Modeling the Impact of Robotics Learning Experience on Programming Interest Using the Structured Equation Modeling Approach

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***Abstract*—Proficiency in programming is crucial for driving the Fourth Industrial Revolution. Therefore, interest in programming needs to be instilled in students starting from the school level. While the use of robotics can attract students' interest in programming, there is still a lack of research modeling, the impact of robotic learning experiences on programming interest using a structural equation modeling (SEM) approach. This study aims to analyze the structural relationship between interest in programming and learning experiences using a specially developed robotics module based on Kolb's experiential learning model and the programming development phases. An experiment involving 76 primary and secondary school students was conducted using the robotics module. Data were collected through a questionnaire containing 12 questions for five constructs: engagement, interaction, challenge, competency, and interest. These constructs, which are latent variables, formed the model using the partial least squares-SEM technique through the SmartPLS 4.0 software. The evaluation of the structural model found that the variables of engagement and competency had a significant impact on interest in programming, while interaction and challenge received low values. The developed model has moderate predictive power, indicating that interest in programming can be moderately predicted based on students' experiences using robots.**

Keywords*—Programming; robotics; Structural Equation Modeling (SEM); experiential learning; student engagement

I. Introduction

Mastery of programming skills is essential for advancing the Fourth Industrial Revolution; however, fostering a genuine interest in programming among students at the school level continues to pose a considerable challenge. One effective way to enhance students' interest in programming is by integrating technology in interactive environments, such as using Turtle Graphics for vector-based graphics [1] and incorporating robots to provide hands-on learning experiences. Robotics education has emerged as an engaging avenue for introducing students to programming concepts and cultivating computational thinking (CT) skills [2] Additionally, a study by [3] demonstrated that integrating CT with Educational Robotics (ER) significantly enhances students' CT and programming skills. Given that robotic learning has the potential to significantly boost interest in programming, this approach can contribute to the increase of Science, Technology, Engineering, and Mathematics (STEM) graduates, a current national priority for many governments worldwide, including the United States [4], the UK [5] and Malaysia. Despite these efforts, Malaysia has not yet met its target ratio of 60:40 for students enrolling in STEM versus non-STEM programs [6].

STEM teachers require educational tools that are affordable, hands-on, conceptually engaging, syllabus-aligned, interactive, extendable, and suitable for extracurricular activities. While some schools have adopted available robotic kits, they face challenges such as a lack of syllabus-related modules and the need for more extendable resources to maximize the kits' use. Moreover, many schools are unable to use robotic kits due to funding constraints, limiting their ability to foster interest in STEM. To address these issues, our research has developed robot prototypes called AkalBot, designed with affordability and educational value in mind, selecting Arduino as the main component. The accompanying learning module includes essential knowledge in computational thinking, such as algorithms, to make robotics an accessible and effective tool for enhancing programming interest and supporting STEM education in Malaysia. However, there remains a notable gap in the literature concerning the comprehensive assessment of how robotics learning experiences influence students' programming interest. This study seeks to address this gap by employing structural equation modeling (SEM) to analyze the intricate relationships between programming interest and robotics learning experiences, drawing on Kolb's experiential learning model as a theoretical framework.

Kolb's experiential learning theory provides a theoretical framework for understanding how students acquire and internalize knowledge through concrete experiences, reflective observation, abstract conceptualization, and active experimentation [7]. Applied to robotics education, this theory suggests that hands-on activities with robots offer students opportunities to engage in concrete experiences, reflect on their learning, conceptualize abstract programming concepts, and apply their knowledge in practical contexts [8]. This study aims to investigate the structural relationships between programming interest and robotics learning experiences. Specifically, it seeks to assess how student engagement, interaction, challenge, competency, and interest within the context of robotics education impact programming interest after using the robotic module based on Kolb's model and our robot, AkalBot. The remainder of this paper reviews related work (Section II), details the research methodology, including the experimental design and data analysis techniques (Section III), presents the results of the structural model analysis (Section IV), discusses the findings (Section V), and offers conclusions (Section VI).

II. A Review of Related Work

The use of robotics as a tool to engage students with programming and technology concepts has been extensively studied, emphasizing its potential to promote critical thinking and creativity. For instance, LEGO Mindstorms has been shown to enhance creativity [9], while LEGO WeDo kits have been explored for their role in fostering CT. A study investigating the effects of LEGO® WeDo and the Scratch programming platform on CT skills, grit, and programming abilities among undergraduate educational science students revealed notable outcomes. Using a quasi-experimental design with a pretest-posttest approach, the six-week intervention involved 246 participants (aged 18–23, mean age 20.5 ± 3.37, with a balanced gender distribution). The findings demonstrated that participants using LEGO® WeDo experienced significant improvements in CT skills, exhibited higher levels of grit, and gained a deeper understanding of Internet of Things (IoT) project creation. This study underscores the educational advantages of tangible robotic tools over purely visual programming platforms [10].

Building on these findings, the development of a robotic module tailored for Malaysian students seeks to replicate these educational benefits by introducing a low-cost robotic prototype aligned with the Malaysian school curriculum. The objective is to leverage similar hands-on, tangible tools to actively engage students in STEM learning, fostering deeper understanding and sustaining their interest in pursuing STEM programs. To ensure its effectiveness, survey feedback from STEM teachers was utilized to identify the core requirements for the module, which include being engaging, curriculum-based, easy to understand, and cost-effective [11].

To address this challenge, a customizable module was developed using Arduino as the microcontroller and Google's Blockly as the visual editor, with potential for further enhancement. A study assessed Malaysian students' perceptions of their competency and interest in STEM after engaging with a STEM module and building a robotic prototype. Conducted at the National Science Centre, Malaysia, this activity aimed to address the under-enrollment in STEM programs. The module, based on Kolb's experiential learning theory, incorporated five key activities: watching videos, reading materials, assembling components, using Blockly for programming, and playing a robotic game. The primary goal was to boost STEM interest through robotics and educational games. Evaluated through qualitative and quantitative case studies with students aged 11 to 15, the results showed a positive response, with significant increases in students' interest in STEM, aligning with the Malaysia Education Blueprint 2013-2025 [12]

In recent years, robots and visual editors have gained significant attention for teaching programming and robotics. AelE: A Versatile Tool for Teaching Programming and Robotics Using Arduino, highlights the role of programming in developing problem-solving and abstract thinking skills. Arduino boards, popular for their open hardware design and educational resources, are commonly programmed through text-based environments like Arduino IDE or block-based tools such as mBlock and Scratch. However, these tools often face challenges, such as the need for specific syntax knowledge and limited sensor support. To address these, AelE was developed as a block-based tool designed to simplify programming for students. The tool has been successfully used in diverse educational settings, including secondary schools, adult education, and prison programs. Students across these contexts, regardless of prior knowledge, responded positively to AelE, which was found to effectively support various learning environments and project types, demonstrating its versatility and broad appeal [13].

Despite the growing body of research on robotics in education, there is still a significant gap in understanding how robotics learning experiences impact students' interest in programming. This study aims to fill this gap by utilizing SEM to explore the complex relationships between students' programming interest and their robotics learning experiences, with Kolb's experiential learning model serving as the theoretical foundation.

III. Materials and Methods

The methods to model the impact of robotics learning experience on programming interest using the structured equation modeling approach consists of six main steps. An explanation of each step is given below.

A. *Step 1: Forming Variables to Model the Impact*

In order to form variables to model the impact of learning experience, existing variables that have been used to analyze learning experiences have been investigated. Five variables have been used to model the impact of interaction, engagement and challenge towards interest and competency in the subject area [14]. They have designed hands-on activities for virtual computer laboratories based on Kolb's experiential learning cycle. The study in [15] have further used the variables to quantitatively analyzed for identifying the impact of the experiential activity. The details of the variables that been used to model the impact of using the educational robotic is given below:

- Interaction (ACT): This construct assesses the degree of collaboration among students during robotics exercises. Working in pairs, students engage in completing tasks, tackling new challenges, and jointly reflecting on their learning experiences.
- Engagement (ENG): This construct evaluates students' readiness and enthusiasm to participate in and complete robotics activities. High engagement is evident through active involvement, enthusiasm, and persistence, which are essential for deep and effective learning experiences in programming.
- Challenge (CHA): This construct gauges the perceived difficulty of the robotics activities from the students' perspective. By assessing the complexity and challenge level, this measure helps to understand how the tasks encourage cognitive development, problem-solving, and critical thinking skills.

- Competency (CMP): This construct focuses on the learning outcomes that students perceive they have achieved through robotics activities. Unlike interaction, engagement, and challenge, which evaluate the learning process, competency reflects the end results, indicating students' mastery of programming concepts and their confidence in applying these concepts.
- Interest (INT): This construct measures the increase in students' interest and curiosity in programming due to robotics activities. Like competency, this construct evaluates the outcomes of the learning experience, showing how effectively the activities have stimulated and maintained students' interest in programming.

These variables were integrated to form the research model as shown in Fig. 1. By integrating these variables into a cohesive framework, we can gain valuable insights into the multifaceted nature of learning experiences and their impact on students' academic outcomes. This framework provides a structured approach for examining the interplay between key factors that shape students' learning trajectories, laying the groundwork for subsequent analyses using structural equation modeling (SEM) techniques. Seven hypotheses were developed:

Hypothesis 1 (H1). Challenge is positively related to students' competency.

Hypothesis 2 (H2). Challenge is positively related to students' interest.

Hypothesis 3 (H3). Competency is positively related to students' interest.

Hypothesis 4 (H4). Engagement is positively related to students' competency.

Hypothesis 5 (H5). Engagement is positively related to students' interest.

Hypothesis 6 (H6). Interaction is positively related to students' competency.

Hypothesis 7 (H7). Interaction is positively related to students' interest.

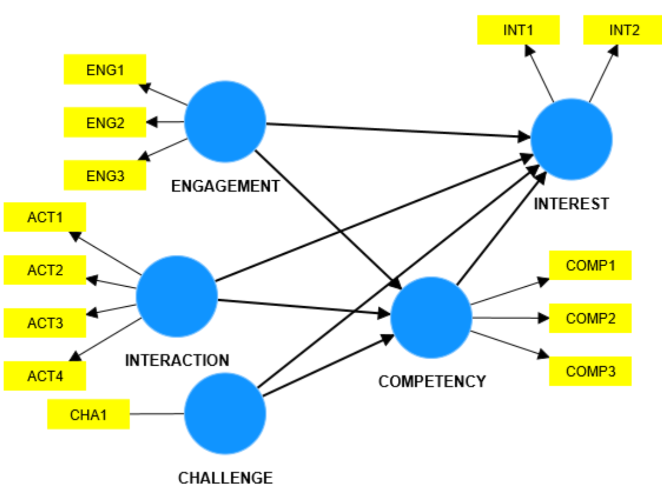

Fig. 1. Research model.

B. *Step 2: Developing Robotic Module Based on the Selected Variables and Kolb's Learning Model*

The working principle of AkalBot is based on the integration of three main components: modules, robot prototypes, and a blockly editor. The robotic kit leverages Kolb's experiential learning theory as the foundation for its modules, which also integrate computational skills like algorithms.

The first component is module design. The module design captures experience as a resource for learning and development [7] through interactive games using robot prototypes. The modules are structured according to the four phases of Kolb's learning theory:

1) Concrete Experience (CE): Students begin with hands-on exercises, such as programming robots, to gain practical experience.

2) Reflective Observation (RO): Students provide feedback on a series of tasks, reflecting on their experiences from the CE phase.

3) Abstract Conceptualization (AC): Students develop strategies to win specified games based on provided theoretical concepts.

4) Active Experimentation (AE): Students implement their strategies to achieve game objectives.

These phases are designed to promote deep learning and engagement by cycling through practical exercises, reflection, strategy formulation, and experimentation.

The second component is robot prototypes. AkalBot (Fig. 2) features low-cost robot prototypes designed with affordability and accessibility in mind, making the robotic kit an attractive option for schools and higher education institutions. The core component of these robots is the Arduino microcontroller board, known for its low cost, ease of use, and flexibility. Arduino can interact with a variety of components such as buttons, motors, LEDs, and GPS modules. The study in [16] highlights several advantages of using Arduino in educational robotics. One of the key strengths is the ability to load experimental scripts directly onto the board's memory, allowing the Arduino to operate independently without the need for continuous interfacing with computers or external software. This feature provides complete independence, portability, and accuracy in experiments. Additionally, Arduino benefits from a large community that supports its use by offering numerous hardware add-ons and hundreds of free scripts for various projects, making it an accessible and versatile tool for educational purposes. Arduino is particularly suitable for educational purposes due to the abundance of available resources, hardware add-ons, and free scripts for various project ideas.

The third key component of AkalBot is its utilization of a block-based editor, which is a visual programming tool developed by Google. Modified blocks within this platform form AkalBlok (Fig. 3), facilitating a drag-and-drop interface that enables students to program the robots without the need to delve into intricate programming languages. This visual approach aims to captivate primary and secondary students, enticing them to explore the realms of robotics and programming. Within the AkalBlok platform, students encounter specific blocks tailored for programming Arduino-related components, neatly categorized into three main types: Arduino Parts, Arduino Sensor, and Arduino Motor.

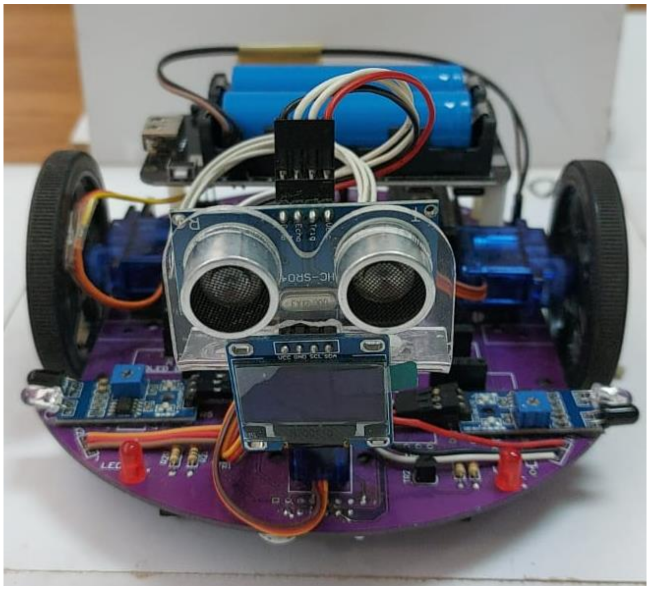

Fig. 2. A robotic prototype named AkalBot.

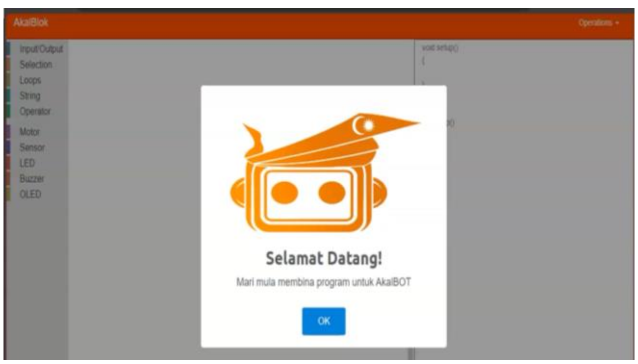

Fig. 3. A block-based editor named AkalBot.

AkalBot's overall design revolves around game-based activities, wherein students apply control over robot prototypes using the block-based editor to create programs. This innovative design framework embraces experiential learning theory, effectively harnessing hands-on experiences as a facilitator for learning and development. By integrating these elements, AkalBot emerges as a comprehensive and immersive educational tool, adept at augmenting students' programming skills and cultivating their interest in the subject matter.

C. *Step 3: Setting Up an Experiment with Students*

In this study, the population consisted of 76 primary and secondary school students who participated in an experiment designed to assess the impact of a robotics learning module on their interest in programming. The robotics module, developed based on Kolb's experiential learning model, guided the students through different programming development phases. Data were collected during the experiment through a questionnaire, which consisted of 12 questions focused on five key constructs: engagement, interaction, challenge, competency, and interest. These constructs were used as latent variables to form the structural model, which was analyzed using partial least squares structural equation modeling (PLS-SEM) through SmartPLS 4.0 software. The experiment consisted of five sessions, each lasting three hours, designed to evaluate the impact of robotics learning on students' programming interest and skills.

1) Session 1: Pre-Test and Introduction (20 minutes): Activity: Students answered pre-test questions to assess their initial knowledge of basic robotics and programming concepts. This session aimed to establish a baseline for their understanding and skills.

2) Session 2: Introduction to Robotic Kit and a Blok-based Editor (30 minutes): Activity: Students were introduced to the AkalBot robotic kit and the AkalBlok programming environment. This session included a detailed explanation of how to use the kit and the drag-and-drop interface of AkalBlok to program the robots.

3) Session 3: Hands-On Robotic Assembly and Initial Programming (60 minutes): Activity: Students engaged in the assembly of robot prototypes and performed initial programming exercises. This session followed the Concrete Experience (CE) phase of Kolb's learning theory, where students learned through hands-on activities.

4) Session 4: Reflective Observation and Strategy Planning (60 minutes): Activity: Based on their hands-on experiences, students reflected on their activities and provided feedback. This session corresponded to the Reflective Observation (RO) phase, where students analyzed their experiences and planned strategies for upcoming tasks.

5) Session 5: Implementation and Experimentation (60 minutes): Activity: Students implemented their strategies and engaged in further programming to accomplish specific tasks using the robots. This session combined the Abstract Conceptualization (AC) and Active Experimentation (AE) phases, encouraging students to apply theoretical concepts in practical scenarios.

D. *Step 4: Collecting Data and Analyzing Model*

The empirical data utilized in this study are considered primary as they were directly gathered through a survey conducted among students. To assess the effectiveness of the robotic educational experience, data collection encompassed a combination of quantitative and qualitative methodologies. The subsequent steps were followed:

1) Surveys and Questionnaires: Students filled out surveys and questionnaires to provide feedback on their learning experiences, engagement, and interest levels throughout the experiment.

2) Observation: Instructors observed student interactions with the robotic kit. The measurement model is foundational to structural equation modeling (SEM), offering a robust assessment of the reliability and validity of the constructs under investigation. In addition to assessing convergent validity through factor loadings, composite reliability (CR), and average variance extracted (AVE), discriminant validity is a critical aspect that ensures the distinctiveness of the constructs [17].

1) Factor loading: Factor loading examines the strength of the relationship between observed variables and their corresponding latent constructs. High factor loadings (> 0.70) indicate that the observed variables effectively capture the underlying constructs [17].

2) Composite Reliability (CR): CR assesses the internal consistency of a set of indicators for each latent construct. CR values exceeding 0.70 indicate satisfactory reliability, implying that the indicators consistently measure the underlying construct [18].

3) Average Variance Extracted (AVE): AVE quantifies the proportion of variance captured by a construct's indicators relative to measurement error. AVE values > 0.50 indicate adequate convergent validity, suggesting that the observed variables collectively represent the latent construct effectively [19].

4) Discriminant validity (Heterotrait-monotrait ratio): Discriminant validity examines whether the constructs are empirically distinct from one another. The heterotrait-monotrait (HTMT) ratio compares the correlations between constructs (heterotrait correlations) with the average correlations within constructs (monotrait correlations). A threshold value of 0.90 is suggested for HTMT ratios to ensure discriminant validity [20]. It measures how much more strongly items within the same construct are related to each other compared to items across different constructs.

Analyzing the structural model is a crucial step in SEM using SmartPLS, as it helps to understand the relationships between constructs and validate the hypothesized paths. This step involves evaluating various metrics such as path coefficients (β), standard errors (SE), t-values, p-values, effect sizes (f^2), variance inflation factors (VIF), and predictive relevance (Q^2 Predict). The following provides a detailed explanation of each component within the context of SmartPLS:

1) Path Coefficients (β): Path coefficients represent the strength and direction of the relationships between constructs, ranging from -1 to +1. Positive values indicate positive relationships, while negative values indicate negative relationships. High absolute values indicate stronger relationships. For example, a path coefficient of 0.45 between robotics learning experience and programming interest suggests a moderate positive relationship [21].

2) Standard Error (SE): The standard error measures the precision of the estimated path coefficients, indicating how much the estimated coefficient would vary from the true population value. Smaller SE values indicate more precise estimates. For instance, an SE of 0.07 for a path coefficient of 0.45 suggests that the estimate is quite precise [22].

3) t-value: The t-value assesses the statistical significance of the path coefficients, calculated by dividing the path coefficient by its standard error ($t = \beta / SE$). A higher absolute t-value indicates stronger evidence against the null hypothesis. Typically, a t-value greater than 1.96 is considered significant at the 0.05 level. For example, a t-value of 6.43 indicates a highly significant relationship [23].

4) p-value: The p-value indicates the probability that the observed relationship is due to chance. A p-value less than 0.05 is typically considered statistically significant. For example, a p-value <0.001 suggests a very low probability that the relationship occurred by chance, thus confirming the significance of the path coefficient [17].

5) Effect Size (f^2): The f^2 effect size measures the impact of a specific exogenous variable on an endogenous variable, calculated based on the change in the R^2 value when the exogenous variable is included in the model. Effect size values are interpreted as follows:

a) Small effect: $f^2 = 0.02$

b) Medium effect: $f^2 = 0.15$

c) Large effect: $f^2 = 0.35$ For instance, an f^2 of 0.20 indicates a medium effect, suggesting that robotics learning experience has a moderate impact on programming interest [24].

6) Variance Inflation Factor (VIF): The VIF assesses multicollinearity among the exogenous constructs. High multicollinearity can inflate the standard errors and affect the reliability of the path coefficients. VIF values greater than 5 indicate significant multicollinearity. A VIF of 1.15 suggests low multicollinearity, indicating that the estimates are reliable [17].

7) Explained Variance (R^2): R^2 quantifies the proportion of variability in the dependent variable explained by the independent variables in the model. A high R^2 value indicates that a large portion of the variability in the dependent variable is captured by the predictors, suggesting a robust model fit. Conversely, a low R^2 suggests that the predictors fail to explain much variability in the dependent variable. According to [24] R^2 values can be categorized as follows:

a) Weak: R^2 values between 0.01 and 0.25

b) Moderate: R^2 values between 0.26 and 0.49

c) High: R^2 values of 0.50 and above

8) Predictive Relevance (Q^2 Predict): PLS Predict assesses the model's predictive power by generating predictions for new data and comparing them with actual observed values. The key metrics include:

a) Q^2 Predict: Indicates the predictive relevance of the model for a specific endogenous construct. A Q^2 Predict value greater than 0 indicates predictive relevance [25].

b) RMSE (Root Mean Squared Error): Evaluates the accuracy of the predictions. Lower RMSE values indicate better predictive performance.

c) MAE (Mean Absolute Error): Measures the average magnitude of the prediction errors. Lower MAE values indicate more accurate predictions.

9) Decision based on Statistical Analysis: The decision indicates whether the hypothesis is supported. If the p-value is less than 0.05 and the path coefficient (β) is in the hypothesized direction, the hypothesis is typically considered supported. For instance, if β is 0.45, t-value is 6.43, and p-value <0.001, the hypothesis that robotics learning experience positively affects programming interest is supported [23].

IV. Results

A. Measurement Model

The measurement model was evaluated to determine the reliability and validity of the constructs used in this study. Table I presents the factor loadings, composite reliability (CR), and average variance extracted (AVE) for the constructs: Engagement (ENG), Interaction (ACT), Challenge (CHA), Competency (COMP), and Interest (INT).

TABLE I. Factor Loadings, Composite Reliability (CR), and Average Variance Extracted (AVE) for Engagement, Interaction, Challenge, Competency, and Interest Constructs

Construct	Items	Factor Loading	CR	AVE
ENG	ENG1The activity was enjoyable.	0.916	0.795	0.829
	ENG2 The activity was interesting.	0.905		
ACT	ACT1 Asking questions to other students.	0.715	0.751	0.571
	ACT2 Observing other students.	0.742		
	ACT3 Discussions with other students.	0.819		
	ACT4 Interacting with other students.	0.741		
CHA	CHA 1 The activity was challenging.	1.000		
COMP	COMP1 I felt that I learned important skills	0.798	0.738	0.656
	COMP1 I felt a sense of accomplishment after completing the activity.	0.807		
	COMP1 The activity improved my competency in the subject area.	0.824		
INT	INT1 The activity increased my curiosity and interest in this area.	0.901	0.724	0.774
	INT2 The activity encouraged me to learn more about this topic.	0.858		

The Engagement construct was assessed through two items: "The activity was enjoyable" (ENG1) and "The activity was interesting" (ENG2), achieving high factor loadings of 0.916 and 0.905, respectively. With a composite reliability (CR) of 0.795 and an average variance extracted (AVE) of 0.829, these results demonstrate strong internal consistency and convergent validity, confirming reliable measurement of Engagement in this study.

The Interaction construct, measured by four items with factor loadings ranging from 0.715 to 0.819, yielded a CR of 0.751 and an AVE of 0.571. While these figures are acceptable, the lower factor loadings suggest the need for item refinement to better capture the essence of interaction in robotics learning.

The Challenge construct was represented by a single item, "The activity was challenging" (CHA1), which showed a perfect factor loading of 1.000. However, reliance on a single item may not fully encompass the multifaceted nature of challenges encountered by students.

For the Competency construct, three items achieved factor loadings between 0.798 and 0.824, resulting in a CR of 0.738 and an AVE of 0.656. These values indicate satisfactory reliability and validity, effectively reflecting students' perceived learning outcomes from robotics activities.

Lastly, the Interest construct comprised two items: "The activity increased my curiosity and interest" (INT1) and "The activity encouraged me to learn more" (INT2), with factor loadings of 0.901 and 0.858, respectively. The CR was 0.724 and the AVE 0.774, confirming robust internal consistency and good convergent validity, indicating effective measurement of increased interest and curiosity in programming.

In summary, while Engagement and Interest exhibited strong psychometric properties, some constructs, particularly Interaction, may benefit from item refinement. Overall, these findings affirm the model's effectiveness in capturing critical dimensions of the robotics learning experience and its influence on programming interest.

B. Structural Model

The structural model, as shown in Fig. 4, was assessed to test the hypothesized relationships among the constructs. Table II presents the results of the hypothesis testing, and Table III displays the R^2 values for the endogenous latent constructs.

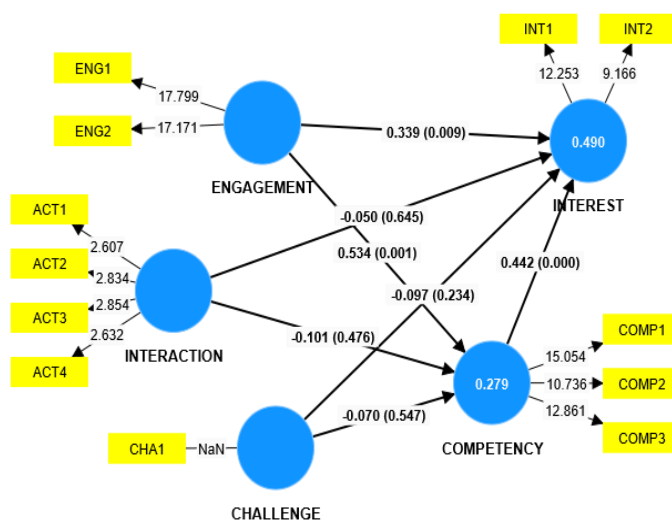

Fig. 4. Structural model analysis using SmartPLS.

TABLE II. HYPOTHESIS TESTING- RESULTS OF STRUCTURAL MODEL (SIGNIFICANT AT $P^{***} < 0.001$, $P^{**} < 0.01$, $P^{*} < 0.05$)

Hypothesis	β,	t-Value	p-Value	f^2	VIF	Decision
H1	-0.070	0.603	0.547	0.006 small	1.059	Not Supported
H2	-0.097	1.189	0.234	0.017 small	1.066	Not Supported
H3	0.442	4.226	0.000	0.276 medium	1.386	Supported***
H4	0.534	3.223	0.001	0.331 medium	1.194	Supported**
H5	0.339	2.602	0.009	0.142 small	1.588	Supported**
H6	-0.101	0.712	0.476	0.012 small	1.151	Not Supported
H7	-0.050	0.461	0.645	0.004 small	1.165	Not Supported

TABLE III. THE R^2 VALUE FOR THE ENDOGENOUS LATENT CONSTRUCTS

Constructs	R^2	Results
Competency	0.279	Weak
Interest	0.490	Moderate

Following this assessment, the study aimed to explore the structural relationships between programming interest and learning experiences within the robotics module using a structural equation modeling (SEM) approach. The analysis indicated that the challenge component did not significantly impact students' perceived competency (H1: β = -0.070, p = 0.547) or their interest in programming (H2: β = -0.097, p = 0.234). This finding underscores a misalignment between the difficulty of tasks and the students' readiness, suggesting that merely increasing challenge levels may not lead to improved learning outcomes unless accompanied by appropriate scaffolding.

Conversely, the hypothesis that competency positively impacts interest (H3: β = 0.442, p < 0.001) was strongly supported, confirming that students who perceive themselves as competent in programming exhibit a higher level of interest.

Engagement also emerged as a significant predictor of both competency (H4: β = 0.534, p < 0.01) and interest (H5: β = 0.339, p < 0.01). These results underscore the dual role of engagement in educational settings, as it not only enhances learning outcomes but also fosters a deeper interest in programming. Engaging and enjoyable activities can captivate students' attention, encouraging active participation and sustained motivation.

However, interaction did not significantly affect competency (H6: β = -0.101, p = 0.476) or interest (H7: β = -0.050, p = 0.645), suggesting that the quality of peer interactions may need enhancement to effectively contribute to learning outcomes. Effective scaffolding and support during collaborative tasks are crucial to maximizing the potential benefits of interaction.

The model demonstrated moderate predictive power, with R^2 values of 0.490 for interest and 0.279 for competency, indicating that it explains a reasonable portion of variance in both constructs.

V. DISCUSSION

The hypothesis testing revealed that engagement and competency had a significant positive effect on students' interest in programming, while the constructs of interaction and challenge showed lower influence. The findings suggest that the developed model has moderate predictive power, indicating that students' experiences with robotics can moderately predict their interest in programming. Overall, this study provides valuable insights into how engagement and competency influence students' interest in programming through robotics. The results suggest that creating engaging learning experiences, aligned with students' skill levels, is essential for fostering interest in programming and preparing students for the demands of the Fourth Industrial Revolution.

In terms of active involvement, students were deeply engaged, especially when the robot successfully moved toward a slipper. This engagement was driven by the necessity to program the robot, as it would not move without the students' input. For example, Fig. 5 depicts a group of students discussing the development of a program during the coding phase.

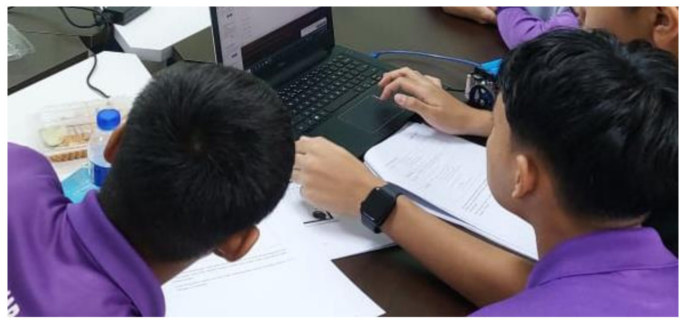

Fig. 5. A group of students engaged in discussion while developing a program during the coding phase.

Regarding enthusiasm, students were excited to tackle the tasks, primarily because the activity required problem-solving. The problems were presented in the form of a game, specifically making the robot knock over a slipper. This game was inspired by a traditional Malaysian game in which a player uses a slipper to topple a stack of slippers. By adapting the game to involve robots, students had the opportunity to explore programming while also appreciating a traditional Malaysian concept. This fusion of elements likely contributed to the increased enthusiasm among the students. Feedback from students supports this:

"I was very happy to use robots in this programming learning session because I could understand the subject more deeply."

"I was excited and curious to code for this robot."

Persistence was another notable aspect, with students showing determination to complete the tasks despite challenges. Some groups encountered difficulties in making the robot move as intended, requiring them to repeatedly adjust program values, such as the delay. The robot's movement varied depending on factors like battery power, tire condition, and servo motor settings. Through a series of tests, students eventually understood the relationship between the program and the robot's output. They also applied computational thinking techniques, such as pattern recognition. Feedback reflecting this persistence includes:

"It was fun yet tiring because of the repeated errors, but we got to learn something new in the end."

"I felt skeptical at first about whether we would manage to finish, but as I worked with my group, I became confident we could succeed."

Beyond engagement, the Interaction construct also demonstrated satisfactory factor loadings, indicating that students actively interacted with their peers during the activity. This was evident from responses like:

"I feel happy because I got to discuss different ideas and solutions with other students."

"I enjoyed this programming learning. Robots and friends made the activities fun."

"I felt confused and worried that I wouldn't be able to contribute to my team, but as the instructor helped us out, I felt more connected."

The structural model results reveal that engagement and perceived competency play a crucial role in fostering students' interest in programming and robotics. Significant relationships were found between engagement and competency (H4) and between engagement and interest (H5). These findings suggest that when students are actively engaged in learning activities, they are more likely to feel competent, which in turn increases their interest in the subject. Additionally, the significant link between competency and interest (H3) indicates that as students perceive an improvement in their skills, their curiosity and eagerness to learn more also grow, reinforcing the positive cycle between competence and interest.

However, the study also found that interaction did not have a significant impact on either competency or interest. Despite the common belief that peer discussions and collaborative learning enhance educational outcomes, the results indicate that these interactions did not translate into measurable improvements in students' competency. Although students enjoyed discussing ideas and solutions with their peers, as reflected in qualitative feedback, these exchanges may not have been sufficiently focused or impactful to deepen their engagement with the subject matter. To enhance the effectiveness of interactions in future implementations, it may be necessary to structure these activities more intentionally, ensuring that they promote meaningful cognitive engagement and skill development rather than just social interaction.

Conversely, the hypotheses examining the impact of challenge on both competency (H1) and interest (H2) were not supported. This suggests that the level of difficulty presented by the activities did not significantly contribute to students' perceptions of their skills or their interest in the subject. While challenges are necessary for learning, they must be carefully balanced to avoid discouragement. Student responses, such as the view that programming was complicated and difficult or that the activity was interesting but challenging, underscore the importance of making challenges approachable. Maintaining this balance is crucial for sustaining engagement and fostering positive learning outcomes. These findings highlight the need for well-designed, appropriately challenging activities to enhance students' perceived competency and sustain their interest in STEM education.

The study's findings highlight the importance of carefully structuring interactions and challenges to enhance competency and interest effectively. Without adequate support, these elements may fail to produce the desired outcomes. Creating meaningful learning experiences in programming requires thoughtful technology integration, including appropriate applications, media, systems, and approaches. Misaligned or improper use of technology can hinder students' confidence and problem-solving skills. A well-designed framework that incorporates contextual and meaningful learning objectives is essential for optimizing technology integration [26]. Furthermore, technologies such as augmented reality (AR) can support STEM-based activities [27] and be seamlessly integrated into such a framework.

Despite these insights, the study has limitations. The relatively lower factor loadings for the Interaction construct indicate that the measurement of this construct could benefit from refinement. Additionally, the reliance on a single item for the Challenge construct may not fully capture the multifaceted nature of the challenge experienced by students. Future research should address these limitations by developing more comprehensive measures for these constructs and exploring their impact in different educational contexts

VI. Conclusions

In conclusion, this study highlights the critical factors influencing students' interest in programming through robotics education. To enhance engagement, educators must focus on creating interactive and enjoyable learning experiences that actively involve students. Incorporating hands-on robotics activities can significantly stimulate curiosity and motivation, leading to improved learning outcomes. Additionally, fostering students' perceived competency in programming is essential; scaffolded learning activities and continuous feedback should be implemented to reinforce their skills and confidence. While interaction and challenge play vital roles in the learning process, they must be carefully structured with adequate support to avoid overwhelming students. Thus, educators should ensure that challenges are appropriate to students' skill levels, enabling meaningful interactions that enhance learning without causing disengagement.

A significant limitation of this study was the students' tendency to hasten through the reflection phase, which limited opportunities for deeper learning. To address this, future iterations of the module could include additional activity cycles with structured reflection phases, allowing students to analyze algorithms and their outcomes to better understand cause-and-effect relationships. Incorporating guided reflection tasks, supported by AI tools such as ChatGPT, could further enhance this process by fostering thoughtful analysis and encouraging meaningful insights.

As advancements in AI continue to reshape education, future modules could also introduce a dedicated phase for students to explore AI concepts and applications. While this presents an exciting opportunity to align with emerging technological trends, it also raises challenges related to resource allocation and the need for specialized teacher training. By addressing these aspects, robotics education can adopt a forward-looking approach, equipping students with essential skills for navigating and contributing to the evolving technological landscape, while maintaining a structured and engaging learning environment.

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