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Beyond Smart Devices: Fostering Critical, Communication and Collaborative Thinking in IoT-Based Sensor and Actuator Competence Learning Outcomes

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Abstract **– This research aims to explore the level of critical and collaborative thinking among university students in IoT-based sensor and actuator competence courses in Surabaya during 2022-2023. This study employs quantitative research methods and utilizes the structural equation modeling approach with partial least squares algorithm for analysis. This paper aims to explore the intricate connections between critical thinking, communication skills, collaboration skills, and learning outcomes in the context of sensor and actuator competence by examining the existing research and exploring practical implications. Respondents comprise of 360 electrical engineering students in Surabaya currently taking sensor and actuator competencies in the 2022/2023 school year. The findings had significant role of collaborative learning in enhancing the association between critical thinking and learning outcomes, particularly in the affective and psychomotor domains. Collaborative learning can be considered an effective strategy to reinforce the connection between critical thinking and academic achievement in these two domains.**

The implications of this study have the potential to guide educational institutions in designing and implementing effective strategies for fostering critical and collaborative thinking skills among students in IoT-related fields.

Keywords **– Critical thinking, learning outcomes, path analysis, sensor and actuator.**

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1. Introduction

In the 21st century, learning and critical thinking are essential for everyone, particularly students, in order to adapt to the rapidly changing times and foster intellectual development.

In the digital age, advancing one's skills necessitates more than just knowledge mastery; it also demands proficiency in a diverse set of abilities. These include problem-solving, critical thinking, communication, collaboration, creativity, and literacy. Additionally, it's crucial to be aware of global issues. The brain plays a pivotal role in connecting the existing pieces of knowledge one possesses [1]. This thinking process is divided into two, namely low order thinking skill and high order thinking skill [2]. High order thinking skill is something that students must possess. However, the current condition is that students have yet to develop their high order thinking skills [3].

Critical thinking is one of the divisions within the realm of high order thinking skills. Critical thinking refers to a mode of thinking that involves analyzing and evaluating information and ideas It can even be based on the reasoning that is focused on determining what to believe or do and being able to argue, analyze, categorize, and reason in reaching information or conclusions [4]. Certain individuals who can think critically can adapt by identifying problems, understanding problems, and analyzing problems to find solutions that are more measurable and effective [5].

Critical thinking can be used as a benchmark for the ability of certain individuals to know something in the surrounding environment by being actively involved and responsive based on certain foundations [6]. The significance of critical thinking is continuously growing in the realm of education. This is becoming increasingly important because by thinking critically, an individual can become more creative, have a productive character, and also be able to have a broader perspective [7].

Critical thinking is needed in many ways, especially in learning to improve learning outcomes for there is an element of analyzing information in the process. Critical thinking has a good impact on teachers and students. Critical thinking is needed in order to help students process their thoughts in getting a way of learning that suits their individual, not only that but also knowing the meaning of learning and knowing the main points of a lesson [8]. Critical thinking does not only stop when taking education [9], but is also important for continuous professional development as needed for social and interpersonal contexts which are used to make decisions in solving problems faced daily [10], [11]. There were 209 tertiary Hong Kong students conducting cross-sectional correlation studies in order to participate in assessing the level of critical thinking, cognitive ability, and critical thinking disposition to identify relevant factors [12].

One's collaboration ability can be measured by self-assessment. Collaboration skills consist of intrapersonal skills and interpersonal skills. Interpersonal skill is the ability of one's individual work which is divided into preparedness, motivation, reflection, quality of work, and time management. Intrapersonal skills are learning abilities and behavior in groups consisting of role flexibility, contribution, interaction with others, team dynamics, and team support [13].

A strong connection exists between effective communication and sensor competence. Through clear communication, learners can effectively express their observations, interpretations, and inquiries related to sensory information [14], [15]. Furthermore, the ability to effectively communicate sensory experiences facilitates the exchange of ideas and promotes collaborative sense-making, leading to deeper learning outcomes [16], [17].

Collaboration skills also significantly impact actuator competence. Collaborative learning environments provide opportunities for learners to engage in hands-on activities, manipulate objects, and apply motor skills to accomplish shared goals. By working together, learners can refine their actuator competence through practice, feedback, and collective problem-solving, resulting in improved learning outcomes.

Understanding the synergistic relationship between critical thinking, collaboration skills, and sensor and actuator competence is crucial for designing effective educational practices. By cultivating these skills, educators can foster an environment that promotes active engagement, critical thinking, and creativity. Integrating communication and collaboration strategies into instructional approaches can enhance learners' sensor and actuator competence, ultimately leading to more learning outcomes.

One of the indicators of a student's ability to apply real-world learning is sensor and actuator competence. Sensor-actuator competence refers to the ability of a system or an individual to understand, operate, and integrate sensors and actuators in a specific context. It involves a deep understanding of the working principles of sensors and actuators, as well as the ability to organize, control, and optimize their performance. Sensor-actuator competence encompasses several aspects, including: understanding of sensors, understanding of actuators, integration of sensors and actuators, control, and data processing. Overall, sensor-actuator competence combines in-depth technical knowledge of sensors and actuators with practical skills to operate, control, and integrate them in various application contexts.

The utilization of sensors can significantly contribute to the learning process. For instance, in 2018, at Universitas Negeri Surabaya (UNESA), students taking the sensor and actuator course achieved the highest grade of B, with a total of 13 students. In 2019, there was an improvement in student performance, with 65% of the 35 students attaining the highest grade of A-. However, in 2020, only 27% of the students obtained a B+ grade, and approximately 15% achieved an A grade out of a total of 77 students. Through the researcher's observations, it was concluded that many students tend to be passive in the learning process, and there is limited interaction between professors and students [18], [19]. Only a small number of students actively engage in learning.

Previous research has examined the role of sensors and actuators in technical contexts, but there have been relatively few studies investigating the importance of communication and collaboration in maximizing the competence of sensors and actuators for learning outcomes. This study aims to bridge this gap by expanding understanding of how critical thinking, effective communication and good collaboration can enhance understanding, information processing, and proper decision-making in the utilization of sensors and actuators.

Therefore, this paper aims to explore the intricate connections between critical thinking, communication skills, collaboration skills, and learning outcomes in the context of sensor and actuator competence by examining the existing research and exploring practical implications. The objectives of this research include: contribution to the correct, rapid, and unmistakable decision-making of students in the conduct of complex sensor and actuator project; fostering the ability of students in the process of any statistical calculations to determine and make adjustments to the cause of the fault or malfunction in project especially in sensor and actuator competence; contribute to the efficiency of different processes when considering certain design works

2. Research Methodology

This research aims to analyze critical thinking, collaboration, and communication skills through the utilization of media as support in learning sensor and actuator competence in the Electrical Engineering department. The objective of this study is to enhance learning outcomes, especially in the new normal era of the education system.

2.1. Research Participants

A total of 360 electrical engineering students in Surabaya who were enrolled in sensor and actuator competencies during the 2022/2023 academic year were surveyed. Using random sampling, 215 students participated in the study. These students were drawn from five different universities in Surabaya: PETRA (24 students), Hang Tuah (18 students), UNESA (136 students), UBHARA (19 students), and UNTAG (18 students). In this study, we examined the implementations of PjBL (project-based learning) using sensor and actuator trainer kits as learning mechanisms. The utilization of project-based learning (PjBL) is prevalent in engineering higher education institutions as it has proven to be an effective approach in cultivating lifelong learners, which is crucial in a rapidly advancing technological world [20].

2.2. Data Collection and Analysis

Data collection was carried out using a structured questionnaire and written tests to assess the learning outcomes of sensor and actuator competence. The data obtained from the questionnaire and written tests were subjected to path analysis using Structural Equation Modeling with Partial Least Squares (SEM-PLS) to examine the influence of critical thinking, collaboration, and communication on sensor and actuator competence.

2.3. Methodology

The research methodology employed in this study is a quantitative approach [21], incorporating descriptive features. This specific method was chosen to evaluate the validity and feasibility of measurement model for the variables under investigation. The critical thinking variables are based on the IAEIE model (Interpreted, Analysis, Evaluation, Inferences, Explanation), with 5 indicator [22]. The communication skill variables are based on the verbal and non-verbal model [23]. Collaboration skills variables use the CCIF model (Cooperate, Contribute, Interaction, Flexibility) with 4 indicators [13]. Learning outcomes variables use the CAP model (Cognitive, affective, Psychomotor) with 9 indicators [24].

In this study, the researcher aims to examine the influence of critical thinking, communication skills and the collaborative effects on learning. The researcher expects that the presence of collaborative effects, both between teams and within teams, in completing the assigned learning project can enhance the individual abilities of students, thus impacting their learning outcomes. This can be observed in Figure 1. Students can also study independently by accessing the site:
https://faridbaskoro.wixsite.com/sensordanaktuator
to study the competence of sensors and actuators. Collaborative abilities refer to the capacity to work flexibility in teams, cooperation, interaction, and contribute to achieving shared goals. To measure collaborative abilities, the following methods can be used: team evaluations: observation and assessment of students' ability to collaborate in group tasks, including their level of engagement, contribution, and cooperation in achieving shared goals; peer evaluations: allowing students to assess their peers' contributions in group work through objective and constructive evaluations.

Measuring learning outcomes (cognitive, affective, and psychomotor domains) in these domains, various methods can be employed: written tests, tests involving objective or essay questions to assess students' understanding and knowledge in the cognitive domain; observations: directly observing students' behaviour and responses to measure learning outcomes in the psychomotor domain, such as tool utilization or practical skills. Self-assessment and peer assessment: providing opportunities for students to reflect on and evaluate their progress and development, as well as assessing the progress and development of their peers in the affective domain.

By utilizing these evaluation methods, a more comprehensive picture can be obtained regarding students' critical thinking, communication skills, collaborative skills, and learning outcomes in the cognitive, affective, and psychomotor domain.

The scores from the individual exams will then be collected and processed using a Likert scale ranging from 1 to 5. The Likert scale is used to measure the level of agreement or disagreement with statements or questions provided. It consists of five options, where 1 indicates disagreement (strongly disagree), while 5 indicates agreement (strongly agree).

After collecting the data of individual exam scores using the Likert scale, the next step is to process the data using SEM PLS (structural equation modeling partial least squares) software through the use of path analysis. SEM PLS is a statistical method used to test conceptual models and relationships between variables in research. This method can help analyze and test hypotheses within the collected data. By employing SEM PLS software, the data of individual exam scores will be processed and analyzed to examine the relationships between variables and test the constructed model [25].

The results of this analysis will provide a deeper understanding of individual performance in the practical sessions and can be used for further evaluation and development purposes. The research was conducted from September 2022 to May 2023.

The researcher uses data collection techniques namely questionnaires (to collect collaboration skills, and communication skills), written tests (to collect cognitive), and interviews (to collect learning outcomes in affective, and Psychomotor).

Hair *et al.* state that SEM PLS is a multivariate statistical method used to simultaneously test a series of interrelated effects within a framework, with the goal of prediction, exploration, or development of structural models [20]. PLS-SEM obtains solutions with small sample sizes, when models comprise many constructs and a large number of items [26]. The advantages of using SEM PLS include: not requiring specific distribution assumptions, being able to work with complex models, and focusing on testing theory models that emphasize prediction, exploration, or development. Analysis is performed on latent variables to obtain values or measurements based on observed metrics. Latent variables are classified into two groups based on their function, i.e. exogenous variables (communication skill, collaboration skill) and endogenous variables (cognitive, affective, psychomotor) [27].

Table 1. Variables, sub-indicators, and benchmarks

Variable	Indicator	Code	Benchmark
Critical thinking-adoption from [24]	Interpreted	Kr1	The ability to describe, be able to explain, classify, or find patterns
	Analysis	Kr2	Ability to define and analyze the information provided
	Evaluation	Kr3	Ability to provide an explanation of a problem
	Inferences	Kr4	The ability to provide alternative answers, the ability to make alternative problem solving when there are problems with the sensor
	Explanation	Kr5	The ability to express the final results and provide conclusions from the experiments carried out on the module
Communication skills adopted [28]	Verbal	km1	Ability to write, read, listen, and speak
	Non-Verbal	km2	The ability to understand gestures, the ability to express oneself, understand facial and gaze behaviour
Collaboration Skills [13]	Cooperate	kl1	Ability to provide information to the group, mutual support, and respect
	Contribute	kl2	Material readiness, work productively, ability to inspire
	Interaction	kl3	Ability to communicate and take initiative
	Flexibility	kl4	Adaptability, time management skills, and self-mastery
Learning outcomes [26]	Cognitive	kg1	Ability to explain motion sensors
		kg2	Ability to apply several types of sensors and actuators
		kg3	Ability to explain light sensors
		kg4	Ability to explain temperature sensors
	affective	af1	Ability to work together
		af2	Ability to be independent
		af3	Responsible ability
	Psychomotor	ps1	Ability to describe processes
		ps2	Ability to describe products / results

Sensors and actuators are two essential components in mechatronic systems and various other technological fields. Sensors function to detect physical or environmental changes and convert them into signals or data that can be processed by the system. The information from sensors helps the system to understand and respond to its surrounding environment. On the other hand, actuators are responsible for transforming signals or data from the system into tangible physical actions or responses. Actuators play a crucial role in moving or controlling a system, enabling it to interact with its environment. The combination of sensors and actuators allows the system to operate automatically, efficiently, and adaptively, with various applications such as in autonomous vehicles, security systems, smart manufacturing, and much more.

The relationship between sensors and actuators is crucial in the development of the Internet of Things (IoT). IoT is a concept where various devices and objects connected to the Internet can communicate and interact with each other to gather data, share information, and take actions automatically.

Sensors in the context of IoT act as the system's eyes and ears, detecting various physical or environmental conditions such as temperature, humidity, light, motion, and more. The data collected by sensors is sent over the Internet to a platform or cloud for further analysis. On the other hand, actuators serve as the system's hands and legs, capable of performing physical actions based on commands received from the platform or cloud via the Internet. These actuators can control physical devices, such as opening or closing doors, turning on or off electronic devices, moving machinery, and much more. With a close relationship between sensors and actuators in an IoT system, information from sensors can be used to trigger relevant and timely actions through actuators. For example, when a sensor detects a high room temperature, the IoT system can send a command to the actuator to activate the air conditioning. This enables the IoT system to create a smarter, more efficient, and automated environment, providing tangible benefits in everyday life, such as energy savings, high-level comfort, and better resource management.

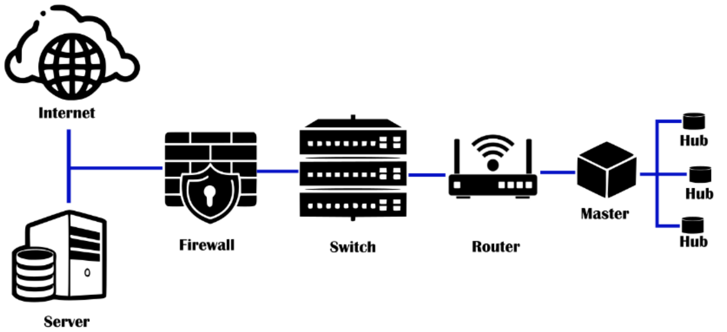
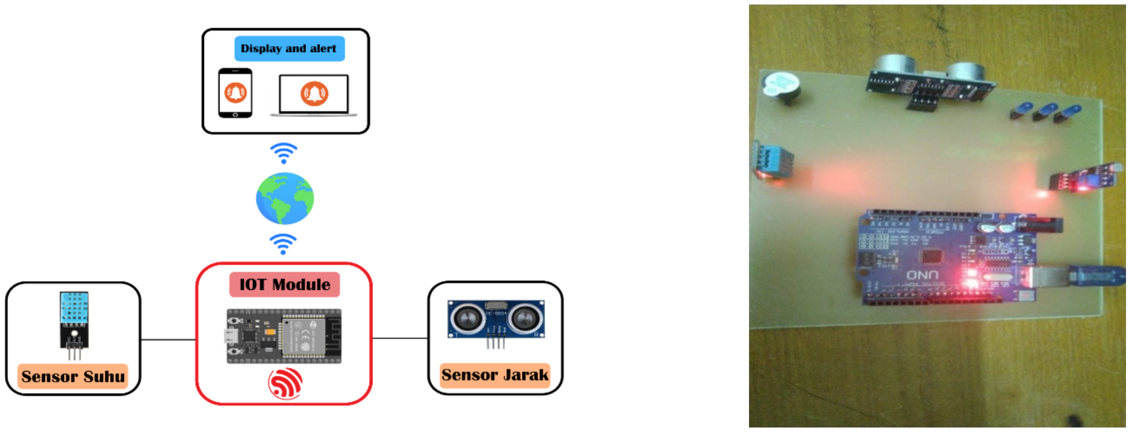


Figure 1. Topology of sensor and actuator in IOT

Figure 1. presents the topology of sensor-actuator readings in the Internet of Things (IoT) while referring to how data is collected from sensors and how actions are controlled by actuators in the connected IoT environment. Several common topologies are used in IoT networks:

1. Hub and Spoke (Star Topology): In this topology, there is a central controller (hub) that serves as the central point to connect and control multiple sensors and actuators scattered around it (spokes). Each sensor sends data to the hub, and the hub then makes decisions and sends commands to the appropriate actuators.
2. Mesh Topology: In this topology, each sensor and actuator is interconnected, forming a network. Data from sensors can be forwarded through other nodes to reach the destination, and actions can be taken by multiple actuators based on information from other sensors. This creates a system that is more fault-tolerant and reliable.
3. Tree Topology: Similar to hub and spoke, this topology uses a hierarchical structure like a tree. The central controller is at the top level (root node), sensors, and actuators are connected to the next level as branches, and the process continues until reaching the end branches. Data and commands can flow from top to bottom or vice versa.
4. Hybrid Topology: Some IoT implementations use a combination of the above topologies to achieve specific goals. For example, a combination of star and mesh for a balance between communication efficiency and system robustness.

The choice of sensor-actuator topology in IoT depends on the application's needs, network size, reliability, and desired system complexity. Each topology has its advantages and limitations, and the appropriate selection will ensure the IoT system functions optimally according to the intended goals. An example of IoT-based sensor and actuator hardware can be seen in Figure 2.



a b.

Figure 2a. Examples of IoT-based temperature sensor and proximity sensor hardware; 2b. an example of one of the boards used for learning sensors and actuators

In this research, critical thinking and collaboration in sensor and actuator competence holds crucial significance in the context of technology and education development. Critical thinking enables professionals and students in the field of sensors and actuators to analytically evaluate and solve complex problems while making informed decisions based on evidence and data. Meanwhile, collaborative skills play a vital role in developing innovative solutions and competitive technological applications. In the continuously evolving era of the Internet of Things (IoT), where sensors and actuators are essential elements in the technology ecosystem, emphasizing critical thinking and collaboration in sensor and actuator competence learning will contribute to creating a skilled workforce capable of tackling future technological challenges effectively.

In accordance with that, students will undergo learning through a series of modules designed in a progressive manner, starting from easy to more complex stages. Students will be required to employ critical thinking skills in analyzing the given problems. The utilization of these modules aims to standardize the learning experience across different universities in examining the influence of critical thinking, collaboration, and communication on sensor and actuator competence, and analyzing students' learning outcomes in the cognitive, affective, and psychomotor domains. By adopting this approach, the research is expected to make a meaningful contribution to enhancing the quality of learning and students' understanding of sensor and actuator competence in a holistic and comprehensive manner. Figure 3. presents an example of an IoT-based temperature and distance display that students can work on and study.

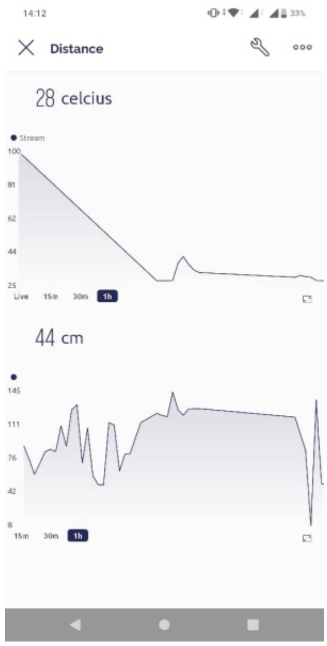


Figure 3. Display of temperature and distance based IoT- on handphone

The research includes a set of 40 questions to measure the collaborative and communicative abilities of the students. Additionally, there are 30 questions designed to assess students' learning outcomes in the cognitive and critical thinking domains. For the psychomotor and affective domains, the assessment will be conducted collaboratively by both the researchers and university faculty members. The responses will be processed on a 5-point Likert scale to facilitate analysis using SEM-PLS software. The path analysis will involve examining the relationships among the independent variables (critical thinking, communicative skills), the intervening variable (collaborative ability), and the dependent variables (cognitive, affective, and psychomotor learning outcomes).

By employing this rigorous methodology, the study aims to provide valuable insights into the connections between students' collaborative and communicative capabilities and their learning achievements in the specified domains.

3. Results

To investigate the causal relationships between the exogenous (independent) and endogenous (dependent) variables, a path analysis using structural equation modeling with partial least squares (SEM-PLS) is employed. The path analysis involves four crucial steps. Firstly, the evaluation of reflective measurement models, where variables are directly measured through indicators that reflect their underlying constructs. Secondly, the evaluation of formative measurement models, where variables are measured through indicators that contribute formatively to their constructs. Thirdly, the evaluation of the structural model, where the causal relationships between the exogenous and endogenous variables are explored and analyzed. Lastly, the model fit evaluation is conducted to ensure the overall model's compatibility with the data and confirm that the resulting model aligns with the characteristics of the analyzed data. By utilizing this path analysis approach, it is expected that the research will provide comprehensive insights into the relationships between the examined variables and their contributions to understanding the phenomenon under investigation.

3.1. Outer Model Test Analysis

The assessment of measurement models for indicators involves the examination of the dependability of individual items, the dependability of internal or combined measures, the variability in sample means, and the discriminated validity. The initial three measurements were categorized based on their ability to converge. From the initial test results, the item value is said to be valid if the test item results with a value (> 0.70); outer test results are shown in Table 2.

Outer model test analysis helps evaluate construct validity. By using path analysis, researchers can examine whether the indicators used to measure a particular variable effectively reflect the measured concept [29]. If these indicators consistently and significantly predict other variables in the model, it suggests a strong relationship and influence within the studied framework. Based on the findings, it can be inferred that the measured construct demonstrates validity. Outer model test analysis can help in selecting the best model that is most suitable for the available data. By comparing the predictive quality of various tested models, researchers can determine the model that best fits the data. Table 2 shows that all of the sub-indicators have a value > 0.7. It can be said that the indicators used to measure critical thinking (kr1, kr2, kr3, kr4, kr5), communication skills (km1, km2), collaboration skills (kl1, kl2, kl3, kl4), cognitive domain (kg1, kg2, kg3, kg4), psychomotor domain (ps1, ps2), and affective domain (af1, af2, af3) effectively reflect the measured concepts.

Table 2. Outer loading

Affective domain		**Cognitive domain**		**Collaborative skill**		**Communicative skill**		**Creative Thinking**		**Psychomotor domain**	
af1	0.953	kg1	0.826	Kl1	0.879	km1	0.919	kr1	0.809	ps1	0.971
af2	0.946	kg2	0.890	kl2	0.926	km2	0.831	kr2	0.784	ps2	0.969
af3	0.948	kg3	0.809	kl3	0.928			kr3	0.760		
		kg4	0.841	kl4	0.884			kr4	0.795		
								kr5	0.747		

3.2. Cronbach's Alfa and Average Variance Extracted

Composite reliability and convergent validity test are two important statistical measures used in the field of research to assess the quality and validity of measurement scales. Composite reliability (CR) is a measure that evaluates the internal consistency and reliability of a measurement scale. It assesses how well the items in a scale collectively measure the underlying construct. Higher values of CR indicate better reliability and consistency of the scale. On the other hand, convergent validity test assesses whether the items within a scale are converging to measure the same construct. This test evaluates the degree to which the items in the scale are positively correlated with each other and with the total scale score. A higher convergent validity indicates that the items are effectively measuring the same construct. Both composite reliability and convergent validity test are crucial in ensuring the accuracy and consistency of the measurement scales used in a research study, providing researchers with confidence in the validity of their findings. According to the data processing results in Table 3, it can be concluded that the validity requirements are met as the AVE value exceeds 0.5. By testing Cronbach's alpha and AVE, researchers can ensure the reliability and validity of the measurement instruments we use.

Table 3. Reliability test results and convergent validity

Variable	Cronbach's Alpha	*Composite Reliability*	*AVE*	Average Communality	Test Results
Affective_domain	0.945	0.965	0.901	0.79	Valid & Reliable
Cognitif_domain	0.863	0.907	0.709		Valid & Reliable
Collaboratif_skills	0.926	0.947	0.818		Valid & Reliable
Communication skill	0.705	0.868	0.767		Valid & Reliable
Critical_thinking	0.839	0.885	0.607		Valid & Reliable
Spychomotor_domain	0.937	0.969	0.941		Valid & Reliable

3.3. Discriminant Validity

The Fornell and Lacker criteria serves as a metric for evaluating discriminant validity, indicating that a variable should be conceptually distinct from other variables and demonstrated as such through empirical evidence [30]. A high level of discriminant validity implies that the measure or indicator captures a unique aspect of the construct, independent from other measures. This is evidenced by the square root of the average variance extracted (AVE) being greater than the correlation between variables. Such differentiation ensures that the measure offers meaningful and independent insights into the specific variable or dimension it represents, without significant overlap or influence from other measures. Additionally, the Heterotrait-Monotrait (HTMT) ratio is another method to evaluate discriminant validity. A HTMT ratio below the recommended threshold of 0.90 signifies discriminant validity, indicating that the constructs are distinct and not strongly correlated with each other. This absence of multicollinearity in the model strengthens the validity of the research findings. When examining the HTMT (Heterotrait-Monotrait) values for all indicators, a threshold of 0.90 is recommended. This threshold indicates that the constructs, namely critical thinking, communicative skills, collaborative abilities, and learning outcomes, are distinct from one another and not strongly correlated.

3.4. Structure Test (Inner and outer Model)

Evaluating the structural model involves testing the hypothesis of influence among research variables. The assessment of the structural model is conducted in three stages, with the first stage focused on verifying the absence of multicollinearity between variables, using the variance inflated factor (VIF) measure where an inner VIF value below 5 indicates there is no multicollinearity between variables. From the results of the structural test, it was found that the inner VIF value was low (<5), this result strengthens the parameter estimation results in the PLS-SEM which are robust (not biased). The second stage is to test the hypothesis between variables by looking at the statistical t-test or p-value if the t-test statistic calculated is higher than 1.96 (as per the t-table), or if the p-value obtained from the test results is below 0.05, indicating a significant influence between the variables. The outcomes of the structural test are presented in Figure 4. The significance test for the direct relationship can be observed in Table 4, while the significance test for the indirect relationship can be observed in Table 5.

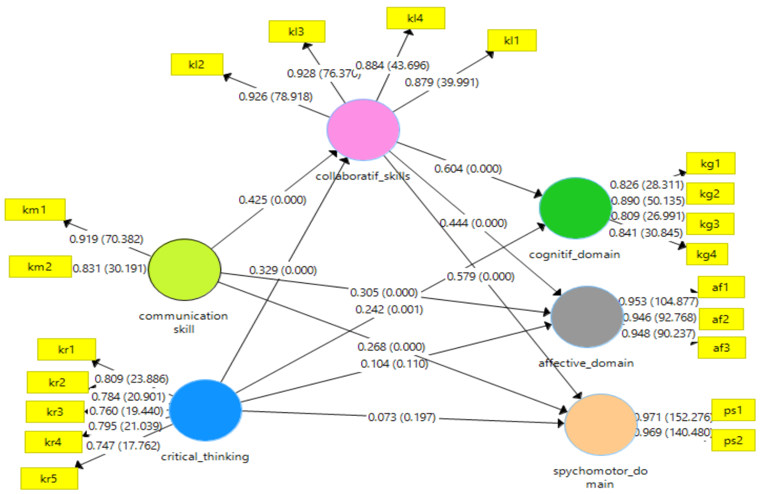


Figure 4. Structure test results of the inner model (path coefficients &p-value) and outer model (outer loading&t-value)

Table 4. Path coefficients direct relationship

	Sample Mean	Original Sample	Standard Deviation	T Statistics (JO/STDEV)	P Values
collaboratif_skills -> affective_domain	0.444	0.437	0.072	6.202	0.000
collaboratif_skills -> cognitif_domain	0.604	0.599	0.072	8.375	0.000
collaboratif_skills -> spychomotor_domain	0.579	0.578	0.058	10.019	0.000
communication skill -> affective_domain	0.305	0.304	0.071	4.328	0.000
communication skill -> collaboratif_skills	0.425	0.420	0.080	5.322	0.000
communication skill -> spychomotor_domain	0.268	0.263	0.061	4.420	0.000
critical_thinking -> affective_domain	0.104	0.110	0.065	1.597	0.110
critical_thinking -> cognitif_domain	0.242	0.248	0.072	3.374	0.001
critical_thinking -> collaboratif_skills	0.329	0.332	0.074	4.452	0.000
critical_thinking -> spychomotor_domain	0.073	0.076	0.057	1.289	0.197
collaboratif_skills -> affective_domain	0.444	0.437	0.072	6.202	0.000
collaboratif_skills -> cognitif_domain	0.604	0.599	0.072	8.375	0.000

Table 5. Path coefficients indirect relationship

	Sample Mean	Original Sample	Standard Deviation	T Statistics (JO/STDEV)	P Values
communication skill -> collaboratif_skills -> affective_domain	0.188	0.185	0.052	3.642	0.000
critical_thinking -> collaboratif_skills -> affective_domain	0.146	0.144	0.037	3.900	0.000
communication skill -> collaboratif_skills -> cognitif_domain	0.257	0.255	0.069	3.731	0.000
critical_thinking -> collaboratif_skills -> cognitif_domain	0.199	0.197	0.043	4.640	0.000
communication skill -> collaboratif_skills -> spychomotor_domain	0.246	0.244	0.058	4.221	0.000
critical_thinking -> collaboratif_skills -> spychomotor_domain	0.191	0.191	0.045	4.228	0.000

In path analysis using the structural equation modeling (SEM) method with partial least squares (PLS) as the analysis technique, "Q square predict" is one of the evaluation metrics to measure the ability of a model to make predictions beyond the data used to build the model itself. A higher Q square prediction value indicates that the model has better predictive ability on data that is not used when building the model. Root mean square error (RMSE) is one of the commonly used evaluation metrics in regression analysis and predictive modeling to measure the extent of the difference between model predicted values and the actual values from the observed data. RMSE calculates the square root of the average of the squared differences between the predicted and observed values across the entire dataset. This metric provides an insight into the level of prediction error of the model, with lower RMSE values indicating higher accuracy of the model in predicting target values. RMSE is useful for comparing the performance of different predictive models and identifying the best model that closely fits the observed data, thereby enabling improvements in model performance and quality.

The inner model analysis plays a vital role in research as it enables researchers to comprehend the relationships between variables, test theories, assess the validity and reliability of instruments, devise intervention strategies, and enhance the overall research quality. Various measures, such as R square (R^2), Q square (Q^2), SRMR, PLS predict, and goodness of fit index (GoF Index), are employed, along with conducting a linearity test to ensure the model's robustness concerning the relationship between variables. The interpretation of R^2 remains consistent with that in linear regression, indicating the degree to which variation in endogenous variables is explained by exogenous variables. On the other hand, Q^2 represents a measure of prediction accuracy, revealing how effectively changes in exogenous and endogenous variables predict the values of endogenous variables.

In the context of structural equation modeling (SEM) with partial least squares (PLS) as its analysis technique, NFI stands for "Normed Fit Index." NFI is one of the evaluation metrics used to measure the quality of model fit with the empirical data used in the analysis.

The normed fit index (NFI) indicates the extent to which the constructed model fits the existing empirical data. NFI values range from 0 to 1, where the closer it is to 1, the better the model fits the data. NFI measures the amount of error in comparing the model to a baseline model, which considers only the correlations between variables without any relationships among the variables.

It is essential to note that NFI does not provide information about the model fit in an absolute sense, but it should be used in conjunction with other evaluation metrics such as goodness of fit index (GoF Index), R square (R2), Q square (Q2), and others to obtain a more comprehensive picture of the quality of the SEM-PLS model that has been constructed

SRMR, or standardized root mean square residual, assesses model fitness by comparing correlation matrices of observed data and the estimated model.

A model is deemed to have a good fit when the SRMR value is below 0.08. If it falls between 0.08 and 0.10, the fit is considered acceptable with room for improvement. In this case, the estimated model yielded an SRMR value of 0.059, indicating an acceptable fit. The goodness of fit index (GoF Index) is utilized to evaluate the overall model fit for the measurement model. Reflective measurements can be computed based on this index, particularly the root average communality with R^2, as shown in Table 3, where the average communality is 0.79, and based on Table 6, the average R^2 value is 0.642, categorizing the model's explanatory power as moderate [20]. These results represent the calculation outcomes for the goodness of fit (GoF). The interpretation of the average GoF Index value is as follows: 0.25 >GoF signifies a low (not fit), 0.25 <GoF <0.75suggests a medium (fit model), and 0.75 <GoF indicates a high (over fit model) [20]. From Table 6, value GOF index is 0.712 which can be categorized as moderate or fit model. The model demonstrates a strong capability in explaining the relationships between critical thinking, communication skills, and collaboration with learning outcomes in the observed data.

Table 6. R square, Q square, SRMR, NFI, Chi-square, and GOF index

	R^2	Q^2_Predict	RMSE	MAE	SRMR	NFI	Gof Index
Affective_domain	0.630	0.498	0.686	0.510	0.059	0.837	0.712
Cognitif_domain	0.675	0.540	0.662	0.454			
Collaboratif_skills	0.511	0.493	0.695	0.518			
Spychomotor_domain	0.750	0.539	0.664	0.473			

Students from the sensor and actuator course are engaged in intriguing group work. A team of students from Petra Christian University's Electrical Engineering department work together on a collaborative project. They engage in discussions about the basic principles of sensors and actuators, and put their knowledge to use by creating innovative sensor systems. The students actively exchange ideas and information, supporting each other in solving problems and enhancing their understanding through in-depth discussions. Additionally, they make use of advanced sensors and simulation software to design and test prototypes of sensor and actuator systems.

On the other hand, at UNESA, a team of Electrical Engineering students work together on their group assignment, with a specific focus on applying sensors and actuators in their field of study. They delve into the practical use of temperature and humidity sensors to monitor room conditions or explore the application of actuators. By leveraging their diverse knowledge, the students synergize their expertise, communicating and collaborating to achieve shared objectives.

They jointly design and implement relevant solutions, making use of laboratory equipment and conducting tests to assess the performance of their developed systems. The collaboration observed in the sensor and actuator course at Petra Christian University and UNESA underscores the significance of working together to integrate knowledge from different disciplines in designing and implementing effective and innovative sensor and actuator systems.

4. Discussion

The main aim of the study is to enhance students' ability to make accurate and efficient decisions while working on challenging projects involving sensors and actuators. By gaining a deeper understanding of the concepts and applications, students will be better equipped to handle complexities and overcome obstacles during project execution. This is evidenced in Tables 4 and 5 that there is a direct and significant influence between critical thinking communication and collaboration skills on learning outcomes in sensor and actuator competencies.

To foster the ability of students in the process of any statistical calculations to determine and rectify faults or malfunctions, especially in sensor and actuator competence: This objective emphasizes the importance of statistical analysis and problem-solving skills in identifying and addressing faults or malfunctions in sensor and actuator systems. By improving their analytical abilities, students can regulate issues effectively, leading to improved system performance and reliability. Based on the findings from Tables 4 and 5, it was observed that individual critical thinking skills had a positive impact on the cognitive domain, but no significant impact on the affective and psychomotor domains. However, when collaborative learning was introduced, it strengthened the relationship between critical thinking and learning outcomes in the affective and psychomotor domains. This enhancement was evident by the statistically significant P-value being less than 0.05 and the t-table value exceeding 1.96. Thus, collaborative learning proved to have a substantial influence on the association between critical thinking and learning outcomes, particularly in the affective and psychomotor domains.

To contribute to the efficiency of different processes when considering certain design works: This objective highlights the significance of optimizing design processes concerning sensor and actuator applications. Students will be encouraged to explore innovative approaches and techniques that streamline design workflows, resulting in more efficient and effective solutions for various engineering challenges. With value GOF index is 0.712, and the model demonstrates a strong capability in explaining the relationships between critical thinking, communication skills, and collaboration with learning outcomes in the observed data.

In summary, these research objectives aim to equip students with the necessary skills and knowledge to excel in the domain of sensor and actuator projects, enabling them to make informed decisions, handle faults efficiently, and enhance the overall efficiency of design processes. By achieving these goals, students can become competent and successful engineers in their future careers.

5. Conclusion

According to the extensive and detailed research regarding mastering the concepts of IoT-based sensor and actuator competence in learning outcomes, several conclusions can be drawn. The obtained conclusions are as follows:

- Individual critical thinking skills have a positive impact on the cognitive domain, but do not significantly influence the affective and psychomotor domains.
- Collaborative learning strengthens the relationship between critical thinking and learning outcomes in the affective and psychomotor domains. This is supported by the statistically significant P-value being less than 0.05 and the t-table value exceeding 1.96, indicating a strong influence.
- These findings demonstrate the significant role of collaborative learning in enhancing the association between critical thinking and learning outcomes, particularly in the affective and psychomotor domains. Collaborative learning can be considered an effective strategy to reinforce the connection between critical thinking and academic achievement in these two domains.
- In this research context, collaborative learning positively contributes to educational goals, especially in developing students' affective and psychomotor skills, which are not solely influenced by individual critical thinking abilities.

Thus, this study provides valuable insights for educators and curriculum designers in designing learning strategies that focus on developing critical thinking skills through collaborative learning approaches to enhance learning outcomes in various domains of student competencies.

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