Impact of Training Kit-Based Internet of Things to Learn Microcontroller Viewed in Cognitive Domain

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Abstract – **This research aims to find out how effective the IoT microcontroller training kit learning media is and to analyze the effect of using the IoT microcontroller training kit compared to the common microcontroller training kit on students' cognitive learning outcomes in learning microcontroller and microprocessor programming techniques. The normalized gain method was used to determine the effectiveness of the IoT microcontroller training kit learning media. The ANOVA method was used to determine the effect of using the IoT microcontroller training kit and common microcontroller training kit on the average student cognitive learning outcomes. The research results show that the IoT microcontroller training kit learning media has a normalized gain value of 59.62% in the effective enough category. The average cognitive learning outcomes of students using the IoT microcontroller training kit are greater than those using the regular microcontroller training kit, according to the results of the study using one-way ANOVA, where the p-value is less than the α value of 0.05. This IoT microcontroller training kit can be used to improve students' cognition regarding microcontroller learning in vocational schools.**

Keywords – **Quality education, IoT, cognitive domain, microcontroller, training kit.**

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1. Introduction

The use of the Internet of Things (IoT) is growing rapidly in the current digital era. Implementation of IoT in the digital era includes smart home [1], telehealth monitoring [2], smart industry [3], and smart agriculture [4]. In the future, the implementation of IoT will expand its coverage area to other fields. IoT is a technology that uses a microprocessor to send and receive data over the Internet network. IoT devices function to collect data from the environment and process this data into a microprocessor which then provides decisions to make processes more efficient, reduce costs, and improve product quality [5].

The cognitive domain is an important aspect of learning and developing students' abilities. The cognitive domain includes the ability to observe, estimate, and judge things. In the world of education, the cognitive domain plays an important role in developing students' knowledge, including in science learning [6]. Vocational education institutions such as vocational schools must prepare their graduates to be able to apply IoT technology. IoT technology applied to education can be in the form of learning media. The use of learning media in education has been shown to have a significant impact on student learning outcomes. Learning media refers to any materials or tools that are used to support the learning process, such as textbooks, videos, interactive software, and other digital resources. Some learning media have developed the use of IoT for learning such as using IoT in laboratory experiments to help students study cell biology [7], science, technology, engineering, and mathematics (STEM) practical kits for learning STEM [8]. Activity-based utilizing IoT with project-based learning can be used to study several academic projects [9]. Virtual reality and web-based 3D are examples of how the Internet of Things (IoT) may be used to enhance learning activities, inspire students, and create new interests and needs [10].

Learning media that follows technological developments can influence students' competence regarding the application of the latest technology such as the use of IoT.

This research uses learning media in the form of an IoT microcontroller training kit using the NodeMCU ESP8266 microcontroller. IoT-based training kit used to help students learn and understand microprocessor and microcontroller programming techniques. Students learn five instructional materials to apply microcontroller programming for 1) temperature monitoring with the DS18B20 sensor; 2) text input on a 16x2 LCD; 3) safety system with PIR and Buzzer; 4) AC light control system with relay module; and 5) DC motor control system with relay module. As a comparison, this research uses learning media in the form of a common microcontroller training kit which is also used to apply microcontroller programming to the 5 instructional materials without using IoT technology.

The research aims to analyze the influence of students' cognitive domain learning outcomes on the use of the IoT microcontroller training kit learning media compared to the cognitive domain learning outcomes of students who use the common microcontroller training kit learning media in learning microprocessor and microcontroller programming techniques. The problems in this research include:

1. What is the normalized gain value and effectiveness category of the IoT microcontroller training kit learning media in learning microcontroller and microprocessor programming techniques?
2. Are the average cognitive learning outcomes of students taught using the IoT microcontroller training kit learning media higher than the average cognitive learning outcomes of students taught using the common microcontroller training kit learning media in learning microcontroller and microprocessor programming techniques?

2. Literature Review

Some of the following literature is related to material that supports research and aims to provide a deeper understanding. These materials are training kit as learning media, the Internet of Things, and cognitive domain.

2.1. Training Kit as Learning Media

Learning media is a tool used to convey or deliver messages and information during learning. Learning media can also be interpreted as a source of teaching materials or intermediaries that help teachers convey material to students effectively so that learning objectives can be achieved well. Learning media in the form of training kits can help educators explain instructional material that is difficult to explain orally, such as in the engineering field. The author [11] used a training kit in the form of a portable prototype of hydrogen fuel cells to teach students the characteristics of the fuel cells. Training kits are designed and created to make it easier to learn the instructional material. However, to ensure that a training kit is effectively implemented in the learning process, its feasibility must be assessed [12].

The form of training kits can vary according to the instructional material to be delivered. In the field of nutrition, training kits can be in the form of a Fruit and Vegetable-Focused Grocery Store Tour [13], or in the form of a A2U Food Training Kit as a learning medium for the management of food loss and waste [14]. In the field of pharmacist training kits, it can be in the form of visual training to teach safe medication practices in the community for student pharmacists [15]. Students can be trained in hazardous chemical processing using virtual reality as a training kit before diving into the real system [16].

A training kit is any object or component that can be used to transmit information messages to establish a favorable learning atmosphere that ensures students complete the learning process quickly and successfully. Training kits can be designed according to educators' needs to convey information to students [17]. Some of the functions of training kits in various forms include: stimulating interest and being useful for students, playing an active role in the learning process [18], [19], training kits can be used to present information on certain instructional materials such as training robots for learning program coding computers [20], and the use of Android for mathematics learning [21].

2.2. Internet of Things (IoT)

IoT is a technology that allows objects such as hardware devices to exchange information with each other through internet infrastructure connectivity [22]. IoT includes other sensor technologies, such as wireless technology, which are all connected to local and global networks based on the Internet. The Internet of Things (IoT) refers to the idea that an object may be set up with software and sensors that enable it to connect, communicate, control, and exchange data with other devices as long as those devices are still online [23].

IoT allows devices to connect and communicate with each other, thereby increasing efficiency and productivity in various fields, such as industry, health, and households. IoT also allows users to operate devices remotely with little or no human assistance.

One example of the application of IoT is a smart home, where electronic devices such as lights, fans, AC, and other devices can be connected via the Internet and operated remotely [24].

To develop and learn IoT, one can use an IoT microcontroller training kit. The IoT microcontroller training kit is specifically designed to help individuals learn and develop IoT systems. This kit comes with various components and sensors that can be used to build IoT devices and applications. Some examples of IoT applications in daily life are smart homes, smart health, and smart cities. The application of a smart home involves connecting electronic devices such as lights, fans, AC, and other devices via the Internet to be operated remotely [25]. Smart health applications include the use of IoT with sensors to monitor health conditions and provide early warnings if health problems occur [26]. Smart city applications include the use of IoT technology to increase efficiency and productivity in various aspects of city life, such as transportation, waste management, and security [27], [28]. In its application, IoT has many benefits, such as making it easier to operate devices remotely, increasing efficiency and productivity, and providing solutions to various problems in everyday life. However, the use of IoT also has security and privacy risks that need to be considered [29], [30]. Along with the development of IoT, microcontrollers have developed modules based on Ethernet and WiFi, starting from the Ethernet shield to the latest, the WiFi module known as NodeMCU ESP8266.

2.3. Cognitive Domain

The cognitive domain is an important aspect for students to study instructional material and to develop their abilities. The cognitive domain plays an important role in developing students' knowledge, including in science learning [31], design education in engineering [32], and the architectural education program [33]. The cognitive domain includes intellectual abilities, such as the ability to think, remember, understand, and solve problems [34]. Bloom's taxonomy is a theory used to categorize the cognitive domain. Bloom's taxonomy has three cognitive domains [35], [36], namely the knowledge domain, namely the ability to remember or recognize certain facts, Understanding domain, namely the ability to understand concepts or ideas, and the Application domain, namely the ability to use knowledge in practical situation.

Research results [37] show that of the 3 educational domains, the cognitive domain is considered the most important and is ranked highest. This is because testing using the cognitive domain is widely used in several aspects.

The authors [38] used Cognitive testing to look for correlations with certain mental and neurological conditions and demographic factors. Cognitive assessment can be used to identify individuals with neurocognitive disorders [39]. Research by [40] showed that individuals' cognitive domains and their ability to hear are significantly correlated. Cognitive domain development can be done in various ways, such as active learning, problem-based learning, and project-based learning. According to [41] learning with the Escape Room – Breakout model in science, technology, engineering, and mathematics (STEM) education, specifically, in scientific and mathematical concepts can improve student performance.

3. Method

The methods section details the target population, the sampling method used to select participants, the data collection procedures, and the process for calculating normalized gain.

3.1. Population and Sample

The research population is the number of students at a vocational school in Surabaya City, Indonesia who take microcontroller and microprocessor programming engineering subjects, namely 70 students. Determination of the sample size is guided by the Slovin formula [42].

$$n = \frac{N}{1+Ne^2} \tag{1}$$

Where n is the number of samples, N is the number of populations, and e is the error percentage (5% = 0,05). Based on the formula above, the size of the research sample can be calculated as follows:

$$n = \frac{N}{1+Ne^2} = \frac{70}{1+70(0{,}05^2)} = 60$$

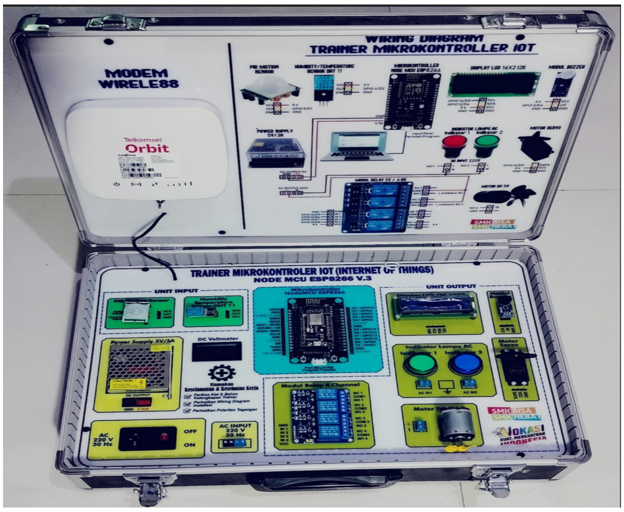


Figure 1. Sequence of learning for microprocessor and microcontroller programming engineering subjects

Furthermore, the sample of 60 students was divided into 2 research classes, namely the experimental class which used the IoT microcontroller training kit with 31 students, and the control class which used the common microcontroller training kit with 29 students. The research was carried out in April – July 2023. The IoT training kit for the research is shown in Figure 1.

The instructional materials (IM) studied are (a) temperature monitoring with the DS18B20 sensor; (b) text input on a 16x2 LCD; (c) safety system with PIR and Buzzer; (d) AC light control system with relay module; and (e) DC motor control system with relay module. The learning used in both classes is problem-based learning.

3.2. Data Collection Method

The instruments used to collect data consisted of two instruments, namely the pre-test and post-test instruments used to measure normalized gain (N-Gain) and the instructional material cognitive testing instruments to measure the cognitive test results of students from two different classes. Pre-tests and post-tests are carried out at the beginning and the end of learning.

Table 1. Basic competencies and their indicators

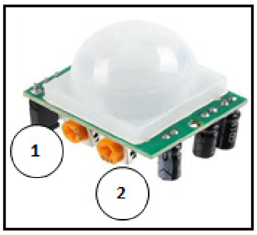
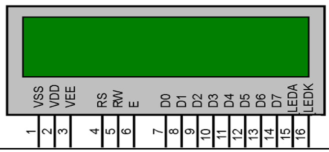
Basic competencies	Indicators
Planning simple application programs with a microcontroller	1. Define the working principle of the NodeMCU microcontroller 2. State the function of microcontroller input and output ports 3. Explain the IoT-based microcontroller system 4. Identify simple sensor system application programs 5. Identify the 16x2 LCD application program 6. Develop a sensor application program flowchart algorithm
Planning a simple application program for a control system with a microcontroller	1. Implement the AC light control/control system program 2. Implement DC motor controller/control system programs 3. Compare input application programs and microcontroller output application programs

Instructional material cognitive testing instrument is used to measure learning outcomes of students in mastering competency in learning microcontroller and microprocessor programming techniques.

The instrument built refers to two basic competencies, namely 1) planning a simple application program with a microcontroller and 2) planning a simple application program for a control system with a microcontroller as shown in Table 1. The indicators shown refer to the experimental class, while for the control class, change the words NodeMCU microprocessor to Arduino Uno microprocessor.

Table 2 shows several examples of the development of the indicators in Table 1 to become pre-test and post-test questions to be asked to students at the start of learning and the end of learning. The instructional material cognitive testing instrument was created for each instructional material with 10 questions per instructional material so that the total material had 50 cognitive test questions. After each meeting, a cognitive test is carried out on each material. The cognitive test questions are multiple choice questions with 5 answer choices for each question where only one answer is correct.

Table 2. Pre-test and post-test questions

No	Question
1	Describe the specifications of the NodeMCU Microcontroller.
2	A sensor sends analog data to the NodeMCU, the right pin to input/send sensor data to the NodeMCU is....
3	Choose practical work steps for programming a microcontroller for a temperature monitoring project with a DS18B20 sensor systematically based on the correct work steps below.....
4	Explain the effect on the PIR sensor below, if VR no.2 is adjusted/trimmed to the right…. 
5	State the most appropriate function of the 16x2 LCD module in a microcontroller application….
6	Based on the image of the 16x2 LCD module below, the functions of pins no. 15 and no. 16 are…… 
7	Choose the most appropriate working principle algorithm for the IoT-based temperature monitoring system application.....

3.3. One-Way Anova Testing

The one-way ANOVA method is used to compare the average student cognitive learning outcomes between classes that used the IoT microcontroller training kit and classes that used the common microcontroller training kit. One-way ANOVA is also used for hypothesis testing to determine whether there are differences in means between groups. The following is the hypothesis of this research:

H_0: The average student cognitive learning outcomes of students taught using the IoT microcontroller training kit learning media is the same as students taught using the common microcontroller training kit learning media

H_1: The average student cognitive learning outcomes of students taught using the IoT microcontroller training kit learning media is higher than students taught using the common microcontroller training kit learning media

3.4. Normalized-Gain (N-Gain)

N-Gain is a measurement used to assess how effectively a subject increases understanding of concepts. N-Gain is calculated by comparing the class average grades before and after a subject. The following is the N-Gain formula:

$$N\ Gain = \frac{Posttest\ Score - Pretest\ Score}{Ideal\ Score - Pretest\ Score}\ x100\% \quad (2)$$

Table 3. N-Gain leveling [43]

Percentage (%)	Assessment
<40	ineffective
40-55	less effective
56-75	effective enough
>76	effective

4. Results

This section explains the research results, which include the results of the reliability and validity tests of the instrument, the results of comparison testing of two classes using ANOVA, and the learning outcomes of the experimental class using N-Gain.

4.1. Reliability and Validity Items for Pre-Test and Post-Test Results

Validation tests and reliability tests used 10 samples of students who were not involved in the experimental class and control class. The number of questions for the pre-test and post-test is 25 questions. The r-table value for a sample of ten individuals with a probability value of 0.05 is 0.632.

The results of running IBM SPSS Statistics 26 obtained reliability statistics as shown in Table 4. The Cronbach's alpha based on the standardized items column in Table 4 is the overall test reliability value. The value shown is 0.975 which is greater than the r-table of 0.632, which shows that the test as a whole is reliable.

Table 4. Reliability statistics pre-test and post-test

Cronbach's Alpha Based on Standardized Items	N of Items
0.975	25

In Table 5 there is a scale-corrected item-total correlation column which is a column for item validity values and a Cronbach's alpha if item deleted column is a column for item reliability values. Table 5 shows that the overall value for each item validity column and item reliability column shows a number greater than 0.632, so it can be stated that the pre-test and post-test questions consisting of 25 questions are valid and reliable.

Table 5. Result of item validity and item reliability for pre-test and post-test

No	Corrected Item-Total Correlation (Item Validity)	Cronbach's Alpha if Item Deleted (Item Reliability)
Qst1	0.789	0.972
Qst2	0.806	0.972
Qst3	0.789	0.972
Qst4	0.840	0.971
Qst5	0.824	0.971
Qst6	0.762	0.972
Qst7	0.658	0.973
Qst8	0.654	0.973
Qst9	0.654	0.973
Qst10	0.722	0.972
Qst11	0.929	0.971
Qst12	0.787	0.972
Qst13	0.658	0.973
Qst14	0.929	0.971
Qst15	0.916	0.971
Qst16	0.747	0.972
Qst17	0.687	0.972
Qst18	0.947	0.970
Qst19	0.787	0.972
Qst20	0.658	0.973
Qst21	0.787	0.972
Qst22	0.687	0.972
Qst23	0.694	0.972
Qst24	0.654	0.973
Qst25	0.947	0.970

Table 6. Result of validity and reliability items for instructional materials

No	IM1		IM2		IM3		IM4		IleM5	
	Item Validity	Item Reliability	Item Validity	Item Reliability	Item Validity	Item Reliability	Item Validity	Item Reliability	Item Validity	Item Reliability
Qst1	0.757	0.896	0.813	0.907	0.793	0.879	0.660	0.879	0.927	0.880
Qst2	0.706	0.900	0.709	0.910	0.752	0.886	0.757	0.871	0.691	0.898
Qst3	0.823	0.892	0.848	0.901	0.682	0.887	0.793	0.868	0.767	0.894
Qst4	0.799	0.892	0.781	0.906	0.743	0.885	0.660	0.879	0.694	0.898
Qst5	0.793	0.891	0.774	0.907	0.757	0.884	0.757	0.871	0.813	0.887
Qst6	0.780	0.894	0.721	0.910	0.743	0.888	0.699	0.876	0.639	0.899
Qst7	0.701	0.897	0.710	0.915	0.743	0.885	0.732	0.874	0.683	0.897
Qst8	0.730	0.896	0.772	0.907	0.721	0.885	0.650	0.880	0.725	0.894
Qst9	0.730	0.896	0.772	0.907	0.654	0.890	0.709	0.875	0.697	0.896
Qst10	0.690	0.898	0.781	0.906	0.793	0.879	0.661	0.882	0.725	0.894

4.2. Reliability and Validity Item for Learning Process Results

In the learning process, it is carried out to study 5 instructional materials (IM1-IM5). Every time students finish learning instructional material, a cognitive test is carried out on each material. The number of cognitive test questions is 10 questions per instructional material so the total material is 50 cognitive test questions. Validation tests and reliability tests at this stage also use the same steps as at the previous stage. Table 6 shows the results of the validity test and reliability test for the cognitive test questions from each instructional material with valid and reliable results because the r-count is greater than the r-table, namely 0.632. Likewise, the overall test reliability value is declared reliable because all values are greater than 0.632, as shown in Table 7.

Table 8 presents the results of the study, which indicate that students in the experimental class had higher cognitive learning outcomes in each IM than students in the control class. Thus, the average cognitive learning outcomes of experimental class students are higher than those in the control class. Table 8 shows students' cognitive learning outcomes based on IM and the average.

Table 7. Reliability statistics cognitive questions for the learning process

Instructional material	Cronbach's Alpha Based on Standardized Items	N of Items
1	0.915	10
2	0.923	10
3	0.909	10
4	0.890	10
5	0.906	10

Table 8. Comparison of students' cognitive learning outcomes

	IM 1	IM 2	IM 3	IM 4	IM 5	Average
IoT microcontroller training kit (experiment class)	80	83	84	87	91	85
Common microcontroller training kit (control class)	78	80	82	85	89	83

4.3. One-Way Anova Result

The results of running one-way ANOVA on SPSS produce several calculation results. Table 9 shows the description of the two classes. The experimental class using the IoT microprocessor training kit has 31 students with an average cognitive learning outcome score of 85 a minimum score of 79 and a maximum score of 89. The control class using the common microprocessor training kit has 29 students with an average cognitive learning outcome score of 83 a minimum score of 80 and a maximum score of 86.

Table 9. Class description

Class	N	Mean	Std. Deviation	Minimum	Maximum
IoT	31	85.03	2.496	79	89
Common	29	83.00	1.581	80	86
Total	60	84.05	2.325	79	89

One of the conditions to be able to carry out the anova test is that the variances are the same. For this reason, a test of homogeneity of variances using the Levene test is needed.

The homogeneity of variance assumption is fulfilled if the p-value is higher than 0.05. In cases where the p-value is equivalent to or less than 0.05, the homogeneity of variance assumption is not fulfilled. From Table 10 it can be seen that the test results show that the variance of the two groups is the same because the p-value (0.065) is greater than 0.05, so the anova test is valid for testing this relationship.

Afterward, to determine if the two experimental and control groups' student learning results differed, Table 11 in the sig column obtained p-value = 0.000, using alpha (α) of 0.05, then the decision is to reject H0, so the conclusion is to accept H1 that student learning outcomes using the IoT microprocessor training kit are higher than student learning outcomes using a common microprocessor training kits.

Table 10. Test of homogeneity of variances

		Levene Statistic	df1	df2	Sig.
Outcome	Based on Mean	3.537	1	58	0.065
	Based on Median	3.435	1	58	0.069
	Based on the Median and with adjusted df	3.435	1	48.978	0.070
	Based on trimmed mean	3.778	1	58	0.057

Table 11. One way anova result

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	61.882	1	61.882	13.967	0.000
Within Groups	256.968	58	4.430		
Total	318.850	59			

4.4. N-Gain Result

By using Equation 2, the N-Gain results for each student are obtained. This N-Gain is the result of calculations between the cognitive pre-test and cognitive post-test of 31 experimental class students. Table 12 shows the results of the learning gain calculation.

Table 12. The experimental class's N-Gain score

Experimental class			
No	**N-Gain Score**	**No**	**N-Gain Score**
1	42.86	18	65.71
2	93.33	19	60.00
3	66.67	20	65.00
4	48.57	21	20.00
5	65.71	22	60.00
6	65.71	23	60.00
7	71.43	24	20.00
8	65.00	25	52.00
9	55.00	26	6.67
10	55.56	27	60.00
11	20.00	28	80.00
12	82.22	29	71.43
13	77.78	30	64.00
14	70.00	31	60.00
15	65.00	**average**	59.62
16	73.33	**minimum**	6.67
17	86.67	**maximum**	93.33

Table 3 indicates that the experimental class's average N-Gain score value is 59.62%, qualifying within the effective enough category based on the results of the N-Gain score test computation. N-Gain score values range from 6.67% at the lowest to 93.33% at the highest. Thus, the use of IoT microprocessor training kit learning materials is useful for enhancing student performance in the subject area of microprocessor and microcontroller programming engineering.

5. Discussion

This research shows that the experimental class that uses the IoT training kit microprocessor learning media has advantages compared to the control class that uses the common microcontroller training kit. The average cognitive learning results of students in the experimental class are greater than those in the control class, which provides evidence of this. Even though the instructional material studied is the same. To attract students' interest in learning media the IoT microprocessor training kit has adapted to the development of 4.0 technology by the demands of the latest technological developments and implemented it with daily life problems in the learning of microprocessor and microcontroller programming techniques. The results of this research are supported by the author [44] who stated that the attractiveness of instructional resources like the usage of the latest technology and a good appearance can attract students to learn compared to simple learning media. Supported research by [45] stated that innovative and applicable learning media can motivate students to understand better.

The increase in student cognitive learning outcomes for each lesson from IM 1 to IM5, for both experimental and control classes is depicted in Figure 2. Furthermore, as can be observed in Figure 2, students in the experimental class have better learning outcomes and receive better scores than those in the control class. Similar to this, the experimental class's average value for the cognitive learning outcomes of its students is higher than that of the control class. The increase in the score of each lesson can be caused by employing instructional resources that can provide learning experiences. The research [46] argued that media can function as teaching tools, learning objects, and instructional resources in a socially networked environment and that employing media can help to enrich the learning experience and promote emotional engagement.

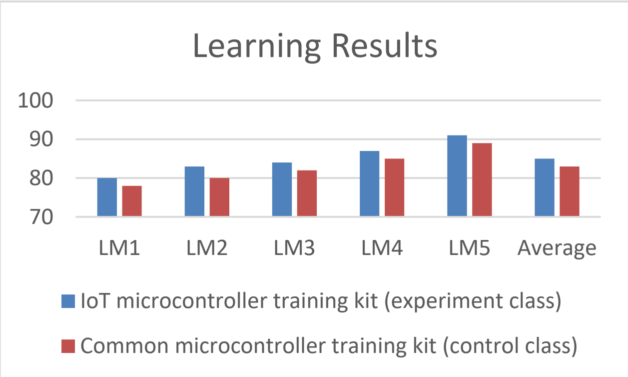


Figure 2. Comparison of student learning outcomes for each instructional material

N-Gain in the experimental class showed good results for using the IoT microprocessor training kit learning media. The N-Gain value is in the enough effective category. The use of instructional media has a significant effect on student learning outcomes [47]. This is also supported by research [48] which stated that the use of learning media has a positive effect on student learning outcomes and contributes effectively to the N-Gain.

6. Conclusion

According to the research results it can be concluded that: 1) The normalized-gain value obtained has a fairly large value in the effective category for IoT microcontroller training kit learning media in learning microcontroller and microprocessor programming techniques, 2) The average cognitive learning outcomes of the experimental class are higher than the control class so that the IoT microcontroller training kit learning media is better used for learning microcontroller and microprocessor programming techniques.

In vocational schools, this IoT microcontroller training kit can assist students in becoming more proficient in understanding microcontrollers. The benefit of this research is that it explains that updating the microcontroller and microprocessor programming techniques training kit according to the needs of current technological developments, such as the use of IoT, can increase students' cognitive learning outcomes. The limitation of this research is that it only measures the cognitive domain; further research is needed regarding student learning outcomes related to the affective and psychomotor domains.

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