing, implement modifications in accordance with the engineering design process for the construction of smart sensors, and apply mathematical techniques for the analysis of machine learning models. The development of crucial computational thinking skills is contingent upon the ability to effectively navigate the algorithms and debugging stages. These stages collectively facilitate the acquisition of the requisite expertise to create both Arduino-based and timeseries forecasting programming, while simultaneously honing the capacity to identify and rectify errors in a manner that yields optimal outcomes. The mastery of computational thinking also has the potential to enhance the abilities that are essential for success in the 21st century skills, including critical thinking, creative thinking, and the collaboration skills. These skills are developed through the design of smart sensors and machine learning programming. It can be concluded that the RBL-STEM makerspace-based learning materials have a significant impact on students' computational thinking abilities, enabling them to solve precision agriculture problems through machine learning. This suggests that the learning materials developed in this study are suitable for use in the RBL-STEM makerspace learning process.

6. Recommendations and Limitations

The positive outcome of using RBL-STEM makerspace-based learning materials for enhancing students' computational thinking skills in precision farming via machine learning suggests a promising direction for educational practices. It is recommended that educators incorporate these learning materials into their curriculum to provide hands-on, practical experiences that align with real-world applications. Furthermore, expanding the use of these materials across different educational levels and contexts can broaden their impact, helping to cultivate a generation of learners proficient in computational thinking and machine learning. To ensure continuous improvement, it is also advised to conduct regular assessments and updates of the learning materials, incorporating feedback from both students and educators to adapt to the evolving needs of learners and advancements in technology.

Despite the significant contributions of this study, there are limitations to consider. The research may have been conducted within a specific educational setting or demographic, which could limit the generalizability of the findings. Additionally, the duration of the study and the sample size might affect the robustness of the outcomes. It's crucial to acknowledge that while the learning materials show promise, their effectiveness can vary based on factors such as the instructor's proficiency, students' prior knowledge, and the resources available in the learning environment. Future research should aim to address these limitations by exploring the effectiveness of the RBL-STEM makerspace-based learning materials across diverse settings and larger populations to validate and extend the findings of this study.

Funding:
This research is supported by the PUI-PT Combinatorics, Graph Theory and Network Topology (CGANT) of year 2024, LP2M and Hibah Pascasarjana from LP2M University of Jember (Grant number: 3388/UN25.3.1/LT/2024).

Institutional Review Board Statement:
The Ethical Committee of the University of Jember, Indonesia has granted approval for this study on 18 September 2023.

Transparency:
The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study adhered to all ethical writing practices.

Competing Interests:
The authors declare that they have no competing interests.

Authors' Contributions:
All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

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